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# The effect of financial regulations on stock markets and bank behaviors

Editor's Introduction

**Hidetomo Takahashi**

We are very glad to introduce this special issue of JIES, entitled "The effect of financial regulations on stock markets and bank behaviors". The five papers contained in this special issue are the outcome of the research project "The role of regulations and systems in the financial markets", which was conducted at the Institute of Comparative Economic Studies, Hosei University, from April 2014 to March 2016. In the project, we mainly explored the relationship between financial regulations and stock markets/corporations/banks through an analysis of stock prices and corporate/bank behaviors.

In this special issue, we believe that we can provide interesting outlets for research. The first paper "Individual investor flows and a cross-section of stock returns: Evidence from Japan" is written by the editor, Hidetomo Takahashi. Using the change in annual ownership of individual investors as a proxy for noise trading, I provide two important results. The study shows that stocks heavily sold by individual investors outperform stocks heavily purchased and that the outperformance of stocks heavily sold by individual investors over the stocks they heavily purchase is stronger among firms with stronger limits to arbitrage, which indicates that stocks with strong purchase pressures tend to be overpriced.

The second paper "The value premium and the market-dynamic conditional momentum effect: Evidence from the Japanese stock market" is written by Naoya Shiomi. The paper shows that a source of the volatility of the value premium can be partly driven by the market-dynamic conditional momentum effect.

The third paper "Does mispricing drive the value effect? Evidence from Japan" is written by Naoya Shiomi, Hidetomo Takahashi, and Peng Xu. The paper provides supportive evidence for the hypothesis that the behavioral biases of investors drive the value effect by finding that the value effect is stronger among stocks with higher degrees of limit-to-arbitrage after controlling for the effects of risks such as investment factors and financial distress.

The fourth paper "Does tax-loss selling affect January returns? Evidence from the capital gain tax rate changes in Japan" is written by Hidetomo Takahashi. The paper points out that tax-loss selling drives the January effect by focusing on changes in the capital gains tax regime and examining whether tax-loss selling affects returns around the turn of the year.

While the first four papers focus on topics related to anomalies in the stock market, the last paper focuses on bank behaviors. This paper, "Bank-specific determinants of capital structure: New evidence from Japan", is written by Taku Kinai and Takeshi Osada. The paper shows that the determinants of the capital structure of Japanese banks vary and change in accordance with the differences in their business models.

Finally, we thank the authors who submitted to this special issue for their cooperation, and hope that this issue will contribute to the existing literature on this subject.

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# Individual investor flows and cross-section of stock returns: Evidence from Japan

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## Abstract

This paper examines whether noise trading has signicant impacts on the cross-section of stock returns by analyzing the relationship between the trading activity of individual investors and future stock returns. I nd that stocks heavily sold by individual investors outperform stocks heavily purchased by 0.73 percent per month, which is more pronounced among rms with stronger limits to arbitrage. These ndings are in accord with the predictions of noise trader models in which the systematic activities of noise traders affect stock returns when they trade in concert and there is limitation to the activities of rational arbitrageurs.

***Keywords***: Individual investor, Noise trader, Behavioral nance

***JEL classification:*** **G10; G12; G14**

## 1. Introduction

The question of whether noise traders significantly distort asset prices has been a much debated topic for decades. Under the traditional finance paradigm, the current price of a stock closely reflects the rationally discounted value of expected cash flows, in which the cross-section of expected returns depends only on the cross-section of systematic risks. Even if there are irrational investors in the market, rational arbitrageurs cancel out the demand of irrational investors, which results in no significant impacts of irrationality on security prices. In contrast, there is an alternative view that noise traders have important roles in the formation of securities prices. [1] Correlated behaviors of noise traders and limits to arbitrage prevent rational investors from fully absorbing correlated shocks of noise trading, which induce commonality in stock returns other than systematic risks and thereby generate the cross-sectional difference in stock returns.

This study examines whether noise trading has significant impacts on the cross-section of stock returns. More specifically, this paper analyzes the future returns to portfolios with buying or selling pressures of individual investors, who are likely to be regarded as noise traders in most theoretical

[1] Shleifer and Summers (1990), De Long et al. (1990), De Long et al. (1991), and Shleifer and Vishny (1997) document that rational and informed traders face risks that are likely to limit their actions if noise trading infuences securities prices, even in the markets where some investors are rational and informed. Without limits to their actions, the effect of noise trading would soon diminish because rational and informed investors arbitrage against the mispricing due to the presence of irrational noise traders.

models. [2] The main finding in this paper is that stocks with a strong selling pressure of individual investors outperform stocks with a strong buying pressure of individual investors. In other words, stocks that individual investors choose to include in their portfolios are more likely to underperform in the subsequent period.

To construct the measure of noise trading pressure of a particular stock, I use annual share-ownership data of listed firms in the Japanese stock markets, which provide the number of shares held by some investor groups: individual investors (including members of manage rial boards), governments, brokerage firms, financial institutions, corporations, and foreign individuals and institutions. As all Japanese listed firms are mandated to disclose their share ownership profiles at the end of the fiscal year, this study can conduct a more robust empirical examination of the noise trading effect on stock prices with broader observations. Furthermore, although the data provide information on trading behaviors less frequently (only annually), the advantage of this data is to identify trading behaviors of noise traders, namely, individual investors more accurately than previous studies. For each stock, I calculate the change in individual investors' holdings, excluding managerial boards' holdings from the end of the last fiscal year to the end of the current fiscal year, which is divided by shares outstanding to normalize across stocks. The variable is defined as the net individual investor trading flow (NIF). Firms with strong individual buying pressure (high NIF) are more likely to have small market capitalizations, low one-year cumulative returns during the change, and high book-to-market ratios than firms with strong individual selling pressure (low NIF).

Using the net individual investor trading flow (NIF), I construct five value-weighted NIF portfolios each month. In each month, stocks are sorted into five value-weighted portfolios according to NIF as measured over a year prior to the latest end of fiscal year from the portfolio formation date. When performance is measured by Jensen's alpha, stocks heavily sold by individual investors do not outperform or underperform stocks heavily purchased. In contrast, when performance is measured by a five-factor model's alpha, results show that stocks heavily sold by individual investors outperform stocks heavily purchased by 0.73 percent per month, that is, about 8.8 percent per annum. This finding indicates that systematic behaviors of noise traders also have important roles in the formation of securities prices. In addition, I find that the NIF long-short portfolio has a positive factor loading on a value factor. This finding indicates that investment tilts of individual investors toward value stocks contribute to the improvement of the market-adjusted return on the NIF longshort portfolio. The results in this study remain unchanged in subsample analyses and other robustness checks. Using the annual ownership change of individual investors in Japan, this study first confirms the existence of a strong relation between the trading behaviors of individual investors and future stock returns. [3]

This study also tests whether the difference of diffculty to arbitrage affects the relationship between noise trading and subsequent stock returns. Theoretically, Shleifer and Vishny (1997)

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[2] Recent empirical studies on individual investors also lend empirical support for the relevance for their irrationality. For example, individuals have the tendency to trade too much (Odean, 1999; Barber and Odean, 2000, 2001), realize capital gains quickly but hold onto capital losses (Odean, 1998), and hold underdiversfied portfolios (Goetzmann and Kumar, 2008). In addition, their trading behaviors are correlated and persistent, which generates a systematic component in stock returns (Kumar and Lee, 2006; Barber, Odean, and Zhu, 2009).

[3] Although Kim and Nofsinger (2007) conduct a similar analysis for this study, they fail to nd that stocks heavily sold by individual investors outperform stocks that are heavily purchased. Instead, they find the opposite result. While I exclude managerial ownership included in individual ownership in this study, they do not. When managers sell stocks they own to individual investors, the raw value of individual ownership does not change. However, as managers are corporate insiders rather than noise traders, the exclusion of managerial ownership is more preferable to calculate a more accurate proxy for the trading behaviors of noise traders. The failure to exclude managerial ownership from individual ownership might generate the difference between their paper and this paper.

document that some limits to arbitrage must exist for mispricing to persist in the presence of sophisticated professional investors. The effect of noise trading on stock prices varies according to the degree to which it is diffcult for rational investors to arbitrage. In recent empirical studies, financial anomalies are found to be more pronounced among firms with higher idiosyncratic risks (Pontiff, 1996; Wurgler and Zhuravskaya, 2002; Ali, Hwang, and Trombley, 2003; Mendenhall, 2004; Mashruwala, Rajgopal, and Shevlin, 2005) and stricter short-sale constraints (Chen, Hong, and Stein, 2002; Diether, Malloy, and Scherbina, 2002; Jones and Lamont, 2002; Lamont, 2004; Ofek, Richardson, and Whitelaw, 2004; Reed, 2003; Nagel, 2005). Therefore, I employ two measures of limits to arbitrage, idiosyncratic risk and residual institutional ownership (a proxy for short-sale constraints). [4] I find that the difference in returns between the lowest NIF portfolio and the highest NIF portfolio is stronger among firms with stronger limits to arbitrage. In particular, when I use a proxy for short-sale constraints as the measure of limits to arbitrage, the return differ ence between the lowest NIF portfolio and the highest NIF portfolio among firms with lower short-sale constraints (higher residual institutional ownership) is no longer significant, while the return difference is still significant among higher short-sale constraints. The findings indicate that stocks with strong purchase pressures tend to be overpriced and experience underperformance in the subsequent year. The underperformance is found to persist over a year when rational investors cannot fully arbitrage away mispricing.

This paper is related to a growing literature in behavioral finance that examines the impact of individual investor behaviors on future stock returns. In similar veins, Hvidkjaer (2008) and Barber, Odean, and Zhu (2006) find that stocks with strong retail investor buying over the prior year underperform those with strong retail investor selling by analyzing small trades in transactions data. [5] Frazzini and Lamont (2008) find that stocks favored by retail investors tend to underperform stocks out of favor in subsequent years by studying the effect of individual investors via mutual fund flows on stock returns. Because there is little evidence on the relation between behaviors of noise traders and future stock returns, further examinations of the issue are needed. In this respect, this study contributes to the existing literature.

The rest of the paper is organized as follows. Section 2 defines a proxy for noise trading, that is, the net individual investor trading. This section also provides data descriptions used in this study. In Section 3, I report characteristics and abnormal returns for the main test portfolios. Concluding remarks are presented in Section 4.

## 2. Data

### *2.1. Primary data*

I obtain annual share-ownership data to measure the trading behaviors of noise traders from Nikkei NEEDS. In Japan, according to the Commercial Code, firms are mandated to report their shareholder profile in their formal annual reports to the stock exchanges. The shareholder profile contains the number of shares held by individual investors (including members of managerial boards), governments, brokerage firms, financial institutions, corporations, and foreign individuals and

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[4] Ali, Hwang, and Trombley (2003) and Nagel (2005) use (residual) institutional ownership as a measure for short-sale constraints. The rationale for these studies' using institutional ownership is that the degree of institutional ownership explains much of the variation in the loan supply across stocks and that stocks with low institutional ownership are more expensive to borrow. D'Avolio (2002) shows that the main suppliers of stock loans are institutional investors.

[5] Although Hvidkjaer (2008) and Barber, Odean, and Zhu (2006) use the same transaction data, the former uses signed small-trade share volume and constructs the measure as the shares bought less shares sold divided by shares outstanding, while the latter construct the measure of order imbalances as the proportion of signed small trades that are purchases.

institutions. Using the data, I construct a variable that captures the trading behaviors of noise traders. In this paper, noise trading is computed as the change in individual investors' holdings, excluding managerial boards' holdings, from the end of the last fiscal year to the end of the current fiscal year. As managerial board members are considered to be corporate insiders among individual investors rather than noise traders, I deduct managerial holdings from shares held by individual investors. To normalize across stocks, I divide the change in individual investors' holdings, excluding managerial boards' holdings, by share outstanding. I define the variable as net individual investor trading flow (NIF).

Table 1 reports summary statistics of NIF. The table describes the time-series average of means, medians, standard deviations, skewness, 20th-percentile values, and 80th-percentile values of NIF. The first five rows in Table 1 show summary statistics in some selective years. As can be seen in these rows, the trading behaviors of individual investors are quite different across time. While individual investors decrease their holdings in 1985 and 1990, they increase their holdings in 1995 and 2000. While the odd moments of NIF are different across time, the standard deviation of NIF is stable across time.

**Table 1.**

Data descriptions on individual investor trading flow. This table reports summary statistics for the net individual investor trading flow (NIF). The NIF is defined as the change of individual investors' holdings, excluding managerial boards' holdings, from the end of the last fiscal year to the end of the current fiscal year. The table reports the time-series average of the cross-sectional mean, standard deviation, skewness, and the first and fifth quintiles for selected years and for the entire period.

| Year | Mean | Median | StDev | Skew | P20 | P80 |
|---|---|---|---|---|---|---|
| 1985 | -0.011 | -0.004 | 0.044 | -1.166 | -0.034 | 0.012 |
| 1990 | -0.014 | -0.008 | 0.040 | -0.676 | -0.039 | 0.011 |
| 1995 | 0.004 | 0.001 | 0.034 | 4.455 | -0.011 | 0.016 |
| 2000 | 0.017 | 0.012 | 0.045 | 1.376 | -0.003 | 0.041 |
| 2005 | -0.006 | -0.006 | 0.048 | 1.594 | -0.032 | 0.015 |
| 1980-2008 | 0.001 | 0.001 | 0.040 | 0.197 | -0.019 | 0.020 |

### *2.2. Market and financial data*

Market and financial data are also obtained from Nikkei NEEDS. Using the data, I calculate excess returns over the government bond (i.e., risk-free) rate and returns on factormimicking portfolios used in time-series regressions. When I calculate returns on factormimicking portfolios used in time-series regressions, I include the excess of value-weighted market returns listed in the Japanese stock markets over the risk-free rate, a size factor, a book-to-market ratio factor, a momentum factor (Carhart, 1997), and a liquidity factor suggested by Pastor and Stambough (2003). In the construction of these factors, I employ a similar method to Fama and French (1993). The size and book-to-market factors are calculated by taking the value-weighted average of the top three deciles in terms of market capitalization and book-to-market portfolio returns and subtracting the average portfolio returns of the bottom three deciles. To calculate size and book-to-market factors, I employ the top three and the bottom three deciles in terms of firm market capitalization and book-to-market ratios as listed in the Tokyo Stock Exchange (TSE) as breakpoints to divide stocks into three portfolios. In these constructions, the market capitalization at the end of the previous month as well as the book-to-market ratio based on the most recently announced book equity value are used. The momentum and liquidity factors are calculated by taking the value-weighted average of the upper quintile in terms of momentum and liquidity portfolio returns and subtracting the average of the lower quintile portfolio returns. In the construction of the momentum factor, the previous three months of cumulative returns are used. Following Pastor and Stambough (2003), I calculate the liquidity ratio and construct the liquidity factor based on these values. [6]

### *2.3. Sample selection*

The sample used in this study covers all ordinary common stock listed in the Japanese stock markets. The sample period ranges from April 1980 to March 2008, in which annual ownership data, market and financial data are suffciently available. As in many previous studies, I exclude financial firms and regulated utilities from the analysis. I also omit firms with stock prices lower than 50 yen, and insufficient observations on data used in this study are excluded. Furthermore, I exclude firms that experience large-scale increases or decreases of their outstanding stock during the period from the end of the last fiscal year to that of the current fiscal year. NIF does not always increase or decrease because of trading behaviors of individual investors. For example, private equity placements to a small number of institutions increase their ownership and decrease the ownership of individual investors. If the scale of private equity placements is large, the trading behaviors of individual investors are less likely to contribute to changes in NIF. Stock repurchases, stock splits, and reverse splits also increase/decrease NIF regardless of individual investor trading. To avoid these effects, I exclude from this analysis firms showing more than 10 percent increases/decreases of their outstanding. This exclusion process also contributes to separating the effect of noise trading on the cross-section of stock returns from the effect of change in outstanding (Pontiff and Woodgate, 2008). The sample of firms used in this study ranges from a minimum of 998 in 1980 to a maximum of 2,897 in 2008.

## 3. Empirical results

### *3.1. Characteristics of NIF-sorted portfolios*

I begin by explaining the construction of the NIF portfolios. I construct five NIF portfolios each month. In each month, stocks are sorted into five value-weighted portfolios according to NIF as measured over a year prior to the latest fiscal year end from the portfolio formation date. Table 2 reports the characteristics of the NIF-sorted portfolios. As can be seen in the table, high NIF firms are more likely to have low individual ownerships, small market capitalizations, low cumulative stock returns, and high book-to-market ratios. The results indicate that individual investors have tendencies to purchase (sell) smaller (larger), value (growth), recently low (high) performing stocks. The investment style tilts of individual investors might complement those of institutions, in particular, foreign investors. Kang and Stulz (1997) document that foreign investors, which are predominantly institutions, in Japanese equity markets prefer large growth stocks.

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[6] Following Pastor and Stambaugh's (2003) liquidity ratio, I calculate a stock's liquidity, which is measured by the interaction between returns and lagged-order flow. As prices of less liquid stocks are expected to overshoot in response to the order flow, the greater value in predicted return reversal for a given dollar volume implies a lower level of stock liquidity. To calculate this measure, I regress a market-adjusted return for a given firm on the lagged stock return and the interaction term of the stock's daily yen volume and the sign of the lagged stock return. The coefficient of the interaction term is expected to be negative and larger in absolute magnitude if the firm's adverse selection problem is severe.

**Table 2.**

Firm characteristics within each NIF quintile. This table reports firm characteristics within each NIF quintile. Quintiles are formed monthly based on the NIF at the latest end of the fiscal year. All characteristics are equally weighted within each quintile, and the table presents averages across formation periods. The table reports the time-series average of the NIF, individual holdings (defined as individual investors' holdings excluding managerial boards' holdings), market capitalization, book-to-market ratio, cumulative returns(CR) measured over a year during the change, turnover ratio, and stock prices. The last two columns in the table report the difference between the high and low NIF portfolios for each charactesistic, along with the Newey-West adjusted t-statistics.

| NIF | 1(L) | 2 | 3 | 4 | 5(H) | 1-5 | t(1-5) |
|---|---|---|---|---|---|---|---|
| change in ind.hold | -0.047 | -0.011 | 0.001 | 0.012 | 0.050 | -0.097 | -48.57 |
| individual holding | 0.329 | 0.287 | 0.285 | 0.292 | 0.292 | 0.036 | 8.84 |
| marketcapitalization(millionyen) | 123,506 | 126,213 | 94,144 | 81,392 | 80,251 | 43,255 | 7.35 |
| book-tomarket | 0.669 | 0.774 | 0.844 | 0.860 | 0.860 | -0.191 | -7.36 |
| CR during the change | 0.391 | 0.138 | 0.051 | -0.006 | -0.062 | 0.453 | 21.46 |
| Turnover | 0.051 | 0.034 | 0.027 | 0.032 | 0.047 | 0.004 | 2.51 |
| Price(yen) | 6,567 | 3,466 | 4,454 | 3,167 | 5,061 | 1,507 | 2.40 |

### *3.2. Returns on NIF sorted portfolios*

The main question addressed in this paper is whether NIF, that is, buying or selling pressures of individual investors, has explanatory power to predict future stock returns. This section examines this predication by analyzing the return difference between stocks within the lowest NIF quintile and stocks within the highest NIF quintile.

Panel A of Table 3 report Jensen's alphas of five value-weighted NIF portfolios. T-statistics described below coefficients are computed using Newey-West adjusted standard errors with four lags. As can be seen in the first row of Panel B, the lowest NIF portfolio shows a value of 0.475 percent with a t-statistic of 2.60. On the other hand, the highest NIF portfolio shows a value of 0.559 percent with a t-statistic of 2.06. The return difference between the lowest- and highest NIF portfolios is -0.083 percent with a t-statistic of -0.55, which is presented in the last column. The results indicate that individual investor behaviors are not useful for predicting future stock returns. However, as documented in Section 3.1, individuals have the tendency to tilt their investments toward small, value stocks, and recent losing stocks. To control the effect of their investment tilts, I employ a five-factor model and characteristics-adjusted returns (Daniel et al., 1997) in empirical analyses.

Subsequently, I report five-factor model alphas on NIF portfolios. Panel B of Table 3 reports five-factor model alphas and factor loadings of five value-weighted NIF portfolios. The table also presents five-factor model alphas and factor loadings of the portfolio, longing stocks within the lowest NIF quintile and shorting stocks within the highest NIF quintile. As can be seen in the first row of Panel B, the lowest NIF portfolio shows a value of 0.230 percent with a t-statistic of 2.07. On the other hand, the highest NIF portfolio shows a value of -0.514 percent with a t-statistic of -3.81. The return difference between the lowest and highest NIF portfolios is 0.744 percent with a t-statistic of 3.77, which is presented in the last column. That is, stocks heavily purchased by individual investors significantly underperform the market, while stocks heavily sold by individual investors significantly outperform the market.

Furthermore, I find that the portfolio long the lowest NIF stocks and short the highest NIF stocks have statistically significant loadings on a value factor (HML) and a momentum factor (WML). The loading on a value factor is negative, while the loading on a momentum factor is positive. As shown in Section 3.1, individuals have tendencies to tilt their investments toward value stocks and recent losers. Although I find an insignificant negative Jensen's alpha of the long-short NIF portfolio, the tilt toward value stocks simply help the portfolio perform well. During the sample period in this study, the value factor shows a monthly average return of 1.015 percent. [7] At the first glance, it seems that stocks heavily purchased by individual investors do not outperform or underperform stocks heavily sold by individual investors. However, after controlling the effect of investment tilts, I can find that stocks heavily purchased by individual investors underperform stocks heavily sold by individual investors.

**Table 3.**

Factor model adjusted alphas on NIF portfolios. This table presents the monthly factor model adjusted alphas on the value-weighted portfolios in each NIF quintile and the value-weighted portfolios that are long the lowest NIF portfolio and short the highest NIF portfolio. Quintiles are formed monthly from April 1980 to March 2008 based on the NIF at the end of the latest fiscal year. Panel A reports the monthly Jensen's alphas, while Panel B reports five-factor model alphas, factor loadings, and adjusted R2 values (reported in percent). Alphas are in monthly percentages, and Newey-West adjusted t-statistics are shown below the coefficient estimates.

| NIF | 1(L) | 2 | 3 | 4 | 5(H) | 1-5 |
|---|---|---|---|---|---|---|
| Panel A: CAPM | 0.475 | 0.678 | 0.857 | 0.810 | 0.559 | -0.083 |
| Intercept | (2.60) | (3.25) | (3.58) | (3.04) | (2.06) | (-0.55) |
| Panel B: 5-factor | 0.230 | -0.067 | -0.189 | -0.137 | -0.514 | 0.744 |
| Intercept | (2.07) | (-0.70) | (-1.98) | (-1.12) | (-3.81) | (3.77) |
| Mkt | 1.001 | 0.962 | 0.958 | 0.958 | 1.014 | -0.013 |
| | (43.93) | (49.80) | (34.51) | (33.03) | (35.53) | (-0.34) |
| SMB | 0.028 | -0.025 | 0.006 | 0.146 | 0.154 | -0.125 |
| | (0.70) | (-0.72) | (0.13) | (2.97) | (2.64) | (-1.43) |
| HML | -0.121 | 0.105 | 0.201 | 0.242 | 0.329 | -0.449 |
| | (-2.66) | (2.65) | (3.94) | (4.80) | (5.52) | (-4.87) |
| WML | 0.024 | 0.022 | -0.048 | -0.041 | -0.109 | 0.133 |
| | (1.08) | (0.97) | (-1.62) | (-1.39) | (-2.88) | (2.66) |
| LIQ | 0.241 | -0.154 | -0.253 | -0.082 | 0.034 | 0.207 |
| | (3.04) | (-1.58) | (-2.58) | (-0.85) | (0.33) | (1.42) |
| Adj. $R^2$ | 89.75 | 87.58 | 86.52 | 87.05 | 84.92 | 47.23 |

### *3.3. Robustness*

#### *3.3.1. Equal-weighted NIF portfolios*

Panel A of Table 4 reports five-factor model alphas on equally weighted NIF portfolios. As the construction of value-weighted portfolios, I construct five equally weighted NIF portfolios. As can be seen in the last column, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.303 with a t-statistic of 2.43. Although the return difference is smaller and less reliable than the return on the value-weighted portfolio, the results are consistent with the main results.

#### *3.3.2. NIF portfolios sorted by individual ownership*

The absolute change in individual investors' ownership is considered to depend on their initial ownership level. For example, a five-percent change of NIF is more likely in firms with a larger initial ownership. Actually, as shown in the second row of Table 2, the lowest NIF portfolio, which

[7] Asness, Moskowittz, and Pedersen (2008) document that the value effect in Japan is pronounced compared to U.S., U.K., and Europe. The value premium in Japan is 11.6 percent per annum during the period from January 1985 to February 2008.

experiences the largest change in ownership, has the largest initial ownership among other four NIF portfolios. To control the effect of the initial ownership level, for each month, I divide the entire sample into the bottom 50 percent and the top 50 percent based on individual ownership at the previous fiscal year end and then construct five NIF portfolios. Panels B and C of Table 4 present five-factor model alphas on value-weighted NIF portfolios. As can be seen in the last column, among both firms with high individual ownership and firms with low individual ownership, the lowest NIF portfolios outperform the highest NIF portfolios. In the case of firms with high individual ownership, the difference in returns is 0.532 (0.435) with a t-statistic of 2.58 (2.02), which is consistent with the main results.

**Table 4.**

Robustness checks. This table reports the five-factor model's alphas for the NIF portfolios. Panel A reports results when I use equally weighted portfolios instead of value-weighted ones. Panels B and C report results for subsamples based on individual investors' ownership levels. The breakpoint is the median ownership at the latest fiscal year-end. Panels D and E report results for subsamples in which I simply divide the entire sample period into two halves. Panel F reports the results when I employ characteristics-adjusted returns (Daniel et al., 1997). Panel G reports the results for NIF normalized by trading volume. Alphas are in monthly percentages, while the Newey-West adjusted t-statistics are shown below the coefficient estimates.

| NIF | 1(L) | 2 | 3 | 4 | 5(H) | 1-5 |
|---|---|---|---|---|---|---|
| A. Equal-weighted portfolio | 0.226 | 0.298 | 0.366 | 0.251 | -0.077 | 0.303 |
| | (2.87) | (4.19) | (5.05) | (3.28) | (-0.91) | (2.43) |
| B. High ind. own. | 0.176 | -0.089 | -0.135 | -0.198 | -0.356 | 0.532 |
| | (1.06) | (-0.48) | (-0.89) | (-1.39) | (-2.30) | (2.58) |
| C. Low ind. own. | 0.168 | 0.031 | -0.057 | -0.070 | -0.268 | 0.435 |
| | (1.44) | (0.31) | (-0.57) | (-0.52) | (-1.86) | (2.02) |
| D. 1980-1994 | 0.361 | -0.175 | -0.361 | -0.202 | -0.539 | 0.900 |
| | (2.00) | (-1.20) | (-2.74) | (-1.12) | (-2.94) | (3.17) |
| E. 1994-2008 | 0.123 | -0.167 | -0.082 | -0.175 | -0.486 | 0.609 |
| | (1.09) | (-1.29) | (-0.52) | (-1.01) | (-2.92) | (2.59) |
| F. DGTW char-adj. | 0.146 | 0.009 | -0.074 | 0.102 | -0.216 | 0.362 |
| | (1.50) | (0.09) | (-0.67) | (0.92) | (-1.47) | (1.86) |
| G. Normalize by trading volume | 0.221 | -0.041 | -0.212 | -0.259 | -0.183 | 0.404 |
| | (1.76) | (-0.46) | (-1.84) | (-2.06) | (-1.14) | (1.92) |

### *3.3.3. Subsample period analysis*

I also examine whether the return difference between two NIF portfolios persists in two subsample periods that are simply divided into two halves. Panels D and E of Table 4 present five-factor model alphas on value-weighted NIF portfolios in the period from April 1980 to March 1994 and from April 1994 to March 2008. As can be seen in the last column, the lowest NIF portfolios outperform the highest NIF portfolios in both periods. The return difference shows a value of 0.900 percent with a t-statistic of 3.17 in the former period, while the difference in the latter period shows a value of 0.609 percent with a t-statistic of 2.59. Although the return difference is small and less reliable in the latter period than in the former period, the main results in this paper remain unchanged.

### *3.3.4. Characteristics-adjusted returns on NIF portfolios*

Panel F of Table 4 shows characteristic-adjusted returns on value-weighted NIF portfolios. In the calculation of the characteristic-adjusted return, I follow a procedure similar to the approach used by Daniel et al. (1997, DGTW). Specifically, I divide each stock into three portfolios based on its market capitalization at the end of the previous month, its book-to-market ratio based on its most recently announced book equity value, and its previous three months of cumulative returns. Using the same breakpoints used in the factor adjustments, I divide all stocks into the top three, middle four, and bottom three portfolios for market capitalization and book-to-market classifications. In the case of momentum classification, all stocks are divided into the top quintile, the bottom quintile, and all others. Therefore, I construct three size, three book-to-market, and three momentum categories, which result in 27 possible classifications for each stock. I calculate monthly value-weighted average returns for each of these 27 stock classifications, taking the characteristic-adjusted return of a particular stock as its realized return minus the average return of a stock with its classification. As can be seen in the last column of Panel F of Table 4, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.362 with a t-statistic of 1.86. Although the return difference is more statistical reliable when I use five-factor model alphas, the main results remain substantially unchanged when I employ other risk adjustment models.

#### *3.3.5. NIF normalized by trading volume*

Up to this section, I use the change in individual investor holdings normalized by shares outstanding as the proxy for noise trading. In this section, instead of the measure, I use the change of individual investor holdings normalized by trading volume during the change. Panel G of Table 4 presents five-factor model alphas on value-weighted portfolios. As can be seen in the last column, the return difference between the lowest NIF portfolio and the highest NIF portfolio is 0.404 percent per month with a t-statistic of 1.92. Compared to NIF normalized by shares outstanding, although the difference in returns and its statistical significance weaken, these values provide empirical support for the main results in this paper.

### *3.4 Limits to arbitrage*

For mispricing to persist in the presence of sophisticated professional investors, some limits to arbitrage must exist (Shleifer and Vishny, 1997). In this section, I investigate whether two proxies for limits to arbitrage, namely, idiosyncratic risk and institutional ownership, affect the return predictability of NIF. If the return predictability of NIF is in accordance with the investor sentiment story, mispricing is more prominent among firms with higher limits to arbitrage.

#### *3.4.1 Idiosyncratic risk*

When investors are limited to arbitrage mispricing opportunities, NIF predicts stronger price reversals. To measure the extent of the limits to arbitrage, I employ the simplest measure, namely, idiosyncratic risk. According to several papers such as Wurgler and Zhuravskaya (2002), Ali, Hwang, and Trombley (2003), Mendenhall (2004), Mushruwala, Rajgopal, and Shevlin (2006), and Pontiff (2006), stocks with high levels of idiosyncratic risk are more diffcult to arbitrage. In fact, some previous studies in this area show that idiosyncratic risk is highly correlated with more sophisticated measures. Specifically, I use the standard deviation of the monthly residual from a time-series regression of the firms' excess returns on the Fama-French three factors over the 36 months preceding the end of our ranking period as our measure of idiosyncratic risk. I then separately analyze return patterns by confining stocks to the bottom 50 percent and top 50 percent based on this measure of idiosyncratic risk.

Panels A and B of Table 5 report five-factor model alphas on value-weighted NIF portfolios, which are first sorted by idiosyncratic risk. As can be seen in the last column of the table, when the sample is confined to firms with higher idiosyncratic risks, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.619 percent with a t-statistic of 2.95. On the other hand, when the sample is confined to firms with the lower idiosyncratic risks, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.444 percent with a t-statistic of 2.43, which is smaller and less reliable than firms with the higher idiosyncratic risks. That is, firms with stricter limits to arbitrage are more likely to generate the higher difference in returns, which is consistent with the investor sentiment story. However, even when the sample is confined to firms with lower idiosyncratic risk, the return difference between the two NIF portfolios is still statistically significant. Idiosyncratic risk is used in empirical analyses not only to represent a limit to arbitrage but also as a sign of informed trading. [8] In the latter case, the level of mispricing declines in idiosyncratic risk. The noisiness of the idiosyncratic risk measure might contribute to the results.

**Table 5.**

NIF and the degree of limits to arbitrage. This table presents the monthly five-factor model alphas for the NIF value-weighted portfolios after dividing all stocks into two groups, according to the degree of the limits to arbitrage. Panels A and B report the results for subsamples based on idiosyncratic risk, which is defined as the monthly residual from a time-series regression of the firms' excess returns on the Fama-French three factors over the 36 months preceding the end of our ranking period. The breakpoint is the median idiosyncratic risk at the formation date. Panels A and B report results for subsamples based on residual institutional ownership. Residual ownership is calculated as the residual by regressing logit-transformed institutional ownership on the logarithm of market capitalization as well as the squared logarithm of market capitalization each month. The breakpoint is the median residual ownership at the formation date. Alphas are in monthly percentages, and Newey-West adjusted t-statistics are shown below the coefficient estimates.

| NIF | 1(L) | 2 | 3 | 4 | 5(H) | 1-5 |
|---|---|---|---|---|---|---|
| A. High idio. risk | 0.203 | -0.252 | -0.303 | -0.480 | -0.416 | 0.619 |
| | (1.56) | (-1.32) | (-1.75) | (-3.07) | (-2.33) | (2.95) |
| B. Low idio. risk | 0.233 | -0.028 | -0.035 | 0.015 | -0.211 | 0.444 |
| | (1.73) | (-0.26) | (-0.31) | (0.13) | (-1.70) | (2.43) |
| C. High residual inst. own. | 0.030 | 0.049 | -0.327 | -0.229 | -0.192 | 0.222 |
| | (0.29) | (0.36) | (-2.85) | (-1.81) | (-1.16) | (1.02) |
| D. Low residual inst. own. | 0.419 | 0.043 | 0.052 | -0.028 | -0.488 | 0.907 |
| | (3.39) | (0.38) | (0.48) | (-0.22) | (-3.19) | (4.01) |

### *3.4.2 Short-sale constraints*

Short-sale constraints are a kind of limit to arbitrage. As Miller (1977) documents, short-sale constraints can prevent pessimistic opinions from being expressed in prices. When there is a divergence of opinions in the market regarding the value of an asset , optimistic investors will end up holding overpriced assets. In empirical studies, institutional ownership is the most frequently used proxy for short-sale constraints. [9] Following Nagel (2005), I employ residual institutional ownership as the proxy for short-sale constraints. After performing a logit transformation of institutional ownership that is bounded by 0 and 1, I regress logittransformed institutional ownership on a logarithm

[8] Pantzalis and Park (2006) find that that the level of mispricing declines with idiosyncratic volatility, which supports the notion that greater levels of firm-specific risk reflect greater participation of informed traders in the market for the stock. However, they also find that the relationship is U-shaped, with mispricing increasing with idiosyncratic risk for stocks with high levels of idiosyncratic volatility.

[9] D'Avolio (2002) finds that the degree of institutional ownership explains 55 percent of cross-sectional variation in loan supply and is its most important determinant.

of market capitalization as well as on a squared logarithm of market capitalization. [10] Regressions are run each month by using the latest value of institutional ownership. I refer to the residuals as residual institutional ownership. I then separately analyze return patterns by confining stocks to the bottom 50 percent and the top 50 percent based on the residual institutional ownership.

Panels C and D of Table 5 report five-factor model alphas on value-weighted NIF portfolios, which are first sorted by residual institutional ownership. As can be seen in the last column of the table, when the sample is confined to firms with the higher level of residual institutional ownership, the lowest NIF portfolio only outperforms the highest NIF portfolio by 0.222 percent, with a t-statistic of 1.02. On the other hand, when the sample is confined to firms with the lower residual institutional ownership, the lowest NIF portfolio outperforms the highest NIF portfolio by 0.907 percent with a t-statistic of 4.01. In other words, the level of mispricing strengthens in the level of short-sale constraints.

## 4. Conclusion

This paper examines the effect of noise trading on the cross-section of stock returns. Using the annual ownership change of individual investors as a proxy for noise trading, I provide two important results. First, I find that stocks heavily sold by individual investors outperform stocks heavily purchased by 0.73 percent per month, that is, about 8.8 percent per annum. This finding indicates that systematic behaviors of noise traders also have important roles in the formation of securities prices. Second, I find that the outperformance of stocks heavily sold by individual investors over stocks heavily purchased by them is stronger among firms with stronger limits to arbitrage. In particular, the tendencies are more pronounced when I use a proxy for short-sale constraints as the measure of limits to arbitrage. The findings indicate that stocks with strong purchase pressures tend to be overpriced and experience underperformance in the subsequent year. Collectively, these findings are broadly consistent with the predictions of noise trader models in which the systematic activities of individual investors affect the returns of those stocks in which they are concentrated and the limits to arbitrage are stricter.

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# The value premium and the market-dynamic conditional momentum effect: Evidence from the Japanese stock market

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## Abstract

The value premium calculated by monthly updated book-to-market ratios contains the past 1-year's price change component (i.e., the momentum component). I argue that the momentum component contained in the book-to-market effect amplifies the volatility of the value premium. The results show that the value premium is sensitive to market conditions. Conversely, the value premium that is free from the momentum component is stable over the different market states and earns a high Sharpe ratio. These findings imply that a source of the volatility can be partly driven by the market-dynamic conditional momentum effect.

## 1. Introduction

The tendency that stocks with high book-to-market ratios earn substantially higher returns than those with low book-to-market ratios is one of the well-known anomalies in the stock market. This is called the value effect. A high book-to-market implies that a stock is cheap and has a high expected return and a low book-to-market means the opposite[1]. The standard approach to calculating the return of book-to-market hedging portfolios, pioneered by Fama and French [1992], updates portfolios once a year, by using market prices that lag six months from the time of the update. This means that the price used to determine the value is always between 6 to 18 months old by the next updates. On the other hand, Asness and Frazzini [2013] propose a method that involves the use of monthly updated prices. They argue that using more current market prices is superior to the standard method as a proxy for the true value and is superior in factor regression.

In this paper, following Asness and Frazzini [2013], I calculate the value premium using monthly updated book-to-market ratios and examine the effect of the change in the current stock price on the value premium. It is obvious that the monthly updated book-to-market ratio contains the recent price change component, which is not contained in the book-to-market ratios that are updated once a year. Basic statistics show that the firms with a high monthly updated book-to-market ratio show price drops and firms with a low monthly updated book-to-market ratio show price rises in the last 12 months. This implies that a 1-year stock price change effect (i.e., momentum) may partly

[1] There exist two competing explanations for the value effect: the risk-based explanation and the mispricing hypothesis. The former argues that the book-to-market ratio reflects the relative distress risk of a firm and the risk to a firm's investment activities (Fama and French [1993]; Griffin and Lemmon [2002]; Zhang [2005]). The latter states that investors tend to overvalue (undervalue) firms with a low (high) book-to-market ratio, which results in mean-reversion in subsequent periods (Lakonishok, Shleifer, and Vishny [1994]).

affect a source of the value premium.[2]

First, I examine the monthly mean excess return and standard deviation of a hedging portfolio constructed by the monthly updated book-to-market ratio (*BM*) and those of a hedging portfolio constructed by the monthly updated book-to-market ratio orthogonal to momentum component ($BM^{otm}$)., For the momentum component, I use the past 12 month's cumulative raw stock return, skipping the most recent 1-month return to avoid the short-term reversal effect. The results show that the mean return of a *BM* hedging portfolio (1.22%) is about the same as that of a $BM^{otm}$ hedging portfolio (1.19%). However, the standard deviation of *BM* hedging portfolio (5.57%) is higher than that of a $BM^{otm}$ hedging portfolio (4.26%). These results indicate that the weak momentum effect in Japan does not directly affect the mean return; however, the momentum component amplifies the volatility of the value premium.[3]

Next, I test whether the value premium is affected by market conditions due to the market-dynamic conditional momentum effect. Asem and Tian [2010] and Matthias [2014] show that momentum profits are conditional on market dynamics; momentum returns are significantly higher when the market stays in the same condition than when it transitions to another state. Consistent with the literature, I find that the value premium is also conditional on market dynamics. The results show that the mean return of a *BM* hedging portfolio is high in market transitions (2.10%) and low in market continuations (0.58%), and this pattern is more pronounced after periods of poor market performance. However, the mean return of a $BM^{otm}$ hedging portfolio is stable over different market states. Overall, the results imply that the source of high volatility of the value premium is partly driven by the market-dynamic conditional momentum effect.

Finally, I examine the Sharpe ratios of the $BM^{otm}$ hedging portfolio and the *BM* and the momentum combination strategy. Asness [2011] shows that the optimal combination of value and momentum strategy earns a high Sharpe ratio because a strong negative correlation between value and momentum reduces portfolio variance. Consistent with Asness [2011], the results show that the optimal *BM* and momentum combination portfolio earns a high Sharpe ratio of 1.10 in all sample periods. However, after BEAR markets, the Sharpe ratio of the optimal portfolio is 1.00, which is lower than that of a $BM^{otm}$ hedging portfolio (1.17). The results of the high Sharpe ratio of a $BM^{otm}$ hedging portfolio implies that the elimination of optionality from the value premium produces a sharp reduction in portfolio variance after BEAR markets.

My study contributes to the finance literature in two ways. First, it is related to book-to-market measures. The results show that the value premium when calculated by monthly updated book-to-market ratios is affected by the past one year's price change component, which is not contained in the book-to-market ratios that are updated annually. This is consistent with Asness and Frazzini [2013], who argue that using more-current market prices is superior to the standard method as a proxy for the true value. Second, my study is related to the literature on the market-dynamic conditional momentum as shown by Asem and Tian [2010] and Matthias [2014]. My findings reveal that the value premium is also sensitive to market conditions due to the market-dynamic conditional momentum effect.

The remainder of this paper is organized as follows. The next section describes the definition of the book-to-market ratio used in this paper. Section 3 describes the basic evidence of the value premium and the value premium that is free from the momentum component and shows the results of the analysis in different market dynamics. Furthermore, I present the results of strategies in this

2 Stocks with a high positive momentum (high 12-month past returns) outperform stocks with a low. momentum. A momentum strategy is generally implemented by buying past winners and selling past losers. (E.g., refer to Jegadeesh and Titman [1993]).

3 Previous literature shows that the momentum returns in Japan are small. (e.g., Asness [2011] and Fama and French [2012]).

section. Section 4 concludes this study.

## 2. Data

### *2.1. Primary data*

The sample consists of firms listed on the first section of the stock exchange in Japan from 1985 to 2015, with market and financial data obtained from the Nikkei NEEDS. I exclude financial institutions and firms with a negative book value. Under these data requirements, the number of firms in the sample range from 889 firms in 1985 to 1,736 firms in 2015, with an average of 1,254 firms per year.[4]

### *2.2. Definition of BM*

In this section, following Asness and Frazzini [2013], I compute three measures of book-to-market ratios. The first measure is equal to the book value divided by the monthly updated market value, *BM*. The second measure is equal to the book value divided by the market value in the next month after the announcement date of the book equity at the end of the fiscal year, $BM^{\text{annual, current}} \equiv BM^{a,c.}$ The last measure is Fama and French's (1992) standard approach, with the book-to-market equal to the book value divided by the market value at the end of the fiscal year, $BM^{\text{annual, lagged}} \equiv BM^{a,l}$. The three measures use the same measure of book value (the most recently announced book equity value), but vary the lag used to update the market price. In this paper, I focus on the first measure, *BM*.

Table 1 reports the relationship between the three measures. At the end of each month, I sort stocks into quintiles using *BM* (the monthly updated book-to-market ratios) breakpoints and calculate the average *BM*, $BM^{a,c,}$ $BM^{a,l}$, and past stock returns in each *BM* quintile. The first three rows show that *BM* (0.14) is lower than either $BM^{a,c,}$ (0.33) or $BM^{a,l}$ (0.36) in the lowest *BM* quintile, while *BM* (1.74) is higher than either $BM^{a,c,}$ (1.46) or $BM^{a,l}$ (1.47) in the highest *BM* quintile. This indicates that *BM* contains a component that is not contained in $BM^{a,c}$ and $BM^{a,l}$. As can be seen in the last two rows, the past 1-year's stock return ($Ret_{t-12,t-1}$) (the 1-year stock return skipping the most recent 1-month return ($Ret_{t-12,t-2}$)) in the lowest *BM* quintile is 27.7% (25%) and that in the highest *BM* quintile is -3.4% (-2.8%). These statistics reveal that low *BM* firms show price rises and high *BM* firms show price drops in the previous 12 months, implying that the value premium calculated by the *BM* hedging portfolio contains price change effect in the recent past, that is, the momentum effect.

## 3. Empirical results

### *3.1. Basic evidence*

In this section, I examine the effect of the momentum component on the value premium. For each month, I form quintile portfolios with the *BM* and construct a *BM* hedging portfolio that longs the highest *BM* portfolio and shorts the lowest *BM* portfolio. For this test, I also construct portfolios based on the *BM* that are free from the momentum component. First, I decompose *BM* into momentum and orthogonal components by estimating cross-sectional regressions of log-*BM* on the past 1-year cumulative log stock return, skipping the most recent month's return.

$$\log(BM_{i,t}) = \alpha_t + \beta_t \log(1 + Ret_{i,t-12,t-2}) + \varepsilon_{i,t}$$

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[4] I restrict my sample to firms listed on the first section of the stock exchange. This is a conservative large-capitalization restriction.

$\beta_t \log(1+Ret_{i,t-12,t-2})$ represents the momentum component ($BM^m$), and the residuals, $\varepsilon_{i,t,}$ represents the component that is orthogonal to momentum component ($BM^{otm}$). Subsequently, I construct $BM^{otm}$ and $BM^m$ hedging portfolios in the same manner as the *BM* hedging portfolio.

I calculate the time series average of monthly mean excess returns and the standard deviation of each quintile and hedging portfolios. I also calculate alphas from the time-series regression of each return series on the return of the market, a value-weighted return of all sample stocks. Panel A of Table 2 shows the results of the value-weighted portfolios. The *t*-statistics are adjusted using Newey and West [1987] robust standard errors with a one month lag. The results show that the return of the *BM* hedging portfolio (high-low) is not different from that of the $BM^{otm}$ hedging portfolio. The mean returns of *BM* and $BM^{otm}$ hedging portfolios are 1.22% and 1.19%, respectively, and both are statistically significant ($t = 4.03$ and $t = 5.02$). The alphas show similar results. However, the volatility of the *BM* hedging portfolio is higher than that of the $BM^{otm}$ hedging portfolio. The standard deviation (Stdev) of the *BM* hedging portfolio is 5.57%, while that of the $BM^{otm}$ hedging portfolio is 4.26%. Panel A also shows the results of $BM^m$ hedging portfolio. The mean return is not statistically significant ($t$ = -0.44), and the standard deviation is high (6.67%), showing that the momentum reruns in Japan are small.[5] Overall, the results in Table 2 indicate that the weak momentum effect in Japan does not affect the mean return of the value premium; however, the momentum component amplifies the variance of the value premium.[6]

### *3.2. Conditional value premium*

Next, I test whether the value premium is affected by market conditions due to the market-dynamic conditional momentum effect. Asem and Tian [2010] show that momentum profits are conditional on market dynamics: momentum returns are significantly higher when the market stays in the same state than when it transitions to another state. Furthermore, Matthias [2014] shows that the momentum returns in Japan are also significantly higher when the market stays in the same condition than when it reverses, and this pattern is more pronounced after periods of negative market returns. Their results imply that the value premium, which contains the momentum component, is also conditional on the market dynamic and the value premium that is free from the momentum component is constant through the market state.

Following Asem and Tian [2010] and Matthias [2014], at the beginning of the current month, I classify the past market as either a BULL market or a BEAR market, depending on whether the past 12-month return of the market is non-negative or negative. Furthermore, I classify the current month UP market or DOWN market if the return of the current market is non-negative or negative. Thus, DOWN after BULL and UP after BEAR capture market transitions and UP after BULL and DOWN after BEAR capture market continuations. This categorization results in 133 (88) subsequent UP (DOWN) market months following BULL markets, 69 (82) subsequent UP (DOWN) market months following BEAR markets, 157 months in market transitions, and 215 months in market continuations.

Panel A of Table 3 shows the results of the value-weighted monthly returns in market transitions and market continuations. The mean excess return of the *BM* hedging portfolio is 2.10% ($t = 4.19$) in market transitions, and 0.58% ($t$ = 1.54) in market continuations. A test of the difference between transitions and continuations is 1.53% and is statistically significant ($t$ = 2.41). I also confirm the consistent results with Matthias [2014] in the $BM^m$ hedging portfolio. The mean return of the $BM^m$ hedging portfolio is 2.07% ($t$ = 3.52) in market transitions, and -1.78% ($t$ = -4.03) in market

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[5] The result is intuitive because $BM^m$ hedging portfolios represent strategies that are contrary to the momentum strategies.

[6] Panel B of Table 2 reports the results of the equal-weighted portfolios. When I employ equal-weighted portfolios, similar results are obtained.

continuations. A test of the difference between the transitions and continuations is 3.86% and is statistically significant ($t$ = 5.51). Conversely, the mean return of the $BM^{otm}$ hedging portfolio is 1.45% ($t$ = 4.50) in market transitions, and 0.99% ($t$ = 3.02) in market continuations. A test of the difference between the transitions and continuations is 0.45% and is not statistically significant ($t$ = 0.97). The results of alphas show the same sign and significance. Overall, the results reveal that the value premium is also sensitive to market conditions due to the market-dynamic conditional momentum effect and they imply that the behavioral biases of the investors' overconfidence partly drive the value premium through the momentum component. This is consistent with the behavioral model of Daniel, Hirshleifer, and Subrahmanyam [1998].

Panel B of Table 3 shows the results of value-weighted monthly returns in four different market states. I can confirm that the market-dynamic conditional effect is more pronounced after BEAR markets than after BULL markets in the $BM$ hedging portfolio, but not in the $BM^{otm}$ hedging portfolio. The last two columns show a test of the difference. In the test of the difference between UP after BULL and DOWN after BULL, neither the mean return of the $BM$ hedging portfolio nor that of the $BM^{otm}$ hedging portfolio are statistically significant ($t$ = -0.91 and -0.54, respectively). However, in the test of the difference between UP after BEAR and DOWN after BEAR, the mean return of the $BM$ hedging portfolio is statistically significant ($t$ = 2.45), while that of the $BM^{otm}$ hedging portfolio is not statistically significant ($t$ = 0.89). The results of alphas also show the same sign and significance.[7]

### *3.3. Optionality*

The previous section shows that the market-dynamic conditional effect on the value premium is more pronounced after BEAR markets than after BULL markets. Daniel and Moskowitz [2016] argued that the momentum portfolio behaves like a short call option on the BEAR market. Matthias [2014] shows that the optionality of the momentum strategy in BEAR markets holds for the Japanese market. In this section, following Matthias [2014], I estimate the optionality of the value premium by using the following regressions:

$$R_t = \alpha + \alpha_B I_B + [\beta + I_B(\beta_B + I_B \beta_{B,U})]\, RMRF_t + \varepsilon_t$$

$$R_t = \alpha + \alpha_L I_L + [\beta + I_L(\beta_L + I_D \beta_{L,D})]\, RMRF_t + \varepsilon_t$$

$R_t$ is the return of the hedging portfolio. $RMRF_t$ is the excess return of the market return over the risk-free rate. $I_B$ and $I_L$ are dummies indicating whether the past cumulative 12-month return of the market is negative ($I_B$) or non-negative ($I_L$), while $I_U$ and $I_D$ are dummies indicating whether the subsequent month is non-negative ($I_U$) or negative ($I_D$).

Panel A of Table 4 reports the results of value-weighted portfolios. BM (1) and BM (2) show the regression results of the return of the $BM$ hedging portfolio after BEAR and BULL markets, respectively. In the regression of BM (1), I observe the optionality after BEAR markets. The results show a negative beta of -0.061 after BEAR markets, while the beta becomes highly positive if the subsequent market is UP. If the subsequent market is DOWN, the beta is 0.009 higher, but if the subsequent market is UP, the beta is an additional 0.469 higher ($t$ = 2.10). This results in an overall market beta of $\beta + \beta_B + \beta_{B,U} = 0.417$ if the market reverses after past BEAR markets, but only in a beta of $\beta + \beta_B = -0.052$ if the market declines further. On the other hand, I do not observe the optionality after BULL markets. BM (2) shows that if the subsequent month is UP, the beta is 0.207 lower, and if

[7] Panels C and D of Table 3 report the results of equal-weight portfolios. When I employ equal-weighted portfolios, similar empirical results are obtained.

the subsequent month is DOWN, the beta is an additional 0.052 lower ($t$=-0.21). This results in a beta of $\beta + \beta_L$ =-0.038 if the market rises further after past BULL markets and in an overall beta of $\beta + \beta_L + \beta_{L,D}$ = -0.090 if the market reverses. These results show that the value premium exhibits a stronger option-like behavior after BEAR markets, which is consistent with Matthias [2014]. Conversely, in the regression of the return of the $BM^{otm}$ hedging portfolio, I do not observe the optionality after either BEAR or BULL markets. BMotm (1) shows that if the subsequent month is DOWN, then the beta is 0.016 lower, and if the subsequent month is UP, the beta is 0.116 higher ($t$ =-0.67) after BEAR markets. BMotm (2) shows that if the subsequent month is UP, the beta is 0.008 lower, and if the subsequent month is DOWN, the beta is 0.067 lower ($t$ =-0.34) after BULL markets. Overall, results reveal that the optionality of the value premium is due to the reversed optionality effect of the momentum.[8]

### *3.4. Strategy*

In this section, I examine Sharpe ratios of the $BM^{otm}$ hedging portfolio and the *BM* and momentum combination strategy. Asness [2011] and Asness, Moskowitz, and Pedersen [2013] show that the combination of value and the momentum strategy earns a high Sharpe ratio because a strong negative correlation between value and momentum reduces portfolio variance. Panel A of Table 5 reports the results of annualized mean returns and annualized Sharpe ratios. "*Optimal portfolio*" is a portfolio that invests an "optimal percent" of its assets in a *BM* hedging portfolio and the remaining assets in a similarly constructed momentum portfolio (*MOM*). "Optimal percent" is a weight added to the *BM* hedging portfolio to maximize the realized Sharpe ratio. The last row reports the highly negative correlation of returns between the *BM* and *MOM* hedging portfolio (−0.64). Consistent with Asness [2011], the results of all the sampled periods show that the optimal portfolio earns a high Sharpe ratio of 1.10, which is higher when compared to the $BM^{otm}$ hedging portfolio (0.96). However, after BEAR markets, the Sharpe ratio of the optimal portfolio is 1.00, which is lower than that of the $BM^{otm}$ hedging portfolio (1.17). Additionally, the mean return of the optimal portfolio (10.86%) is also lower than that of the BMotm hedging portfolio (15.61%). As shown in the previous section, the $BM^{otm}$ hedging portfolio does not contain the optionality in BEAR markets. The results of the high Sharpe ratio of the $BM^{otm}$ hedging portfolio imply that the elimination of optionality from the value premium produces a reduction in portfolio variance.[9]

## 4. Conclusion

I calculate the value premium using the monthly updated book-to-market ratios and examine the effect of the change in the current stock's price (the momentum effect) on the value premium. First, I find that the momentum component contained in the book-to-market effect amplifies the volatility of the value premium. Results show that the standard deviation of the *BM* hedging portfolio (5.57%) is higher than that of the $BM^{otm}$ hedging portfolio (4.26%). Next, I reveal that a source of the volatility of the value premium is partly driven by the market-dynamic conditional momentum effect. Results show that the return of the *BM* hedging portfolio is high in market transitions (2.10%) and low in market continuations (0.58%), and that this pattern is more pronounced after periods of poor market performance. Conversely, the return of the $BM^{otm}$ hedging portfolio is stable over different market states. Finally, I show that, after periods of poor market performance, the $BM^{otm}$ hedging portfolio

[8] Panel B of Table 4 reports the results of equal-weight portfolios. When I employ equal-weighted portfolios, similar empirical results are obtained.

[9] Panel B of Table 5 reports the results of equal-weight portfolios. When I employ equal-weighted portfolios, similar empirical results are obtained.

earns a high Sharpe ratio (1.17), which is higher when compared to the optimal *BM* and *MOM* strategy (1.00), implying that the elimination of optionality from the value premium produces a sharp reduction in portfolio variance after bear markets.

In this paper, I investigate the effect of the momentum component on the value premium in the Japanese stock market. Overall, results show that a source of the volatility of the value premium can be partly driven by the market-dynamic conditional momentum effect. However, the weak momentum effect in Japan is a remarkable exception in the world's financial markets. Different empirical results may be obtained if the momentum component is investigated in other markets.

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# Does mispricing drive the value effect? Evidence from Japan

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## Abstract

This paper shows that the residual book-to-market, which is free of the effects of investment factors and distress risk, can predict future stock appreciation. In addition, we nd that the tendency is stronger among stocks with higher idiosyncratic volatility and lower investor sophistication. Our ndings indicate that mispricing is the main driver of the value effect.

***Keywords***: Value effect, Japanese stock market

***JEL classification:*** **G10, G14**

## 1. Introduction

The tendency that stocks with high book-to-market ratios (BM) earn substantially higher returns than do those with low BMs is one of well-known anomalies in the stock market. It is called the value effect. In the literature, there exist two competing explanations for this phenomenon: the risk-based explanation and the mispricing hypothesis. The former argues that the BM reflects the relative distress risk of a firm and the risk of a firm's investment activities (Fama and French, 2006; Griffn and Lemmon, 2002; Zhang, 2005). The latter states that investors tend to overvalue (undervalue) firms with low (high) BMs, which results in mean-reverting in the subsequent periods (Lakonishok, Shleifer, and Vishny, 1994).

In this paper, we examine whether the value effect is due to systematic risks or whether it occurs because of behavioral reasons. First, we test whether the value effect disappears after eliminating the effects of systematic risks on the BM. After estimating residuals (RedBM) by regressing BMs on proxies for financial distress and investment activities (i.e., asset growth, investment to asset, new stock issue), we form quintile portfolios according to RedBM and evaluate monthly return spreads between the highest RedBM portfolio and the lowest RedBM portfolio (RedBM hedging portfolio). We find that the RedBM hedging portfolio yields positive returns with statistical significance. The return is not different from that of the BM hedging portfolio. Our results indicate that the relative distress risk of a firm and the risk of the firm's investment activities do not seem to be a main driver of the value effect, which means that the value effect is due to mispricing.

Second, we test whether the value effect is driven by misevaluation by investors. To test this prediction, we examine the effect of limit-to-arbitrage on the value effect. As suggested by Shleifer and Vishny (1997), when arbitrages are costly, risky, and limited, there is a possibility that mispricing may not be corrected quickly. By employing two proxies for limit to-arbitrage, we form 15 portfolios with RedBM and each limit-to-arbitrage proxy. Following Ali, Hwang, and Trombley (2003), we use idiosyncratic volatility and investor sophistication as proxies for limit-to-arbitrage. Then, we evaluate the monthly return spreads between the highest RedBM portfolio and the lowest RedBM portfolio on the subsample splits by using a given limit-to-arbitrage proxy. We find that the returns of RedBM hedging portfolios take larger values among the subsamples that have higher idiosyncratic volatility and lower investor sophistication. The results lend support for the prediction that the value effect is due to mispricing.

Our findings contribute to the literature on the value effect, in which it is still controversial whether the value effect is driven by systematic risks or mispricing. Xing (2008) finds that the value effect disappears after controlling for investment factors, which is consistent with the q-theory suggested by Zhang (2005). However, Ali, Hwang, and Trombley (2003) find that the value effect is stronger among stocks with higher idiosyncratic risk, higher transaction costs, and lower analyst following, which is consistent with Shleifer and Vishny (1997). We provide robust evidence supporting the mispricing hypothesis by using residual BMs that are not affected by systematic risks.

The remainder of this paper is organized as follows. The next section describes the primary data and calculates the book-to-market equity residuals used in our tests. Section 3 describes the results of comprehensive analysis whether the value effect is due to risk or mispricing. Section 4 presents the conclusion of this study.

## 2. Data

### *2.1. Primary data*

Our sample consists of firms listed in the first section of the stock exchanges in Japan from the period of 1980 to 2010, based on market and financial data available from the Nikkei Economic Electronic Databank System. We exclude financial institutions and firms with negative book values. We also winsorize firms with highest and lowest 0.5% of BMs to alleviate the effect of outliers. Under these data requirements, the number of firms in our sample ranges from 846 firms in 1980 to 1,523 firms in 2010, with an average of 1,195 firms per year.

### *2.2. Definition of variables*

We define variables used in our tests as follows. BM is defined as the ratio of book value of equity to market value of equity (MCAP). We employ asset growth (AG), investment to asset (IA), and net stock issue (NSI) as proxies for the systematic risk of investment activities. Following Cooper, Gulen, and Schill (2008), we measure AG as the change in total assets. Following Lyandres, Sun, and Zhang (2008), IA is measured as the change in gross property, plant, and equipment (PPE) plus the change in inventories. [1] To standardize AG and IA, both values are divided by the total assets at

[1] Gross PPE are calculated as the sum of the net PPE plus depreciation plus impairment loss. Because the impairment loss on the Nikkei NEEDS database includes both impairment loss on PPE and intangibles, we allocate the impairment loss for PPE in proportion to the amount of net PPE divided by the sum of net PPE plus intangibles.

the previous fiscal year end. Following Li and Zhang (2010), net stock issue (NSI) is defined as the natural log of the ratio of the shares outstanding divided by the shares outstanding at the end of the previous fiscal year. Variables from financial data are used as of the most recent fiscal year end. The variables are revised a month after the release of financial statements. We also employ a proxy for financial distress. We calculate probability of financial distress (Pnaive) following Bharath and Shumway (2008).

Panel A of Table 1 presents time-series averages of the mean, standard deviation, mini mum, and maximum of firm characteristics. The mean of BM is 0.699, which indicates that, on average, the firm's market value exceeds its book value. The mean of AG is 0.044, with a standard deviation of 0.110; the mean of IA is 0.039, with a standard deviation of 0.073; and the mean of NSI is 0.015, with a standard deviation of 0.043. These values indicate that there are significant variations in investment-related variables both across firms and over time.

**Table 1.**

Summary statistics of firm characteristics. Panel A reports descriptive statistics of firma characteristics and Fama-MacBeth (annually) regression results of book-to-market ratios on firm characteristics from 1980 to 2010. BM is defined as the ratio of book value of equity to market value of equity (MCAP). Asset growth (AG) is the change in total assets. Investment-to-asset (IA) is measured as the change in gross property, plant, and equipment (PPE) plus the change in inventories. Net stock issue (NSI) is defined as the natural log of the ratio of the shares outstanding divided by the shares outstanding at the previous fiscal year. Probability of financial distress (Pnaive) is calculated following Bharath and Shumway (2008). Panel B reports time-series average of regressions of BM on AG, IA, NSI, Pnaive, and MCAP. *t*-statistics are adjusted for the Newey and West (1987) robust standard errors with one year lag.

| Panel A:Descriptive statistics of firm characteristics | | | | | | |
|---|---|---|---|---|---|---|
| | BM | AG | IA | NSI | Pnaive | MCAP($*10^6$) |
| Mean | 0.699 | 0.044 | 0.039 | 0.015 | 0.041 | 211,411 |
| SD | 0.378 | 0.110 | 0.073 | 0.043 | 0.102 | 639,804 |
| Min | 0.045 | -0.281 | -0.229 | -0.027 | 0.000 | 4,855 |
| Max | 2.555 | 0.657 | 0.457 | 0.355 | 0.780 | 14,120,658 |
| Panel B:Fama-MacBeth regression of BM on firm characteristics | | | | | | |
| | Intercept | AG | IA | NSI | Pnaive | MCAP |
| coef. | 1.649 | -0.225 | -0.004 | -0.980 | 0.443 | -0.089 |
| t-stat. | 5.43 | -3.06 | -0.04 | -5.78 | 3.05 | -4.28 |

### *2.3. Residual book-to-market ratios (RedBMs)*

To calculate RedBMs, we regress BM on AG, IA, NSI, Pnaive, and the natural logarithm of MCAP (LnMCAP) and obtain residuals. Panel B of Table 1 reports the results of time series average of annual regressions (Fama-MacBeth regression results). The *t*-statistics are adjusted using Newey and West's (1987) robust standard errors with a one-month lag. Panel B shows the multiple regression result with all risk-related variables. As shown in Panel B, the slope coeffcients of AG and NSI are negative (-0.313 and -1.018) and are statistically significant ($t = -10.03$ and $-16.36$). However, the slope coeffcient of IA is slightly positive (0.041) and is not statistically significant ($t = 1.24$). This result indicates that the slope coeffcient of IA is subsumed. Panel B also shows that the slope coeffcient of Pnaive is positive (0.392), with a *t*-statistic of 2.81, and that the slope coeffcient of LnMCAP is negative (-0.095), with a *t*-statistic of -14.66. Overall, the above results imply that risks of investment activities and financial distress affect BM.

## 3. Empirical results

### *3.1. Portfolios sorted by BM and RedBM*

In this section, by using RedBM predicted in formula Panel B of Table 1, we evaluate the value effect after controlling for the effect of systematic risks on BM. For each month, we form quintile portfolios with the latest RedBM and construct a hedging portfolio that longs the highest RedBM portfolio and shorts the lowest RedBM portfolio. Then, we calculate time series average of monthly equal- and value-weighted returns of quintile and hedging portfolios. We also estimate alphas by regressing the monthly excess returns on Fama and French (1993) three-factors plus a momentum factor (Carhart, 1997). [2] Table 2 reports the results of alphas. After controlling for four factors, the equal-weighted alpha is 0.51% and statistically significant ($t = -4.51$); the value-weighted alpha is 0.51% and is statistically significant ($t = 4.52$). These results show that the mispricing is still a strong driver of the value effect, even after controlling for traditional factors.

**Table 2.**

Alphas of BM/RedBM quintile and hedging portfolios. This table reports the 4-factor model (Fama and French three-factors plus momentum factor) adjusted alphas of BM/RedBM quintile and hedging portfolios. For each month, we construct a hedging portfolio that has a long position in the highest BM/RedBM portfolio and a short position in the lowest BM/RedBM portfolio, using the latest BM/RedBM. This table report equal- and value-weighted returns of portfolios with *t*-statistics, which are adjusted using Newey and West (1987) robust standard errors with one month lag.

| Sorting by | EW/VW | 1(low) | 2 | 3 | 4 | 5(high) | 5–1 | t(5-1) |
|---|---|---|---|---|---|---|---|---|
| BM | EW | -0.205% | -0.200% | -0.094% | -0.120% | 0.046% | 0.251% | 2.53 |
| BM | VW | -0.168% | -0.191% | -0.094% | -0.126% | 0.044% | 0.212% | 2.12 |
| RedBM | EW | -0.449% | -0.135% | -0.096% | 0.050% | 0.059% | 0.508% | 4.51 |
| RedBM | VW | -0.444% | -0.130% | -0.087% | 0.057% | 0.062% | 0.506% | 4.52 |

### *3.2. Portfolios sorted by BM/RedBM and proxies for limit-to-arbitrage*

The mispricing hypothesis suggests that the value effect reflects mispricing due to the market participant's behavioral biases. If mispricing is a main driver of the value effect, the value effect is expected to be stronger among firms with a stricter limit-to-arbitrage. To test this prediction, we employ two proxies for limit-to-arbitrage. The first one is idiosyncratic volatility (IVOL). Because arbitrageurs are poorly diversified, idiosyncratic risk adds substantially to the total risk of their portfolios. Therefore, arbitrageurs tend to avoid investing in firms with high IVOL, which leads to diffculty in hedging (Shleifer and Vishny, 1997). Following Ali, Hwang, and Trombley (2003), IVOL is defined as the standard deviation of the residuals obtained from regressions of excess returns of individual stocks over the past 36 months on the 4-factor, Fama-French three factors and a momentum factor. The second proxy is foreign investors ownership (FORGN), which is defined as the percentage of outstanding shares held by foreign investors. According to Hamao and Mei (2001), foreign investors have more sophisticated investment technology than do their domestic investors in Japan.

Using proxies for the degree of limit-to-arbitrage, we examine the return predictability of RedBM. First, we divide all stocks into three groups according to each proxy for limit to-arbitrage. We employ the top three and bottom three deciles based on each proxy for limit-to-arbitrage as

[2] These factors are calculated using the Japanese market data following the description in the Kenneth R. French Data Library Web site.

breakpoints. Then, we form quintile portfolios with the latest RedBM and construct a hedging portfolio. Table 3 reports four-factor model-adjusted alphas of the portfolios in each subsample with t-statistics using Newey and West's (1987) robust standard errors.

Panel A of Table 3 shows that when we employ equal-weighted portfolios, the RedBM hedging portfolio with high IVOL yields larger returns than does a portfolio with a low IVOL. The spread between the RedBM hedging portfolio with a high IVOL and that with a low IVOL is 0.48%, and this difference is statistically significant ($t$ = 2.83). Panel B of Table 3 presents, when we employ equal-weighted portfolios, the RedBM hedging portfolio with low FORGN yields larger returns than does that with high FORGN. The spread between high FORGN and low FORGN is -1.07% and is statistically significant ($t$ = −5.36). [3] The above findings indicate that the degree of limit-to-arbitrage affects the magnitude of the value effect, which means that mispricing is a strong driver of the value effect.

**Table 3.**

Alphas of hedging portfolio sorted by RedBM in subsamples sorted by proxies for limit-to-arbitrage. This table reports 4-factor model adjusted alphas of quintile and hedging portfolio sorted by RedBM on subsamples that were first sorted by proxies for limit-to-arbitrage: Idiosyncratic volatility(IVOL) and foreign investor ownership(FORGN). IVOL is defined as the standard deviation of residuals estimated by regressing e individual returns on Fama and French three-factors plus momentum factor over the past 36 months. FORGN is defined as the percentage of outstanding shares held by foreign investors at the previous fiscal year end. First, all stocks are divided into three groups according to each proxy for limit-to-arbitrage. The top three and bottom three deciles based on each proxy for limit-to-arbitrage are employed as breakpoints. Then, in each subsample, quintile and hedging portfolios are constructed using the latest RedBM. Panels A and B report the results when IVOL is employed as a proxy for limit-to-arbitrage. Panels C and D report the results when FORGN is employed as aproxy for limit-to-arbitrage. $t$-statistics are adjusted using Newey and West(1987) robust standard errors with one month lag.

| Panel A: Equal-weighted returns of portfolio sorted by RedBM in subsamples sorted by IVOL | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1(low RedBM) | 2 | 3 | 4 | 5(high RedBM) | 5–1 | t(5-1) |
| 1(low IVOL) | -0.091% | -0.050% | 0.080% | 0.142% | 0.191% | 0.282% | 2.36 |
| 2 | -0.181% | -0.040% | -0.104% | 0.070% | 0.100% | 0.281% | 2.29 |
| 3(high IVOL) | -0.914% | -0.378% | -0.255% | -0.270% | -0.154% | 0.760% | 4.74 |
| 3(high)-1(low) | | | | | | 0.477% | 2.83 |
| **Panel B: Value-weighted returns of portfolio sorted by RedBM in subsamples sorted by IVOL** | | | | | | | |
| | 1(low RedBM) | 2 | 3 | 4 | 5(high RedBM) | 5–1 | t(5-1) |
| 1(low IVOL) | -0.091% | -0.056% | 0.086% | 0.150% | 0.199% | 0.290% | 2.40 |
| 2 | -0.190% | -0.054% | -0.099% | 0.062% | 0.085% | 0.275% | 2.25 |
| 3(high IVOL) | -0.928% | -0.371% | -0.223% | -0.247% | -0.152% | 0.776% | 4.84 |
| 3(high)-1(low) | | | | | | 0.486% | 2.92 |
| **Panel C: Equal-weighted returns of portfolio sorted by RedBM in subsamples sorted by FORGN** | | | | | | | |
| | 1(low RedBM) | 2 | 3 | 4 | 5(high RedBM) | 5–1 | t(5-1) |
| 1(low FORGN) | -0.888% | -0.253% | -0.208% | 0.008% | 0.227% | 1.116% | 6.59 |
| 2 | -0.237% | -0.245% | -0.085% | -0.118% | 0.021% | 0.259% | 2.03 |
| 3(high FORGN) | -0.029% | -0.031% | 0.100% | 0.060% | 0.015% | 0.044% | 0.31 |
| 3(high)-1(low) | | | | | | -1.071% | -5.36 |
| **Panel D: Value-weighted returns of portfolio sorted by RedBM in subsamples sorted by FORGN** | | | | | | | |
| | 1(low RedBM) | 2 | 3 | 4 | 5(high RedBM) | 5–1 | t(5-1) |
| 1(low FORGN) | -0.924% | -0.266% | -0.214% | -0.001% | 0.226% | 1.149% | 6.86 |
| 2 | -0.247% | -0.255% | -0.083% | -0.106% | 0.023% | 0.270% | 2.12 |
| 3(high FORGN) | -0.012% | -0.023% | 0.116% | 0.070% | 0.026% | 0.038% | 0.26 |
| 3(high)-1(low) | | | | | | -1.111% | -5.54 |

[3] In the case of both proxies, when we employ value-weighted portfolios, we obtain similar empirical results.

## 4. Conclusion

In this paper, we show that the effect of mispricing on the value effect persists, even after we control for the effect of risks such as investment factors and financial distress. Using BMs free of investment factors and financial distress (RedBM), we find that RedBM can predict future price appreciations. We also find that the tendency is stronger among stocks with higher degrees of limit-to-arbitrage. Our findings provide supportive evidence for the hypothesis that the behavioral biases of investors drive the value effect. We contribute to the literature on the value effect in that we provide more robust empirical evidence than do Ali, Hwang, and Trombley (2003). We obtain similar results to Ali, Hwang, and Trombley (2003), even after eliminating the effect of investment factors and distress risks.

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# Does tax-loss selling affect January returns? Evidence from the capital gain tax rate changes in Japan

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## Abstract

Focusing on changes in the capital gains tax rate in Japan, this paper examines whether tax-loss selling is a main driver of the January effect. Empirical findings in this study lend support for the tax-loss selling hypothesis. I find that the stocks most likely to be subject to tax-loss selling are more likely to yield higher returns around the turn of the year and tend to show excessive year-end trading in the high capital gain tax regime.

***Keywords***: January effect, Tax-loss selling, Seasonality

***JEL classification:*** **G12, G14**

## 1. Introduction

Among some anomalies in the stock market, the January effect is one of the most noted phenomena. Among some explanations, tax-loss selling is the most plausible to explain the anomaly. According to the tax-loss selling hypothesis, taxable investors are more likely to realize capital losses in order to defer their tax burden from capital gains before the end of the tax year, which results in price depreciation toward the end of the year and return reversals at the turn of the year. [1]

By focusing on individual tax regime changes, some empirical studies provide evidence supporting the tax-loss selling hypothesis (Schultz, 1985; Jones, Lee, and Apebrink, 1991; Bhara, Dhillon, and Ramirez, 1999; Poterba and Weisbenner, 2001; Grinblatt and Moskowitz, 2004). In a similar spirit to those previous studies, I also examine whether tax-loss selling drives the January effect by regarding individual tax regime changes in Japan as natural experiments. During the period from January 1980 to March 2014, the Japanese government introduced capital gain tax rules in 1990 and deregulated trades of financial commodities in the 2003 tax reform, in which tax rates on capital gains were reduced from 26 percent to 10 percent. [2] Because tax introduction (reduction) laws result in generating (reducing) benefits from the realization of capital losses and stronger (weaker) effects on turn-of-the-year returns, it is beneficial to analyze the Japanese stock market,

[1] Dyl (1977) finds that trading volume in December is larger for losing stocks. In recent studies analyzing trading behaviors of individual investors (Badrinath and Lewellen (1991), Dyl and Maberly (1992), Grinblatt and Keloharju (2001), Odean (1998), Ritter (1988), and Ivkovic, Poterba, and Weisbenner (2005)), it is shown that individual investors realize capital losses around December.

[2] Before 1999, Japanese individual investors faced a higher capital gains tax rate of 26 percent. Details on the capital gains tax system in Japan are described in Hayashida and Ono (2010).

which experienced the individual tax regime changes. In addition, as most Japanese institutional investors and listed firms set their fiscal year ends as the end of March, I can mitigate the effect of window dressing and information release on turn-of-the-year returns. [3]

To examine whether tax-loss selling affects turn-of-the-year returns in the Japanese market, I divide the sample period into three periods, Jan80-Mar90, Apr90-Mar03, and Apr03Mar14. According to the capital gain tax rates, I define the first, second, and third tax regimes as the low, high, and moderate tax regimes, respectively. If tax-loss selling has an important role in turn-of-the-year returns, higher turn-of-the-year returns can be observed among stocks subject to tax-loss selling during the high capital gain tax regime. To identify stocks that have the potential to be subject to tax-loss selling, I employ the measure of unrealized capital gains that is defined in Grinblatt and Han (2005), which is the ratio of the current price to the 52-week high price. Constructing 10 portfolios sorted by the potential tax-loss selling measures, I hold the portfolios for 20 days after the formation. I also construct a portfolio that takes long positions in stocks with the highest potential tax-loss selling and takes short positions in stocks with the least potential tax-loss selling. If the tax-loss selling hypothesis is a more compelling explanation for price appreciations in January, the long-short portfolio yields higher turn-of-the-year returns during the high capital gain tax regime. In empirical examinations, I find evidence confirming this prediction. The long-short portfolio yields statistically significant January alphas in the highest capital gain tax period. However, during the lowest capital gain tax period, the alphas on the long-short portfolio are statistically insignificant. Volume-based analysis shows that trading induced by tax-loss selling is prominent in the highest capital gain tax regime. Return and volume analyses in this study lend empirical support for the hypothesis that tax-loss selling is a main driver of the January effect. The contribution of this paper is that even under conditions where information release or window dressing is least likely to affect turn-of-the-year returns, I can find evidence consistent with the tax-loss selling hypothesis.

The remainder of this paper is organized as follows. In the next section, I describe the main variables and provide the empirical methods used in this study. Section 3 reports empirical results on return and volume analyses for the portfolios that are more likely to be subject to tax-loss selling. The conclusions are documented in the last section.

## 2. Data and methods

### *2.1. Primary data*

In this paper, I analyze daily returns obtained from stock price data provided by the Nikkei NEEDS. The sample period ranges from January 1980 to March 2014. According to the National Tax Agency Statistical Annuals, taxes on capital gains were introduced in 1990. At that time, individual investors faced 26 percent taxes on their realized capital gains. After the tax reduction law became effective in January 2003, individual investors faced 10 percent taxes on their realized gain. To examine the effect of tax-loss selling, I divide the sample period into three periods according to capital gain tax rates: the period from January 1980 to March 1990 (low capital gains tax regime), the period from April 1990 to March 2003 (high capital gains tax regime), and the period from April 2003 to March 2014 (moderate capital gains tax regime). As in many previous studies, I exclude financial firms and regulated utilities from the analysis.

[3] Details on window dressing are presented in Lakonishok et al. (1991). The effect of information release is summarized in Jones and Lee (1995).

### 2.2. *Potential tax-loss selling measure*

To identify stocks that are more likely to be subject to tax-loss selling, I employ two potential tax-loss selling measures. The first one is a proxy for capital gains following Grinblatt and Han (2005). The measure is defined as

$$\begin{aligned} g_t &= \frac{P_t - RP_t}{P_t} \\ \text{with } RP_t &= \phi^{-1} \sum_{n=0}^{250} \hat{V}_{t,t-n} P_{t-n} \\ \text{where } \hat{V}_{t,t-n} &= TO_{t,t-n} \prod_{\tau=1}^{n-1} (1 - TO_{t-n+\tau}) \\ \text{and } \phi &= \sum_{n=0}^{250} \hat{V}_{t,t-n}. \end{aligned}$$

In the equations, $P_{i,t}$ is the (split- and dividend-adjusted) close price of stock *i* at date *t*, and $TO_{i,t}$ is the turnover ratio (daily trading volume divided by share outstanding) of stock i at date t. $RP_{i,t}$ is the reference point that weights close prices by turnover ratio. $RP_{i,t}$ can be regarded as an average purchase price using a moving-average method. I regard stocks with lower $g_{i,t}$ (henceforth, GHCG) as higher potential tax-loss selling stocks.

The second measure for potential tax-loss selling is the ratio of the current price to the 52-week high price (52WH). As Baker and Wurgler (2013) document, the 52-week high price serves as a reference point for the decisions of many market participants. As in the case of GHCG, I regard stocks with lower 52WHs (facing capital losses) as higher potential tax-loss selling stocks.

### 2.3. *Empirical strategy*

To examine the effect of tax-loss selling, I construct 10 testing portfolios according to measures for potential tax-loss selling at the previous date before the formation period and calculate each portfolio's returns on a day-to-day basis. I also construct a long-short portfolio that takes long positions in the stocks most subject to potential tax-loss selling and takes short positions in the stocks least subject to potential tax-loss selling. The testing portfolios are equally weighted and formed employing a rolling portfolio approach. [4] That is, I calculate overlapping returns on trading strategies that hold a series of portfolios that are selected in the current day as well as the previous *k*-days. Lastly, I run the following regression model.

$$\begin{aligned} r_{p,t} - r_{f,t} &= \alpha_1 FebDec_1 + \alpha_2 FebDec_2 + \alpha_3 FebDec_3 \\ &\quad + \alpha_4 Jan_1 + \alpha_5 Jan_2 + \alpha_6 Jan_3 + \beta_1 Mkt_t + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_t \quad (1) \end{aligned}$$

$r_{p,t}$ is the daily return of a testing portfolio. More specifically, we define it as follows.

$$r_{p,t} = \frac{1}{K} \sum_{k=1}^{K} \frac{1}{N_{p,t-k}} \sum_{n=1}^{N_{p,t-k}} r_{i,t}, \quad p \in (CL, CG)$$

[4] See Jegadeesh and Titman (1993). To avoid the effect of idiosyncratic shocks on larger firms, I employ equal-weighting strategies.

$K$ is a holding period, and $N_{p,t-k}$ denotes the number of stocks included in a particular decile portfolio sorted by potential tax-loss selling measures at date $t-k$. $r_{f,t}$ is an overnight call rate at day t. $FebDec_i$ is a dummy variable, which takes one if day $t$ belongs to the months from February to December in the first ($i$ = 1), second ($i$ = 2), and third ($i$ = 3) tax regimes. $Jan_i$ is a dummy variable, which takes one if day $t$ belongs to January in the first, second, and third tax regimes. Fama and French's (1993) three factors, $Mkt_t$, $SMB_t$, and $HML_t$, are obtained from Financial Data Solutions, Inc. Time-series coefficients on $Jan_i$s in the above model are interpreted as risk-adjusted alphas in January in the three different tax regimes. If the tax-loss selling hypothesis is more dominant, I expect a positive and larger coefficient on $Jan_2$ than those on $Jan_1$ and $Jan_3$.

I also conduct a volume-based analysis in a similar manner as Dyl (1977) and Bhabra, Dhillon, and Ramirez (1999). I examine whether trading volume in December is excessive during the high tax regime. In the examination, I calculate daily relative trading volume following a methodology in Dyl (1977). Relative trading volume $RVOL_{i,t}$ is defined as the turnover ratio at day $t$ for firm $i$ divided by the mean of the daily turnover ratio of the preceding 12 months. After regressing the relative trading volume on mean relative trading volume ($RVOL_{m,t}$), which is the equal-weighted cross-sectional average of $RVOL_{i,t}$, and obtaining coefficients, I calculate excess relative trading volume ($EVOL_{i,t}$). That is, I conduct the following regression model and obtain estimates of $\alpha_i$ and $\beta_i$ for each firm.

$$RVOL_{i,t} = \alpha_i + \beta_i RVOL_{m,t} + \epsilon_{i,t} \tag{2}$$

Using the estimates, I calculate the excess relative trading volume defined in the following equation.

$$EVOL_{i,t} = RVOL_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i RVOL_{m,t}) \tag{3}$$

Similar to return analysis, stocks are grouped into 10 portfolios according to the potential tax-loss selling measures. To examine the effect of the changes in the capital gain tax regime, I compare the excess trading volume in December across the three different periods.

## 3. Empirical results

### 3.1. Return analysis

Table 1 reports the factor model alphas and loadings on testing portfolios when the holding period $k$ is 20 days. The t-statistics below the coefficients are computed using Newey-West adjusted standard errors with 15 lags. [5] The testing portfolios are divided into 10 portfolios according to the potential tax-loss selling measures. As seen in the first column in Panels A and B of Table 1, stocks with a high potential for tax-loss selling show positive January returns in any period and the largest returns in the high capital gain tax regime. Subsequently, I report January returns of the portfolio that takes long positions in the stocks most likely to experience tax-loss selling and takes short positions in the stocks least likely to experience tax-loss selling. The third column in Panel A of Table 1 shows that the longshort portfolio based on GHCG generates significant January returns only in the high capital gain tax regime. The long-short portfolio yields 44.0 bps per day in January with statistical significance in the high capital gain tax regime, while the portfolio generates a smaller and statistically insignificant January return of 10.2 (0) bps per day in the moderate (low) capital gain tax regime. In addition, the Wald test, which examines the difference in January returns between the high-,

5 Following Andrews (1991), I set the number of lags as 15, which is the maximum number in the case of approximately 9,000 observations.

moderate- and low-tax regimes, shows that the difference is significant at least at the 10 percent significance level. The third column in Panel B of Table 1 also shows a similar tendency. The long-short portfolio sorted by 52WH generates significant January returns only in the high capital gain tax regime. The long-short portfolio yields 46.8 bps per day in January with statistical significance in the high capital gain tax regime. The Wald test examining the difference of January returns between the high-, moderate- and low-tax regimes shows that the difference is significant at least at the 5 percent significance level. As a whole, the results in Table 1 indicate that the January returns of most stocks potentially subject to tax-loss selling are higher in the high capital gain tax regime. This empirical finding is consistent with the tax-loss selling hypothesis.

## Table 1.

This table presents daily Fama-French (FF) alphas in each calendar time (February to December and January) of the equal-weighted portfolios for the most and the least potential tax-loss selling (PTS) decile portfolios and the equal-weighted portfolios that are a combination of long the most PTS decile portfolio and short the least PTS decile portfolio. Deciles are formed on a day-to-day basis from January 1980 to March 2014 based on Grinblatt and Han's (2005) capital gains (GHCG) or the ratio of the current price to the 52-week high price (52WH) at the previous date. Stocks with the lowest (highest) values of GHCGs or 52WHs are included in the most (least) PTS decile portfolio. Testing portfolios are held for 20 days after the formation period, and returns on testing portfolios are computed by averaging the current day's return on the previous 20 days' portfolios. $FebDec_i$ is a dummy variable, which takes one if day $t$ belongs to the month from February to December in the rst ($i$ = 1), second ($i$ = 2), and third ($i$ = 3) tax regimes. $Jan_i s$ are dummy variables, which take one if day $t$ belongs to January in the rst, second, and third tax regimes. FF alphas are reported in daily percentages, and Newey-West adjusted t-statistics with 15 lags are shown below the coefficient estimates.

| | Panel A: sorting by GHCG | | | Panel B: sorting by 52WH | | |
|---|---|---|---|---|---|---|
| | High PTS | Low PTS | High-Low | High PTS | Low PTS | High-Low |
| $FebDec_1$ | 0.013 | 0.013 | 0.001 | 0.009 | 0.024 | -0.015 |
| | (1.02) | (1.09) | (0.02) | (0.68) | (2.70) | (-0.81) |
| $FebDec_2$ | 0.060 | 0.014 | 0.046 | 0.055 | 0.004 | 0.051 |
| | (3.35) | (1.07) | (1.67) | (3.27) | (0.37) | (2.20) |
| $FebDec_3$ | 0.043 | 0.030 | 0.013 | 0.024 | 0.022 | 0.002 |
| | (1.88) | (2.69) | (0.48) | (0.94) | (2.64) | (0.06) |
| $Jan_1$ | 0.039 | 0.039 | 0.000 | 0.015 | 0.059 | -0.044 |
| | (1.18) | (1.07) | (0.00) | (0.46) | (1.78) | (-0.97) |
| $Jan_2$ | 0.373 | -0.067 | 0.440 | 0.384 | -0.084 | 0.468 |
| | (3.32) | (-1.39) | (2.87) | (3.49) | (-2.34) | (3.32) |
| $Jan_3$ | 0.129 | 0.028 | 0.102 | 0.083 | 0.030 | 0.053 |
| | (2.04) | (0.84) | (1.46) | (1.25) | (1.11) | (0.74) |
| Mkt | 1.056 | 0.805 | 0.252 | 1.137 | 0.621 | 0.516 |
| | (47.99) | (28.98) | (6.51) | (52.35) | (29.88) | (15.64) |
| SMB | 1.084 | 0.627 | 0.458 | 1.185 | 0.439 | 0.746 |
| | (22.33) | (15.26) | (6.53) | (25.04) | (15.07) | (12.13) |
| HML | 0.259 | -0.031 | 0.291 | 0.240 | 0.097 | 0.143 |
| | (4.95) | (-0.92) | (3.74) | (4.64) | (3.73) | (2.08) |
| Wald test P-value | | | | | | |
| $Jan_1 = Jan_2$ | | | 0.009 | | | 0.001 |
| $Jan_2 = Jan_3$ | | | 0.051 | | | 0.011 |

### *3.2. Volume-based analysis*

I also examine the trading activity of portfolios that are potentially subject to tax-loss selling in December. Averages of excess relative trading volume in December during three different capital gain tax regimes are reported in Table 2. Differences among the three tax regimes are reported in the last six rows. As reported in the first column in Panel A of Table 2, the high potential tax-loss selling portfolio shows negative excess trading volume in the low capital gain tax regime. Meanwhile, in the second and third columns, excessive trading volume of the high potential tax-loss selling portfolio is positive, which indicates that tax-loss selling tendency is stronger during the second and third tax regimes. In addition, the last six rows in Panel A of Table 2 show that excessive trading volume is statistically significantly higher in the high-tax regime than in the moderate-tax regime. This evidence is consistent with the tax-loss selling hypothesis. The tendency does not change even if I employ 52WH, as reported in Panel B of Table 2.

**Table 2.**

This table presents excess trading volume in December of the most and the least potential tax-loss selling(PTS) decile portfolios sorting by GHCG or 52WH in three different tax regimes. Relative trading volume $RVOL_{i,t}$ is defined as turnove rratio at day $t$ for firm $i$ divided by the mean of the daily turnover ratio of the preceding 12 months. After regressing the relative trading volume on the mean relative trading volume, the equal-weighted average of $RVOL_{i,t}$ (denoted as $RVOL_{m,t}$), and obtaining coefficient estimates, the excess relative trading volume ($EVOL_{i,t}$) is calculated as $EVOL_{i,t} = RVOL_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i RVOL_{m,t})$.The last six rows in this table also report differences in excess trading volume among three different tax regimes with those t-statistics.

| | Panel A: sorting by GHCG | | Panel B: sorting by 52WH | |
|---|---|---|---|---|
| | High PTS | Low PTS | High PTS | Low PTS |
| Regime1 (Low tax) | -0.962 | 2.051 | -0.958 | 2.685 |
| Regime2 (High tax) | -0.156 | 0.712 | -0.196 | 0.675 |
| Regime3 (Moderate tax) | -0.487 | 0.805 | -0.510 | 1.022 |
| Regime1-Regime2 | -0.806 | 1.340 | -0.762 | 2.010 |
| | (-12.39) | (10.86) | (-12.43) | (15.14) |
| Regime1-Regime3 | -0.475 | 1.247 | -0.448 | 1.663 |
| | (-5.58) | (12.61) | (-5.29) | (14.45) |
| Regime2-Regime3 | 0.331 | -0.093 | 0.314 | -0.348 |
| | (3.93) | (-0.93) | (3.72) | (-3.44) |

## 4. Conclusion

Japan introduced capital gains taxes in 1990 and reduced the tax rate on capital gains from 26 percent to 10 percent. Focusing on these changes in the capital gains tax regime, I examine whether tax-loss selling affects returns around the turn of the year. The empirical findings in this study lend support for the tax-loss selling hypothesis. First, I find that a long-short portfolio that takes long positions in the stocks most subject to potential taxloss selling and takes short positions in the stocks least subject to potential tax-loss selling yields higher turn-of-the-year returns in the high capital gain tax regime than in the low or moderate capital gain tax regimes. In the volume-based analysis, trading volume is higher during the high capital gain tax regime. As a whole, I provide empirical evidence that tax-loss selling drives the January effect.

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# Bank-specific Determinants of Capital Structure: New Evidence from Japan

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## Abstract

This paper is the first empirical research on the determinants of the capital structure of Japanese banks, using Japanese banks' financial data for two decades from 2000 to 2017 and adding new evidence to previous literature on the banks' capital structure. Previous researches show that the determinants of capital structure are different among countries or continents. We show that determinants vary and change in accordance with differences in business models among banks even within one country. By focusing on different business models between four sub-samples, "International banks before the Global Financial Crisis," "Domestic banks before the GFC," "International banks after the GFC," and "Domestic banks after the GFC", we analyze whether the determinants of capital structure differ among these sub-samples. The results are totally different and we find no determinants which can significantly and commonly explain all four sub-samples.

***Keywords***: Japanese banks, Capital Structure

***JEL classification:* G21, G28**

## 1. Introduction

Banks' capital ratio is generally kept much lower than that of non-financial companies. This is puzzling for economists from a positive-theory viewpoint (DeAngelo and Stulz [2015]). Monetary and financial economists have examined the determinants of banks' capital structure for decades, and this became a hotter research field after the Global Financial Crisis that caused financial regulatory reforms.

There are two approaches that explain the determinants of banks' capital structure. The first approach is a corporate financial approach, which tries to explain banks' capital structure based on the theory of Modigliani and Miller (1958) and its development in corporate finance, such as tax savings on the financing of debt, a pecking order hypothesis, and so on.

The second approach is a banking approach, which places more focus on a bank's unique business model compared to non-financial companies and regards this uniqueness as a factor causing the bank's unique balance sheet structure: its low capital ratio (Diamond and Dybvig [1983], Diamond and Rajan [2000], Allen et al. [2011], DeAngelo and Stulz [2015]). DeAngelo and Stulz

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(2015), the latest theoretical research using this approach, shows that a bank's low capital ratio is optimal for banks whose central function is liquidity production. Banks provide deposits to the economy, and these are its most liquid assets. Deposits can bear a negative liquidity premium placed on it by the depositor, which enables the banks to earn external funds with lower costs than other external funds. This lower cost can explain the higher deposit-to-asset ratio, or the lower capital ratio.

Previous empirical works have tried to tackle this puzzle by using explanatory variables which are based on both banking and corporate-finance approaches. However, they can explain only some of the determinants of banks' capital structure. Gropp and Heider (2010), examining the capital structure of large U.S. and European banks from 1991 to 2004, found that an individual bank's specific factors are ultimately the most important determinant of a bank's capital structure. Kinai (2018), in subsequent research by Gropp and Heider (2010), examined the capital structure of U.S. and European banks by adding new explanatory variables that are based on both approaches. Although these new variables have significant effects, this research also concluded that a firm's capital structure is mostly driven by unobserved individual firm-specific factors.

What is the source of an individual bank's specific factors? Kinai (2018), examining the difference he found between the estimation results of U.S. and European banks, pointed out the possibility that the difference comes from differences in their business models. Although banks are categorized into one business type, "the banking industry", their business models differ from country to country as well as within a country. This difference is probably due to their cultural and historical backgrounds.

Taking Japan as an example, while we have more than 100 commercial banks in Japan, their business models differ. Some do business in international markets and can access several financial markets to receive and invest funds, while others only operate in one small, prefecture-level market, and deposits from this market are their single, most important source of external funds. Different back histories should also affect their different business models and capital structures. Some international banks have longer histories as commercial banks and have engaged in nationwide and international business for more than 100 years since Japanese modernization. On the other hand, some regional banks were originally saving banks or mutual banks and they have operated in a very small business area (Hoshi and Kashyap [2004]).

In this research, we categorize Japan's banks into two groups based on their business models as well as their back histories: "the international banks" which do business in international markets and have a relatively long history as commercial banks, and "the regional banks (the domestic banks)" which have operated only in one small, prefecture-level market since the middle of the 20$^{th}$ century[3]. Then, focusing on the possible difference between the two groups, we examine whether banks with different business models differ in what determines their capital structure.

As is clearly shown by Hoshi and Kashyap (2004), Japanese banks' business models have been strongly affected by regulatory changes during their long history since the 19$^{th}$ century. The current regulatory reforms since the Global Financial Crisis may have changed their business models as well. So, we will split the sample into before-2008 and after-2009 and examine whether the determinants of their capital structure changed before and after the GFC.

Using the unbalanced panel financial data of all Japan's banks from 2000 to 2017, we estimated a fixed effects model to examine the effects of possible factors on banks' capital ratios. By comparing the results between four sub-samples – "International banks before the Global Financial Crisis,"

[3] Most of the current regional banks were born under a "one prefecture, one bank" government program in the 1940s (Hoshi and Kashyap [2004] p.58).

"Domestic banks before the GFC," "International banks after the GFC," and "Domestic banks after the GFC" – we show that the determinants differ among banks and eras even within one country. We find no determinants that can significantly and commonly explain all four sub-samples.

Previous researches, such as Gropp and Heider (2010) and Kinai (2018), show that the determinants of capital structure differ among countries, and point out that these differences are probably caused by differences in business models due to the differences in their cultural and historical backgrounds. This paper contributes to this literature by showing differences among banks even within "one" country that are also due to their different business models.

To the best of our knowledge, this is the first study which examines the determinants of banks' capital structure by using Japanese financial data. There is a lot of literature that examines the effects of capital structure on banks' behavior in Japan (such as Montgomery [2005], Osada, Onji and Vera [2017]). Our research will also contribute to future work that examines the interaction between banks' capital structure and other economic variables.

The paper is organized as follows. Section 2 describes the models and econometric estimation as well as explaining the definition of variables in our model. In section 3, we present the estimation results and analyze them. Section 4 concludes.

## 2. Models and econometric estimation

In this paper, we employ following the seven independent variables affecting banks capital structure using annual data in an unbalanced panel: *P Loan Ratio, M Loan Ratio, Depo Ratio, Loan Rate, Depo Rate, Cost Ratio,* and *ln(Asset)*.

*P Loan Ratio* and *M Loan Ratio* are the ratio of Retail Loans to Total Assets and the ratio of Loans to SMEs to Total Assets, respectively. We use these two independent variables as the degree of asymmetric information between banks and borrowers as well as the degree of liquidity of their assets. According to Diamond and Rajan (2000), Retail and SME loans are less liquid assets with more asymmetric information between banks and borrowers than loans to big companies. So, banks with a higher ratio for these two assets have a stronger incentive to hold capital to cope with liquidity shocks and borrowers' moral hazard.

*Depo Ratio* is the ratio of Deposits to Total Assets. We use it to capture the liquidity premium, a concept used by DeAngelo and Stults (2015), one of the newer theoretical banking papers. Deposits are a source of funding with a negative liquidity premium. Depositors who favor this liquidity will accept a negative premium so banks can obtain funds at lower costs, which produces more profit resulting higher capital ratio.

*Loan Rate* is the ratio of interest income on loans to total loans. There are two conflicting hypotheses which explain the relationship between this rate and capital structure. According to DeAngelo and Stulz (2015), the higher *Loan Rate* produces more profit resulting in a higher capital ratio. On the other hand, we can hypothesize that worse banks with a lower capital ratio have more of an incentive to make loans to riskier borrowers, or borrowers with a higher interest rate, which leads to a negative relationship between this rate and the capital ratio.

*Depo Rate* is the ratio of interest expenditure on deposits to total deposits. A lower *Depo Rate* produces more profits resulting in a higher capital ratio, which leads to a negative relationship. This relationship can also be explained by hypothesizing that worse banks with a lower capital ratio have to pay a higher Depo Rate to depositors when they raise money.

*Cost Ratio* is the ratio of operating expenses to total assets. We use it as a measure of financial intermediary costs, in other words a bank's efficiency. A lower Cost Ratio produces more profits resulting in a higher capital ratio (DeAngelo and Stultz [2015]).

When we explain the relationship between a capital ratio and the first six independent variables, we often use the banking theory of DeAngelo and Stults (2015), where profitable variables can cause a higher capital ratio through the channel of capital accumulation. However, from the corporate financial view based on trade-off theory, there can be a negative relationship between profits and capital ratios. Companies with higher profits can enjoy higher tax saving benefits from debt financing. As a result, they have a stronger incentive to keep a lower capital ratio (Frank and Goyal [2009]).

The seventh variable is a logarithm of total assets, *ln(Asset)*, which is used to measure size effects. According to corporate finance theories, such as a pecking-order hypothesis, bigger companies have less incentive to finance through stocks because they dislike the mispricing in the stock market caused by asymmetric information with investors (Myers and Majluf [1984]). Also, bigger companies are less likely to go bankrupt so they have a stronger incentive to prefer debt-financing.

Expected estimation signs on coefficients are as follows: *P Loan Ratio* (+), *M Loan Ratio* (+), *Depo Ratio* (+), *Loan Rate* (+/-), *Depo Rate* (+/-), *Cost Ratio* (+/-), and *ln(Asset)* (-).

As for dependent variables that measure banks' capital structure, following previous studies (Gropp and Heider [2010], Kinai [2018]), we use three different capital ratios: the Ratio of capital to assets (Equity Ratio), the Regulatory capital adequacy ratio (Cap Ratio), and the Tier 1 Ratio.

Table 1 provides descriptive statistics for the variables we use. All the data are for the end of each fiscal year and unconsolidated-base data, at the end of each March from 2000 to 2017. Table 2 shows their correlations, VIF and Tolerance, where there is no multi-collinearity among our explanatory variables. Our data source is Nikkei Financial Data (NEEDS-CD ROM database)[4].

Using unbalanced panel data, we estimate a static model with fixed effects as follows[5]:

$$Cap_{it} = \beta_0 + BX_{it} + c_t + c_i + u_{it},$$

where $Cap_{it}$ is a dependent variable into which we put three different capital ratios. $X_{it}$ signifies independent variables based on both banking and corporate-financial views. The regression includes time and individual-bank fixed effects ($c_t$,$c_i$) to account for unobserved heterogeneity at the individual-bank level and across time that may be correlated with the explanatory variables. Standard errors are clustered at the bank level to account for heteroscedasticity and the serial correlation of errors (Peterson [2009]).

Our estimations were conducted using both the full sample and two different sub-samples: one is "international banks" which do business in international markets and the other is "regional banks (domestic banks)" which operate only in one small, prefecture-level market. We also divide sample periods into two sub-sample periods: one is before the Global Financial Crisis, or 2008, and the other is after 2009. As explained in the introduction, we focus on the different business models that probably affect the determinants of capital structure. Comparing and analyzing the results for each sub-sample, we can focus on the significant implications from what we find.

## 3. Results

Estimation results in Tables 3, 4 and 5 show the coefficients of the explanatory variables and their corresponding standard errors adjusted for clustering at the individual bank level. From the estimation

[4] This database records regulatory capital ratios only since 2000.

[5] We do not use dynamic types of models which are often used in panel date analysis. Also, we do not use the market data which were used in a prominent previous study (Gropp and Heider [2010]). These improvements are left for future research.

## Table 1.

The sample consists of 130 Japanese banks from FY 1999 to FY 2016. Subsample A consists of 25 international banks which conduct overseas operations. Sub-sample B consists of 105 domestic banks which do not operate overseas.

| | Mean | Median | St. Dev. | Max | Min |
|---|---|---|---|---|---|
| **All banks** | | | | | |
| Equity Ratio | 0.049 | 0.048 | 0.014 | 0.127 | 0.001 |
| Cap Ratio | 0.105 | 0.101 | 0.024 | 0.245 | 0.005 |
| Tier 1 Ratio | 0.083 | 0.079 | 0.026 | 0.196 | 0.002 |
| P Loan Ratio | 0.187 | 0.178 | 0.072 | 0.653 | 0.007 |
| M Loan Ratio | 0.507 | 0.518 | 0.128 | 0.797 | 0.071 |
| Depo Ratio | 0.858 | 0.893 | 0.119 | 0.963 | 0.132 |
| Loan Rate | 0.020 | 0.020 | 0.005 | 0.064 | 0.001 |
| Depo Rate | 0.002 | 0.001 | 0.002 | 0.029 | 0.000 |
| Cost Ratio | 0.012 | 0.012 | 0.003 | 0.028 | 0.000 |
| ln（Asset） | 14.753 | 14.697 | 1.200 | 19.135 | 12.320 |
| **Sub-sample A (International banks)** | | | | | |
| Equity Ratio | 0.056 | 0.057 | 0.014 | 0.088 | 0.017 |
| Cap Ratio | 0.130 | 0.124 | 0.027 | 0.219 | 0.067 |
| Tier 1 Ratio | 0.099 | 0.095 | 0.031 | 0.196 | 0.034 |
| P Loan Ratio | 0.153 | 0.151 | 0.064 | 0.339 | 0.011 |
| M Loan Ratio | 0.397 | 0.413 | 0.125 | 0.634 | 0.071 |
| Depo Ratio | 0.720 | 0.795 | 0.183 | 0.924 | 0.132 |
| Loan Rate | 0.017 | 0.017 | 0.004 | 0.027 | 0.001 |
| Depo Rate | 0.003 | 0.002 | 0.004 | 0.029 | 0.000 |
| Cost Ratio | 0.009 | 0.009 | 0.003 | 0.028 | 0.000 |
| ln（Asset） | 16.360 | 15.922 | 1.193 | 19.135 | 13.749 |
| **Sub-sample B (Domestic banks)** | | | | | |
| Equity Ratio | 0.048 | 0.047 | 0.014 | 0.127 | 0.001 |
| Cap Ratio | 0.099 | 0.098 | 0.020 | 0.245 | 0.005 |
| Tier 1 Ratio | 0.079 | 0.077 | 0.023 | 0.193 | 0.002 |
| P Loan Ratio | 0.195 | 0.185 | 0.072 | 0.653 | 0.007 |
| M Loan Ratio | 0.529 | 0.539 | 0.117 | 0.797 | 0.183 |
| Depo Ratio | 0.886 | 0.903 | 0.075 | 0.963 | 0.152 |
| Loan Rate | 0.021 | 0.021 | 0.005 | 0.064 | 0.009 |
| Depo Rate | 0.002 | 0.001 | 0.001 | 0.012 | 0.000 |
| Cost Ratio | 0.012 | 0.012 | 0.003 | 0.022 | 0.004 |
| ln（Asset） | 14.430 | 14.522 | 0.907 | 17.297 | 12.320 |

## Table 2. Correlations, VIF and Tolerance

| | Equity Ratio | Cap Ratio | Tier 1 Ratio | P Loan Ratio | M Loan Ratio | Depo Ratio | Loan Rate | Depo Rate | Cost Ratio | ln (Asset) | VIF | Tolerance |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Equity Ratio | 1.000 | | | | | | | | | | | |
| Cap Ratio | 0.625 | 1.000 | | | | | | | | | | |
| Tier 1 Ratio | 0.748 | 0.869 | 1.000 | | | | | | | | | |
| P Loan Ratio | -0.259 | -0.322 | -0.261 | 1.000 | | | | | | | 1.68 | 0.594 |
| M Loan Ratio | -0.273 | -0.683 | -0.528 | 0.601 | 1.000 | | | | | | 3.68 | 0.272 |
| Depo Ratio | -0.305 | -0.562 | -0.331 | 0.385 | 0.633 | 1.000 | | | | | 2.74 | 0.365 |
| Loan Rate | -0.297 | -0.656 | -0.524 | 0.352 | 0.717 | 0.426 | 1.000 | | | | 4.11 | 0.243 |
| Depo Rate | -0.006 | 0.052 | -0.106 | -0.158 | -0.152 | -0.522 | 0.187 | 1.000 | | | 2.12 | 0.472 |
| Cost Ratio | -0.278 | -0.642 | -0.451 | 0.253 | 0.668 | 0.524 | 0.734 | -0.120 | 1.000 | 4.66 | 0.215 | |
| ln(Asset) | 0.200 | 0.599 | 0.343 | -0.294 | -0.673 | -0.645 | -0.604 | 0.221 | -0.819 | 1.000 | 3.33 | 0.300 |

results in Table 3, we can find the effects of each factor on capital structure on average in the full sample period. More importantly for our research, by comparing the results of the two sub-sample periods, or between Tables 4 and 5, we can find the effects of changes in banks' business models caused by regulatory reforms which happened before and after the Global Financial Crisis in Japan. Also, by comparing the results between the International and Domestic Banks in each sample period, we can find the effects of the difference in business models on their capital structure. The following are the results and analyses of the four sub-samples: "International banks before the Global Financial Crisis," "Domestic banks before the GFC," "International banks after the GFC," and "Domestic banks after the GFC".

Starting with the results for the international banks before the GFC in Table 4, they have negatively significant results in *ln(Asset)* and *Loan Rate*. In support of the corporate-financial hypothesis, the bigger international banks tended to hold less capital, and, worse, international banks with a lower capital ratio had more incentive to make loans to riskier borrowers, or borrowers with higher interest rates, before the GFC.

However, international banks' behavior changed after the GFC. The results in Table 5 show that *Depo Ratio*, *Depo Rate* and *Cost Ratio* have significant results. The *Cost Ratio* has especially significant positive results on all the three dependent variables at the 1% level. Because these three independent variables relate to banks' costs, we can say that after the GFC, international banks tried to heighten their capital ratio by reducing their costs: by increasing deposits with negative liquidity premiums (DeAngelo and Stultz [2015]), lowering their deposit interest-rate and reducing their operating expenses. As we predicted, international banks' behavior, or their business models, changed after the GFC in terms of their capital structure.

As for the domestic banks, their results are different both from those for the international banks and for the two sample periods. Domestic banks before the GFC have significant positive results in *P*

**Table 3. Full sample period: from 1999 to 2017**

| | All Banks | | | International | | | Domestic Banks | | |
|---|---|---|---|---|---|---|---|---|---|
| | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio |
| P Loan Ratio | 0.012 | 0.019 | 0.022 | -0.007 | -0.032 | -0.039 | 0.014 | 0.050** | 0.055** |
| *se* | (0.012) | (0.023) | (0.025) | (0.026) | (0.056) | (0.068) | (0.013) | (0.022) | (0.026) |
| M Loan Ratio | 0.009 | -0.055*** | -0.022 | 0.013 | -0.049 | -0.045 | 0.007 | -0.073*** | -0.039 |
| *se* | (0.011) | (0.019) | (0.021) | (0.021) | (0.033) | (0.037) | (0.013) | (0.019) | (0.028) |
| Depo Ratio | -0.028* | -0.098*** | -0.083** | -0.004 | -0.064** | -0.054*** | -0.040 | -0.078* | -0.057 |
| *se* | (0.015) | (0.029) | (0.032) | (0.014) | (0.025) | (0.019) | (0.024) | (0.046) | (0.063) |
| Loan Rate | -0.551* | 0.309 | 0.270 | -0.368 | 0.581 | 0.609 | -0.441 | -0.177 | -0.147 |
| *se* | (0.289) | (0.457) | (0.489) | (0.677) | (0.737) | (0.930) | (0.315) | (0.456) | (0.539) |
| Depo Rate | -0.697* | -3.935*** | -4.000*** | -0.811* | -2.491** | -3.815*** | -0.151 | -0.987 | -1.370 |
| *se* | (0.420) | (0.925) | (0.912) | (0.442) | (0.894) | (0.974) | (1.390) | (1.993) | (2.123) |
| Cost Ratio | 0.619 | 1.054 | 0.916 | 0.076 | 1.001 | 1.085 | 0.597 | -0.052 | -0.204 |
| *se* | (0.404) | (0.814) | (0.916) | (0.477) | (1.151) | (1.116) | (0.543) | (0.943) | (1.014) |
| ln(Asset) | -0.006* | -0.001 | -0.002 | -0.011* | 0.000 | -0.009 | -0.006 | -0.012* | -0.007 |
| *se* | (0.003) | (0.005) | (0.007) | (0.006) | (0.010) | (0.013) | (0.004) | (0.006) | (0.008) |
| Constant | 0.162*** | 0.220** | 0.231** | 0.256** | 0.207 | 0.339 | 0.170** | 0.363*** | 0.263* |
| *se* | (0.053) | (0.093) | (0.115) | (0.105) | (0.165) | (0.221) | (0.070) | (0.113) | (0.134) |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 1,829 | 1,823 | 1,507 | 309 | 305 | 301 | 1,520 | 1,518 | 1,206 |
| Adjusted $R^2$ | 0.306 | 0.439 | 0.544 | 0.582 | 0.742 | 0.820 | 0.268 | 0.387 | 0.322 |
| Unique Banks | 130 | 130 | 130 | 25 | 25 | 25 | 105 | 105 | 105 |

Standard errors are adjusted for clustering at the bank level.
***, ** and * denote statistical significance at the 1%, 5 % and 10% levels, respectively.

**Table 4. Before the Global Financial Crisis: from 1999 to 2008**

| | All Banks | | | International | | | Domestic Banks | | |
|---|---|---|---|---|---|---|---|---|---|
| | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio |
| P Loan Ratio | 0.039** | 0.090*** | 0.074*** | 0.046 | 0.075 | 0.087 | 0.035* | 0.097*** | 0.069** |
| *se* | (0.019) | (0.027) | (0.024) | (0.050) | (0.070) | (0.059) | (0.021) | (0.033) | (0.029) |
| M Loan Ratio | 0.000 | -0.034* | -0.010 | 0.001 | -0.025 | -0.017* | -0.001 | -0.042 | -0.011 |
| *se* | (0.018) | (0.019) | (0.018) | (0.024) | (0.016) | (0.010) | (0.020) | (0.027) | (0.029) |
| Depo Ratio | -0.030 | -0.053** | -0.023 | -0.015 | -0.055 | -0.010 | -0.030 | -0.041 | -0.027 |
| *se* | (0.026) | (0.025) | (0.028) | (0.024) | (0.035) | (0.027) | (0.044) | (0.037) | (0.047) |
| Loan Rate | -0.790** | -0.889*** | -0.996** | -0.873 | -1.179* | -1.213*** | -0.581 | -0.679 | -0.837* |
| *se* | (0.396) | (0.327) | (0.390) | (0.702) | (0.641) | (0.420) | (0.469) | (0.421) | (0.498) |
| Depo Rate | -0.478 | -0.338 | -0.199 | -0.258 | 0.085 | 0.037 | 0.289 | 0.654 | 0.212 |
| *se* | (0.736) | (0.666) | (0.831) | (0.425) | (0.718) | (0.608) | (1.272) | (1.547) | (1.829) |
| Cost Ratio | 0.641 | -0.358 | 0.139 | -0.323 | 0.394 | -0.400 | 0.420 | -0.978 | -0.394 |
| *se* | (0.583) | (0.777) | (0.780) | (0.846) | (0.981) | (0.920) | (0.753) | (0.903) | (0.997) |
| ln(Asset) | -0.006 | -0.008 | -0.004 | -0.019** | -0.010 | -0.015* | -0.004 | -0.007 | -0.005 |
| *se* | (0.005) | (0.006) | (0.006) | (0.008) | (0.007) | (0.009) | (0.006) | (0.007) | (0.007) |
| Constant | 0.161** | 0.285*** | 0.165* | 0.387** | 0.337*** | 0.362** | 0.128 | 0.267** | 0.185* |
| *se* | (0.074) | (0.083) | (0.084) | (0.149) | (0.114) | (0.139) | (0.090) | (0.108) | (0.106) |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of Observations | 917 | 916 | 914 | 153 | 153 | 151 | 764 | 763 | 763 |
| Adjusted $R^2$ | 0.258 | 0.343 | 0.241 | 0.688 | 0.548 | 0.703 | 0.179 | 0.324 | 0.182 |
| Unique Banks | 129 | 129 | 129 | 25 | 25 | 25 | 104 | 104 | 104 |

Standard errors are adjusted for clustering at the bank level.
***, ** and * denote statistical significance at the 1%, 5 % and 10% levels, respectively.

**Table 5. After the Global Financial Crisis: from 2009 to 2017**

| | All Banks | | | International | | | Domestic Banks | | |
|---|---|---|---|---|---|---|---|---|---|
| | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio | Eqiuty Ratio | Cap Ratio | Tier 1 Ratio |
| P Loan Ratio | -0.003 | 0.016 | 0.009 | -0.019 | 0.019 | -0.034 | 0.011 | 0.048 | 0.035 |
| *se* | (0.022) | (0.040) | (0.042) | (0.030) | (0.107) | (0.086) | (0.018) | (0.033) | (0.028) |
| M Loan Ratio | -0.001 | -0.082** | -0.034 | 0.015 | -0.090 | -0.085 | -0.010 | -0.103*** | -0.053* |
| *se* | (0.014) | (0.034) | (0.044) | (0.029) | (0.098) | (0.090) | (0.015) | (0.029) | (0.028) |
| Depo Ratio | -0.001 | -0.040 | -0.032 | 0.043*** | 0.031 | 0.055* | -0.017 | 0.015 | 0.005 |
| *se* | (0.008) | (0.031) | (0.027) | (0.007) | (0.034) | (0.032) | (0.015) | (0.032) | (0.047) |
| Loan Rate | 0.789** | 1.146 | -0.135 | -0.138 | 1.639 | -0.260 | 0.945*** | 0.453 | -1.230 |
| *se* | (0.365) | (0.749) | (1.360) | (0.627) | (2.526) | (2.731) | (0.351) | (0.681) | (1.050) |
| Depo Rate | -0.656 | -2.719 | -3.623* | -1.056* | -1.192 | -3.608* | 1.035 | 0.942 | 3.034 |
| *se* | (1.478) | (2.841) | (1.939) | (0.531) | (1.926) | (2.077) | (2.796) | (5.094) | (3.540) |
| Cost Ratio | -0.171 | 0.366 | -1.453 | -4.087*** | -9.784*** | -10.351*** | 0.659 | 1.362 | 2.400 |
| *se* | (0.604) | (1.181) | (1.773) | (0.703) | (3.006) | (2.237) | (0.526) | (1.106) | (1.497) |
| ln(Asset) | -0.015** | -0.005 | -0.028** | -0.019*** | -0.008 | -0.017 | -0.013* | -0.007 | -0.005 |
| *se* | (0.006) | (0.010) | (0.011) | (0.005) | (0.017) | (0.017) | (0.007) | (0.010) | (0.016) |
| Constant | 0.279*** | 0.233 | 0.615*** | 0.381*** | 0.350 | 0.493* | 0.244** | 0.211 | 0.167 |
| *se* | (0.093) | (0.146) | (0.171) | (0.074) | (0.261) | (0.265) | (0.115) | (0.153) | (0.261) |
| Bank Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time Fixed Effects | Yes | No | Yes | Yes | No | Yes | Yes | Yes | No |
| Number of Observations | 802 | 797 | 483 | 138 | 134 | 132 | 664 | 663 | 351 |
| Adjusted $R^2$ | 0.411 | 0.170 | 0.429 | 0.624 | 0.419 | 0.629 | 0.420 | 0.292 | 0.250 |
| Unique Banks | 117 | 117 | 115 | 19 | 19 | 19 | 98 | 98 | 96 |

Standard errors are adjusted for clustering at the bank level.
***, ** and * denote statistical significance at the 1%, 5 % and 10% levels, respectively.

*Loan Ratio* on all the three dependent variables in Table 4. Domestic banks which increased their retail loans during this period have a stronger incentive to hold capital to cope with liquidity shocks and borrowers' moral hazard.

Like international banks, the determinants of domestic banks also changed after the GFC, After the GFC, they have had significant "negative" results in *M Loan Ratio* and positive results in *Loan Rate* at the 1% level. Although the negative results of *M Loan Ratio* are hard to explain by the hypothesis introduced in the previous section, by combining the positive results of *Loan Rate*, it can be assumed that domestic banks reduced the amount of their SME loans and raised their lending rate to make more profits and heighten their regulatory capital ratio in order to cope with regulatory reforms after the GFC.

As you can see from the different results among these four sub-samples, we do not get any determinants which can significantly and commonly explain all the four groups' behavior in terms of their capital structure. Our results show that the determinants differ among banks and eras even in one country.

## 4. Conclusions

This paper is the first empirical research on the determinants of the capital structure of Japanese banks. Using the unbalanced panel financial data for all the Japanese banks from 2000 to 2017, we estimated a fixed effects model to examine the effects of possible factors on banks' capital ratios: the Ratio of capital to assets (Equity Ratio), the Regulatory capital adequacy ratio (Cap Ratio), and the Tier 1 Ratio.

Focusing on the different business models between the sub-samples, we analyzed whether the determinants of capital structure differ among sub-samples. By dividing the full sample into four sub-samples: "International banks before the Global Financial Crisis," "Domestic banks before the GFC," "International banks after the GFC," and "Domestic banks after the GFC"; we compared their estimation results.

The results and our analysis show that the determinants differ among banks and eras even within one country; we find no determinants which can significantly and commonly explain all the four sub-samples.

Previous researches, such as Gropp and Heider (2010) and Kinai (2018), show that the determinants of capital structure differ among countries or continents, or between EU countries and the US, and points out that these differences are probably caused by differences in business models due to their different cultural and historical backgrounds. This paper contributes to this literature by showing the differences among banks even within one country.

We provide new evidence which shows that the determinants of banks' capital structure vary and change in accordance with differences in the business models among banks. However, for a more detailed investigation, we need to improve our estimation models, data sets and so on. This we leave for future research.

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# A Micro-Analysis of the Life Cycle Model and Savings Determinants with Late Labour Engagement[1]

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## Abstract

The Nigerian economy has grown moderately in the past years. A major way of increasing economic output is raising investment, through savings mobilization. Scanty evidence exists on the savings' determinants from a micro perspective in Nigeria.

Using a synthetic cohort approach and six waves of surveys (1980, 1985, 1992, 1996, 2004 and 2009), this study profiled the savings pattern of households and examined savings determinants in Nigeria. Household savings pattern validated the Life Cycle Hypothesis, but did not hold for age group 65-79. Savings rate among the working group peaked late at 60-64, indicating increased saving till retirement due to poor retirement income security during the periods.

The empirical findings show that rural dwellers and women are thriftier and higher educational attainment reduces savings. The latter finding suggests that higher education may not necessarily increase savings in Nigeria due possibly to high unemployment among the educated, and trade-off between higher savings and increased spending on children's education. The government should provide a more conducive environment for informal sector actors due to its high employment absorptive capacity. Rapid financial inclusion in the rural sector and women empowerment are key ways of mobilizing savings for growth.

***Keywords***: Labour, Life Cycle Hypothesis, Savings

***JEL classification:*** **D14, D15**

## 1. INTRODUCTION

The performance of the Nigerian economy in the last three decades as measured by the growth rate of the gross domestic product has been moderate. Average yearly GDP growth rate over this period

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[1] We acknowledge the efforts of the reviewers of this paper in improving its quality.

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was only 4.2 percent. The growth rate of per capita income has performed poorly, averaging 2.2% between 2008 and 2016 (WDI, 2016).

One major way to increase economic output is raising the level of investment. Accumulation of capital however depends to a large extent on the amount of savings mobilized in the economy. The role of savings in stimulating economic growth is well documented in the literature, although evidence on the direction of causality are inconclusive.[3] The positive relationship between economic growth and saving is the most cogent and central prediction of relevant growth theories as well as the Life Cycle Hypothesis (LCH). This hypothesis provides a comprehensive analysis of the savings pattern of households over their lifetime. The LCH, due primarily to the contribution of Modigliani and Brumberg (1954, 1979), has been the mainstream theoretical framework used by economists to understand the dynamic savings behaviour of consumers.

The assumption is that individuals smooth consumption over their lifetimes using savings and borrowing. Since labour income flows are uneven over the course of life, this theory implies that savings rates will be uneven over the path of life. In particular, savings rates will be low during early adult years, will rise with age as income increases, and will decrease in retirement as earnings fall. A number of studies have examined the effects of increasing-population, education and government expenditure on the savings pattern of households (Mikesell and Zinser, 1973; Fry, 1978; Deaton, 1989; Webb and Zia, 1990; and Deaton et al., 1997). The literature on savings has also been extended to the effects of demographic variables on the savings' patterns of households.

In Nigeria, a significant number of studies that have examined the determinants of savings pattern have done so within the macro-economic perspective. The micro aspect of this topic has not been fully exploited. To fully understand savings behaviour, particularly in a country with diverse ethnic group and widened income inequality, it is essential that a micro perspective is adopted to capture these heterogenous features. This is one of the gaps filled by this study. The outcome of our empirical findings could aid policy decisions in mobilizing savings for investment purposes, thereby growing the economy.

Another distinctive feature of this study is that it attempts to study the determinants of savings in Nigeria within the Life-Cycle framework using a synthetic cohort approach. Unemployment rate in Nigeria is high, particularly among the youths[4]. It is therefore important to investigate if high jobless rate distorts savings pattern within the Life-Cycle framework.

The paper is in two folds. The first part analyzes the profile of household saving in Nigeria using data from the National Consumer Surveys of 1980, 1985, 1992, 1996; and the Nigeria Living Standards Surveys of 2004 and 2009. The second section involves an empirical estimation of the determinants of savings in Nigeria using the same data set. Following the introduction is a review of literature on savings' determinants in Nigeria. Section three presents the analytical framework for the study. Section four presents the methodology. The savings patterns of households at the national, geo-political zones[5] and across national per capita income deciles are presented in section five. In addition to this, the Life-Cycle profile is also examined. Section six empirically investigates the determinants of private savings in Nigeria, and section seven concludes.

## 2. EMPIRICAL LITERATURE

Numerous studies have documented the determinants of private savings in both the developed and

[3] See Aghion et al. (2009), and Bankole and Fatai (2013) for some of these studies.

[4] Unemployment rate was 33.2% in 2016, using the old computation (NBS, 2016).

[5] Nigeria is delineated into six Geo-Political Zones (South East, South South, South West, North East, North West and North Central).

developing economies. Nevertheless, there has not been a conclusive empirical evidence to accord the effects of real interest rate, demographic factors and per capita income on private savings (Massonet al., 1998). Some of the factors often highlighted as possible determinants of private savings in Nigeria include; income, financial depth, real interest rate, inflation rate, age, education, and dependency ratio. Soyibo and Adekanye (1992) examined the effect of the financial sector liberalization during the Structural Adjustment Programme on savings mobilization in Nigeria. Applying the Ordinary Least Squares estimation technique on a time-series data, they found that past aggregate savings, current level of the gross domestic product, foreign savings, and ex-post real interest rate were the determinants of savings in Nigeria. Foreign savings was negatively correlated with savings, while gross domestic product and real interest rate positively affect savings. Their results pointed out that real interest rate is correlated with savings behaviour, as a one percentage point increase in real interest rate only resulted to a 0.13% increase in savings. Financial system deregulation was not statistically significant in explaining savings pattern in Nigeria.

The role of demographics in the savings behaviour was emphasized by Nwakeze and Omoju (2011). In their paper, they studied the effect of an increasing population on savings. Using time-series data spanning 1980-2007 and the error correction mechanism, they found that rapid population growth depresses savings, while income level positively drives savings in Nigeria. They found inflation rate to have a negative and statistically significant effect on savings behaviour. Their study also indicated that financial depth does not explain savings in Nigeria, thus supporting Soyibo and Adekanye (1992).

Nwachukwu (2012) examined both the short run and long run effects of some variables on private savings in Nigeria. The study used the error correction method on a time-series data from 1970 to 2010. The findings revealed that in the short run, only growth in income positively influences private savings rate. However, in the long run, private savings rate is driven by income growth and real interest rate with positive coefficients of 0.50 and 0.0028, respectively. The coefficient of real interest rate obtained in this study although positive and statistically significant indicates a weak relationship between real interest rate and savings rate. It is smaller than what Soyibo and Adekanye (1992) obtained. The study also showed that financial development does not play a significant role in savings mobilization in Nigeria.

Ogwumike and Ofoegbu(2012) also studied the impact of financial sector liberalization on domestic savings in Nigeria. Applying the Autoregressive Distributed Lag (ARDL) estimation technique on a time-series data covering 1970 to 2009, they found that financial liberalisation has a temporary positive and significant effect on domestic savings. They explained further that the shift to a negative and significant relationship could be attributed to the non-sustainability of financial liberalisation reforms in the country. Credit to the private sector however had a positive short and long run impact on domestic savings.

One of the few studies that adopted a micro data in studying the determinants of savings in Nigeria is, Ike and Umuedafe (2013). The study used a survey data of 150 households in Isoko Local government in Delta state, Nigeria. The authors adopted the Ordinary Least Squares estimation technique and their findings showed that farm income, non-farm income, experience in savings programme, age, and distance to financial institutions were all statistically significant in explaining savings behaviour among households. Distance to financial institutions had a negative coefficient, implying that shorter distance to both formal and informal financial institutions increased savings rate.

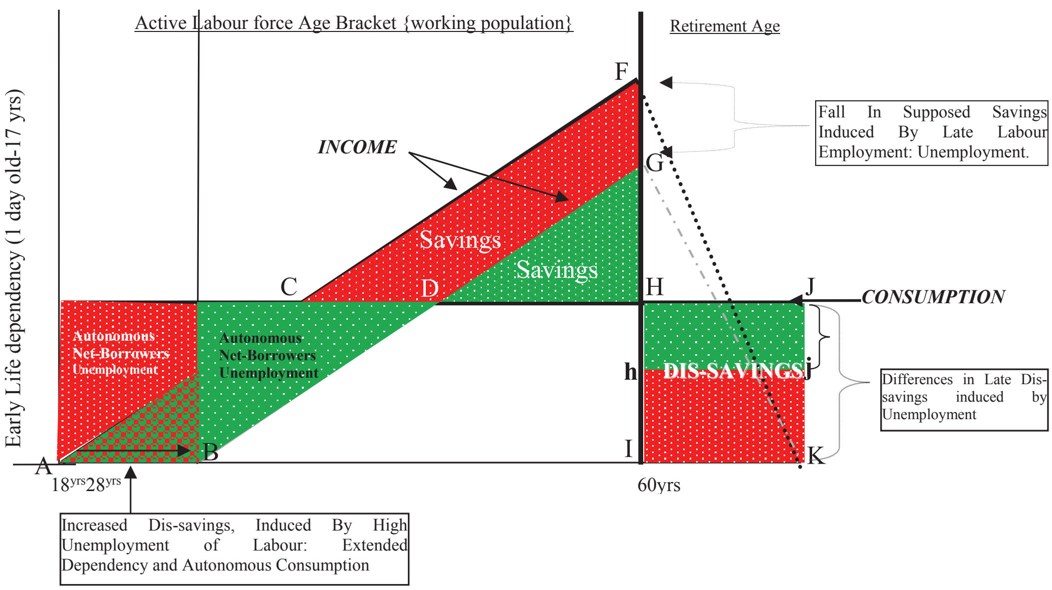
Some inferences can be drawn from this brief literature review. In the Nigerian literature, there appears to be some consensus on the impact of income, inflation rate, real interest rate, and financial depth on savings pattern. The possible roles of education, unemployment, late labour engagement, and other micro variables have not been fully exploited. That points to the paucity of micro-data studies on this topic. Similarly, since we attempt to use a survey data, our focus is household saving rather than aggregate saving. This feature allows us to analyze the saving behaviour under the LCH and for different per capita income deciles.

## 3. ANALYTICAL FRAMEWORK

***The Life Cycle-Model of Savings***

According to the Life Cycle model, individuals try to smoothing consumption pattern over their lifetimes. Since labour income flows are uneven over the course of life, this theory implies that savings rates will be uneven over the course of life. In particular, savings rates will be zero and then low during early adult years, will rise with age as income increases, and will decrease in retirement as earnings fall. Thus, consumption behaviour is influenced not only by the short term or long term consideration alone but also by the consumer's expectation about his entire life time earnings. The major assumption of the life cycle hypothesis is that households operate under the condition of certainty. In developing countries however, labour income flows are often distorted and measures to cushion the negative effect of these unexpected exogenous shocks do not exist. For instance, in Nigeria unemployment benefits do not exist. Therefore, a household head that loses his job will have a distorted savings. The pattern of savings rate is further worsened by the high unemployment rate which reduces the likelihood of such person being integrated back into the active labour force.

Similarly, late labour engagement of able-bodied men and women into the active labour force is prevalent in Nigeria. This may alter the savings pattern as predicted by the life cycle model. When people get engaged late into the active labour force, years of zero savings increase, while there is a high possibility of carrying over increased savings into retirement. Figure 1 illustrates the stylized pattern of income, savings and consumption, when late-labour engagement is incorporated into the standard life cycle model.




Source: Authors' analysis

**Figure 1. Stylized Individual Consumption-Savings Life Cycle Hypothesis with Unemployed Labour.**

In Figure 1, the lifetime income stream "**ACFK**", represents a typical life-cycle model. It shows that during the first part of the individual's lifetimes, an individual earns relatively little or no income and consume a relatively large amount of goods and services at the youthful stage where his consumption therefore exceeds his income and he therefore borrows. Because income tends to increase with the level of education and age, the individual reaches a point where he no longer needs to borrow (Point **C**). Beyond this point, at a middle age, savings become positive (**CFH**), income grows to a point, then begins to decline (Point **F**) beyond a certain age (age 60 representing the peak of the labour force) shortly after this point savings eventually begins to decline (**F** down to **K**) as he dis-saves to ensure consumption for the remaining time he has to live. The household therefore maintains a complete smooth consumption path across periods. With a constant consumption, an individual with an early income stream "**ACF**", can easily smooth consumption over a lifetime given larger accumulated wealth (savings) area "**CFH**" due to early engagement in labour. Consequently he has enough to dis-save after retirement "**HJKI**" to smooth the remaining lifetime consumption and possibly leave a bequest.

Figure 1 also presents another scenario; the same life cycle model for the individual, but instead, with late engagement into the labour market as a result of prevalent unemployment. The individual has his lifetime income stream as "**BDG**", instead of "ACF". This reduces accumulated wealth to "**DGH**", and consequently less to be dis-saved "**Hjih**". This deficit in consumption smoothing over the individual's lifetime is on account of the late engagement into the labour market. Consequently, the individual may have little or nothing to dis-save after retirement due to low accumulated savings and constraint of fixed retirement age.[6]

## 4. METHODOLOGY

### *4.1. DATA*

The data used in this study draws from the Nigerian National Consumer (NCS) Surveys of 1980, 1985, 1992, and 1996; and the Nigerian Living Standards Surveys (NLSS) of 2004 and 2009. These surveys involved a sample of enumeration areas selected in each state which is a representative of both the urban and rural areas. In the 1980, 1985, 1992, and 1996 surveys, 11,110; 9,317; 9,697; and 14,951 households were surveyed respectively. The 2004 survey was individual and household-based, and contained detailed information on respondents. The 2004 survey covered 19,158 households and 92,610 individuals. The 2009 survey had 73,329 households and 332, 938 individuals. Data set from the survey years 1980 to 2009 is used to profile the savings rate and Life Cycle Pattern among households.

### *4.2. MODEL*

In investigating the determinants of savings, a cross-sectional regression was adopted using the individual surveys. The main reason for this is that the available household surveys are not longitudinal in nature (i.e. different households are surveyed over time). This makes it difficult to track changes in a particular household over time. In Nigeria, remittances play a major contributory factor in augmenting household income. According to the World Bank data, Nigeria is the largest recipient of remittances in Africa, estimated at $18.9 billion in 2016 [7]. Remittance was included as an explanatory variable only in the 2004 and 2009 cross-sectional regression, since the National

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[6] It is a common practice in Nigeria, particularly for employees of private sector jobs to depend on their children for survival after retirement.

[7] See 2016 World Development Indicator (WDI) data on remittances inflow.

Consumer Surveys do not provide information on remittances.

Following the literature on the determinants of savings rate within the Life-Cycle Hypothesis, this study considered a set of explanatory variables, which were augmented with some variables peculiar to the determinants of savings in Nigeria. In the literature, the possible reverse causality between savings and education, on one hand, and saving and income has been well documented as a potential cause of endogeneity problems[8]. To overcome this problem, we adopted a two-stage least squares technique and specify the model below.

$$Savgs = \alpha_{i1} + \beta_{i1} inc + \gamma_{i1} educ + \delta_{i1} x_{i1} + \varepsilon_{i1} \text{--------------------}1$$

$$Educ = \alpha_{i2} + \beta_{i2} savgs + \gamma_{i2} fedu + \delta_{i2} y_{i2} + \theta_{i2} \text{---------------------------}2$$

Where i= 1980, 1985, 1992, 1996, 2004 and 2009.

In equation 1, savgs and inc. denotes savings and income level, respectively. $X_{i1}$ is a vector of control variables including age, gender, location, occupation dummy, States of residence, remittances, and household size. Income, savings and remittances were adjusted for price changes in the different periods. In the second equation, fathers' educational attainment ( $fedu$ ) was used as an instrument for education of respondents in the 2004 and 2009 estimation. The 1980 to 1996 household surveys do not provide information on the respondent father's educational status or a suitable instrument, thus Ordinary Least Squares technique was adopted. In addition, getting a valid and appropriate instrument for income was difficult. Hence, the relationship between income and savings would be treated as associative rather than causative. $y_{i2}$ account for other factors affecting educational attainment.

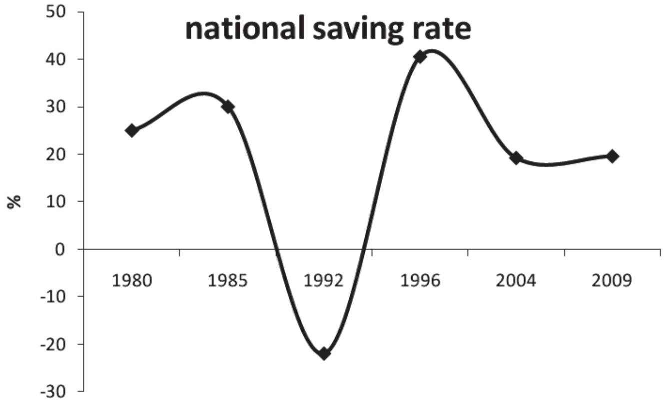
## 5. SAVING PROFILE OF NIGERIAN HOUSEHOLDS (1980-2009) AND LIFE-CYCLE PATTERN

### *5.1. Saving Profile of Households*

The saving pattern of households at the national level is presented in this section. The definition of saving in this study is a residual and the difference between the expenditure and income of households, while saving rate is this residual divided by total income of household and expressed as a percentage of 100. This definition has been used extensively in the savings literature and follows from Bersales and Mapa (2006). Also presented is the saving rate by per capita income deciles.

Figure 2 shows the saving pattern of households in Nigeria between 1980 and 2009. Aggregate saving rate declined to 18% in 2009 from 25% in 1980. Also evident, is the high dis-saving in 1992. The national saving rate reached a peak of 40.6% in 1996, but was not sustained, as it declined to 19.3% in 2004 and experienced a marginal increase in 2009. It is worth pointing out that even at this level, saving rate among households in Nigeria is much higher than in most developed countries. For instance, average saving rate in the United Kingdom and United States of America in 2000-2007 was 1.7% and 4.1%. Similarly, in the post financial crisis period (2012-2016) it was 0.56% and 6.05%, respectively (OECD data).

[8] See Bersales and Mapa (2006).




Source: Authors' computation from Household Surveys

**Figure 2. National Saving Rates, using NCS and NLSS survey years: 1980-2009**

Table 1 shows the saving rate of households by per capita income deciles between 1980 and 2009. In 1980, savings rate across the deciles increased gradually. A similar trend is exhibited in 1985, where the top deciles had higher savings rates than the bottom deciles. Almost all deciles dis-saved in 1992, except the top deciles (8$^{th}$, 9$^{th}$ and 10$^{th}$ deciles) that saved marginally. The dis-saving observed during this period may partly be attributed to significant decline in real income arising from unprecedented increase in the Consumer Price Index (CPI). For instance, the CPI rose by 48.8% between December 1991 and December 1992 (CBN, 2008). The sharp rise in consumer prices was largely due to imported inflation arising from rapid Naira depreciation against the United States Dollar. Naira depreciated by 75% from ₦9.90/$ in 1991 to ₦17.298 in 1992. Generally, Consumer Price Index (CPI) increased by 451% and Naira lost about 1,835% of its value to the US Dollar, between 1985 and 1992 (CBN, 2008).

**Table 1. Household Saving Rates by National Per Capita Income Deciles**

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **1980** | 3.92 | 21.22 | 25.35 | 27.12 | 22.68 | 26.12 | 27.28 | 27.23 | 32.49 | 36.94 |
| **1985** | 3.56 | 25.48 | 29.18 | 35.66 | 34.67 | 31.53 | 28.34 | 38.49 | 35.93 | 37.52 |
| **1992** | -111.56 | -54.84 | -29.43 | -25.22 | -12.28 | -10.79 | -4.33 | 0.63 | 6.45 | 26.01 |
| **1996** | 18.29 | 45.34 | 46.44 | 48.21 | 46.45 | 46.15 | 43.18 | 39.22 | 34.35 | 36.93 |
| **2004** | -27.66 | 3.85 | 10.28 | 22.35 | 25.58 | 22.35 | 28.77 | 31.35 | 33.85 | 39.65 |
| **2009** | -25.31 | 4.28 | 11.63 | 23.11 | 26 | 22.48 | 28.22 | 32.1 | 33.9 | 39.69 |

Source: Authors' computation from Survey data

The saving pattern of deciles 1-3 significantly declined over the years, as they have been the worst hit by harsh economic conditions. Nevertheless, the saving rate increased across all deciles in 1996 (deciles 1-3 inclusive), as they benefitted from relative stability in the Naira value, moderated inflation rate and two successive minimum wage increases in 1991 and 1993. The Consumer Price Index (CPI) grew by only 14.3% in 1996, compared to historically high CPI growth of above 49%. The 45% increase in the minimum wage in 1993 was not implemented in most states of the country until 1994/1995. The magnitude of the saving of deciles 4-10 did not change significantly over the survey years.

Household saving rates by geo-political zones, location, and age-group are also presented in the

Appendix. Overall, we observed a general decline in the savings rates pattern in the geo-political zones over the years, except in the South-West which increased marginally. The largest decline was recorded by South-South, from 20.8% in 1980 to 12.2% in 2004. Average savings rate pattern increased with age, reaching a peak among individuals who are 65 years old and above. This may be attributed to the extended retirement age for some public officials. Retirement age for Professors in academic institutions in Nigeria is age 70 years, while it is 65 years old for other faculty and administrative staff. In addition, retirement ages for judges range from 65-70 years depending on the Court of law.

Higher saving rate among the $65^{+}$ category may also be explained by increased savings as retirement approaches and remittances to retired people from their children. It is the practice of children to send money home to parents. In addition, rural dwellers have higher savings rates compared to those in the urban areas.

### *5.2. Life Cycle Profiles*

Tracing out the life cycle profiles of saving rate among households requires a longitudinal household survey in which the same households are sampled over time. The Nigeria National Consumer Surveys and Nigeria Living Standard Survey however do not follow the same household through time. One way to overcome this problem is using a synthetic cohort approach (see Attanasio and Szekely, 2000; Bersales and Mapa, 2006). This technique uses the average behaviour of group of households instead of individual households. Following these authors, we adopted this technique in studying the dynamic pattern of household saving in Nigeria. The age-groups of household heads are grouped using the National Consumer Surveys and Nigeria Living Standard Surveys of the available years (1980-2009). The average behaviour of these groups is assumed to be representative of cohort behaviours overtime.

**Table 2. Household Saving Rate by Age Groups (1980-2009)**

| Age-Group | National Average Saving Rate % |
|---|---|
| 15-19 | 10.9 |
| 20-24 | 13.2 |
| 25-29 | 14.8 |
| 30-34 | 15.6 |
| 35-39 | 17.9 |
| 40-44 | 18.0 |
| 45-49 | 19.8 |
| 50-54 | 20.9 |
| 55-59 | 19.7 |
| 60-64 | 22.4 |
| 65-69 | 23.1 |
| 70-74 | 23.3 |
| 75-79 | 24.1 |
| 80+ | 22.5 |

Highest saving rate= 24.1; Lowest saving Rate= 10.9
Standard deviation= 4.1; Coefficient of variation= 0.2

Source: Authors' computation from NCS and NLSS surveys

As shown in Table 2, the national saving rates are highest and lowest among age-groups 75-79 and 15-19, respectively. This indicates that household saving rate is higher among the older population than the younger ones. The coefficient of variation of 0.2 suggests that the degree of variation in the saving rates across households is marginal. The standard deviation of 4.1 reflects stability across the savings distribution of different age-groups.

The survey data validated the life-cycle pattern as household saving rates increase with age as shown in Table 2. Decline in savings started late at above 80 years. The LCH did not hold for the age-group 65-79 whose saving rates continued on an upward trend instead of declining. This pattern mimics that observed by Bersales and Mapa (2006) for households in Phillipines; also a developing country. The saving rate among the labour force i.e. (15-64), peaked very late at the age-group 60-64. An intuition from this is that due to poor retirement scheme in the country during a larger part of the period covered, workers saved heavily till retirement[9].

Another striking observation from Table 2 is that high youth unemployment of the Nigerian labour force does not seem to distort the savings pattern of households. Saving rates among age-groups 20-24 and 25-29 increased on average. These age-groups constitute a larger fraction of the unemployed and it is expected that their saving rates would decline or they will dis-save. In 2015, unemployment rate among age-group 15-24 was 19 percent, and 34.5 percent were under-employed (NBS, 2016). The non-conformity of their saving rates pattern to the expected trend may be attributed to the fact that many unemployed graduates get engaged in the informal sector either as self-employed or paid-employee, thus maintaining their saving habits.

## 6. RESULTS AND DISCUSSION

Table 3 presents the findings of empirical estimation using cohort groupings of household surveys of 1980, 1985, 1992, 1996, 2004 and 2009. Incomplete, missing observations and households who reported no income were dropped from the final sample. Individuals aged 0-14 years were not included in the analysis since they are not categorized as part of the labour force.

The surveys of 1980-1996 were estimated individually using Ordinary Least Squares method. The potential endogeneity arising from education variable was not accounted for in the model. This is due to lack of viable instruments in the cross-sectional data. The relationship between the covariates and dependent variable were therefore interpreted as associative rather than causative (see Malapit et al., 2015; Malapit and Quisumbing, 2015). In estimating the 2004 and 2009 surveys, Two-Stage Least Squares method was adopted, and father's education was used as an instrument to correct for potential endogeneity problems as specified in equation 2 of the model. Diagnostic tests to ascertain the appropriateness of the chosen instrument are presented in the lower panel of Table 3.

As shown in column 2 of Table 3, income, household size, gender, and location are statistically significant in explaining household savings in 1980. Income and household size had the expected signs and are both positively and negatively associated with savings, respectively. The latter result suggests that a household with a larger size saves less than a smaller household. Women and rural dwellers are more favourably disposed to savings than men and those who reside in urban centres. Educational attainment was not statistically significant in influencing savings in the year 1980.

Findings from the 1985 survey were not different from the earlier presented results, except that educational attainment is statistically significant and negatively affects savings. Generally, this trend is repeated in the results for 1996, 2004 and 2009, with larger reduction in savings. This appears surprising and does not conform to apriori expectations. Numerous studies, particularly using developed country data have documented positive correlation between education and savings behaviour (Bersales and Mapa, 2006; Messacar, 2017).

Some reasons may however be given for this anomaly. In developing countries, savings could

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[9] Prior to the enactment of the Pension Reform Act (2004), pension administration was mired by challenges such as malpractices and accumulation of arrears of payments of pension rights. The enactment of the Act, restructured pension administration in Nigeria and mandated both Public and Private sector organizations to key into a Contributory Pension Scheme, in which both the employer and employee contribute towards the latter's retirement benefit.

## Table 3. Estimates of Savings Determinants in Nigeria using Household Survey Data (1980-2009)

| | Real Savings | | | | | |
|---|---|---|---|---|---|---|
| **Independent variable** | **OLS (1980)** | **OLS (1985)** | **OLS (1992)** | **OLS (1996)** | **2SLS (2004)** | **2SLS (2009)** |
| Real income | 0.2032*** | 0.1906*** | 0.4261*** | 0.1999*** | | |
| | (0.0138) | (0.0172) | (0.0226) | (0.0089) | | |
| Log(income less remit) | | | | | 0.5600*** | 0.4401*** |
| | | | | | (0.0706) | (0.0737) |
| Household size | -0.0084*** | -0.0042** | -0.01706*** | 0.1207*** | 0.1145*** | 0.1026** |
| | (0.0025) | (0.0019) | (0.0048) | (0.0031) | (0.0138) | (0.0451) |
| Gender(male) | -0.0558** | 0.0729 | -0.0723* | -0.1007*** | -0.1105*** | -0.1422*** |
| | (0.0276) | (0.0243) | (0.0435) | (0.0222) | (0.0217) | (0.0301) |
| Location(urban) | -0.0644*** | -0.3475*** | -0.0977*** | -0.1160*** | -0.0970*** | -0.1303*** |
| | (0.0191) | (0.0175) | (0.0348) | (0.0174) | (0.0222) | (0.0148) |
| Remittance | | | | | 0.2140*** | 0.1200** |
| | | | | | (0.0150) | (0.0585) |
| Education(level) | 0.0002 | -0.0732*** | 0.0212 | -0.0449*** | -0.0618*** | -0.0440** |
| | (0.0020) | (0.0083) | (0.0181) | (0.0074) | (0.0165) | (0.0220) |
| Reference(15-24) | | | | | | |
| Age 25-34 | -0.0264 | -0.01705 | 0.0742 | 0.2647*** | -0.0062 | -0.0187 |
| | (0.0482) | (0.0498) | (0.0866) | (0.0620) | (0.0688) | (0.0504) |
| Age 35-44 | -0.0519 | -0.0152 | -0.0460 | 0.3558*** | -0.0438 | 0.0015 |
| | (0.0485) | (0.0496) | (0.0879) | (0.0609) | (0.0682) | (0.0502) |
| Age 45-54 | -0.0577 | 0.0163 | -0.0236 | 0.3118*** | -0.0474 | 0.0457 |
| | (0.0500) | (0.0499) | (0.0893) | (0.0612) | (0.0689) | (0.0506) |
| Age 55-64 | 0.0088 | 0.0057 | 0.0162 | 0.2537*** | -0.0053 | 0.0385 |
| | (0.0529) | (0.0529) | (0.0931) | (0.0626) | (0.0691) | (0.0536) |
| Age 65+ | 0.0749 | 0.0293 | -0.0475 | 0.2093*** | 0.0434 | 0.0550 |
| | (0.0536) | (0.0545) | (0.0977) | (0.0636) | (0.0706) | (0.0554) |
| Adjusted $R^2$ | 0.5082 | 0.4570 | 0.5013 | 0.6891 | 0.6160 | 0.6259 |
| Observations | 10264 | 9316 | 8885 | 14864 | 7826 | 9856 |
| F-statistic | 351.96 | 564.32 | 476.55 | 2283.11 | 2170.67 | 2921.44 |
| P-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| ***Endogeneity test*** | | | | | | |
| Anderson-Rubin Null: endogvars irrelevant | | | | | | |
| A-R Wald test, p-value | | | | | 0.0000 | 0.0000 |
| A-R Wald $Chi^2$ test,p-value | | | | | 0.0000 | 0.0000 |
| ***Weak instrument test:*** | | | | | | |
| First stage F | | | | | 69.55 | 85.23 |
| Critical value for IV bias relative to OLS | | | | | 20.08 | 24.40 |

Notes: *, **, *** indicate 10, 5, and 1 percent significance levels. Robust Standard Errors are in parenthesis. Structural differences in savings arising from occupation and State of work place have been accounted for, through the inclusion of these variables as controls in the model. It is not shown here due to space constraints, but available upon request.

decline with higher education, if parents consider investment in children's education as an asset diversification option (Virmani, 1986). Due to poor or non-existent social benefits and retirement plans, literate parents may consider increased spending on their children as a future investment strategy. The second plausible reason is that, since the expected positive relationship between higher educational attainment and savings is closely tied to gainful employment, high unemployment or under-employment among educated people in Nigeria may negatively correlate savings rate. Ahmad and Asghar (2004) also found that savings declined with higher schooling levels in Pakistan as educated parents increase educational expenditure on children. Income, household size and location were also statistically significant in explaining savings rate.

Generally, the positive relationship between income and savings as found in this study is well established in the Nigerian literature (see Soyibo and Adekanye, 1992; Nwakeze and Omoju, 2011). Using micro data, Umuedafe (2013) also supports this finding. Household size negatively affects savings profile and rural households save more than urban dwellers. The summary statistics presented in the Appendix provides credence to higher savings among the rural households.

Estimations using the 1992 survey also exhibit the same trend, as income, household size, gender, location and education are the major influencing factors of savings. The results for 1996, 2004 and 2009 showed a divergent pattern of effect of household size on savings. As shown in Table 3 (columns 5, 6 and 7) household size positively correlates savings.

One interpretation for this is that the composition of household structure changed during these periods, such that more adult workers within the household who are economically engaged increased their savings. Age dependency ratio declined continuously during the survey periods, with larger decline between 1994 and 2010. This could have relieved the household head of financial burden and increased savings. For instance age dependency ratio declined from 91.3 in 1985 to 86.6 in 2004, and rose marginally to 87.7 in 2009 (data.worldbank.org/indicators/). Other variables had the expected signs and interpretation as given in the previous discussion. For instance, rural dwellers and women were more likely to have had higher savings in 1996. Higher educational attainment is associated with reduced savings.

As noted earlier, the estimation of 2004 and 2009 surveys accounted for potential endogeneity bias of the education variable. Father's educational status was used as an instrument to correct for potential endogeneity of education variable. The chosen instrument correlates with the endogenous variable, but is uncorrelated with the error term except through the dependent variable. Similar instrument was adopted by Bargain and Melly (2008) in their paper on "gender wage differentials and selectivity into the public sector". They used a variable "whether the father is a civil servant or not" as an instrument. The lower panel of columns 6 and 7 present the results of exogeneity test. The Anderson-Rubin test rejects the null hypothesis of exogeneity, as the endogenous variables are relevant. We therefore adopted Two-Stage Least squares technique to correct this anomaly.

The F-test, confirming the reliability of the instruments is also presented in columns 6 and 7. For both years, the F-statistic is greater than ten, and above the critical values of F. Thus, we can conclude that that the Instrumental Variable bias in our model is less than 5% of OLS bias (Stock and Yogo, 2005).

Our analysis in 2004 and 2009 shows that a unit increase in income would lead to ₦0.56 and ₦0.44 increase in real savings. A higher educational level completed (between primary to secondary and tertiary levels), reduces monthly real savings by ₦0.06 and ₦0.04, in 2004 and 2009, respectively. Increase in remittances has a positive impact on savings. This buttresses the evidence that remittances are major sources of income for households in Nigeria and that they have poverty-reducing effects (Chukwuone, 2012). Rural dwellers also save more than urban households.

Generally, the findings of this study point to the depressing influence of higher educational attainment on savings pattern in Nigeria. This unveils the fact that education is not sufficient for savings mobilization in developing countries. In this context, the high unemployment rate in the country may be a contributing factor. Gainful employment may play a vital role, as education without jobs could limit the ability to save. This is a promising area for further research using micro-data information on respondents' unemployment and labour characteristics. The surveys used in this research do not provide adequate information to compute respondents' labour supply or the extent of involvement in the labour market.

Thus, policy makers should view job creation as a way to mobilize savings for economic growth. Another inference drawn from these results is that literate parents appear to trade-off higher current savings for increased spending on children's education. In this perspective, children are seen as investment which would yield positive future returns (see Virmani, 1986; Ahmad and Asghar, 2004). Our findings show that women have higher likelihood to save more than men. Therefore, ongoing women empowerment programmes should be strengthened and newer ones initiated as a way of rapidly mobilizing savings for development purposes.

## 7. CONCLUSION

This study used household surveys of 1980, 1985, 1992, 1996, 2004 and 2009 to investigate the Life Cycle Pattern within the framework of labour engagement in Nigeria. Two approaches were adopted in this regard. The first method involved the use of a synthetic cohort system to trace the savings pattern of households over the survey years, while an econometric estimation of the determinants of private savings was presented in the second method. The second part used a nationally representative micro-data, which is relatively new to studies on savings' determinants in Nigeria.

Taking into consideration the Life Cycle Hypothesis and labour engagement in Nigeria, the findings show that average household saving rate was high between 1980 and 2009. This indicates that there are huge potentials for savings mobilization for investment and economic growth in the country. A volatile savings pattern by income deciles was also observed during the period. Another novel finding of the study, which conforms to findings from developing countries, is that higher educational attainment reduces savings rate. This is explained by the trade-off between higher current savings and increased spending on children's education.

The saving pattern validated the Life Cycle Hypothesis (LCH). However, the LCH did not hold for age-group 65-79 whose saving rate increased instead of declining. Savings peaked late among the labour force at age 60-64. As pointed out earlier, insecurity at old age, as a result of irregular or non-payment of pension may have prompted such savings behavioural pattern among the elderly.

Generally, results of the empirical estimation show that income, household size, years of education, gender, and location influence private savings in Nigeria. While income positively drives savings, the relationship between household size and savings appears mixed. Education was found to negatively impact savings. This notable finding is supported by other developing country studies and suggests that a highly educated population may not necessarily translate into increased savings. The trade-off between higher savings and investment in children's education plays an important role. Similarly, gainfully employment among educated people also matters for savings mobilization. This further reiterates the need for the government to provide a more conducive atmosphere for job creation. Remittances received by households, increased their savings. In addition, women and rural dwellers were found to be thriftier. In this regard, aggressive promotion of financial services and products in rural areas would aid increased savings mobilization and boost economic growth.

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# Appendix

**Savings Rate by Geo-political Zones, Age, and Location**

| | Savings rate (%) | | | | | | |
|---|---|---|---|---|---|---|---|
| | **1980** | **1985** | **1992** | **1996** | **2004** | **2009** | **Average** |
| **Geo-Political Zones** | | | | | | | |
| South-West | 23.6 | 23.2 | 14.4 | 34 | 23.6 | 24.1 | 23.8 |
| South-East | 22.9 | 18.1 | 8.7 | 42.6 | 19 | 19.5 | 21.8 |
| South-South | 20.8 | 18.4 | 6.9 | 35.1 | 12.2 | 12.3 | 17.6 |
| North-Central | 27.1 | 32.1 | 15.1 | 44.6 | 19.9 | 20.1 | 26.5 |
| North-West | 24.5 | 34.9 | 6.6 | 40.1 | 19.5 | 20.0 | 24.3 |
| North-East | 26.7 | 39.7 | 2.1 | 46.6 | 20.2 | 21.0 | 26.1 |
| **Age Group** | | | | | | | |
| 15-24 | 23.6 | 25.2 | 5.3 | 18.9 | 22.4 | 22.8 | 19.7 |
| 25-34 | 23.9 | 24.7 | 7.3 | 29.8 | 21 | 21.6 | 21.4 |
| 35-44 | 23.8 | 31.4 | 7.1 | 41.8 | 17.3 | 18.6 | 23.3 |
| 45-54 | 25.6 | 31.7 | 9.9 | 47.7 | 18.7 | 19.2 | 25.5 |
| 55-64 | 27.6 | 31.1 | 14.8 | 44.4 | 19.5 | 20.6 | 26.3 |
| 65+ | 31.6 | 36.2 | 16.3 | 40.5 | 21.1 | 21.9 | 27.9 |
| **Location** | | | | | | | |
| Urban | 20.4 | 18.4 | 16.2 | 35.6 | 14.2 | 15.5 | 20.1 |
| Rural | 30.4 | 45.1 | 40.1 | 41.8 | 20.7 | 22.7 | 33.5 |

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# Is it efficient to discriminate passengers in airport charges according to flight distance?

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## Abstract

This paper examines the pricing strategy of private airports. To capture the relationship between airport fees and airport locations, we develop a model with the asymmetric hub-spoke network. We obtain the following results. First, spoke airports which are far from the hub set their airport fees low. Second, the hub airport offers a large discount for transit passengers when the average distance between the hub and spokes is long. Finally, when all cities possess the same population, the policy maker can improve social welfare by allowing the hub to discriminate transit passengers in the setting of airport fees.

***Keywords***: Airport Pricing, Hub–Spoke Network, Asymmetric Network, Price Discrimination, Private Airports, Transit Passengers

***JEL classification:*** **R48** (Government Pricing and Policy), **L93** (Air Transportation)

## 1. Introduction

After the liberalization in the aviation industry, the networks of airlines changed from the point-to-point to the hub-spoke design. As a result, passengers departing from airports at a spoke node (spoke airport) now have to transit at a hub when they travel. This transit at the hub imposes some additional costs on passengers from spoke airports. Therefore, transit passengers incur larger trip cost than those departing from hub airports. The cost related to the transit may include the airport fee payment; that is, transit passengers have to pay the airport fees at the departing spoke and hub airports. However, hub airport operators offer a discounted fee for transit passengers. Figure 1 summarizes the ratio of the discounted transit airport fee against the departing airport fee for the five largest airports in Europe in 2011: London Heathrow (LHR), Charles de Gaulle (CDG), Frankfurt (FRA), Amsterdam (AMS) and Madrid (MAD). In Figure 1, the degree of the discount differs among these five airports: LHR offers the highest transit fee, 82% of the departing fee, while MAD offers the lowest, 53% of the departing fee. Here, the fees include both airline fees (landing fees, noise charges and parking charges) and passenger fees (the Passenger Service Facility Charge (PSFC) and Passenger Security Service Charge (PSSC)). The object of discount is the latter.

The formation of the hub-spoke network may also affect the spoke airport fee. Figure 2 shows the relationship between the fee of European airports and the minimal distance to the five largest airports in Europe: LHR, CDG, FRA, AMS, and MAD. Each dot represents an European airport with more than one million passengers in 2011, while the bold line in Figure 2 represents the fitted line. The fitted line may suggest that the airport fee decreases as the minimal distance to the major hubs increases. This paper aims to clarify the mechanisms of the data presented in Figures 1 and 2; that is, (i) why do spoke airports, which are farther from the hubs, set their airport fees lower and (ii) what is the determinant of the discount rate for the transit passengers offered by hub airports?

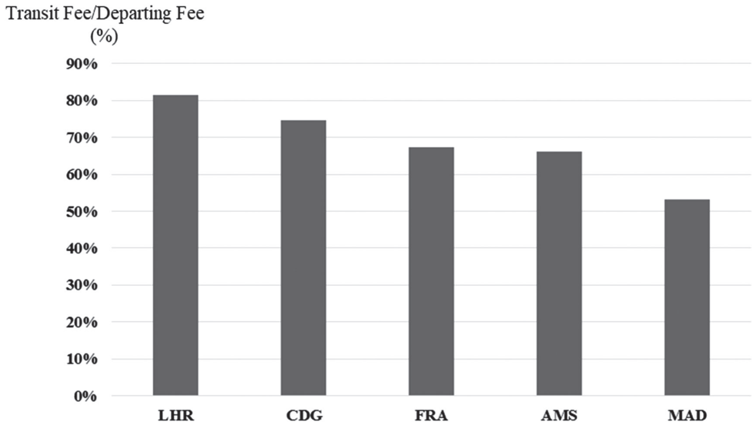


**Figure 1: The ratio of the transit fee against the departing fee***

*This figure compares the fees of departing and transit passengers from a B787 passenger jet (280 seats). To compute the fees, we use the IATA Airport, ATC and Fuel Charges Monitor (IATA, 2013) and set several assumptions: the aircraft utilises the parking for three hours during the daytime; the loading factor is 71%; and the MTOW (Maximum Takeoff Weight) is 301 t.

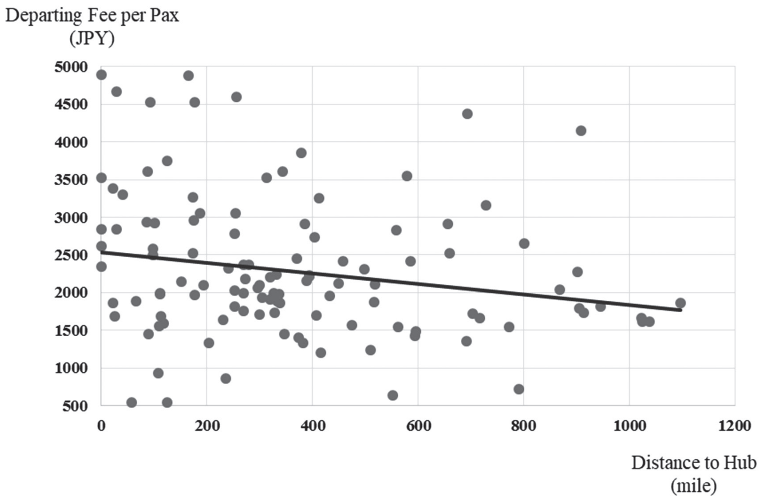


**Figure 2: The relationship between the airport fee and the distance to the hub***

*: This figure demonstrates the departing fees for passengers boarding a B787 passenger jet (280 seats) for European international airports, which are appeared in the IATA Airport, ATC and Fuel Charges Monitor (IATA, 2013). In computing the airport charges, we set the same assumptions as in Figure1.

Focusing on the relationship between airports, by its nature, the services provided by airports may become the substitute or the complementary goods. In case of the substitute goods, airports compete for passengers from the common catchment area; therefore, the airport fees become the strategic complements (for example, Czerny et al. (2014) and Teraji and Morimoto (2014)).[1] When passengers utilize a pair of airports as the origin and destination, the airport services are the complementary goods. In such case, the airport fees become the strategic substitutes (Mantin (2012) and Matsumura and Matsushima (2012)).[2] In order to explain the mechanism behind Figures 1 and 2, we employ the second approach: namely, the airports are the complementary goods.

In terms of network structures, most papers that focus on airports in complementary goods relationship consider a network with one hub airport and two spoke airports. Based on this network, Lin (2013) treated pricing strategy of privatized airport to analyze airport congestion problem. Brueckner (2005) expanded the network to two hab airports and two spoke airports in order to capture decisions of network carriers. However, this type of networks has a problem that it is impossible to analyze effects of distance between airports on pricing strategy. Oum et.al. (1996) established a model of network with one hub airport and arbitrary number of spoke airports. Kawasaki (2014) applied this network for relationship among international hub and domestic spoke airports. However, their network structures are symmetric and distances from spoke airports to the hub are the same.

This paper also besed on the network of Oum et.al. (1996) and improved it to "asymmetric" structure. That is, spoke airports locate at an arbitrary distance from the hub. Using this model, we analyze how distance between the hub and spoke airports affects airport charges.

The rest of this paper is organized as follows. In Section 2, we describe the model, which is used to clarify the reason why spoke airports that are farther from the hubs set their airport fees lower and what affects the discount rate for the transit passengers at hub airports. In Section 3, we solve the game among airports and compare the analytical results with some stylized facts described above. In Section 4, we derive the welfare effect for each spoke market and analyse how the distance to the hub affects the welfare loss of each market. In Section 5, we suggest the discriminatory pricing policy to improve the social welfare. Finally, Section 6 states concluding remarks.

## 2. The Model

Let us consider a situation in which an airline connects $S$+1 airports with a foreign country by forming a hub-spoke network as shown in Figure 3.[3] In Figure 3, $\gamma_s$ represents the distance between the hub and each spoke $s$, and we normalize the distance between the hub and foreign country to 1. Hereafter, we refer to the hub airport as *Airport h*, each spoke airport as *Airport s* ($s$=1,2,…,$S$ ), and *City i* ($i$=$h$ and 1,2,…,$S$ ) is the city in which *Airport i* is located. The population of *City i* is represented by $n_i$ and we normalize the population of *City h* to 1, $n_h$ =1.

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1 Czerny et al. (2014) focued on the case where the two ports compete for the demand from the third region and evaluate the welfare effects of the port privatization. Teraji and Morimoto (2014) dealt with the competition of airports to become a regional hub. In their model, two airports locate in a same country and compete for the international trip demand from the country.

2 Similar to Czerny et al. (2014), Mantin (2012) and Matsumura and Matsushima (2012) evaluated the welfare effects of the airport privatization. Different from Czerny et al. (2014), however, they dealt with the situation where the two airports constitute the origin-destination pair.

3 Long-haul flights from *Airport h* to the foreign county represent flights such as those from Europe to Asia or to the United States.

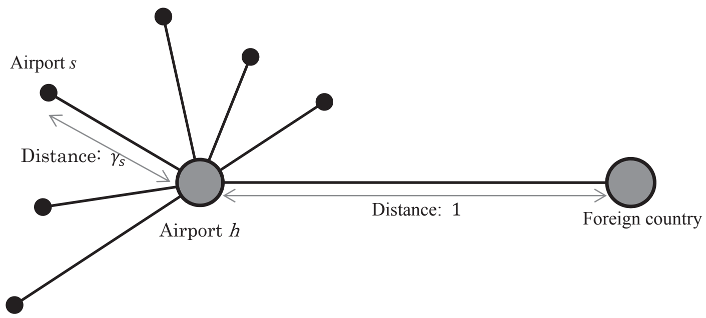


**Figure 3: Hub–Spoke Network**

The economy has three agents: the airports, the airline, and consumers. The sequence of decisions among these agents is as follows. First, all airports set their airport fees simultaneously to maximize their revenue. Second, the airline sets its fares to maximize its profit. Finally, consumers in each city decide their demand for flights to the foreign country. Hereafter, we trace the decision-making process.

The demand for air services is

$$d_h = 1 - p_h - a_d \tag{1.1}$$

$$d_s = n_s(1 - p_s - a_t - a_s) \text{ for } s = 1, 2, \ldots S, \tag{1.2}$$

where $p_i$ denotes the airfare. $a_d$ and $a_t$ denote the airport fees of the hub for the departing passengers and for the transit passengers, respectively. We call the former "departing fee" and the latter "transit fee." In (1.2), $a_s$ is the airport fee of a spoke airport. Hereafter, we refer to passengers departing from *Airport h* as "hub passengers" and passengers departing from *Airport s* as "spoke passengers."

The airline creates the hub-spoke network and provides two types of flights, connecting flights between *Airport h* and each spoke airport, and direct flights between *Airport h* and the foreign country. We assume that the airline's operating cost is proportional to the passenger-kilometer. Specifically, operating cost per passenger is $c\gamma_s$ for the connecting flight and $c$ for the direct flight. The total operating cost is

$$C = cd_h + \sum_{s=1}^{S}(1 + \gamma_s)cd_s. \tag{2}$$

The first term is the operating cost for shipping hub passengers and the second term is the operating cost for shipping spoke passengers. Here, we assume that the airline does not pay airport fees. In reality, while airlines pay airport fees such as landing, aircraft parking and handling fees, they are shifted onto passengers through the airfare. Therefore, the equilibrium demand and social welfare are given just as functions of total airport fees (= the sum of all the fees levied by airport operators). Therefore, in our model, only passengers pay airport fees. Similar assumptions are used in Oum et al. (1996) and Kawasaki (2014).

Using (2), we obtain the airline's profit as

$$\pi = (p_h - c)d_h + \sum_{s=1}^{S}[p_s - (1+\gamma_s)c]d_s. \tag{3}$$

The first term is the profit from hub passengers and the second term is the profit from spoke passengers. The airline sets its airfare  to maximize profit:

$$\max_{p_i} \pi. \tag{4}$$

Each airport levies airport fees on passengers. Total fee revenue is computed as

$$R_h = a_d d_h + a_t \sum_{s=1}^{S} d_s \tag{5.1}$$

$$R_s = a_s d_s \tag{5.2}$$

The first term of (5.1) is the revenue from hub passengers and the second term is from spoke passengers. We ignore airports' operating cost; therefore, private airports set their airport fees to maximize their fee revenue, that is, $\max_{a_d, a_t} R_h$ for the hub and $\max_{a_s} R_s$ for the spokes.

## 3. Equilibrium

This section derives the equilibrium airport fees in the hub-spoke network. Furthermore, we verify the stylized facts given in Figures 1 and 2; specifically, whether the distance to the hub affects the airport fees of each spoke airport and whether the hub operator reduces its transit fee as the network size expands. Subsection 3.1 derives the airfares and the demand whereas Subsection 3.2 solves the game among airports. Finally, Subsection 3.3 uses these solutions to check if the two stylized facts work in our setting.

### *3.1. The Airline's Choice*

By solving the airline's profit maximization problem, we obtain the equilibrium airfares:

$$p_h = \frac{1 + c - a_d}{2}, \tag{6.1}$$

$$p_s = \frac{1 + (1+\gamma_s)c - a_t - a_s}{2}. \tag{6.2}$$

Substituting these two equations into (1), we rewrite the demand as a function of airport fees, $a_d$, $a_t$, and $a_s$:

$$d_h = \frac{1 - c - a_d}{2}, \tag{7.1}$$

$$d_s = \frac{n_s[1 - (1+\gamma_s)c - a_t - a_s)]}{2}. \tag{7.2}$$

Hereafter, we assume that all spoke routes have the positive potential demand:

$$1 - c(1 + \gamma_s) > 0 \text{ for } s = 1, \dots, S.$$

### 3.2. Equilibrium Airport Fees

Solving each airport's revenue maximizing problem, we obtain the best response functions as follows:

$$a_d = \frac{1-c}{2}, \tag{8.1}$$

$$a_t(a_1, \dots, a_s) = \frac{1-c}{2} - \frac{1}{2}\left(c\bar{\gamma} + \frac{\sum_{s=1}^{S} a_s n_s}{\sum_{s=1}^{S} n_s}\right), \tag{8.2}$$

$$a_s(a_t) = \frac{1-(1+\gamma_s)c - a_t}{2} \tag{8.3}$$

Here, $\bar{\gamma} \equiv \sum_{s=1}^{S} n_s \gamma_s / \sum_{s=1}^{S} n_s$ is the population-weighted average distance between the hub and spokes. According to (8), we obtain Lemma 1:

### *Lemma 1*

*The transit fee of the hub and the airport fee of spoke airports are strategic substitutes.*
For spoke passengers, airport services at the hub and each spoke are complementary goods. Therefore, if one airport increases its fee, the other airport has to decreases its fee.

By solving (8), we obtain the equilibrium airport fees as

$$a_d = \frac{1-c}{2}, \tag{8.1}$$

$$a_t = \frac{1-(1+\bar{\gamma})c}{3}, \tag{9.1}$$

$$a_s = \frac{1-c}{3} + \frac{1}{6}c(\bar{\gamma} - 3\gamma_s). \tag{9.2}$$

### 3.3. Pricing Strategies of Private Airports

In this subsection, we discuss pricing strategies by focusing on the distance. We start with airport fees of spoke airports. Hereafter, *Airport s'* is farther from the hub than *Airport s*, that is, $\gamma_{s'} > \gamma_s$. From (9.2), we obtain

$$\begin{aligned} a_s - a_{s'} &= \frac{c}{6}(\bar{\gamma} - 3\gamma_s) - \frac{c}{6}(\bar{\gamma} - 3\gamma_{s'}) \\ &= \frac{c}{2}(\gamma_{s'} - \gamma_s) > 0. \end{aligned}$$

This result is summarized in Proposition 1.

***Proposition 1***

*Airport fees of the spoke airport decreases as the distance to the hub, $\gamma_s$ , increases.*
Demand for connecting flights decreases and becomes more elastic as the distance between a spoke airport and the hub increases because airfares become higher due to the airline's higher operating cost. Therefore, the spoke airport lowers its airport fee to boost demand. This result explains the fitted line in Figure 2. When the distance to the hub is long, the spoke airport chooses the lower airport fee, which offsets the higher airfare and increases the demand.

We move to pricing strategies of the hub airport and investigate the discount for transit passengers. According to (8.1) and (9.1), we obtain the ratio of the transit fee to departing fee as follows:

$$\frac{a_t}{a_d} = \frac{2}{3} - \frac{2c}{3(1-c)}\bar{\gamma}. \tag{10}$$

Differentiating (10) with respect to $\bar{\gamma}$, we obtain Proposition 2.

***Proposition 2***

*The ratio of the transit fee to the departing fee decreases as the weighted average distance, $\bar{\gamma}$, increases.*

The hub lowers its transit fee and compensates for higher airfare of spoke routes to attract more transit passengers when spoke airports are located far from the hub. On the other hand, the departing fee is independent from the location pattern of spoke airports. Therefore, the transit fee gets relatively small compared to the departing fee as the average distance becomes large. Note that in Figure 1, the discount ratio of MAD is the lowest among the five largest airports. This can be interpreted as follows. Since MAD locates at the fringe of Europe compared to the other four airports, the operator of MAD discounts the transit fee more than the others to attract more transit passengers from spoke airports.

## 4. Welfare Analysis

This section clarifies the effect of distance to the hub upon the social welfare for each spoke route. To deal with this problem, we designate *Route s* as the route from *Airport s* to the foreign country via the hub. We define the social welfare for *Route s* as the gross consumer benefit minus the social cost.

$$W_s = \frac{1}{2}(1 + p_s + a_t + a_s)\, d_s - (1+\gamma_s)cd_s. \tag{11}$$

The first term is the lower part of the inverse demand function and the second term is the operating cost. The social welfare in the equilibrium is [4]

$$W_s^* = \frac{1}{288}(21X_s + Y)(3X_s - Y)n_s. \tag{12}$$

Here, $X_s = 1 - c - c\gamma_s$ and $Y = 1 - c - c\bar{\gamma}$ . Since we consider the case of fixed airline network

[4] Detailed process of the derivation is summarized in Appendix A.

in this paper, demand should be positive for all routes. Thus, $X_s$ is positive for all $s$ and then $Y > 0$. At the optimum, airfare should be equal to the airline's marginal cost, and airport fees should be zero. Therefore, the social welfare at the optimum, , is $W_s^o$, is [5]

$$W_s^o = \frac{1}{2} X_s^2 n_s. \tag{13}$$

The welfare loss is $W_s^o - W_s^*$, and we define the welfare loss ratio on *Route s* as

$$\begin{aligned} \theta_s &\equiv \frac{W_s^o - W_s^*}{W_s^o} \\ &= \frac{1}{144}\left(81 + 18\frac{Y}{X_s} + \frac{Y^2}{X_s^2}\right). \end{aligned} \tag{14}$$

This ratio indicates the degree of market distortion. A large $\theta_s$ means large welfare loss and large market distortion.

To analyze the relationship between the welfare loss and the distance, let us compare the two spoke airports, $s$ and $s'$ ($\gamma_{s'} > \gamma_s$). From (14), we can state

$$\theta_s - \theta_{s'} = \frac{1}{144}\left[18\left(\frac{1}{X_s} - \frac{1}{X_{s'}}\right)Y + \left(\frac{1}{X_s^2} - \frac{1}{X_{s'}^2}\right)Y^2\right] < 0.$$

Since, $\gamma_{s'} > \gamma_s$, $X_{s'} = 1 - c - c\gamma_{s'} < X_s = 1 - c - c\gamma_s$: therefore, $\theta_s - \theta_{s'} < 0$. From this, we obtain Proposition 3.

***Proposition 3***

*The welfare loss ratio, $\theta_s$, increases as the distance between the hub and spoke, $\gamma_s$, increases.*

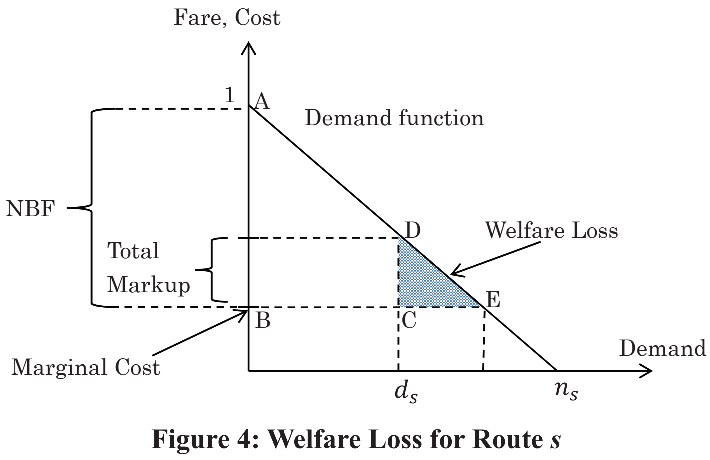


**Figure 4: Welfare Loss for Route *s***

[5] See Appendix A for the derivation of these social welfare functions.

This result is derived from the hub's transit fee which is identical for all transit passengers. To clarify this mechanism, we define the "Net Benefit of the First trip ($NBF_s$)" and the "Total Markup ($TM_s$)." $NBF_s$ captures the net social gain of the first trip along *Route s*, which is computed as the highest willingness to pay (equal to unity) minus marginal cost of the flight operation, $(1+\gamma_s)c$. That is, $NBF_s = 1-(1+\gamma_s)c$. $TM_s$ captures the aggregate private gains of the airline, the hub and *Airport s*: that is,

$$TM_s = [p_s - (1+\gamma_s)c] + a_t + a_s = \frac{1 + a_t + a_s - (1+\gamma_s)c}{2}$$
$$= \frac{1-(1+\overline{\gamma})c}{12} + \frac{9\{1-(1+\gamma_s)c\}}{12} = \frac{Y + 9X_s}{12}. \quad (15)$$

In Figure 4, the area CDE is the welfare loss and the area ABE is the social welfare at the optimum. Therefore, according to Figure 4, the welfare loss ratio is written as $\theta_s = (TM_s/NBF_s)^2$. While both $TM_s$ and $NBF_s$ are decreasing in $\gamma_s$, the decrease of $TM_s$ is less significant than $NBF_s$ due to the identical transit fee at the hub. Therefore, $\theta_s$ is increasing in $\gamma_s$.

## 5. Discriminatory Airport Fee Policy

Proposition 3 shows that the relative welfare loss is increasing with the distance to the hub due to the uniform transit fee at the hub. To avoid the welfare loss due to uniform pricing for transit passengers, we consider the case where the hub can set its transit fee for each spoke route separately according to the demand elasticity. We call this case "discriminatory fee case." In this case, the hub's revenue maximizing problem is reduced to maximize the fee revenue for each route. That is,

$$\max_{a_{t,s}} a_{t,s} d_s.$$

Here, $a_{t,s}$ is the transit fee for *Route s* passengers. The best response is

$$a_{t,s}(a_s) = \frac{1-(1+\gamma_s)c - a_s}{2}.$$

Using the spoke's best response in (8.3), we obtain the transit fee as

$$a_{t,s}^d = a_s^d = \frac{1-(1+\gamma_s)c}{3}.$$

In the discriminatory fee scheme, $TM_s^d$ is computed as:

$$TM_s^d = [p_s - (1+\gamma_s)c] + a_{t,s}^d + a_s^d = \frac{5[1-(1+\gamma_s)c]}{6} = \frac{5X_s}{6}. \quad (16)$$

In contrast, the total markup under the uniform fee scheme, $TM_s^u$, is computed in (15). In comparison of these two,

$$TM_s^u - TM_s^d = \frac{Y}{12} + \frac{9X_s}{12} - \frac{5X_s}{6} = \frac{c(\gamma_s - \overline{\gamma})}{12}.$$

This indicates that, for the routes where $\gamma_s > \bar{\gamma}$, the discriminatory fee scheme improves the economic welfare. This is because, in these routes, the discriminatory fee scheme results in the airport fee payments reduction[6] and the lower total mark up. In contrast, due to the rise in the airport fee payments, the economic welfare of the routes for $\gamma_s < \bar{\gamma}$ is decreased when the discriminatory fee scheme is introduced.

Next, we focus on change in the welfare loss of the entire network. Because the welfare loss for each route is expressed as the triangle CDE in Figure 4, the loss for each is calculated as $n_s TM_s^2/2$. Aggregating the loss for all routes, the differential in the welfare loss of the entire network under the two alternative fee schemes is computed as:[7]

$$\Delta WL = \sum_{s=1}^{S} \frac{n_s[(TM_s^d)^2 - (TM_s^u)^2]}{2}. \tag{17}$$

If this sign is negative, the discriminatory fee scheme is more efficient than the uniform scheme; that is, the discriminatory fee scheme improves the economic welfare.

Although the sign of (17) may depend on the difference in the aggregate demand between the two alternatives, it is difficult to derive a clear result without assuming the population distribution. Therefore, we focus on the case where all spoke cities have the same population, that is, $n_s = n$. We rewrite (17) as:

$$\Delta WL = -\frac{1}{288S} nc^2\sigma^2 < 0, \tag{18}$$

where $\sigma^2$ is the variance of $\gamma_s$.[8] This result is summarised as follows:

***Proposition 4***

*When all the spoke cities have an identical population size, the discriminatory fee scheme is more efficient than the uniform scheme in terms of the entire welfare.*

As shown in Proposition 4, when all the spoke cities have an identical population size, the policy maker can improve social welfare by allowing hub airports to discriminate passengers in setting airport fees. However in reality, price discrimination is banned in many countries. For example, the EU Airport Charges Directive (2009/12/EC) prohibits differentiated fees to airlines using the same service. In the US, airports are compelled to offer same fees for same service by 2013 FAA's Policy Regarding Airport Rates and Charges. In some situation, however, Proposition 4 states that the uniform fee scheme harms the economic welfare.

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[6] The differentials in the fees incurred by transit passengers in two cases are computed as:

$$a_t^u - a_{t,s}^d = \frac{1}{3}(\gamma_s - \bar{\gamma})c,$$

$$a_s^u - a_s^d = \frac{1}{6}(\bar{\gamma} - \gamma_s)c.$$

Superscripts $u$ and $d$ indicate the uniform fee and the discriminatory fee cases, respectively. Also note that the fees under the uniform case (with the superscript $u$ ) are derived as in (9).

[7] Since, under the two alternative fee schemes, the hub passengers incur the same level of airfare and airport fee, the loss at the hub airport remains at the same level; therefore, we ignore the change in the loss at the hub.

[8] See Appendix B for derivation of (18).

## 6. Conclusion

In this study, we analyzed airport pricing in an asymmetric hub-spoke network and obtained three results. First, the airport fees of a spoke airport decrease as the distance to the hub increases. This is because the demand from the spoke airport gets relatively smaller as the distance between the spoke and the hub increases, due to the high operating cost and airfare. Second, the ratio of the transit fee to the departing fee diminishes as the weighted average distance increases. Demand of a spoke route is a decreasing function of the distance. Therefore, the hub lowers its transit fee in attempt to boost the demand for transit services when spoke airports locate farther from the hub. Third, the welfare loss ratio increases as the distance between the hub and spoke increases. The mark-up ratio of a long spoke route is large due to the identical transit fee. Due to the large mark-up ratio, the welfare loss ratio also becomes large. Moreover, we showed the possibility that the discriminatory fee scheme improves the social welfare.

We need to extend our model in two aspects. First, we should establish a multi-hub model. It is often observed that some large airports compete for hub positions. Such competitions lead to discounting of airport fees. Second, we should consider airport groups and alliances among airports. If some airports are in one group or operated by a parent company, airport operators try to maximize the total profit of their group or company.

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## Appendix A: Derivation of social welfare

(i) The social welfare in the equilibrium

Plugging (1.2) into (11), we obtain

$$W_s = \left[\frac{1}{2}(1 + p_s + a_t + a_s) - (1 + \gamma_s)c\right](1 - p_s - a_t - a_s)n_s. \quad \text{(A. 1)}$$

Plugging (6.2) into (A.1),

$$W_s = \frac{1}{8}[3 - 3(1 + \gamma_s)c + a_t + a_s][1 - (1 + \gamma_s)c - a_t - a_s]n_s. \quad \text{(A. 2)}$$

Finally, substituting (9.1) and (9.2) into (A.2),

$$\begin{aligned} W_s^* &= \frac{1}{288}(22 - 22c - 21\gamma_s c - \bar{\gamma}c)(2 - 2c - 3\gamma_s c + \bar{\gamma}c)n_s \\ &= \frac{1}{288}(21X_s + Y)(3X_s - Y)n_s. \end{aligned} \quad \text{(A. 3)}$$

Here, $X_s = 1 - c - c\gamma_s$ and $Y = 1 - c - c\bar{\gamma}$.

(ii) The social welfare at the optimum condition

At the optimum, $a_t = a_s = 0$ and $p_s = (1 + \gamma_s)c$. Hence, the demand at the optimum is

$$d_s = n_s[1 - (1 + \gamma_s)c]. \quad \text{(A. 4)}$$

Plugging (A.4) into (11), we obtain the welfare function at the optimum as

$$\begin{aligned} W_s^o &= \frac{1}{2}(1 - c - c\gamma_s)^2 n_s \\ &= \frac{1}{2}X_s^2 n_s. \end{aligned}$$

## Appendix B: Comparison of two airport fee schemes

The difference of the welfare loss under both schemes is

$$\Delta WL = \frac{1}{2} n \sum_s [(TM_s^d)^2 - (TM_s^u)^2 ]$$
$$= \frac{1}{2} n \sum_s (TM_s^d + TM_s^u)(TM_s^d - TM_s^u). \tag{B.1}$$

Here,

$$TM_s^d + TM_s^u = \frac{1}{12}(20 - 20c - c\bar{\gamma} - c\gamma_s),$$
$$TM_s^d - TM_s^u = \frac{1}{12}c(\gamma_s - \bar{\gamma}).$$

Substituting them into (B.1), we obtain

$$\Delta WL = \frac{1}{288} nc \sum_s [(20 - 20c - c\bar{\gamma} - c\gamma_s)(\gamma_s - \bar{\gamma})]$$
$$= \frac{1}{288} nc \sum_s [-c\gamma_s^2 + 20(1-c)\gamma_s + c\bar{\gamma}^2 - 20(1-c)\bar{\gamma}]$$
$$= \frac{1}{288} nc \left[-c \sum_s \gamma_s^2 + 20(1-c) \sum_s \gamma_s + Sc\bar{\gamma}^2 - 20S(1-c)\bar{\gamma}\right]. \tag{B.2}$$

Because $n \equiv n_1 = n_2 = \cdots = n_S$, we rewrite the weighted average distance as

$$\bar{\gamma} = \frac{\sum_s \gamma_s}{S} \Leftrightarrow \sum_s \gamma_s = S\bar{\gamma}.$$

We simplify (B.2) as

$$\Delta WL = \frac{1}{288} nc \left(-c \sum_s \gamma_s^2 + Sc\bar{\gamma}^2\right)$$
$$= \frac{1}{288S} nc^2 \left(-\frac{\sum_s \gamma_s^2}{S} + \bar{\gamma}^2\right)$$
$$= -\frac{1}{288S} nc^2 \sigma^2 < 0,$$

where $\sigma^2 \equiv \left(\frac{\sum_s \gamma_s^2}{S} - \bar{\gamma}^2\right) > 0$ is the variance of $\gamma_s$.

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