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The Credit Card Act of 2009: Its Financial Impact on the Retail Industry

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Abstract

This study analyzes the House passage of the Credit Card Accountability Responsibility and Disclosure Act of 2009 (Credit Card Act) on the retail industry. Furthermore, this study evaluates the financial impact on those retailers that profit from both: (i) the sale of merchandise and (ii) the financing of the sale through in-house credit card (IHCC) programs. An event study methodology is used to isolate the financial impact on the retail industry by examining changes in market value of equity (MVE). Our results support that retailers with IHCC programs were negatively impacted as two-thirds of these retailers experienced stock prices decline when the House passed the Credit Card Act. Additionally, 78 percent of the large retailers suffered losses and these large retailers, on average, suffered a stock price decline of almost 3.5% which equates to a decline in MVE of $500 million.

I. Introduction

According to a 2009 Nilson Report, the total credit card debt in America reached $972 billion in 2008. Myfico.com goes even further and states that the average consumer has access to $19,000 in credit between all household cards. Additionally, a Federal Reserve Survey indicates that in 2007 nearly 60% of households had store credit cards and over 96% of the households had bank cards (Survey of Consumer Finances, February 2009). Visa, MasterCard, American Express and Discover have approximately 630 million credit cards outstanding with Visa and MasterCard having an additional 500 million debit cards outstanding. The convenience of credit cards and the move towards electronic mechanisms of purchases have driven credit card use from convenience to necessity for many consumers. Bottom line: credit cards are indispensable for consumer use and convenience and have become an important method of paying for goods and services in our economy. Therefore, any change that impacts the ability to use credit cards may have a direct impact not only on consumers, but also on retailers.

The financial crisis began in 2008 with a significant slowdown in the economy that nearly coincided with the bursting of the real estate bubble. Personal residences had been a large source of consumer credit for consumption spending which caused an even more pronounced economic crunch since consumer spending accounts for roughly 70% of the U.S. GDP. These factors along with high unemployment and extreme mortgage delinquencies led a constituent-driven congress to revamp credit card legislation. On May 22, 2009 President Obama signed into law the Credit Card Accountability Responsibility and Disclosure Act of 2009 (Credit Card Act). The bill originally passed in the House was named the Credit Cardholders' Bill of Rights, but was subsequently named Credit Card Accountability Responsibility and Disclosure Act of 2009. Policy makers passed the Credit Card Act with the intention of better protecting consumers from credit card fees and expenses. Some key provisions of the legislation included:

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(i) amending the Truth in Lending Act to provide consumers more advance notice of card changes; (ii) prohibiting changes in the APR, fees, or finance charges unless specific conditions are met; (iii) prohibiting a creditor from changing the terms governing repayment of an outstanding balance. While it is likely that credit card issuers will be impacted by the Credit Card Act, it is unclear how retailers with in-house credit card programs will be impacted.

This paper evaluates the impact of the Credit Card Act on retailers, especially those retailers whose profit is a function of both: (i) the sale of merchandise and (ii) the financing of the sale through in-house credit card (IHCC) programs. The customers of retailers depend on store credit cards for access to retail credit which directly influences their ability to purchase retail products and services. In turn, retailers use the data and information collected to more effectively market their merchandise to consumers and to maximize profits of the IHCC program. Thus, legislation such as the Credit Card Act may directly impact retailers with IHCC programs by placing a greater compliance burden upon them. If the Credit Card Act is expected to benefit retailers via increased consumer savings and ultimately consumer spending as suggested by legislators, then passage of the Act should be viewed positively by investors. Alternatively, if the passage of the Act is expected to hurt retailers via increase compliance costs, especially for retailers with IHCC programs, then passage of the Act should be viewed negatively by investors. Retailers that would experience greater compliance costs would include retailers with their own store-issued credit cards such as Kohl's and JC Penney. While some retailers will outsource their card operations to a third-party, we expect these third-parties to pass on the compliance costs to the retailer just as if the retailer held these costs in-house. In summary, we anticipate retailers with IHCC programs to experience a *net loss* as the present value of compliance costs will outweigh the present value of any potential benefits.

Home Depot can be used as an example of the compliance costs of the Credit Card Act. For example, Home Depot previously offered consumers a no-interest and no-payment option prior to the legislative change. The change in the legislation mandates that retailers require consumers to make monthly payments which could impact Home Depot in several ways. A consumer may now choose to make his purchase at a different home improvement store whereby Home Depot would lose the profit from the sale of the merchandise. A consumer may now choose obtain his financing from his financial institution whereby Home Depot would lose the profit from the financing of the sale. In fact, Home Depot may even lose the customer entirely, thereby losing both: (i) the profit from the sale of the merchandise and (ii) the profit from the financing of the sale. Further, a change in marketing strategies has to take place going forward which will add costs and eliminate a way of doing business with many consumers. Home Depot will experience a large negative impact today from the costs associated with changing statement presentations, managing pre- and post-Act purchases, informing customers, and other similar activities. The benefit of consumers having additional savings will enhance spending at some point, but it is unlikely these benefits will outweigh the costs of compliance.

II. Literature Review

Consumer use of credit and debit cards has continued to evolve as society moves towards a paperless transaction system. The recent consolidation of the commercial banking industry combined with gains in efficiencies of larger card issuers is driving smaller issuers into unique segments (e.g., Health Savings Accounts) or causing store credit issuers to sell their portfolios to other third-party firms (Mercator Advisory Group 2005). Credit has historically played an important function in generating sales with store credit playing a unique role because of the alternative financing medium, but these operations are increasingly being sold to third-party entities (Bloomberg 2009, Lee and Kwon 2002). In the Bloomberg report, the CFO of Target is attributed to stating that the Credit Card Act could shave up to ½ of 1% off same store sales growth (open at least one year) and that available consumer credit on cards shrunk by nearly one-fourth from a peak in 2008 to 2009.

Governmental regulatory changes are known to impact cash flows through either the revenue or expense side of operations as well as changing the underlying risk factor facing individual firms or entire industries (Reynolds 2008). The probability of such regulatory changes is altered as possible policies or legislation are discussed or introduced. The resolution of some portion of the change in uncertainty occurs as the legislation fails or passes (Cornett and Musumeci 1999; Hoag 2002; and Lamdin 1999).

Llewellyn (1999) argues that effective competition is a key component of consumer protection as well as competitive pricing so that market imperfections are corrected by regulations and makes markets operate even more efficiently. In doing so, he states there are six avenues of generating benefits from regulation: (i) lower consumer transaction costs; (ii) greater market efficiency; (iii) increased consumer confidence; (iv) ability to remove problem firms; (v) externality gains; and (vi) greater transparency. In this case, the Credit Card Act is driven with a stated focus on lowering the costs for consumers and increasing transparency to the public.

Following the efficient-market hypothesis, information that is released to the public will alter investors' views on future earnings as well as the uncertainty of those earnings (Fama 1965, 1970). We accept the validity that information is quickly assimilated by the stock market and that stock prices react quickly to that new information. Common stock valuation models employ variations of the Capital Asset Pricing Model into a cash flow discounting approach that drives asset valuations. As such, the event study methodology is a widely accepted model that can be used to evaluate the initial and immediate response of the market place on regulatory changes.

III. Data

To be included in the sample, a retailer must have: (i) a primary four-digit SIC code of 5200, 5300, 5600, or 5700; (ii) daily stock return data available for the event window on Compustat North America; (iii) no major news announcement reported in the *Wall Street Journal* during the event window. There are 85 retailers that meet these criteria.

The sample is then subdivided into retailers: (i) without an IHCC program and (ii) with an IHCC program. We examine external websites of retailers in December 2009 to determine which retailers have an IHCC program. There are 43 retailers without an IHCC program and 41 retailers with an IHCC program. The retailers with an IHCC program include those firms with a traditional credit card program, a store credit card program, or both. A traditional credit card program includes cards issued through Visa, Mastercard, Discover, and American Express that are branded for the retailer. Retailers with such card programs include Costco, Abercrombie & Fitch, and Coldwater Creek. A store credit card program includes cards that are branded with the retailer's name and can only be used in that family of stores. Retailers with such card programs include Eddie Bauer, GAP, and Kohl's. In GAP's case, the card can be used at GAP, Old Navy and Banana Republic stores. Some retailers in our sample have both a traditional credit card program and a store credit card program. Retailers with both card programs include Sears and Target. Customers with strong credit histories qualify for either card whereas consumers with weak credit histories may qualify for only the store credit card. The retailers with an IHCC program are listed in Table I along with their market value of equity.

The retailers with an IHCC programs are then subdivided by size into two samples: (i) large retailers and (ii) small retailers. Retailers with a market value of equity (MVE) of $1 billion or more are defined as large retailers while retailers with less than $1 billion in MVE are defined as small retailers. There are 18 large retailers with an average MVE of $10 billion. The large retailers include Home Depot, the largest with $36.5 billion in MVE, and Abercrombie & Fitch, the smallest with $1.6 billion in MVE. There are 23 small retailers with average MVE of $326 million. The average small retailer is about 1/30th of the size of a large retailer. The small retailers include Buckle, the largest with $983 million in MVE, and Eddie Bauer, the smallest with $15.7 million in MVE. We choose the subsamples in this manner out of curiosity so we can appraise how large and small retailers are impacted. We speculate that large retailers might have the ability to mine customer data, cross-sell more products, and exploit extensive and targeted marketing campaigns. One might then expect to find these large retailers suffered greatly due to greater costs related to their reliance on these activities. We might also speculate that these large retailers suffered little because they can spread large fixed compliance costs over many customers. Similarly, small retailers with fewer customer accounts and smaller customer balance might face a large negative impact by the Credit Card Act.

IV. Methodology

We use an event study methodology to determine the immediate impact of the Credit Card Act on the stock prices of retailers (Brown and Warner 1985; Peterson 1989; Schweitzer 1989). It is possible to isolate the immediate impact of the Credit Card Act on stock prices because of two unique stock price characteristics. First, expected future earnings drive stock prices. Second, the U.S. stock market is efficient such that stock prices react quickly and efficiently to the announcement of an event that impacts expected future earnings. Thus, if investors conclude the Credit Card Act will decrease future sales of retailers with IHCC programs, thereby decreasing future earnings, then stock prices will decline. On the other hand, if investors perceive retailers with IHCC programs can circumvent the Credit Card Act such that future earnings do not decline, then stocks will not decline. This means that policy makers can immediately gauge the expected economic impact on retailers with IHCC programs by examining their stock price reaction to the Credit Card Act via an event study methodology. The event study methodology divides a stock return into two components. The stock return's first component is driven by a general stock market movement. The stock return's second component is driven by the informational event, the Credit Card Act.

We define an event window that was centered on the announcement date that we call day zero ($t = 0$). On April 30, 2009 the House passed the bill by a recorded vote of 357-70. This event was the critical event as the strong bipartisan support behind the bill was immediately followed by the White House putting forth a Press Release indicating that the President strongly supported the intent of the bill while stating he would be working with Congress in "the weeks to come" to generate an acceptable piece of legislation. Congress Daily is quoted upon House passage that the result is now "placing additional pressure on Senate negotiators to strike a deal on a measure that resonates with the public." Clearly, the quintessential event was the overwhelming House passage and the associated signals clearly indicating to the market that the legislation would eventually pass the Senate and be signed by the President. This process culminated with the President signing the bill three weeks later on May 22, 2009.[1]

To capture how the Credit Card Act affected stock prices, we use a six-day event window surrounding the announcement date as shown in Exhibit 1. Day zero, (t = 0), is the announcement date while day minus one, (t = -1), is one trading day before the announcement date. Day plus one, (t = +1), is one trading day after the announcement date, and so forth where day plus four, (t = +4), is four trading days after the announcement date.

Exhibit 1. Event Window for Credit Card Act of 2009

Event Day	-1	0	+1	+2	+3	+4
Event: House Passage of Bill	4/29	4/30	5/1	5/4	5/5	5/6

After identifying the six-day event window, we calculate the predicted return for each retailer for each day in the event window. The predicted return is what one would expect if there were no Credit Card Act. The predicted return is the daily market return of the S&P 500 Index which is commonly used as the predicted return since it represents America's 500 largest firms that account for approximately 75% of the U.S. stock market's value.

We then calculate the daily abnormal return for each retailer stock for each day over the six-day event window. The daily abnormal return, AR_{it}, for each retailer i on day t is defined as:

$$AR_{it} = R_{it} - R_{mt} \tag{1}$$

where R_{it} is the return on the stock of retailer i on day t and R_{mt} is the predicted return (S&P 500 Index) on day t. The daily abnormal return represents the return not predicted by the market index and is an estimate of the change in the stock price on that day due to the Credit Card Act.

We calculate cumulative abnormal returns for each retailer because in many cases the market reaction to the announcement of an event may linger for days. For example, it may take financial analysts and investors several days to determine the impact of the Credit Card Act upon future expected earnings. Thus, the cumulative abnormal return is an estimate of the stock return

[1] Credit card reform legislation has been long discussed in this country. Beginning in January 2009, the possibility of action started to take form. The difficulty in legislative actions is that bills can be killed, changed, delayed or let die in a variety of ways. Sunlight Foundation notes that in the 110th Congress just 4% or 442 of the 11,059 bills introduced became law. As such, we carefully read news releases to determine the point in which we believed the market could foresee that the possibility of passage moving towards the probability of passage. We determine that this occurs at the point of house passage. The authors have available, upon request, the results of the initial bill introduction which were statistically insignificant.

caused by the event over the six-day event window. The cumulative abnormal return, CAR_i, for each retailer i for the six-day event window beginning with day -1 through day +4 is defined as:

$$CAR_i = \sum_{t=-1}^{+4} AR_{it} \tag{2}$$

where AR_{it} is the daily abnormal return for retailer i on day t.

We then calculate the average cumulative abnormal return, ACAR, for the retailers in the sample which is defined as:

$$ACAR = [\sum_{i=1}^{N} CAR_i]/N \tag{3}$$

where CAR_i is the cumulative abnormal return for retailer i and N is the number of retailers in the sample. The average cumulative abnormal return, ACAR, can be viewed as a diversified portfolio which eliminates unique individual stock returns by offsetting random positive stock returns with random negative stock returns. In summary, if the Credit Card Act did not impact the future earnings of retailers, then the ACAR should not be significantly different from zero.

Lastly, we examine the percent of cumulative abnormal returns, CAR_i, that are negative for each event window. If the Credit Card Act did not impact the future earnings of retailers, then the percent of cumulative abnormal returns that are negative should not be significantly different from fifty percent.

V. Results

a. All Retailers

We examine all retailers in the sample and find they experienced an ACAR of +2.87% which is significant at the ten percent level. This means these retailers, on average, saw their stock price increase 2.87% above expectations when the House passed the Credit Card Act. However, 58% of the retailers experienced a negative CAR. Thus, the results are mixed so we find little support that the House passage of the Credit Card Act impacted retailers either favorably or unfavorably as a group. Likewise, these results do not support that consumers necessarily benefited from the passage in the House. Table II provides a summary of all the test results.

b. Retailers without in-house credit card programs

Next, we examine the subsample of retailers without IHCC programs. When the House passed the Credit Card Act, these retailers experienced an ACAR of +3.27% which is also significant at the ten percent level. Again, this result is tempered by the fact that the 50% of these retailers experienced a negative CAR. So the results provide little support that consumers benefited from the act as touted by legislators.

c. Retailers with in-house credit card programs

We now examine those retailers whose profit is a function of both: (i) the sale of merchandise and (ii) the financing of the sale through IHCC programs. While we find these retailers experience ACAR of +2.44%, the result is not significant. As a secondary test, we examine the binomial statistic and find just 66% of the retailers have a negative CAR which is significantly different from fifty percent at a ten percent level. The results are mixed and we find little or no support that the House passage of the Credit Card Act had a favorable impact on retailers with IHCC programs.

d. Size effect: large and small retailers with in-house credit card programs

In this section test whether there is a size effect by examining large and small retailers with IHCC programs. As with the earlier samples, we examine: (i) the ACAR and (ii) the percent of retailers that experience a loss, negative CAR. We also examine the retailer's absolute dollar change in market value of equity (ΔMVE) when the House passed the Credit Card Act. The ΔMVE is calculated by multiplying each retailer's MVE by its CAR. The ΔMVE represents the dollar amount that stockholders have gained or lost.

We find the large retailers experienced an ACAR of -3.46%. Additionally, we find that 78% of the large retailers experienced a negative CAR when the House passed the Credit Card Act. The test statistics on the ACAR and CAR are significant at the one and five percent levels, respectively. These test results strongly support that large retailers were negatively impacted by the passage of the Credit Card Act. Next we calculate the median and mean ΔMVE for the large retailers. For large retailers, we find the median and mean ΔMVE to be -$143 million and -$551 million, respectively. Based on the mean and median, the stockholders lost between $143 million and $551 million. This means that collectively, the stockholders of these eighteen large retailers lost $9.9 billion (18 retailers x $551 million loss). These results clearly support that large retailers suffered when the House passed the Credit Card Act.

The impact on small retailers is much different than that of the large retailers. We find the small retailers experienced a robust ACAR of +7.05%, but this number is not significantly different from zero at even the ten percent level due to significant variation in the ACARs of the sample. The binomial test supports this statistical finding as only 44% of the CARs are positive. When we examine the dollar impact (ΔMVE) on the small retailers, we find the median and mean ΔMVE to be -$354,000 and +$5 million, respectively. Thus, one summary measure shows stockholders lost money while the other measure shows stockholders gained. These results are weak and support that the House passage of the Credit Card Act had little impact on small retailers.

Our last test is to determine whether the ACARs of large retailers are statistically different from small retailers by conducting a difference of means test on the ACARs of both groups. There is a 10.5% difference in ACARs, significant at the five-percent level, which supports there is a major difference between the ACARs of the large and small retailers. In summary, when the House passed the Credit Card Act, investors perceived this as a significantly negative event for large retailers, but a nonevent for small retailers.

VI. Conclusions

On April 30, 2009 the House of Representatives passed the Credit Cardholders' Bill of Rights which subsequently became the Credit Card Accountability Responsibility and Disclosure Act of 2009 (Credit Card Act). After passing in the House, the bill was quickly passed by the Senate on May 19, 2009 and signed into law by the President on May 22, 2009. While the Credit

Card Act was meant to impact commercial banks that issue credit cards, it also impacted retailers with in house credit card (IHCC) programs. Thus, we examine the impact of the House passage of the Credit Card Act on the retail industry. An event study methodology is used to isolate the immediate financial impact on that segment of the retail industry. When retailers without IHCC programs are examined, we find there is little financial impact on the retail industry. We find a similar result when we examine retailers with IHCC programs. However, when the retailers as subdivided into a sample of large and small retailers, we find only the larger retailers suffered significant losses when the House passed Credit Card Act. Large retailers, on average, suffered a loss of -3.46% in their stock price and 78% of the large retailers suffered losses. In dollar terms large retailers, on average, suffered a $500 million loss in MVE and cumulatively, the eighteen large retailers lost almost $10 billion in MVE. While the Credit Card Act may have benefited consumers, our results do not conclusively support this hypothesis. Furthermore, when we look specifically at large retailers with IHCC programs, we find they are significantly negatively impacted. When we examine the small retailers, we find they experienced neither significant gains nor losses.

This topic is open to additional future research in the areas related to the benefits and costs of store credit cards on the value of the operations. In our study, we divided the initial sample into two smaller subsamples based on the retailer's MVE for exploration. While the results were interesting, the next step for researchers would be to develop a data set with specific account information that details how store credit cards are utilized. This would enable the researcher to determine the value-added differentials of each practice or choice and help explain our results. This would then allow legislators to more better understand how their legislation will impact different organizations in the future.

Table I. Retailers and their market value of equity (MVE) as of December 31, 2008.

Large Retailers	MVE ($ millions)	Small Retailers	MVE ($ millions)
1. Home Depot, Inc.	36,493	1. Buckle Inc.	983
2. Costco Wholesale Corp	29,175	2. Dress Barn Inc.	972
3. Lowe's Companies, Inc.	26,802	3. PriceSmart Inc.	631
4. Target Corp.	23,487	4. J. Crew Group, Inc.	625
5. Best Buy Co. Inc.	11,915	5. Mens Wearhouse, Inc.	603
6. Kohls Corp.	11,186	6. Children's Place Retail Stores	553
7. TJX Companies, Inc.	8,085	7. HHGregg, Inc.	458
8. Gap Inc.	7,964	8. Saks Inc.	358
9. Bed Bath & Beyond, Inc.	5,532	9. Dillard's, Inc.	320
10. Sears Holdings Corp.	5,115	10. Lumber Liquidators Holdings	283
11. Macy's Inc.	3,764	11. AnnTaylor Stores Corp.	281
12. J.C. Penney Co., Inc.	3,720	12. Stage Stores Inc.	273
13. Nordstrom Inc.	2,733	13. Conn's, Inc.	273
14. American Eagle Outfitters	1,849	14. Coldwater Creek Inc.	257
15. BJ's Wholesale Club, Inc.	1,685	15. Charming Shoppes Inc.	123
16. Abercrombie & Fitch Co.	1,554	16. New York & Company Inc.	119
17. RadioShack Corp.	1,493	17. Talbots Inc.	112
18. Big Lots Inc.	1,094	18. Pacific Sunwear of California	81
		19. Syms Corp.	79
		20. Stein Mart Inc.	50
		21. Cache Inc.	27
		22. Casual Male Retail Group	16
		23. Eddie Bauer Holdings, Inc.	16

Table II. The impact of the U.S. House passage of the Credit Card Act of 2009 on retailers with and without in-house credit card programs (IHCCP) based on the average cumulative abnormal returns (ACAR), percent negative of cumulative abnormal returns (CAR), mean change in market value of equity (ΔMVE) per retailer, and cumulative ΔMVE for sample.

	Sample Size	ACAR (%)	Percent Negative CAR	Mean ΔMVE ($ millions)	Cumulative ΔMVE ($ billions)
I. Retailers with and without IHCCP	85	2.87***	57.7	-130	-11.0
A. Retailers without IHCCP	44	3.27***	50.0	-28	-1.2
B. Retailers with IHCCP	41	2.44	65.8**	-239	-9.8
1. Large Retailers with IHCCP	18	-3.46*	77.8**	-551	-9.9
2. Small Retailers with IHCCP	23	7.05	56.5	5	0.1

*, **, and *** denote significance at the 1, 5 and 10 percent levels, respectively; large retailers have a market value of equity of $1 billion or greater; small retailers have a market value of equity of less than $1 billion

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Recent Evidence on Insurance Stock Interest Rate Sensitivity

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Abstract

A number of researchers analyzed the relationship between stock returns and interest rate risk for financial institutions with mixed results. The assets and liabilities holdings of insurance companies are regulated to reduce interest rate risk to policyholders, but not stockholders. Given the recent increase in the number of stock companies and the recent volatility in financial stocks, this paper reexamines the direction and characteristics of the relationship between interest rate risk and stock returns with more recent evidence. Our results have important policy implications for stock investors in insurance companies.

I. Introduction

Insurance companies face several risks ranging from traditional insurance risk, asset risk, legal risk, and interest rate risk. Interest rate risk is the risk from changes in interest rates that affect firm value. The extent of exposure to interest rate risk is vitally important to individual investors (for the purpose of hedging and performance measures) and regulators (for the purpose of assessing systematic risk).

Insurance companies as financial intermediaries hold financial assets. These companies issue contingent claims and use premiums to invest in a variety of assets. Insurers' liabilities are measured by policy reserves while insurers' assets are mainly comprised of bonds and stocks.

The economic value of a financial asset or liability is the discounted value of its future cash flows. Thus, if interest rates increase, the economic value of future cash flows will decrease and vice versa. The direction and magnitude of the movement in values of both the assets and the liabilities, according to this principle, will be the same if the duration of assets and liabilities are perfectly matched then there would be no effect from changes in interest rates. The problem, however, is that asset and liability values will generally not move by the same amount in response to a particular change in interest rate. If they do not move proportionately, the net worth of an insurer will change over time.

Moreover, the liabilities of insurers, reserves, computed as the expected discounted claims, is subject to interest rate risk through the variation in the discounting term and indirectly through the variation in expected outstanding claims due to the inflation rate. If the value of policyholders' surplus decreases then the degree of leverage increases and the cost of capital will increase. Another implication of the increase in leverage is the increased likelihood of default.

A large number of studies analyzed the impact of interest rate risk on stock returns of financial institutions most notable banks as prime candidates for exposure to interest rate risk given their function of asset transformation. Assessment of the magnitude of interest rate risk

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will be useful for regulators and company risk managers. Regulators emphasizing solvency of the insurance industry, are concerned with the different risk exposures that may affect the financial health of insurance companies. There are minimum capital requirements for insurance risk, asset risk, business risk, and interest rate risk. These risk based capital requirements are to protect policyholders' future claims and not to insulate shareholders investment from volatility in the financial markets. Insurance companies risk managers would be interested in measuring and controlling interest rate risk. Shareholders/investors have a vested interest in the value of their investment other than systematic risk.

The propensity to be exposed to interest rate risk is affected by macroeconomic conditions and industry trends. The last decade was marked by a major financial crisis and a higher volatility in interest rates. In the life insurance industry, there has been an unprecedented growth in asset accumulation products such as variable annuities with interest guarantees such as equity indexed annuities. These factors make earnings of insurance companies more volatile as a higher proportion of insurance business is linked to equity markets.

This paper will add to the literature by having more companies included in the study as the number of publicly traded insurance companies increased in recent years. Our study will use more recent data compared to other studies that examined the sensitivity of insurance returns to interest rate risk. Our study covers a more recent time span. Also, the increased use of financial derivatives to hedge interest rate risk as well as other types of risk started to be significantly employed by large insurance companies managers may have contributed to the reduction of exposure to interest rate risk in the insurance sector. We collected monthly stock returns for insurance companies, measures of market index and 90-day Treasury bills and 20–year Treasury bonds change in yields as measures of interest rate covering the most recent 10 years.

II. Literature Review

The effect of interest rate risk has been extensively investigated for financial institutions, mainly financial depositories. A handful of studies focused on insurance companies' equity returns and interest rate risk. In the banking literature, empirical studies show that the relationship between equity returns and interest rate risk is generally significant and negative. Flannery and James (1984) find that bank and savings and loans stock returns are sensitive to interest rates of U.S. government securities and the sensitivity varies according to maturity mismatch between assets and liabilities; Bae (1990) finds that the negative interest rate sensitivity is greater for savings and loans, insurance companies, and commercial banks using a medium-term interest index. Fraser, Madura, and Weigand (2002) analyzing the impact of real estate on insurance stock returns included a long-term measure of interest rate. The authors found that interest rate sensitivity is greatest for health insurance companies. The most recent study of interest rate risk in the banking industry (2009) reaffirms the findings of previous studies. Notably this latter study finds a negative and significant relationship between stock returns and measures of interest rate risk.

Recent studies in insurance show that interest rate risk affects stock returns. Brewer et al., (2007) using a sample of 60 life insurance companies covering the period from January 1972 through December 2000 find evidence that stock returns of life insurance companies are affected by changes in interest rates. The study by Carson, Elyasiani, and Mansur (2008) includes three segments of the insurance industry: life, accident and health, and property and casualty and finds significant interest rate sensitivity to changes in interest rates in the three segments of the insurance industry. The most recent study by Elyasiani, Mansur, and Wetmore (2010) analyze the real estate risk effect on financial institutions stock returns covering banks, S&Ls, and life insurance companies. The authors find a positive and significant of the 10-year Treasury rate on monthly stock returns of life insurance companies. The above studies used a GARCH model to study the impact of interest rate volatility on insurance stock returns.

III. Methodology

a. Sample Selection

The stock return data is monthly returns from the CRSP database covering the period from January 2000 to December 2009. To be included in our sample, a firm must be in the industry defined by SIC codes 6311 (Life insurance), 6321 (Accident & Health), and 6331(Property & Casualty) excluding reinsurance companies. Descriptive statistics of insurance companies by SIC codes are reported in Table 1. Second a company must have stock returns covering the entire 10-year period. The continuous trading requirement is designed to eliminate any bias due to infrequent trading and may introduce survivorship bias. Sixty one companies met these criteria resulting in 7320 observations.

The focus of our analysis is the sensitivity of insurance stock returns to interest rate risk. In the literature, there is no consensus on how to measure the interest rate risk. Some researchers have used short term rate others used long term rates with mixed results. Many insurance companies liabilities and assets are of long-term nature. Two series of interest rates long-term and short-term interest rates are used in this paper. The long-term return is the yield on 20-year government bonds constant maturity. The short-term rate is the 3-month U.S Treasury rate. Both rates are from FRED II database from the web site of the Federal Reserve Bank of St Louis. According to the market efficiency hypothesis, the level of interest rate will have no bearing on stock returns but unanticipated changes would affect equity returns.

For this study, first difference of monthly holding period returns for both short-term and long-term interest rates are used as proxy for innovations in interest rates that affect stock returns and not levels of interest rates. Alternatively, we used the residuals from regression analysis of the level of interest rate against the market index as a measure of interest rate surprises. Using this measure produced quantitatively similar results and therefore are not reported. The change in the short-term and long-term interest rate is used separately and then the spread between the two measures is used as measure of maturity risk premium since the short term interest rate measured by the 3 month US T-bills is often used as proxy for the difference in time horizon. The purpose of using three different measures is to determine whether the relationship is relatively stronger for any of the maturity classification and whether the maturity risk premium is priced by the market.

Two measures of market returns are used for the study: CRSP value weighted total returns and S&P500 Composite index to test whether our results are sensitive to choice of the proxy for the market index.

b. Estimation

Following Flannery and James (1984) the two-factor model with a market factor and interest rate factor is applied to the data set:

$R_{i,t} = \alpha_{it} + \beta_{i,m}R_{m,t} + \beta_{iI}\Delta I_{it} + \varepsilon_{i,t}$

Where,

$R_{i,t}$ = return of company i at time t (last trading day of each month),

$R_{m,t}$ = market index at time t, (last trading day of each month) and ;

ΔI_{it} = change in interest rate.

The coefficients α_{it} and $\beta_{i,m}$are analogous to the CAPM model and β_{iI} measures interest rate risk. When estimating a panel data specifications about the error term must be made. Initial tests for the fixed and random effect models were inconclusive. We opted for autoregressive model where the error term is modeled as given the time series nature of our data set. The monthly returns over a ten year period were tested for serial correlation. The results confirm significant first order correlation. For this reason, the estimation procedure uses the following specification for the error term:

- $\varepsilon_{i,t} = \rho_i\varepsilon_{i,t-1} + u_{it}$

The ρ measures the serial correlation between the error terms. Controlling for this effect gave us a better fit for a data.

IV. Results

Table 2 reports summary statistics for the variables used in the study. The average monthly return of insurance stocks (1.06 percent compounded to average annualized returns of 13.5 percent) is higher than the S&P 500 Composite or the CRSP market return. The insurance stock returns exhibit a much higher variability than market returns as shown by the much wider range of stock returns.

Table 3 provides estimates of the interest rate sensitivity of insurance stock returns using time-series cross section balanced data. The first panel of Table 3 report results using the CRSP value weighted as proxy for the market index while panel B uses the S&P 500 monthly returns. The results show remarkable similarity between the different models. First, the systematic risk of insurance stocks as measured by $\beta_{i,m}$ is less than one implying that insurance stocks even though positively correlated to the market index has below average systematic risk. For the general investor, adding insurance sector to their investment portfolio would have with diversification.

We find that both the short-term and long-term interest rates have an inverse relationship with the monthly stock returns of insurance companies. Comparing our results to previous studies focusing on insurance sector, our results show a significant and negative impact of changes in interest rate on insurance stock but in terms of magnitude our coefficients are much lower than previous insurance studies. Brewer et al., (2007) find a beta coefficient ranging between 0.123 and 0.494 depending on their model specification for life insurance companies. Carson et al., (2008) find a beta 0.879 for life insurance, 0.132 for accident and health and 0.198 for property liability companies. Our results show a negative and significant interest rate sensitivity beta of 0.012 for long-term rate. A possible explanation is the use of futures and options to hedge by insurance companies that has proved to be effective in reducing interest rate risk. The change in short-term interest is not statistically significant but the maturity spread significant and has a negative sign. This reinforces the previous finding on long term interest rates. The rationale for including the maturity spread is to measure the relative strength compared to short-term interest rate to stockholders.

Our results are comparable to previous studies with respect to systematic risk. Using the S&P 500 Composite Index as proxy of market portfolio, our beta coefficient is very similar to previous studies (0.765 (Brewer et al., 2007), 0.714 (Carson et al., 2008) for life insurance and 0.866 accident and health and 0.508 for property insurance). The market risk of insurance companies has remained about the same over the past two decades. No noticeable changes are detected. Last but not least the intercept in all models is significant implying the omission of other factors determining the return generating process such as the exchange rate changes as the insurance business has become global and real estate holdings.

V. Conclusion

Exposure to interest rate risk in the insurance industry has been important to regulators, managers, and investors. Regulators objective has been to protect policyholders against insurance industry's financial distress. For the insurance industry, there is a mandatory capital requirement for interest rate risk. To reduce their exposure to interest rate risk insurance companies managers have relied on asset liability management. As reported by Cummins, Phillips and Smith (2001) insurance companies increasingly are using derivatives to hedge noninsurance risk including interest rate risk.

We have investigated the effects of interest risk on insurance stock returns. The findings provide evidence of significant sensitivity of equity returns to surprises in long-term interest rate. Despite the attempt by insurance companies to hedge their interest rate risk, we find that stockholders remain exposed to changes in long-term interest rate and changes in the maturity spread. The focus of insurance companies' management and regulators has been on reducing the long-term interest rate risk to policyholders. One implication for insurance companies is to further focus on reducing interest rate risk to stockholders. The existence of interest rate risk for stockholders increases the cost of capital for insurance companies. An increase in the cost of capital will be passed on to policyholders in the form of higher premiums. There is more room for active hedging policies especially of long term interest rate risk by incorporating best practices for hedging with financial derivatives.

Table 1 Descriptive Statistics by Industry, Monthly Stock Returns from January 2000 through December 2009

	Life Insurance SIC= 6311	Accident & Health SIC =6321	Property and Liability SIC=6331
Number of Companies	43	12	108
Average Monthly Return	0.0084	0.0040	0.0076
Minimum Return	-0.7608	-0.7837	-0.8348
Maximum Return	1.5085	0.9091	2.4498
Number of Observations	3925	2075	9713

Table 2 Descriptive Statistics

Variable	Mean	Std Dev	Min	Max
Monthly Returns	0.0106	0.1115	-0.8342	2.4497
CRSP Index	0.0014	0.0488	-0.1847	0.1093
S&P 500	-0.0012	0.0463	-0.1694	0.0967
Long-term Rate	0.0503	0.0006	0.0318	0.0686
Short-term Rate	0.0276	0.0017	0.0003	0.0636
Spread	0.0227	0.0015	-0.0038	0.0442

Table 3 Panel Data Results, N= 61 Companies, T= 120 Monthly Returns

Variable	Coefficient	t-Statistics	Significance
Panel A: Model using CRSP Value Weighted Total Returns			
Intercept	0.0078	5.94	0.0001
Market Index	0.7617	27.88	0.0001
Long-term Rate	-0.0158	-2.52	0.0119
Intercept	0.0076	5.68	0.0001
Market Index	0.7578	27.00	0.0001
Short-term Rate	-0.0211	-1.53	0.1255
Intercept	0.0074	5.61	0.0001
Market Index	0.7708	27.47	0.0001
Spread	-0.0152	-2.40	0.0163
Short-term Rate	-0.0226	-2.85	0.0043
Panel B: Model using S&P500			
Intercept	0.0095	7.19	0.0001
Market	0.8359	28.35	0.0001
Long-term Rate	-0.0137	-2.13	0.0329
Intercept	0.0093	6.93	0.0001
Market Index	0.8336	27.64	0.0001
Short-term Rate	-0.0080	-1.39	0.1638
Intercept	0.0092	6.90	0.0001
Market Index	0.8446	27.94	0.0001
Spread	-0.0131	-2.03	0.0427
Short-term Rate	-0.0200	-2.48	0.0026

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A Review of the Psychology of Risk Taking Behavior for Individual Investors

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Abstract

This paper reviews the extensive literature within psychology and behavioral finance in order to outline the psychological underpinnings of investor risk behavior. Its objective is to provide a comprehensive understanding of the factors that influence risk propensity in investment markets. It provides an enumeration of influential factors that play a role in understanding an individual's propensity for risk including psychological biases, personality characteristics, demographic and socio-economic factors. Such a list should be valuable, not only to researchers in behavioral finance, but also to practitioners interested in improving trading skills and recruitment practices.

I. Introduction

Although the psychology of risk has been studied extensively (cf. Ricciardi 2004 and Barberis & Thaler 2002; Hunton, J., McEwen, R., and Bhattacharjee, S. 2001), there is still controversy surrounding the influences that shape an individual's inclination toward risk. Why do such stark contrasts exist among individual investors with regard to risk-tolerance and risk-management strategies? What is it that allows certain investors to assume risk with such a high degree of confidence, while others, with an equal knowledge of the investments, are highly risk averse in their capital allocation decisions? Of equal importance, what factors are endemic to psychological risk propensity in the market?

In order to explore such questions, the focus of this paper revolves around the psychological underpinnings of individuals in the domains of risk and investment decision-making. This paper outlines the underlying factors that contribute to the risk-related behaviors that often debilitate investors, resulting in undesirable or inadequate return on investment. In an attempt to contribute to this growing field of research, the paper presents reviews the relevant literature and comments on the implications of such research. The literature review centers on research from articles on the psychology of trading.

The structure of the paper is as follows. This first section defines the topic while the second section provides the salient definitions, concepts and models of risk that have been identified in previous studies. The next sections highlight the important factors that need to be taken into account when assessing the psychology of risk. The initial thrust of these sections includes the psychological obstacles prevalent in the field of investor psychology followed by an examination of the various demographic and socioeconomic factors that have been correlated with risk propensity. An assessment of different investor categorizations complements these sections. Finally, recommendations for future research conclude the paper.

II. Defining Risk

The concepts of both risk and risk tolerance have been defined in different ways depending on the source. However, consistencies and similarities characterize the majority of

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these definitions. There are subtle distinctions that lie between the theoretical frameworks of traditional finance and the more recently developed behavioral models. These models attempt to assess an individual's propensity and tolerance for risk. Risk taking can be considered any behavior that has a significant degree of uncertainty associated with the extent of loss or gain in the outcome (Rosenbloom, 2003). In terms of investment risk tolerance, Grable, Lytton and O'Neil (2004) describe the concept as a willingness to engage in behaviors whereby the outcomes are uncertain and withhold the possibility of a negative outcome. Investment risk tolerance can be divided into four elements: propensity, attitude, capacity (in the form of financial capability to incur risk), and knowledge (Corter and Chen, 2006).

III. Theoretical Models

The literature on financial risk tolerance is heavily skewed toward economic theory, whereby the explanation of risk revolves around the concept of risk aversion (Chaulk, Johnson and Bulcroft, 2003). Risk aversion is often measured as the ratio of risky assets to wealth (Chaulk et al., 2003). Such traditional theories suggest that judgments are used to establish the attitudes impacting financial decision-making and behavior, thereby assuming that individuals' financial risk propensity is developed through rational thought while utilizing the laws of probability (Grable et al., 2004).

Variance measures originated in the Subjective Expected Utility Model (SEU), which proposes that risk aversion is the result of diminishing marginal utility of wealth (Olsen and Cox, 2001). Prospect theory is an alternative model of financial risk tolerance contending that decisions are considered in relation to an individual's accumulated wealth position. The contention is that increases in wealth lead to an increase in risk tolerance (Chaulk et al., 2003). However, prospect theory takes variation into account when considering the 'mental accounting' of losses and gains and proposes that that losses are perceived with twice the significance as gains (Chaulk et al., 2003).

From a macroeconomic perspective, the majority of modern finance theories conceptualize risk as an internal attribute of an asset (Olsen and Cox, 2001). However, these types of approaches to variability of return exclude psychologically derived assumptions of how individuals perceive uncertainty (Olsen, 2008). Olsen and Cox (2001) argue that an asset that 'feels' risky to one investor may not be categorized or 'felt' as such by another owing to unique life experiences and differences in social, cultural, and economic circumstances. Research in behavioral fields has indicated that traditional models may be insufficient in explaining financial risk attitudes, as individuals are not purely logical and rational (Grable et al., 2004).

Behavioral finance models treat risk as a multi-dimensional perception (Olsen, 2008). Risk tolerance is conceptualized as a subjective construct that is the product of a perceptive, judgmental, and psychologically bias process (Chaulk et al., 2003). Financial risk tolerance is, therefore, defined as a psychological component of decision-making in the context of financial uncertainty (Chaulk et al., 2003). In terms of emotion, variability of outcomes in and of itself is considered to be neutral. When investors claim to detest uncertain returns, it appears that what they detest, and what acts as a motivator, is the emotion of fear associated with incurring losses (Olsen and Cox, 2001). The motivating force is not the variability itself but is instead the associated emotion. Therefore, *risk* aversion is really *loss* aversion. Behavioral finance has significant relevance as this field aims to identify the behavioral biases frequently displayed by individual investors and to design strategies (Mittal and Vyas, 2008).

The field of neuroscience has also offered valuable insights into the domain of behavioral research by presenting an explanation of investor behavior based on different decision processes located within systems of the brain (Peterson, 2007). The characteristics and motivations driving these decision processes are closely integrated with emotion. Activating one of these neural mechanisms leads to a shift in risk preferences. For instance, activation of the NAcc, a particular brain region, has been shown to precede both risky choices and risk-seeking behavior. However, activation of the anterior insula, the brain region responsible for the second decision processing system, precedes both riskless choices and highly risk-averse behavior (Peterson, 2007). Neuroscience evidence suggests that both processes must be simultaneously functioning for an individual to make appropriate investment decisions that involve an optimal degree of risk (Olsen, 2008).

IV. The Multi-Dimensional Nature of Risk

Just as the realms of risk definition and risk tolerance are highly debated in the literature, so are the domains of assessing and predicting individual financial risk tolerance. Such a task is highly complicated due to its obscure, multi-dimensional nature, as previously outlined (Grable et al., 2004; Morse, 1998). Grable et al. (2004) argued that risk attitude, like other attitudes, can be influenced by numerous factors and that risk tolerance is adaptable and easily manipulated. Sevdalis and Harvey (2007) illustrated the influence of context on investment behavior. More specifically, if the context of an investment is manipulated and made to appear highly salient, investors are more likely to choose investment decisions that minimize risk. Individuals' own self-evoked investment contexts can also manipulate investment risk preferences (Sevdalis and Harvey, 2007).

V. The Role of Investor Psychology in Risk

Throughout the literature, the role of investor psychology as a factor influencing the perception of risk and investment decisions has rapidly increased. A component of investor psychology that has received much attention by both researchers and practitioners is the role of psychological obstacles in investor risk taking (Kiev, 2002). Kahneman and Riepe (1998) have referred to biases in judgment and decision-making as cognitive illusions. The authors indicate that the objective of learning about cognitive illusions is to enhance the skill of recognizing instances in which a particular type of error or bias may be likely, in order to mitigate the influence of illusions.

a. Psychological and Cognitive Biases

In investments, important decisions are considered to be a choice between various gambles since the outcomes of alternative options, as well as the probabilities of outcomes, are rarely known in advance (Kahneman and Riepe, 1998). Individuals tend to formulate judgments about the probabilities of outcomes, assign values to these outcomes and combine individual beliefs and values in the construction of preferences about risky alternatives. As investment decisions are made in situations characterized by complexity and uncertainty, there tends to be a dependence on both fixed rules and intuition. The latter plays a crucial role in most financial and investment decisions (Kahneman and Riepe, 1998).

Biases of judgment are displayed in numerous forms, including overconfidence, optimism, hindsight, and over-reaction to chance events. Optimism is believed to be a powerful bias as it leads individuals to underestimate the likelihood of negative outcomes beyond one's control (Kahneman and Riepe, 1998; Kiev, 2002). Optimists are prone to what is termed 'illusion of control', whereby the degree to which one controls personal fate is highly exaggerated. Optimists are likely to underestimate the role of chance in human matters and inaccurately perceive *games of chance* as *games of skill* (Kahneman and Riepe, 1998). Hindsight also acts as an influential bias. Psychological evidence indicates that individual investors can seldom reconstruct, after the fact, what they believed the probability of an event to be before it occurred. Due to this hindsight bias, market events that expert analysts did not anticipate often appear to have been inevitable after they have occurred. If the event had indeed been predictable, it would have led numerous individuals to alter their trading behavior, which would influence the behavior of the markets themselves (Kahneman and Riepe, 1998). Individuals who are regularly exposed to market events are quite familiar with this line of reasoning, but even still, the allure of interpreting past events persists.

The cognitive bias of over-reaction to chance events also plays an important role in understanding the psychology of risk-taking. Individual investors tend to be easily manipulated into perceiving a causal regularity in random sequences of events. This is a natural tendency as the human mind is a pattern-seeking device being biased to the notion that a causal factor is present in any significant sequence of events (Kahneman and Riepe, 1998). This psychological tendency causes investors to perceive trends that are non-existent and to take action on this severely flawed intuition.

b. Errors of Preference

Kahneman and Riepe (1998) indicate that errors of preference are an important component of investor psychology and are appropriate in the analysis of investment decisions and risk-related behavior. Such errors arise either from mistakes in the assignment of values to potential outcomes or from unsuitable combinations of probabilities and values (Kahneman and Riepe, 1998). These errors of preference play an integral role in understanding the way in which individuals use stochastic processes to evaluate risk in financial assets. The theory of rational choice indicates that prospects characterized by uncertainty should be evaluated by a weighted average of the utilities of potential outcomes with each outcome weighted by its probability. However, individuals have a tendency to exhibit non-linear weighting of probabilities and deviate from the principle of probability weighting in a systematic manner (Kahneman and Riepe, 1998). Individuals have a tendency to overweight low probabilities and underweight high probabilities. The latter is especially prominent in investments. This preference error highlights what is known about investors in situations of risk and uncertainty. An individual's inclination toward non-linear weighting of probabilities helps explain why long shots are preferred to other gambles of equal expected value. Long shots appear as attractive alternatives since the low probabilities of winning are significantly overweighed. Most individuals will consider a 1% chance of winning $1000 to be more attractive than a $10 reward. Generally, this type of non-proportional probability weighting attracts individuals to both lottery tickets and insurance policies.

Another error of preference that is evident in individual investors is the tendency to be influenced by the emotions associated with gains and losses, rather than focusing on the more crucial goal of maximizing the utility of wealth (Kahneman and Riepe, 1998). There are two characteristics of the value function that are essential in understanding an individual investor's risk propensity and decision-making approach. First, the function is steeper for losses than for gains. This concept is referred to as loss aversion, as was previously outlined. Second, the two branches of the function are described by a mathematical relationship, which implies a certain result that Kahneman and Riepe (1998) refer to as *near-proportionality of risk attitudes*. Loss aversion is characterized by the sharp asymmetry between the values that individuals place on gains and losses that aids in the explanation of decision-making in finance.

VI. The Influence of Demographic, Socio-Economic, and Personality Factors

Although investor-related psychological factors play a significant role in understanding the financial risk propensity and decision-making ability of individual investors, it is postulated that demographic, socio-economic, and personality characteristics should also be taken into account in order to determine how these factors influence an individual's risk tolerance (Grable, 2000). The literature reveals that variables such as gender, age, personality, culture, ethnicity and occupation among others, can significantly influence an individual's level of investment risk tolerance (Chaulk et al., 2003; Filbeck et al., 2005; Mittal and Vyas, 2008; Olsen and Cox, 2001).

With respect to gender, a prominent belief is that males often take greater risks than females (Grable, 2000). This assumption is consistent with the extant literature that postulates women tend to be more risk averse than men in their financial decisions. Both genders perceive and respond to risk differently as outlined in Chaulk et al. (2003), Felton, Gibson, and Sanbonmatsu), 2003. Olsen and Cox (2001) suggest that, even when comparing professionally trained investors, female investors tend to emphasize risk attributes, such as ambiguity and potential loss, more significantly than their male colleagues. Felton et al. (2003) and Olsen and Cox (2001) have suggested that gender differences in risk propensity are rooted in biological and evolutionary factors. From a biological perspective, Zuckerman (1994) notes that females have higher levels of the enzyme monoamine oxidase, which impedes sensation seeking and heightens risk aversion tendencies. Socio-cultural perspectives are often quoted as an explanation for females' more conservative investment behavior, based on the perception of lower confidence in female investors, due to the inherent masculine nature of the investment arena (Olsen and Cox, 2001).

When assessing age as a determinant of investor risk propensity, contradictory findings have been identified. On the one hand, increasing age has been correlated with a decline in risk tolerance as demonstrated by Chaulk et al. (2003) and Grable (2000). On the contrary, other researchers suggest a positive relationship between age and investment risk tolerance, with explanations based on the assumption that, all else equal, age is a proxy for wealth as identified in Chaulk et al. (2003). A more complicated relationship between age and risk tolerance has been identified, which indicates that risk tolerance increases with age until the period five years prior to retirement, at which point the direction of the relationship reverses. Then risk tolerance begins to decrease with age (Filbeck, Hatfield and Horvath, 2005). Given the conflicting evidence, researchers have yet to identify an empirically sound relationship between age and investment risk tolerance.

Several personality dimensions have also been linked to investors' level of risk propensity. Filbeck et al. (2005) outlines how researchers have used the Myers-Briggs Type Indicator (MBTI) to measure the strength of individuals' preferences on four dimensions (extroversion-introversion; sensing-intuitive; thinking-feeling; judging-perceiving). The results have indicated that certain personality traits are correlated with individual risk tolerance. Aside from the MBTI, a different personality factor that has been linked to individual risk propensity in the field of investments is the Type A-Type B personality profiles. Conclusions indicate that individuals characterized as Type A personalities displayed increased risk-taking capability compared to their Type B counterparts.

Race and ethnicity have also been identified as a determinant of financial risk tolerance (Yao, Gutter and Hanna, 2005; Zinkhan and Karande, 1990). Yao et al. (2005) in examining investment risk tolerance between different ethnic backgrounds in American households found that Caucasian individuals tend to have an increased tolerance for risk in investment decision making. Caucasians, on average, held a significantly higher proportion of equity investments, while African-Americans held a higher proportion of low-yield financial assets. However, explanations behind the influence of race on investment choice include the fact that African-Americans and Caucasians may have different perceptions of investment instruments and investment risk, due to differences in the available choices, as well as the cultural belief system regarding these choices (Yao et al., 2005). Another explanation relates to the fact that Caucasian households, on average, have a higher access to financial information and investment options than do African-Americans. Lastly, Yao et al. (2005) demonstrate that marketing of financial products is often targeted toward Caucasians which may help explain why African-American individuals tend to have a lower risk tolerance in the investment arena and display lower levels of participation in the financial markets.

There are additional other demographic and socio-economic factors that are believed to influence investors' psychological trading tendencies and propensity for risk. According to Chaulk et al. (2003), family structure was identified as having an impact on investment risk propensity. More specifically, the presence of children in the household was associated with lower risk tolerance in financial decision-making, suggesting that households with children require higher levels of security in the return on investment (Chaulk et al., 2003). Occupation has also been considered a determinant of risk tolerance. Individuals in occupations such as small business entrepreneurs, independent professionals and self-employed consultants displaying, on average, a higher propensity for risk in investment decisions than individuals in occupations such as doctors, lawyers, and teachers (Mittal and Vyas, 2008). Additional factors, such as increased levels of income and education are also associated with higher risk tolerance, although discrepancies exist within the literature (Grable, 2000; Nagpal and Bodla, 2009).

VII. Segmentation and Categorization of Investors

Although the various demographic, socio-economic, and psychological characteristics discussed in previous sections have significant predictive value for risk propensity and investment behavior, these factors are also be used to differentiate investors as risk-tolerance or risk-taking (Grable, 2000; Keller and Siegrist, 2006).

Previous research has examined the differentiation of researchers on the basis of risk propensity. Mittal and Vyas (2008) classify individuals into distinct personality types, and investigate the relationship between demographic factors and investment personality displayed by the investor. An attempt was made to measure correlation between this relationship and level of risk tolerance, as well as the preferred choice of investment products among these different categories of investors. The results of the study revealed four dominant investment personality types: casual, technical, informed, and cautious (Mittal and Vyas, 2008).

Nagpal and Bodla (2009) also clustered individual investors into categories based on dominant characteristics and identified three distinct categories based on demographics and investment risk propensity termed as aggressive, moderate, and conservative investors. The findings indicate that each cluster of individuals varies significantly with respect to expected rate of return on investments. Investors in these categories also differ in the realm of time perspectives for investments, with aggressive and conservative investor groups preferring a long-term strategy, and moderate investors inclined towards a more short-term vision. The typologies presented by Mittal and Vyas (2008) and Nagpal and Bodla (2009) are just two such examples with other investor categorizations evident in the literature.

VII. Conclusion and Future Research

Exploring the psychology of risk is highly significant as an investor's trading methods are beneficial or limiting, conscious or unconscious; there is a psychology behind each investor's risk-taking methods (Kiev, 2002). Given the psychological underpinnings of risk-related decision-making in investments, it is important to have a comprehensive understanding of the factors that influence risk propensity.

In light of these implications, the necessity of gaining insight into investment behavior and psychological risk tendencies is of paramount importance. From an individual perspective, investors can use this type of research to better improve investment decision-making by increasing awareness to emotional and cognitive weaknesses that have been identifies in the literature. As Kiev (2002) suggests, what differentiates successful from unsuccessful investors is the capacity to maintain an appropriate level of risk despite psychological stress responses and emotional reactivity that is often triggered by the uncertainty of the marketplace. From an organizational perspective, such findings can be valuable both as a recruitment measure and a customer-oriented marketing tool, as illustrated in the previous section. Such research offers valuable insights into why certain investors may be psychologically predisposed to favor a particular set of investment products which can be dependent on the individual's personality, and demographic and socio-economic orientation (Olsen, 2007).

Understanding an individual's investment risk tolerance is an intricate process, with numerous multi-dimensional, interactive elements at play. Despite the amount of literature, there remains much to be learned about the role of psychology as a determinant of risk propensity and investment behavior. The nature of relationships between risk tolerance and the various factors that have been identified need to be more fully explored.

A number of limitations were identified throughout the literature in this field of research. For instance, a number of the studies assessing the influence of different variables on an individual's financial risk tolerance used high-school and college students as the subjects of the research experiment (Felton et al., 2003; Sevdalis and Harvey, 2007), which may not be the ideal sample of participants when assessing risk propensity in the context of investor behavior. The environment in which these participants were assessed was often highly superficial, which could be problematic when considering the external validity of such research studies. Another identified limitation was the use of risk measurement tools that lack both validity and predictive value (Chaulk et al., 2003). Thus, in the absence of highly reliable and valid risk measurement tools, researchers should incorporate more than one measure of subjective risk in experimental studies.

Longitudinal studies could offer valuable insights into this field of research. Chaulk et al. (2003), among others, have indicated that investors' propensity for risk has a tendency to change throughout the distinct life cycle stages. Historical and generational effects have the potential to influence how individuals perceive expectations about financial losses and gains within family stages, thereby influencing tolerance for risk. Therefore, research experiments could aim at exploring financial risk propensity through different life stages to assess why and how such changes in risk behavior take place. Researchers should also consider assessing investor risk propensity on a more global scale by expanding the scope of cross-cultural studies. Such research can be highly valuable, given the continual rise of both globalization and cultural diversity in the business community.

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Recent Trends for the Importance of State Exports

Kevin M. Bahr, William E. Maas, and Sean Carey

Abstract

Exports have continued to play an increasingly important role in the United States economy. The purpose of this paper is to look at the change in the relative importance of state exports over the last decade. Two major categories of analysis are conducted: 1) the change in state exports as a percent of U.S. exports, and 2) the change in state exports as a percent of state gross domestic product (GDP). The empirical results reveal a change in the relative importance of state exports for several states. Fifteen states had statistically significant increases in the mean percentage of state exports as a percent of U.S. exports; five states had statistically significant decreases. Eighteen states had statistically significant increases in the mean percentage of state exports as a percent of state GDP; no states had decreases.

I. Introduction

The development of the global economy has caused an explosion in the importance of exports to the U.S. economy. Figure I shows the total of U.S. exports of goods and services since 1930. As the graph indicates, export growth began to occur significantly in the 1970s, and rapidly increased in the 1990s and 2000s. Figure II indicates that, since 1970, the annual percentage change in exports has been consistently positive and in some years approaches 20%. Only in the recessionary periods of the early 1980s and early 2000s did the annual percentage change in exports decline.

Given the growing importance of exports to the United States economy, this research will extend the analysis of exports to the state level. The focus of this research is to analyze the change in the relative importance of state exports over the last decade. Two major categories of analysis are conducted: 1) the change in state exports as a percent of U.S. exports, and 2) the change in state exports as a percent of state gross domestic product (GDP). As exports have become more important to the United States economy, this research will analyze how recent trends in exports have impacted state economies.

II. Literature Review

Previous research has explored a variety of issues concerning state exports. Coughlin (2004) examines the geographic distribution of state exports and finds that generally, for most states, state trade becomes more intense with nearby as opposed to relatively distant countries. Coughlin and Wall (2003) estimated the effects of NAFTA on a state-by-state basis and found that NAFTA had different effects across states. Brooks (2007) analyzes trends in state agricultural exports. Katz (2009) found that the Midwest region of the U.S. remains the nation's top region for imports and exports despite the U.S. auto industry's economic recession. Researchers graded each state in different areas affecting trade, including logistic health, human capital, and tax climate. Illinois, Indiana, Michigan, Kentucky and Ohio were the top five states for international trade. Wilkinson, Keillor, and D'Amico (2005) examined the relationship

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between state spending on export promotion, export levels, and state appropriations directed at increasing export activity, and found that enterprises can take advantage of this information by utilizing state export promotion programs to defray the cost of their initial information gathering activities. Coughlin and Pollard (2000) examined the microeconomic effects of the Asian crisis focusing on the manufacturing sector of individual states.

III. Data

Using data from TradeStats Express[1], total state exports as a percent of total U.S. exports is calculated for each state in each year from 1999 to 2008. The mean percentage of state exports as a percent of U.S. exports between 1999 and 2003 will be compared to the mean percentage of state exports as a percent of U.S. exports between 2004 and 2008. The objective is to determine any statistically significant change in the importance of a state's exports relative to total U.S. exports. Data from the Bureau of Economic Analysis[2] and TradeStats Express is used to calculate total state exports as a percentage of state GDP for each state in each year from 1999 to 2008. The mean percentage of state exports as a percent of state GDP between 1999 and 2003 will be compared to the mean percentage of state exports as a percent of state GDP between 2004 and 2008. The objective is to determine any statistically significant change in the importance of a state's exports relative to its GDP.

IV. Hypotheses

For each state, two statistical tests are performed; a total of one-hundred tests are performed over the two categories of analysis. The following tests are performed for each state.

Test 1

H_0: mean percentage of state exports as a percent of U.S. exports between 1999 and 2003 = mean percentage of state exports as a percent of U.S. exports between 2004 and 2008

H_a: mean percentage of state exports as a percent of U.S. exports between 1999 and 2003 ≠ mean percentage of state exports as a percent of U.S. exports between 2004 and 2008

Test 2

H_0: mean percentage of state exports as a percent of state GDP between 1999 and 2003 = mean percentage of state exports as a percent of state GDP between 2004 and 2008

H_a: mean percentage of state exports as a percent of state GDP between 1999 and 2003 ≠ mean percentage of state exports as a percent of state GDP between 2004 and 2008

Each test splits the last decade into two five-year periods. Test 1 will determine the statistical significance of the change in the mean percentage of state exports as a percent of U.S. exports between the two five-year periods. Test 2 will determine the statistical significance of the change in the mean percentage of state exports as a percent of state GDP between the two five-year periods. A t-test is performed to determine the statistical significance of the change in the mean percentage of state exports as a percent of U.S. exports in test 1 and the statistical significance of the change in the mean percentage of state exports as a percent of state GDP in

[1] http://tse.export.gov/
[2] http://www.bea.gov/regional/gsp/

test 2. The results of the t-tests will show the probability that the two groups have the same mean.

V. Results

Table I shows state exports as a percent of U.S. exports for each state in each year over the period from 1999 to 2008. The mean percentage of state exports as a percent of U.S. exports is calculated for two five year periods, from 1999 to 2003 and from 2004 to 2008. The results of the t-test to determine statistically significant changes in the mean percentage of state exports as a percent of U.S. exports are shown in the last column in Table I. Statistically significant changes are highlighted in bold. States that had statistically significant changes in the mean percentage of state exports as a percent of U.S. exports are listed in Table III. Fifteen states had statistically significant increases in the mean percentage of state exports as a percent of U.S. exports: Alabama, Arkansas, Iowa, Kentucky, Maryland, Missouri, Montana, Nevada, North Dakota, South Dakota, Tennessee, Texas, Utah, West Virginia, and Wisconsin. Five states had statistically significant decreases: California, Colorado, Rhode Island, Virginia, and Washington.

Table II shows state exports as a percent of state GDP for each state in each year over the period from 1999 to 2008. The mean percentage of state exports as a percent of state GDP is calculated for two five year periods, from 1999 to 2003 and from 2004 to 2008. The results of the t-test to determine statistically significant changes in the mean percentage of state exports as a percent of state GDP are shown in the last column in Table II. Statistically significant changes are highlighted in bold. States that had statistically significant changes in the mean percentage of state exports as a percent of state GDP are listed in Table IV. Eighteen states had statistically significant increases in the mean percentage of state exports as a percent of state GDP: Alabama, Arkansas, Georgia, Indiana, Iowa, Kentucky, Maryland, Minnesota, Missouri, Montana, Nevada, North Dakota, Ohio, South Carolina, South Dakota, Tennessee, Texas, West Virginia, and Wisconsin. No states had statistically significant decreases.

VI. Conclusion

Exports have become increasingly important to the United States; this research extends the analysis of exports to the state level to determine relative changes in importance over the last decade. Two major categories of analysis were conducted: 1) the change in state exports as a percent of U.S. exports, and 2) the change in state exports as a percent of state gross domestic product (GDP). The empirical results showed a change in the relative importance of state exports for several states over the last decade. Fifteen states had statistically significant increases in the mean percentage of state exports as a percent of U.S. exports; five states had statistically significant decreases. Eighteen states had statistically significant increases in the mean percentage of state exports as a percent of state GDP; no states had decreases.

Twelve states experienced both a statistically significant increase in the mean percentage of state exports as a percent of U.S. exports and a statistically significant increase in the mean percentage of state exports as a percent of state GDP. These states are Alabama, Arkansas, Iowa, Kentucky, Maryland, Missouri, Nevada, North Dakota, Tennessee, Utah, West Virginia, and Wisconsin. This research has indicated which states have benefitted from recent, significant increases in the relative importance of exports to their economies; further research could explore why these states experienced an increased economic importance on exports. This could have significant implications for corporate expansion, as firms placing a strategic importance on increasing exports could look favorably upon states with the infrastructure and policies that favor export growth.

The research indicates the increasingly important role that exports play in state economies. Eighteen states had statistically significant increases in the mean percentage of state exports as a percent of state GDP; no states had statistically significant decreases. In the current political environment in which the benefits of free trade are being openly discussed, the impact of any trade restrictions could be a significant negative effect on a number of states, particularly in states whose economies have become more dependent on exports. In addition, any adverse consequences to trade resulting from currency wars could also have a significant adverse effect on states. Finally, although the macroeconomic changes in trade impact state economies, these changes are reflected by corporate profitability and shareholder returns. Policies adversely affecting exports will be felt at the firm level, which in turn will affect employment and economic growth.

Analyzing the role of exports, and the relative importance of a state's exports to state GDP and U.S. total exports, can provide insight as to importance that exports play in a state's economic development. Exports can offer some insulation from a drop in domestic demand, and provide entry into new geographical markets. Understanding trends in exports, and understanding the businesses and industries that are fueling export growth, can help states foster policies that provide job creation through export expansion. In addition, understanding the importance that exports have played on state economic growth can have implications for corporate expansion, and should have implications for U.S. trade policy.

Figure I U.S. Exports of Goods and Services

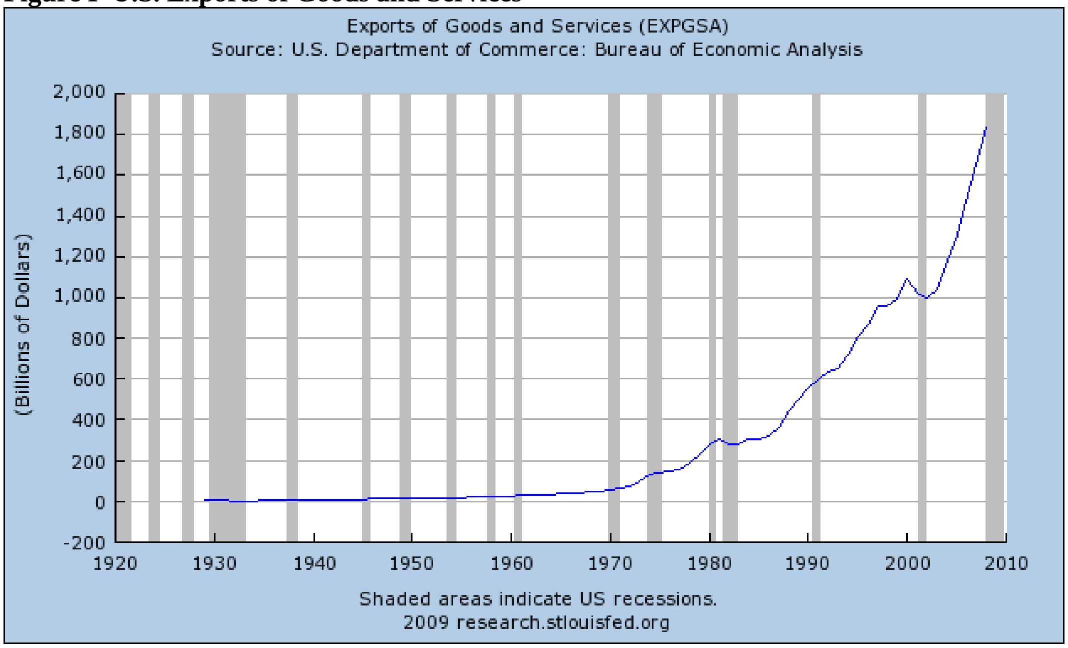

Figure II Percent Change from Prior Year for U.S. Exports of Goods and Services

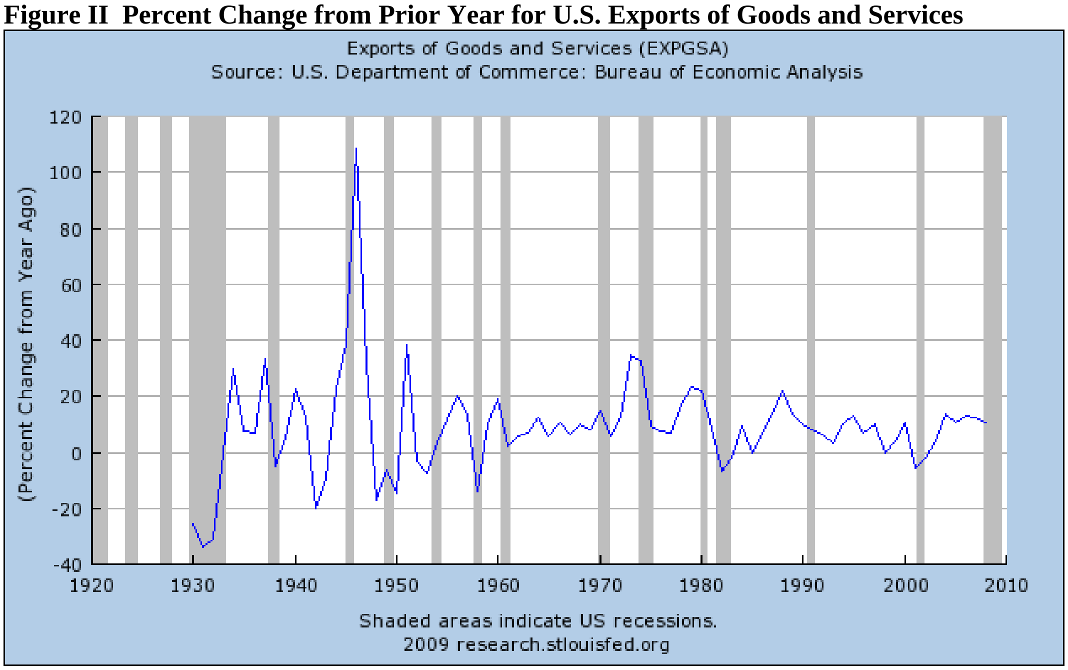

Table I State Exports as a Percent of Total U.S. Exports

				Percent of Total U.S. Exports						Mean	Mean	
	1999	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**99-03**	**04-08**	**t-test**
Alabama	0.89	0.94	1.04	1.19	1.15	1.11	1.21	1.35	1.25	1.23	1.04	1.23	**0.019**
Alaska	0.37	0.32	0.33	0.36	0.38	0.39	0.40	0.39	0.35	0.28	0.35	0.36	0.771
Arizona	1.71	1.84	1.71	1.71	1.84	1.65	1.66	1.78	1.67	1.54	1.76	1.66	0.197
Arkansas	0.31	0.33	0.40	0.41	0.41	0.43	0.43	0.42	0.43	0.45	0.37	0.43	**0.044**
California	14.13	15.33	14.61	13.30	12.96	13.52	12.95	12.45	11.70	11.25	14.07	12.37	**0.005**
Colorado	0.86	0.84	0.84	0.80	0.84	0.82	0.75	0.78	0.64	0.60	0.84	0.72	**0.031**
Connecticut	1.04	1.03	1.18	1.20	1.12	1.05	1.08	1.19	1.20	1.19	1.11	1.14	0.090
Delaware	0.33	0.28	0.27	0.29	0.26	0.25	0.28	0.38	0.35	0.38	0.29	0.33	0.317
D.C.	0.06	0.13	0.14	0.15	0.11	0.14	0.09	0.10	0.09	0.09	0.12	0.10	0.599
Florida	3.49	3.40	3.72	3.53	3.44	3.56	3.71	3.76	3.91	4.21	3.51	3.83	0.075
Georgia	1.98	1.91	2.00	2.08	2.25	2.42	2.29	1.96	2.04	2.14	2.05	2.17	0.351
Hawaii	0.04	0.05	0.05	0.07	0.05	0.05	0.11	0.07	0.05	0.07	0.05	0.07	0.275
Idaho	0.32	0.46	0.29	0.28	0.29	0.36	0.36	0.36	0.41	0.39	0.33	0.38	0.265
Illinois	4.25	4.03	4.16	3.70	3.66	3.72	4.01	4.11	4.26	4.17	3.96	4.05	0.666
Indiana	1.86	1.97	1.97	2.16	2.27	2.36	2.40	2.21	2.26	2.06	2.05	2.26	0.171
Iowa	0.59	0.57	0.64	0.69	0.72	0.79	0.82	0.82	0.84	0.94	0.64	0.84	**0.000**
Kansas	0.67	0.66	0.68	0.72	0.63	0.61	0.75	0.84	0.90	0.97	0.67	0.81	0.105
Kentucky	1.28	1.23	1.24	1.54	1.48	1.60	1.66	1.68	1.71	1.49	1.35	1.63	**0.030**
Louisiana	2.29	2.15	2.27	2.54	2.53	2.44	2.15	2.29	2.64	3.26	2.36	2.56	0.209
Maine	0.29	0.23	0.25	0.29	0.30	0.30	0.26	0.26	0.24	0.23	0.27	0.26	0.516
Maryland	0.58	0.59	0.68	0.65	0.68	0.71	0.79	0.74	0.78	0.88	0.63	0.78	**0.006**
Massachusetts	2.43	2.63	2.39	2.41	2.57	2.69	2.45	2.34	2.21	2.20	2.49	2.38	0.365
Michigan	4.49	4.34	4.43	4.90	4.62	4.41	4.20	3.95	3.88	3.51	4.55	3.99	0.060
Minnesota	1.35	1.32	1.44	1.50	1.55	1.56	1.64	1.59	1.57	1.49	1.43	1.57	0.099
Mississippi	0.32	0.35	0.49	0.44	0.35	0.39	0.45	0.44	0.45	0.57	0.39	0.46	0.200
Missouri	0.87	0.83	0.84	0.98	1.00	1.11	1.17	1.25	1.17	1.00	0.91	1.14	**0.028**
Montana	0.06	0.07	0.07	0.06	0.05	0.07	0.08	0.09	0.10	0.11	0.06	0.09	**0.046**
Nebraska	0.30	0.32	0.37	0.36	0.37	0.29	0.33	0.35	0.37	0.42	0.35	0.35	0.576
Nevada	0.15	0.19	0.19	0.17	0.28	0.36	0.44	0.54	0.50	0.48	0.20	0.46	**0.001**
New Hampshire	0.28	0.30	0.33	0.27	0.27	0.28	0.28	0.27	0.25	0.29	0.29	0.28	0.398
New Jersey	2.22	2.39	2.59	2.45	2.32	2.35	2.34	2.65	2.69	2.77	2.39	2.56	0.117
New Mexico	0.45	0.31	0.19	0.17	0.32	0.25	0.28	0.28	0.23	0.22	0.29	0.25	0.521
New York	5.35	5.49	5.77	5.45	5.54	5.60	5.75	5.76	6.19	6.32	5.52	5.93	0.057
North Carolina	2.17	2.30	2.30	2.12	2.24	2.23	2.16	2.07	2.03	1.95	2.22	2.09	0.087
North Dakota	0.10	0.08	0.11	0.12	0.12	0.12	0.13	0.15	0.18	0.22	0.11	0.16	**0.013**
Ohio	3.59	3.37	3.71	4.01	4.11	3.89	3.90	3.72	3.71	3.54	3.76	3.75	0.977
Oklahoma	0.43	0.39	0.36	0.35	0.37	0.39	0.48	0.43	0.40	0.39	0.38	0.42	0.163
Oregon	1.51	1.47	1.22	1.45	1.43	1.38	1.38	1.49	1.44	1.50	1.42	1.44	0.775
Pennsylvania	2.33	2.41	2.38	2.27	2.24	2.28	2.48	2.57	2.54	2.69	2.33	2.51	0.102
Rhode Island	0.16	0.15	0.17	0.16	0.16	0.16	0.14	0.15	0.14	0.15	0.16	0.15	**0.024**
South Carolina	1.03	1.10	1.36	1.39	1.63	1.65	1.55	1.33	1.44	1.54	1.30	1.50	0.227
South Dakota	0.07	0.09	0.08	0.09	0.09	0.10	0.11	0.12	0.13	0.13	0.08	0.12	**0.002**
Tennessee	1.42	1.49	1.55	1.68	1.74	1.98	2.13	2.11	1.90	1.80	1.58	1.99	**0.022**
Texas	12.01	13.31	12.99	13.77	13.65	14.41	14.35	14.71	14.65	14.93	13.15	14.61	**0.006**
Utah	0.45	0.41	0.48	0.66	0.57	0.58	0.67	0.66	0.68	0.80	0.51	0.68	**0.016**
Vermont	0.58	0.52	0.39	0.36	0.36	0.41	0.52	0.38	0.32	0.29	0.44	0.38	0.113
Virginia	1.66	1.50	1.59	1.56	1.50	1.43	1.36	1.38	1.47	1.47	1.56	1.42	**0.021**
Washington	5.30	4.13	4.78	5.01	4.88	3.63	3.67	4.13	4.54	4.23	4.82	4.04	**0.026**
West Virginia	0.27	0.28	0.31	0.32	0.33	0.40	0.35	0.32	0.35	0.44	0.30	0.37	**0.044**
Wisconsin	1.40	1.35	1.43	1.54	1.59	1.56	1.66	1.67	1.64	1.60	1.46	1.63	**0.036**
Wyoming	0.07	0.06	0.07	0.08	0.08	0.08	0.07	0.08	0.07	0.08	0.07	0.08	0.227

T-test results in bold indicate statistical significance at the 5% level.

Table II. State Exports as a Percent of State Gross Domestic Product

	Exports as a percent of State Gross Domestic Product										Mean	Mean	
	1999	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**99-03**	**04-08**	**t-test**
Alabama	5.53	6.39	6.38	6.67	6.40	6.40	7.22	8.75	8.76	9.34	6.27	8.09	**0.012**
Alaska	10.54	9.11	9.09	8.58	8.77	8.99	9.18	9.35	8.93	7.39	9.22	8.77	0.343
Arizona	7.96	9.04	7.57	6.90	7.32	6.97	6.95	7.74	7.82	7.95	7.76	7.48	0.651
Arkansas	3.32	3.89	4.22	3.89	3.91	4.24	4.47	4.70	5.14	5.87	3.85	4.89	**0.018**
California	8.29	9.30	8.21	6.88	6.68	7.25	7.17	7.40	7.45	7.84	7.87	7.42	0.490
Colorado	3.80	3.84	3.44	3.03	3.25	3.37	3.19	3.53	3.12	3.10	3.47	3.26	0.226
Connecticut	4.81	5.02	5.22	5.00	4.79	4.71	5.12	6.07	6.50	7.12	4.97	5.90	0.105
Delaware	5.80	5.30	4.49	4.45	3.88	3.93	4.40	6.58	6.54	7.92	4.78	5.87	0.371
D.C.	0.73	1.71	1.62	1.57	1.13	1.49	0.99	1.18	1.17	1.23	1.35	1.21	0.620
Florida	5.46	5.63	5.47	4.68	4.46	4.78	4.99	5.34	6.05	7.29	5.14	5.69	0.462
Georgia	4.96	5.13	4.89	4.70	5.12	5.83	5.75	5.35	5.97	6.92	4.96	5.96	**0.014**
Hawaii	0.71	0.96	0.88	1.18	0.79	0.82	1.88	1.17	0.90	1.50	0.91	1.26	0.177
Idaho	6.71	10.17	5.96	5.35	5.49	6.84	7.03	7.68	9.03	9.49	6.74	8.01	0.385
Illinois	6.63	6.77	6.39	5.27	5.19	5.67	6.54	7.16	7.92	8.47	6.05	7.15	0.248
Indiana	6.95	7.91	7.36	7.30	7.64	8.41	9.27	9.45	10.41	10.40	7.43	9.59	**0.003**
Iowa	4.75	4.95	5.07	4.88	5.13	5.73	6.37	6.96	7.43	8.93	4.96	7.09	**0.013**
Kansas	5.94	6.21	5.79	5.57	4.86	5.02	6.55	7.86	8.79	10.20	5.67	7.68	0.140
Kentucky	7.82	8.59	7.86	8.85	8.59	9.91	10.79	11.79	12.92	12.22	8.34	11.53	**0.002**
Louisiana	12.77	12.78	12.41	13.09	12.49	12.19	10.60	11.88	14.62	18.86	12.71	13.63	0.569
Maine	6.04	5.00	4.88	5.13	5.48	5.63	5.25	5.70	5.73	6.07	5.31	5.67	0.161
Maryland	2.34	2.55	2.58	2.19	2.31	2.52	2.96	3.00	3.38	4.16	2.39	3.21	**0.060**
Massachusetts	6.65	7.46	6.24	5.87	6.35	7.14	6.95	7.19	7.20	7.77	6.51	7.25	0.106
Michigan	9.53	10.04	9.68	9.71	9.33	9.90	10.17	10.80	11.73	11.80	9.66	10.88	0.054
Minnesota	5.42	5.57	5.53	5.24	5.41	5.68	6.33	6.79	7.15	7.30	5.43	6.65	**0.019**
Mississippi	3.52	4.24	5.39	4.50	3.53	4.16	5.06	5.35	5.91	7.98	4.24	5.69	0.137
Missouri	3.59	3.68	3.39	3.60	3.70	4.40	4.93	5.82	5.89	5.40	3.59	5.29	**0.005**
Montana	2.09	2.53	2.17	1.64	1.42	2.06	2.40	2.83	3.31	3.89	1.97	2.90	0.138
Nebraska	3.93	4.53	4.70	4.19	4.20	3.41	4.23	4.85	5.31	6.50	4.31	4.86	0.350
Nevada	1.55	2.01	1.84	1.45	2.31	2.90	3.51	4.51	4.42	4.66	1.83	4.00	**0.002**
New Hampshire	4.80	5.45	5.42	4.04	4.01	4.46	4.78	5.03	5.04	6.25	4.74	5.11	0.543
New Jersey	4.69	5.40	5.22	4.56	4.32	4.68	4.96	6.11	6.68	7.50	4.84	5.99	0.163
New Mexico	6.39	4.71	2.73	2.26	4.05	3.23	3.74	4.03	3.44	3.48	4.03	3.58	0.614
New York	5.08	5.51	5.22	4.60	4.72	5.09	5.42	5.72	6.44	7.11	5.02	5.96	0.137
North Carolina	5.71	6.56	5.88	4.97	5.29	5.60	5.60	5.62	5.98	6.27	5.68	5.81	0.747
North Dakota	4.15	3.53	4.35	4.33	3.93	4.46	4.91	5.98	7.18	8.88	4.06	6.28	**0.048**
Ohio	6.90	7.08	7.23	7.13	7.40	7.48	8.00	8.50	9.20	9.68	7.15	8.57	**0.012**
Oklahoma	3.59	3.42	2.82	2.52	2.57	2.86	3.58	3.39	3.36	3.47	2.98	3.33	0.311
Oregon	10.04	10.18	8.02	8.61	8.51	8.44	8.99	10.12	10.44	11.98	9.07	10.00	0.403
Pennsylvania	4.30	4.82	4.29	3.72	3.68	4.03	4.63	5.18	5.48	6.26	4.16	5.12	0.159
Rhode Island	3.62	3.53	3.61	3.04	2.99	3.06	2.94	3.37	3.53	4.17	3.36	3.41	0.876
South Carolina	6.58	7.61	8.49	7.94	9.22	10.19	10.07	9.30	10.93	12.69	7.97	10.64	**0.006**
South Dakota	2.29	2.94	2.49	2.26	2.45	2.81	3.09	3.82	4.29	4.47	2.49	3.70	**0.035**
Tennessee	5.82	6.63	6.27	6.07	6.30	7.52	8.57	9.17	8.92	9.22	6.22	8.68	**0.001**
Texas	12.43	14.28	12.46	12.18	11.94	13.02	13.17	14.10	14.65	15.71	12.66	14.13	0.151
Utah	4.91	4.77	5.00	6.25	5.46	5.85	6.81	6.92	7.40	9.39	5.28	7.27	**0.019**
Vermont	23.97	23.04	15.03	12.90	12.77	15.30	20.53	16.37	14.96	14.53	17.54	16.34	0.587
Virginia	4.73	4.49	4.20	3.78	3.58	3.59	3.49	3.85	4.39	4.77	4.16	4.02	0.773
Washington	17.13	14.51	15.47	15.01	14.70	11.69	12.13	14.66	16.79	16.88	15.37	14.43	0.543
West Virginia	4.60	5.35	5.17	4.99	5.13	6.55	5.97	5.81	6.89	9.15	5.05	6.87	**0.042**
Wisconsin	5.72	5.98	5.77	5.66	5.88	6.17	6.96	7.64	8.07	8.56	5.80	7.48	**0.016**
Wyoming	2.87	2.90	2.66	2.82	2.68	2.91	2.54	2.77	2.54	3.06	2.79	2.76	0.871

T-test results in bold indicate statistical significance at the 5% level.

Table III Statistically Significant Change in State Exports as a Percent of U.S. Exports

Increase		Decrease
Alabama		California
Arkansas		Colorado
Iowa		Rhode Island
Kentucky		Virginia
Maryland		Washington
Missouri		
Montana		
Nevada		
North Dakota		
South Dakota		
Tennessee		
Texas		
Utah		
West Virginia		
Wisconsin		

Table IV Statistically Significant Change in State Exports as a Percent of State GDP

Increase		Decrease
Alabama		None
Arkansas		
Georgia		
Indiana		
Iowa		
Kentucky		
Maryland		
Minnesota		
Missouri		
Nevada		
North Dakota		
Ohio		
South Carolina		
South Dakota		
Tennessee		
Utah		
West Virginia		
Wisconsin		

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The Impact of Morningstar Five-Star Stock Ratings

Shantanu Namjoshi and Kent A. Hickman

Abstract

We examine the behavior of stocks whose ratings by Morningstar are up-graded to the highest Five Star category. Our findings show that these up-grades follow a period of poor performance, are met with significant negative responses, and seem to foretell slightly improved performance relative to the pre-up-grade period. Additionally, trading volume is markedly higher at Morningstar's announcement.

I. Introduction

Morningstar is a well known investment information service, probably most famous for its ratings of mutual funds. Previous studies by Blake and Morey [2000] and Del Guercio and Tkac [2007] have shown that Morningstar's mutual fund ratings have some power to predict the underperformance of low-rated funds and have an impact on fund flows, respectively. Although the method Morningstar uses to rate funds or equities is a bit of a puzzle [Blume 1998], the concern of this paper is the effect of Morningstar's rating of individual firm's equities, specifically their Five Star rating that is purported to indicate good value relative to the share price.

Each day subscribers to Morningstar.com receive an email announcing stocks that are newly-qualified for the investment information service's Five Star Rating. According to Morningstar: *"This daily update lists the tickers of the stocks that became 5-star investments according to Morningstar as of the last market close. A stock is awarded 5 stars when its price hits what Morningstar deems is a "Consider Buying" level."*

II. Data

To gauge the impact of Morningstar's following among investors; we conducted an event study to determine whether the Five Star classification leads to increased demand sufficient to be reflected in the stock's price and whether there appears to be any economic value to the recommendations. Data for Morningstar's Five Star Rating service were collected from email alerts received from October 2007 through May 2008. A total of 924 firm-announcements were identified. It was observed that sometimes the ratings alerts included firms multiple times within a short span of time. This seems to indicate that there is no specific period of time a five-star rating lasts. Multiple occurrences in the data indicate that the rating for these had fallen from the five-star level and risen again.

Dates reflect periods in relation to the arrival of the Morningstar email, thus t=0 is the day of the email arrival (in early morning). Abnormal returns are calculated in two ways: as market-adjusted returns, using the S&P 500 Index as the market proxy and as risk-adjusted returns utilizing betas estimated over 255-trading days period prior to a 60-day window around the announcement. Calculations using the CRSP value-weighted index as a market-proxy led to

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the same conclusions as those using the S&P 500 Index, and are not repeated here. Interestingly, the announcement abnormal return's Z-score is significantly negative, as are the Z-scores of the prior day's price decreases. It appears that Morningstar's ratings may be triggered, at least in part, by a recent price decline. There appears to be some weak evidence of a market reaction to the announcement as 2-day cumulative market-adjusted returns for the days t=0 and t=+1 appear to dampen the negative trend prior to the announcement.

III. Results

Table I includes results for 924 firm-announcements spanning the period from October 2007 through May 2008.

Calculations for the range's of [0,30] and [0,60], shown in Table I, demonstrate that over the thirty and sixty day periods after the Five Star recommendation, the subject firms' shares significantly under-perform the market on a market-adjusted basis and perform about as expected on a risk-adjusted basis. Thus, there appears little predictive value in the Morningstar ratings.

The strongest evidence of a Morningstar-effect is presented in Table II. Here we have calculated trading volume for the recommended firms and test whether there is a significant difference in volume on the announcement date versus that average daily volume over various periods prior to the event. As the table makes clear, regardless of the length of the sample used to estimate 'normal' volume, Morningstar's email leads to a significant increase in activity with z-scores consistently exceeding 4.0

IV. Conclusions

Our findings are interesting in at least two respects. First, it is apparent that Morningstar's recommendations are, at least in part, triggered by a period of under-performance relative to the market. As a triggering event, this underperformance would fall within the realm of technical analysis, a much-maligned stock selection technique. Consistent with the academic skepticism surrounding technical analysis, we find little evidence of Morningstar's ability to forecast superior performance using their Five Star selection system. It is also possible that Morningstar is simply using some sort of book-to-market criterion. The second contribution of our study is the statistically discernable impact that Morningstar's announcement has on the volume of trading. It is clear that someone is listening and acting on the advisory service's advice, yet judging by the stock's performance, any increase in demand motivated by the ratings up-grade, is more than equaled by the willingness of the shares' holders to sell. Thus, we observe no up-tick in performance despite the higher volume.

Table I: Z-scores for Abnormal Returns of 924 firms Around Morningstar's Five Star Up-Grade Date

	AR = R_{stock}- R_{market}	**AR=R_{stock}-R_{market}**	**AR = R_{stock}-R_{market}**	**AR=R_{stock}-R_{market}**
	Z-Statistic	Z-Statistic	Returns	Returns
[-15,+0]	-4.4796	-0.1514	-12.30%	-2.78%
[-10,+0]	-4.9171	-0.1457	-9.93%	-1.86%
[-5,+0]	-7.3100	-0.8264	-7.21%	-3.29%
[-4,+0]	-7.1001	-0.4570	-6.57%	-1.64%
[-3,+0]	-7.1875	0.5887	-6.01%	4.92%
[-2,+0]	-6.8792	0.7464	-5.73%	5.73%
[-1,+0]	-8.3298	-0.5288	-4.57%	-2.03%
[-0,+0]	-6.0119	0.7593	-1.96%	3.35%
[+0,+1]	-4.6914	1.1123	-2.39%	5.10%
[0,+2]	-4.8502	1.2400	-2.77%	12.04%
[0,+3]	-4.2020	0.8031	-3.31%	4.95%
[0,+4]	-3.6277	0.9449	-3.82%	9.63%
[0,+5]	-3.2294	0.6964	-4.33%	4.73%
[0,+10]	-2.9032	-1.2782	-7.20%	-5.41%
[0,+15]	-2.5327	0.1326	-7.36%	1.65%
[-1,+1]	-7.4613	-0.0874	-4.99%	-0.27%
[-2,+2]	-6.2369	1.0015	-6.53%	14.42%
[3,+3]	-5.5130	0.6225	-7.36%	6.52%
[-4,+4]	-5.0304	0.4504	-8.43%	4.64%
[-5,+5]	-4.8550	-0.3010	-9.58%	-1.92%
[-10,+10]	-3.6647	-1.1758	-15.17%	-10.62%
[-15,+15]	-3.3660	-0.4118	-17.70%	-4.48%
[-20,+20]	-3.1207	-0.2348	-21.93%	-3.28%
[-30,+30]	-2.8940	0.5577	-28.79%	18.29%
[0,+30]	-2.2604	0.6476	-11.73%	13.64%
[0,+60]	-2.3013	0.6720	-23.40%	23.66%

Note: [a,b] indicates the abnormal returns calculated for a period of "a" and "b" days before(after) the Morningstar five-star up-grade date. Z-scores were calculated using S&P 500 Index as a proxy for the market. The Z-values presented are all significant at 5%.

Table II: Z-scores for Abnormal Trading Volume for 924 firms Around Morningstar's Five Star Up-Grade Date

Day	30-day Z Statistic	20-day Z Statistic	10-day Z Statistic	30-day Volume	20-day Volume	10-day Volume
5	2.5437	2.2904	1.4896	282315	255631	190899
4	2.8724	2.8984	2.4902	386962	360279	295547
3	3.8513	3.6042	2.6211	365761	339077	274345
2	4.5243	4.6818	4.5719	616683	590000	525267
1	4.9297	5.0029	4.5925	706003	679320	614587
0	4.9035	5.0635	5.0029	746623	719940	655207
-1	3.3144	3.2399	2.9570	732910	706227	641494
-2	1.3878	1.3475	1.1989	345988	319305	254572
-3	1.6351	1.4551	0.9382	206188	179504	114772
-4	1.2018	0.9971	0.4950	158324	131641	66908
-5	0.4857	0.3009	-0.1034	74475	47791	16941

Note: The abnormal trading volumes were calculated using Fixed Averages using 30, 20, and 10-day windows using an offset of -5 days around the Morningstar five-star up-grade date. Results using Moving-averages with a -1 day offset show similar results and are not repeated here. The Z statistics for days 5 to -1 are significant at 1%,, and days -2 to -3 at 10%.

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Pursuing a Career in Finance: A Survey of Upper Division Finance Students at Three Universities

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Abstract

This paper explores the attitudes and impressions of upper division finance students in three major regions of the United States (the midwest, the west, and the south) with respect to their discipline, the reasons for selecting it, and their future in it. The research also explores whether students will increase their education through degrees and certifications after they graduate and how they became interested in the finance area.

I. Objective

The objective of this paper is to ascertain the reasons why Finance majors are pursuing a degree in Finance. Does a degree in Finance mean that students want a career in Finance?

This study also investigates whether the decision to pursue a degree in Finance has been influenced by parents, family members, noted personalities, current news and events, or other sources. Conversely, has the recent financial crisis and recession made them question their decision, or have family and friends suggested that the respondent question his or her decision to be a Finance major or pursue a career in Finance?

On another level, students are asked whether other factors are important in their decision such as the potential for an excellent salary or simply being interested in Finance. Also, what area(s) of Finance is the respondent most interested in?

Students are asked whether their earning expectations in Finance are comparable or higher to other academic disciplines, as accounting, marketing, information systems, engineering, or science.

Of particular interest to this study is the student's interest in the accounting discipline, including the number of accounting credit hours that they have taken or will be taking. Previous experience has shown that majors in Finance that have a large concentration in accounting are in greater demand than students with little interest in accounting.

In order to further explore the future aspirations of those being surveyed, respondents will be asked if they will likely pursue a CFA@, CFP@, CTP@, or other certifying credential. Furthermore, do many students envision a master's degree, a law degree, or PhD in their future? Respondents will be asked if they are contemplating a second major to complement their finance major.

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One of the major aspects of this study is to explore the attitudes and impressions of students in three major regions of the United States: the midwest, the west, and the south. This is done by querying students at three large universities in these geographical regions: Illinois State University, California State University, Sacramento, and Mississippi State University. If the results of this study appear interesting, or if there are significant differences by region, the authors will expand this investigation to the eastern region of the United States.

Furthermore, data are analyzed by gender, GPA, and whether the student was born in the United States.

II. Methodology

Data will be analyzed by Analysis of Variance (ANOVA) and T tests and other statistical procedures that appear appropriate. The survey instrument is in the Appendix. The number of students responding to the survey was 78 at Illinois State University (ISU), 86 at California State University, Sacramento (CSUS), and 41 at Mississippi State University (MSU). All students were upper division students--students that have already completed the first course in Finance. Most of the students are Finance majors; many have double majors.

III. Descriptive Information

Total Students Participating: 205

ISU:

Finance Majors: 73
Accounting as a Second Major: 11
Students without a Second Major: 43
Total Students Participating: 78

CSUS:

Finance Majors: 70
Accounting as a Second Major: 12
Students without a Second Major: 37
Total Students Participating: 86

MSU:

Finance Majors: 38
Accounting as a Second Major: 2
Students without a Second Major: 28
Total Students Participating: 41

The GPAs of the respondents from the three universities are given below:

	GPA MEANS
ISU	3.3105
CSUS	3.1442
MSU	3.1362
All Students	3.2088

The GPA of students with a double major in Finance and Accounting was 3.290. The GPA of the 22 students who were not Finance majors was 3.1545.

IV. Results

The main reason for the survey was stated in this question: "If you are thinking of pursuing a career in Finance, what are the reasons for your career choice?" Please rate each statement on a 1 to 5 scale, 1 being the lowest, 5 being the highest.

These results were analyzed using a one way ANOVA. The data was analyzed as a whole, then that data was analyzed by university. The results are shown in Tables I and II below.

Table I
Reasons for Career Choice

Statements		**N**	**Mean**
1	Excellent Salary and Profit Potential	199	4.181
2	Working in the Finance Area will be Interesting	199	3.809
3	I Know Someone Who Can Get Me a Job in Finance	197	2.660
4	The Current State of the Economy and Financial World is Very Important	198	3.424
5	I Enjoy Dealing and Communicating with People From Different Cultures with Respect to Finance Concepts	199	3.387
		F = 61.55, p = .000	

Table II
Results of Each University

Statements	**N**	**ISU Mean**	**N**	**CSUS Mean**	**N**	**MSU Mean**
1	75	4.1333	83	4.217	41	4.1951
2	75	3.8933	83	3.819	41	3.6341
3	75	2.4800	83	2.542	39	3.2564
4	75	3.5000	83	3.349	41	3.4390
5	75	3.5067	83	3.253	41	3.4390
	F = 31.39 p = .000		F = 29.56 p = .000		F = 5.74 p = .000	

"Excellent salary and profit potential" was ranked the highest for all respondents as well as the respondents for each of the three universities. For statement 3, "I know someone who can get me a job in finance," was ranked the lowest for all three universities. For ISU and CSUS the means are well below 3.00. The reason for the MSU ranking—although still the lowest for MSU—was significantly higher than those for ISU and CSUS. The authors suggest that the reason is because Mississippi is a small state—with a population of approximately 2.5 million people. People know more people on a small town basis (as school or church) and retain those relationships, often for a lifetime. Their interactions may be with fewer people than those respondents from Illinois or California.

It should be noted that the rankings for the three universities are very similar regardless of the location of the university.

The five statements were also tested with respect to whether the students were male or female. No significant difference was found at the .10 level of significance. Also, the five statements were tested using an ANOVA with respect to whether the students were born in the U.S. or outside the U.S. No relation was found at the .10 level of significance.

Students were also presented with the statement "Over my entire working lifetime I expect that my degree in Finance will allow me to earn more/less than majors from the following programs." The 5-point scale was labeled, A Lot Less (1), Less (2), About the Same (3), More (4), A Lot More (5). An ANOVA was used followed by a T-test. The majors, their means, and the results of a T-test are listed in Table III.

Table III
Speculative Earnings with Respect to Different Majors

Major	Mean	95% Confidence Interval	T	p
Accounting	3.3015	3.1799, 3.4231	4.89	.000
Economics	3.6212	3.5172, 3.7253	11.77	.000
Marketing	3.6912	3.5728, 3.8110	11.46	.000
Management	3.5505	3.4278, 3.6732	8.85	.000
Information Systems	3.2929	3.1631, 3.4227	4.45	.000
Other Business	3.5990	3.4866, 3.7113	10.51	.000
Engineering	2.4673	2.3342, 2.6005	-7.89	.000
Science	2.8040	2.6582, 2.9498	-2.65	.009

Finance majors believe that they will earn more than the first 6 majors listed. Also, finance majors believe that their degree in finance will result in them earning less than engineering and science majors. This would correspond to the belief that students believe that finance majors have excellent (or very good) salary and profit potential.

Students were also asked: "If I was to enter a career in the finance field, I would be interested in the following." Respondents were asked to choose on a five-point scale from Strongly Disagree (1) to Strongly Agree (5). An ANOVA was used according to the university.

Table IV
Interest in Areas by Universities

	N	Financial Management	N	Banking	N	Other Financial Institutions
ISU	77	3.8052	76	3.579	75	3.4533
CSUS	84	3.8452	85	3.635	84	3.4524
MSU	40	3.6000	40	4.000	40	3.4750
		F = .87 p = .419		F = .80 p = .451		F = .01 p = .992

	N	Investment or Portfolio Management	N	Insurance	N	Real Estate
ISU	76	3.513	76	2.961	76	3.382
CSUS	85	3.765	84	2.835	84	3.143
MSU	39	3.359	40	3.050	40	3.175
		F = 1.70 p = .186		F = .47 p = .628		F = .80 p = .451

	N	Other	N	None
ISU	55	2.927	50	1.740
CSUS	70	2.986	58	1.776
MSU	37	2.568	32	1.594
		F = 1.42 p = .244		F = .29 p = .746

None of the above are significant at the 10 percent level of significance.

The averages for all three universities are now listed in descending order.

Table V
Areas in Descending Order

Financial Management	3.7811
Banking	3.6866
Investments or Portfolio Management	3.590
Other Financial Institutions	3.4573
Real Estate	3.240
Other	2.870
None	1.7214

On a scale of Strongly Disagree (1) to Strongly Agree (5), students were asked to evaluate the following: "My decision to pursue finance as a major was impacted by:"

Table VI
Finance Major Decision Impacted by the Following

	N	All Data ($\bar{X}$ = Mean)
Parents	198	2.404
Siblings	197	1.579
Other Family Members	198	2.056
Friends	198	2.313
Noted Personality (e.g., Warren Buffet, Donald Trump, etc.)	197	2.406
Newspaper/Magazine Articles	198	2.359
Other	118	3.076

The data was then analyzed for the three universities.

Table VII
The Data Analyzed by the Three Universities

	ISU			CSUS			MSU		
	$\bar{X}$	T	p	$\bar{X}$	T	p	$\bar{X}$	T	p
Parents	2.434	-3.58	.001	2.415	-3.98	.000	2.325	-3.31	.002
Siblings	1.547	-12.89	.000	1.561	-14.20	.000	1.675	-7.20	.000
Other Family	2.143	-5.81	.000	1.840	-9.39	.000	2.325	-2.77	.009
Friends	2.342	-4.41	.000	2.146	-6.98	.000	2.600	-1.84	.073
Noted Personality	2.237	-5.10	.000	2.556	-2.88	.005	2.425	-2.76	.009
Articles	2.421	-3.89	.000	2.329	-4.40	.000	2.300	-3.45	.001
Other	3.683	-2.56	.011	2.736	-1.04	.304	2.792	-.57	.575

Only one of the means was over 3.00. When analyzing the results of the three universities, only one of the means was over 3.00. This was for "Other" on the surveys of the students at ISU. Since the phrase was "Other (Please Identify) __________" several students expressed a reason. These responses are stated below:

Myself
Originally actuarial science
Co-workers
Classes
Interest
Like the idea of numbers/business so my high school counselor mentioned finance
My own interest in finance/numbers
Myself—advisor at community college helped direct me
The economy (wanted to know what was happening)

Personal research
Dr. B's introduction to Financial Management
Interesting jobs
Experience and preference
God's direction
Research on careers
Financial/monetary opportunities
Need for more hours to get CPA
My self-confidence
My high school teacher
Teachers
Advisor, professors
My own personal ambition
Love math
Personal and counselor

It has been this author's past experience that finance students would find it easier to obtain job interviews in Finance the greater the number of Accounting courses on the candidate's transcript. Looking at this from a slightly different perspective, students were asked these three questions:

"I would like to pursue a career in the Finance area." (Please Circle One). Strongly Disagree was assigned a (1) and Strongly Agree was assigned a (5.)

"Generally speaking, do you like Accounting?" (1) Yes, (2) No.

"How many hours of accounting (excluding CIS courses) will you have by the time that you graduate?"

(1)	6 to 8 Hours	(5)	18 to 20 Hours
(2)	9 to 11 Hours	(6)	21 to 24 Hours
(3)	12 to 14 Hours	(7)	More than 24 Hours
(4)	15 to 17 Hours		

The authors are testing the hypotheses that those students more interested in pursuing a career in Finance would be more interested in Accounting and would take more accounting courses.

Two ANOVA tests were undertaken. The first used "I would like to pursue a career in the Finance area," as the response variable. The factors were "Yes" and "No" with respect to "Do you like Accounting."

Table VIII
Do You Like Accounting?

	N	$\bar{X}$	
Yes	82	3.927	F = .61
No	116	4.052	p = .436

The results of the first ANOVA suggest that there is no difference between those that like and dislike Accounting. This is shown in Table VIII.

The second ANOVA examined the interest students have with respect to a career in the Finance area and the number of hours taken or will take in Accounting (excluding CIS). This is shown in Table IX.

Table IX
Pursuing a Career in Finance vs. Accounting Hours

Accounting Hours	N	Pursuing a Career in Finance (1…5) ($\bar{X}$)	
6 – 8	65	3.923	F = 1.16
9 – 11	44	4.182	p = .327
12 – 14	28	4.179	
15 – 17	9	3.778	
18 – 20	4	4.000	
21 – 24	8	4.625	
>24	38	3.630	

Again, the data suggests that there is no relationship between having an interest in a career in Finance and having an interest in Accounting.

V. Additional Findings

Students were asked what additional certifications they would attempt. The following is a summation of what was reported. As can be seen, the CFA has become very popular in recent years; however, several students are going to study for the CPA (out of 25 accounting majors at all schools). The data is show in Table X.

Table X
Additional Certifications

CFA	58
CFP	10
CTP	1
CPA	15
CPCU	3
CMA	1
Actuarial	1

Students were asked: "Are you likely to pursue a graduate degree?" This is shown below.

Table XI
To Pursue a Graduate Degree

	Count	Percent
Yes	146	71.22
No	59	28.78

N = 205

Also, "In what areas will you likely pursue a graduate degree?"

Table XII

	Count	Percent
MBA	115	77.70
MS in Finance	18	12.16
Ph.D. in Finance	0	0
Law	8	5.73
Other	7	4.73

N = 148

77.7% of the 148 responding selected the MBA degree.

Students were asked whether the recent financial crisis/recession has made you question your decision to pursue a finance/business major. Two answers were available, Yes and No.

Table XIII
Recent Financial Crises

	Count	Percent
Yes	71	35.15
No	131	64.85

A little over one-third of the 202 students responding answered yes.

Students were also asked "Has the recent financial crisis/recession caused your family or friends to question your decision to pursue a finance/business major?

The results are shown in Table XIV.

Table XIV

	Count	Percent
Yes	51	25.25
No	151	74.75

VI. Conclusions

The most important conclusions from this study are that there appears to be little difference among the finance students at the three universities with respect to the reasons for a career choice in finance (at least the choices mentioned in the survey). Also, the students at the three universities have very similar views with respect to who or what had a strong influence (or lack of influence) on their career choice. The most interest are those from ISU with respect to "Other." These are listed below Table VII. Finally, the students have a strong interest to learn more, further their education and to stand out by pursuing additional credentials, especially the CFA designation. This is shown in Tables X, XI, and XII.

APPENDIX

PURSUING A CAREER IN FINANCE
A SURVEY

1. Which university are you attending?
   1) Illinois State University
   2) California State University–Sacramento
   3) Mississippi State University

2. What is your gender?
   1) Male
   2) Female

3. What is your approximate GPA? ____________

4. Were you born in the United States?
   1) Yes
   2) No

5. What is your major?
   1) Finance
   2) Accounting
   3) Economics
   4) Real Estate
   5) Insurance
   6) Other ____ (Please State)

6. What course are you taking this survey in?
   1) The second course in Financial Management
   2) Investments
   3) Portfolio Management
   4) Banking
   5) Financial Institutions and/or Markets
   6) Senior Seminar
   7) International Finance

7. Are you currently pursuing or contemplating taking a second major?
   1) Yes
   2) No

8. What is (or will be) your second major? (***Please Circle One)***
   1) Accounting
   2) Marketing
   3) Management

4) Economics
5) Information Systems or Computer Science
6) International Business/Foreign Language
7) Other____
8) No second major for me.

9. I would like to pursue a career in the Finance area. ***(Please Circle One)***

Strongly Disagree				***Strongly Agree***
1	2	3	4	5

10. Please evaluate the following statement: If I were to enter a career in the finance field, I would be interested in the following:

	Strongly Disagree				***Strongly Agree***
Financial Management	1	2	3	4	5
Banking	1	2	3	4	5
Other Financial Institutions	1	2	3	4	5
Investments or Portfolio Management	1	2	3	4	5
Insurance	1	2	3	4	5
Real Estate	1	2	3	4	5
Other	1	2	3	4	5
None	1	2	3	4	5

11. Generally speaking, do you like *Accounting*?
1) Yes
2) No

12. How many hours of accounting (excluding computer/management information system courses) will you have by the time that you graduate?
1) 6 to 8 Hours
2) 9 to 11 Hours
3) 12 to 14 Hours
4) 15 to 17 Hours

5) 18 to 20 Hours
6) 21 to 24 Hours
7) More than 24 hours

13. Which of the following credentials are you likely to pursue or are currently pursuing?
1) CFA®
2) CFP®
3) CTP®
4) Other____
5) None

14. Please evaluate the following: My decision to pursue finance as a major was impacted by:

	Strongly Disagree				***Strongly Agree***
Parents	1	2	3	4	5
Siblings	1	2	3	4	5
Other Family Members	1	2	3	4	5
Friend	1	2	3	4	5
Noted Personality (e.g., Warren Buffett, Donald Trump, etc.)	1	2	3	4	5
Newspapers/Magazine Articles	1	2	3	4	5
Other (Please Identify)	1	2	3	4	5

____

15. Are you likely to pursue a graduate degree?
1) Yes
2) No

16. If you answered "yes" for question 15, in what area will you likely pursue a graduate degree?
1) MBA
2) MS in Finance

3) PhD in Finance
4) Law
5) Other :____

17. If you are thinking of pursuing a career in Finance, what are the reasons for your career choice? Please rate *each statement* on a 1 to 5 scale, 1 being the lowest, 5 being the highest.

Excellent salary and profit potential.
Lowest ***Highest***
1 2 3 4 5
Working in the Finance area will be interesting.
Lowest ***Highest***
1 2 3 4 5
I know someone who can get me a job in finance.
Lowest ***Highest***
1 2 3 4 5
The current state of the economy and financial world is very important.
Lowest ***Highest***
1 2 3 4 5
I enjoy dealing and communicating with people from different cultures with respect to finance
concepts.
Lowest ***Highest***
1 2 3 4 5

18. Over my entire working lifetime I expect that my degree in finance will allow me to earn more/less than majors from the following programs:

	A Lot Less	***Less***	***About the Same***	***More***	***A Lot More***
Accounting	1	2	3	4	5
Economics	1	2	3	4	5
Marketing	1	2	3	4	5
Management	1	2	3	4	5
Info. Systems	1	2	3	4	5
Other Business	1	2	3	4	5
Engineering	1	2	3	4	5
Science	1	2	3	4	5

19. Has the recent financial crisis/recession made you question your decision to pursue a finance/business major?
1) Yes

2) No

20. Has the recent financial crisis/recession caused your family or friends to question your decision to pursue a finance/business major?
1) Yes
2) No

Characteristics of Short-Term Equity Management of Property-Liability Insurers

Jin Park

Abstract

This paper investigates short-term equity trading practices of non-group affiliated P/L insurers in the U.S. Using the NAIC's Annual Statements, all trading records reported on the statements are utilized to identify short-term trading activities. This study documents that about one-third of the sample insurers report at least short-term equity trading, and financial characteristics of insurers are highly associated with the insurers' short-term equity trading activity than underwriting and firm characteristics.

I. Introduction

U.S. property-liability (P/L) insurance companies manage their investment risk by maintaining diversified portfolio, mostly consisted of investment grade bonds and equities. Although the purchasing power of P/L insurance companies for equity in the U.S. stock markets is less significant than that of other institutional investors such as investment banks, pension funds and mutual funds (Jiao & Liu, 2008; Brancato & Rabimov, 2008), equity is an important investment component for P/L insurers. According to Brancato and Rabimov, all institutional investors in 2006 controlled assets totaling $27.1 trillion. P/L insurers as a whole invest about $240 billion in equity in 2007, which is about 25 percent of the insurers' total invested assets.

It is generally noted that the P/L insurers hold financial securities long-term, matching their expected claim payout patterns from their lines of business. The focus of the most extant studies of an insurance company's investment choices is to examine long-term perspective of the insurer's investment choices. Another line of research investigates how to create the insurer's portfolio to achieve surplus immunization to interest rate changes (i.e., Tzeng, Wang & Soo, 2000; Park & Choi, 2010). However, an actively managed asset portfolio may involve frequent portfolio adjustments for various reasons, resulting in more frequent trading, including day-trading. Yan and Zhang (2009) documented that institutional investors with a short-term investment horizon, called short-term institutions including banks and insurance companies, are better informed and they trade frequently to exploit their informational advantage.[11]

A large body of studies of institutional investors examines the extent of institutional investors' informational roles in the stock market (i.e., Piotroski & Roulstone, 2004; Yan & Zhang, 2009) and the extent of managerial influences such as capital structure and performance (i.e., Chaganti & Damanpour, 1991) and dividend payout policy (i.e., Grinstein & Michaely, 2005). Extant studies document mixed results regarding institutional investors' informational

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[1] A large body of literature also suggests more limited evidence of informed trading by institutional investors. For example, Bushee and Goodman (2007) document that informed trading is not as widespread as extant studies suggest.

roles in the stock market, and Yan and Zhang (2009) attribute the mixed results to studies not considering the investment horizon of institutional investors. They state that institutional investors "may have different investment horizons because of differences in investment objectives and styles, legal restrictions, and competitive pressures; in addition, their investment horizons may differ because of their different informational roles" (p894).

Understanding how the P/L insurers as institutional investors manage their equity portfolio, especially short-term investment horizon, is important due a few reasons. For insurance regulators, understanding the extent of the P/L insurers' short-term investment management is important because the frequent equity trading can increase P/L insurers' investment risk, which may jeopardize the insurers' financial stability. This is particularly problematic, if equity (or asset) managers of the P/L insurers do short-term trading to earn a higher return and there is little supervision of those managers trading behavior. Although two regulatory tools to evaluate the financial condition of insurers by the National Association of Insurance Commissioners (NAIC) include a measure of the P/L insurers' investment performance, no regulatory tool is available to accurately quantify the amount of investment risk, especially associated with short-term equity trading. The Insurance Regulatory Information System (IRIS), which has been used since 1973, includes a measure of investment yield. The Financial Analysis and Surveillance Tracking (FAST) is another solvency monitoring system used since 1993, which includes an investment yield deviation.

The purpose of this study is twofold. First, this study investigates short-term equity trading practices of fund managers of the P/L insurers. This study explores preferred and common stocks trading records reported on the NAIC's Annual Statement filed by all P/L insurers in the U.S. The NAIC's Annual Statement is the comprehensive report of the P/L insurers' financial conditions and it is the only data source to have comprehensive trading records at the individual insurer's level. Little research has documented to understand the short-term trading choices of the P/L insurers. Not only does this study add to the literature on investment behaviors of institutional investors and the P/L insurers, it also opens a new line of literature on the P/L insurer's short-term trading behaviors. Short-term equity trading is defined as buy and sell of the same security in the same calendar year. This definition undermines actual short-term transaction activities since this definition does not include a short-term transaction involving buy and selling the same security in different years with a holding period less than a year. For example, an insurer buys a security in December of one year and dispose of it in January of a following year, and this study does not include this transaction. Second, this study attempts to identify factors affecting the P/L insurers' short-term equity trading behavior using a logistic model. Factors studied include financial, operational and organizational factors of the P/L insurers.

Park & Query (2009) document an organizational difference among P/L insurers engaging in short-term trading with any type of financial securities, and they report that about 62 percent of all P/L insurers in 2000 engage in short-term trading with bonds or stocks. Unlike they study of Park & Query, this study focuses on non-group affiliated P/L insurers' short-term equity trading practices. Although many insurers in the U.S. are group affiliated and dominate in certain lines of business, there is a potential benefit of limiting the study to non-group affiliated P/L insurers. Investment decision for a group affiliated insurer is most likely affected by its parent company, and fund managers at the parent company may manage all funds held by all companies within the group. That is, the decision making unit for managing assets for group affiliated P/L insurers would be the group rather than individual company. Analyzing a group as a decision making unit complicates the use of the NAIC's Annual Statement when equity trading information of all individual insurers under the same group has to be merged to create a group level data. Limiting the sample to non-group affiliated P/L insurers simplifies the study design without weakening the purpose and findings. Among insurers that are not group affiliated, about 37 percent of them engage in short-term equity trading.

The rest of the paper is organized as follow: The logit model used in the study is explained in the next, followed by Data section, which describes the NAIC data and samples used in the study. Finding and Discussion section presents findings of study and the conclusion section concludes.

II. Econometric Model

When it comes to identifying factors affecting the insurers decision to engage in short-term equity trading, logistic regression analyzes binomially distributed data of the form

$Y_i \sim B(N_i, P_i)$ for $i = 1, \ldots, k$,

where the numbers of N_i, Bernoulli trials, are known and the probabilities of event P_i are unknown. Given a set of explanatory variables, X_i, the logistic regression model is written as;

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \ldots \beta_k X_{k,i}\,.$$

If an insurer engages in short-term trading, the probability of event $P_i = 1$, where we obtain $L_i = \ln\left(\frac{1}{0}\right)$ and $L_i = \ln\left(\frac{0}{1}\right)$ otherwise.

In the logit regression, this study examines demographic, financial, and underwriting variables. Demographic variables include an insurer's organizational structure (stock or mutual corporation) and group affiliation; financial variables include cash holdings, amount of total assets, amount of risk based capital, amount of invested assets, and measures of investment performance; and underwriting variables include each insurer's mix of lines of business.

III. Data

The main source of the data used in this study is Schedule D of the National Association of Insurance Commissioners' (NAIC) Annual Statement reports comprehensive records of the P/L insurers' bond and stock holdings in detail and whether the financial securities are sold or held by the end of a fiscal year. Some examples of what are reported on the various parts of Schedule D of the NAIC Annual Statements include:

- stocks and bonds owned at the end of year
- stocks and bonds acquired during the year
- stocks and bonds sold, redeemed or otherwise disposed of during the year
- long-term stocks and bonds acquired and fully disposed of during the year
- various financial derivatives owned, open at the end of year
- various financial derivatives owned, opened during the year

- various financial derivatives owned, terminated open at the end of year
- counterparty exposure for derivative instruments open at the end of year

Most stocks and bonds reported on the NAIC statements have very comprehensive information about the securities, including CUSIP, date acquired and disposed of, cost to acquire, book value, number of shares, dividends and interest, adjustment for foreign exchange, if applicable, and transaction partner, to name a few.

IV. Findings and Discussion

Out of 774 non-group affiliated P/L insurers, 689 insurers of them (89 percent) are used in this study. Criteria to eliminate insurers include negative surplus (equity), negative risk based capital (RBC), or no insurance transaction. About 37.3 percent (257 insurers) of 689 insurers report at least one short term equity transaction in 2001.[1] As shown in Table 1, non-group affiliated P/L insurers with short-term equity trading (Trading Insurers) are larger in absolute size than non-group affiliated P/L insurers with no short-term equity transaction (No-trading Insurers). The mean value of Trading Insurers' total assets is $111.2 million, while that of No-trading Insurers' is $29.4 million. However, in terms of surplus to total assets ratio[2] and cash to total assets ratio, No-trading Insurers have a higher surplus ratio (52.7%) and cash ratio (28.8%) than Trading Insurers (43.9% for the surplus ratio and 12.7% for the cash ratio). If practicing short-term equity transaction is considered risky (or aggressive), the descriptive statistics is consistent with the view that conservative insurers (No-trading Insurers) are likely to hold more assets in very liquid assets such as cash and have a higher surplus ratio than other less conservative or aggressive insurers (Trading Insurers).

Both groups of insurers are relatively similar and dissimilar in several aspects. The proportion of premiums from automobile insurance to all insurance both groups of insurers is very comparable at 19.5% for No-trading Insurers vs. 21.9% for Trading Insurers. However, if the lines of business are dichotomized into property and liability, Trading Insurers underwrites more in liability lines of business (41.3% vs. 44.9%), while its counterpart underwrites more in property lines of business (24.1% vs. 18.3%). Assuming short-term equity trading is a risky activity and Trading Insurers are more risk taker (or less risk averse) than its counterpart, this difference in lines of business is also consistent with the findings of insurance literature. Property lines of insurance is known as "short-tail," which means the length of time between a claiming triggering incident and the settlement of the resultant claim is relatively short; typically a few days to a few months. In addition, property lines of insurance are less uncertain about claims payout pattern to insurance companies. On the other hand, liability lines of insurance are known as "long-tail" and more uncertainty about the payment amount and pattern is associated with the lines. Trading-Insurers have higher premiums earned from liability lines of insurance, but lower from property lines of insurance, than its counterpart. Another similarity between the groups of insurers is the organizational structure. The proportion of stock incorporated insurers is 47.4% for No-trading Insurers and 45.9% for Trading insurers. Two main organizational

[1] The purposes of the study and implications of findings will not be undermined by the age of the dataset.

[2] Insurers are required to report their financial statements following Statutory Accounting Principles (SAP) to state department of insurance, and the term "surplus" is used in lieu of the "equity." Total Assets used in this study also follows the definition of SAP, known as total admitted assets, which is smaller than total assets if it is reported using Generally Accepted Accounting Principles (GAAP).

structures in the insurance industry are stock and mutual incorporation. When it comes to profitability measures, mixed results are documented. Trading Insurers have higher ROE, but lower ROA than No-trading Insurers. ROI for both groups is comparable at 4.36% and 4.25% for No-trading Insurers and Trading Insurers, respectively.[3]

Table 2 summarizes short-term equity trading activities in detail for insurers reporting short-term equity trading by type of stock issuer. Out of 689 insurers, over one-third (257 insurers) of them report at least one short-term equity transaction. Not surprisingly, over 98% (4,369 out of 4,455 transactions) of short-term transactions is with common stocks, and Trading Insurers on average report 17.34 short-term transactions.[4] The mean holding period in days for all short-term transactions is about just over three months (96 days)[5]. Table 2 shows that on average, the holding period for both preferred and common stocks are almost the same (93.7 days and. 96.3 days, respectively). However, preferred stocks of public utility companies are held the longest (133.7 days) followed by preferred stocks of financial institutions with 133.1 days. The insurers more frequently trade stocks of industrial and miscellaneous companies. In terms of the trading size, the mean acquiring cost of a preferred stock is about 3.5 times larger than that of a common stock ($1.25 million for preferred stock vs. $372,000 for common stock). By type of stock issuer, the mean acquiring cost of a preferred stock of public utility companies is $1.8 million while that of common stock of public utility companies is mere $150,000. For common stocks of industrial and miscellaneous companies, the mean acquiring cost is $386,000.

A logistic regression is performed to identify factors associated with the P/L insurer's short-term equity trading behavior, where the dependent variable is a binomial variable with 1 for Trading Insurers and 0 for No-Trading Insurers. Three separate logistic regressions are performed to study factors affecting different short-term equity trading behaviors; (1) insurers with any short-term stock trading activity, (2) insurers with short-term common stock trading only, and (3) insurers with short-term preferred stock trading only. Since over 98 percent of short-term equity trading is with common stocks, the results between Regression (1) and (2) are almost identical.

The regression results are reported in Table 3. For insurers with short-term common stock trading, financial variables are statistically significant, while none of demographic and underwriting variables are statistically significant. The variables that are positively associated with Trading Insurers are total assets (*Log of Total Assets*$_{, t-1}$), the invested asset ratio (*Invested Assets to Total Assets*$_{, t-1}$), and returns on security trading (*Net Realized Capital Gain to Invested Assets*$_{, t-1}$) from the previous year. This result shows that the larger the P/L insurer, the greater the chance that the insurer will engage in short-term equity trading. There are two plausible explanations for this. One explanation is that the larger the insurer, the greater the insurer's ability to absorb risk, so it can engage in a risky investment activity. Another explanation is that

[3] ROI is calculated as Net Investment Income Earned to Invested Assets.

[4] Because some transactions result in significantly high or low annualized returns, which distort the mean return from short-term transactions, reporting the annualized returns is less meaningful. However, the results are available upon request.

[5] About 14% of all preferred stock transactions are the same day transactions. That is, buy and sell are recorded on the same day. On the other hand, about 3.5% of all common stock transactions are the same day transactions. The result of the holding period distribution by type of stock is available by author upon request.

it's more difficult to monitor fund managers investment activities as the organization is bigger. Although it is difficult to conclude from the finding that the short-term equity trading results in a higher investment yield, reflecting the greater risk the insurers have taken, the probability that non-group affiliated P/L insurers will engage in short-term equity trading increases as non-group affiliated P/L insurers had higher returns from previous years security transactions.

Not surprisingly, insurers with more cash holding are negatively significant to the short-term equity trading activity. This is consistent with the view that the more conservative a P/L insurer is, the more safe assets it holds and the less risky activity it engages. When it comes to the insurer's short-term preferred stock trading activity, two financial variables, *Log of Total Assets*$_{,\,t-1}$ and *Net Realized Capital Gain to Invested Assets*$_{,\,t-1}$ are positively associated.

V. Conclusion

This study investigates a short-term equity trading behavior of 689 non-group affiliated P/L insurers in the United States in 2001, and finds that over one-third of the sample insurers report at least one short-term equity trading activity. Stocks issued by industrial and miscellaneous companies are most frequently traded, followed by financial institution's stocks. This is simply because more number of stocks falls under these two categories. However, in terms of the mean transaction size, the average acquisition cost of preferred stock is 3.5 times larger than that of common stocks. This finding suggests that the insurers may engage in short-term trading with preferred stocks to earn dividends. The mean holding period for short-term equity transaction is about 96 days.

This study also identifies a few factors associated with short-equity term trading activity of non-group affiliated P/L insurers. Logistic regressions show that financial variables, especially total assets, are more strongly tied to insurers' short-term equity trading behavior than underwriting and demographic variables.

Future research should investigate the short-term equity and/or fixed income security trading behavior of group affiliated insurers and compare the trading behavior between them. Another improvement to the study can be made by incorporating market data from CRSP to further explore the insurer's motivation to engage in short-term equity trading. With the CRSP data, study can document whether the P/L insurers are selling stocks to capture extraordinary short-term returns, to limit excessive losses, to increase dividend yield, or something else.

Table 1. Descriptive Statistics for Selected Variables
(figures are in $ millions except ratios in %, and N is the number of insurers)

	No-trading (N=430)			Insurers	Trading Insurers (N=257)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Cash	4.2	9.0	-0.6	134	7.6	17.2	-1.2	187
Bonds	15.5	35.3	0.0	352	65.8	186.5	0.0	2,087
Stocks	1.6	6.4	0.0	95	23.4	144.1	0.0	2,189
Invested Assets	23.9	68.9	0.0	1,119	99.8	332.2	0.9	3,927
Total Assets	29.4	77.5	0.1	1,127	111.2	344.8	1.0	3,965
Cash to Invested Assets, %	35.8	33.0	-43	100	15.3	15.7	-6.2	100
Cash to Total Assets, %	28.8	28.1	-5	110	12.7	12.5	-5	71
Bonds to Invested Assets, %	50.9	32.7	0.0	100	61.5	21.9	0.0	100
Stocks to Invested Assets, %	9.2	16.1	0.0	100	20.0	17.3	0.0	90
Invested Assets to Total Assets, %	82.2	18.4	0	110	85.1	10.0	48	100
Surplus to Total Assets, %	52.7	24.5	0.3	100	43.9	19.4	3.2	100
Direct Premium Written	14.8	28.9	0.0	247	34.7	50.7	0.0	319
Net Premium Written	10.3	22.4	-0.1	299	29.1	46.4	0.0	316
Earned Premium	9.6	21.1	0.0	287	27.7	45.5	0.0	315
Auto Lines Ratio, %	19.5	35.8	0	100	21.9	33.5	0	100
Personal Lines Ratio, %	29.2	38.1	0	100	31.6	37.1	0	100
Liability Lines Ratio, %	41.3	42.9	0	100	44.9	40.8	0	100
Property Lines Ratio, %	24.1	32.2	0	100	18.3	23.8	0	100
Net Realized Capital Gain	0.11	0.6	-1.4	7	1.48	14.2	-9.5	216
Net Investment Gain	1.30	4.4	-1.2	75	5.81	23.8	-2.7	338
Net Income	0.13	3.6	-22.8	54	0.92	7.3	-47.5	72
ROI, % [a]	4.36	1.7	-1.7	145	4.25	1.2	0.9	86
ROE, %	-2,13	37.2	-48.8	181	-1.42	21.0	-126	55
ROA, %	0.81	9.5	-98.5	45	0. 29	5.8	-31.1	17
RBC to Surplus, %	84.7	35.5	0.0	106	94.2	23.3	0.0	115
Stock, %	47.4	50	0.0	100	45.9	50	0.0	100

Note [a] ROI is calculated as Net Investment Income earned to Invested Assets.

Table 2. Short-Term Equity Transactions, Holding Period and Acquiring Cost by Type of Stock Issuer (N = # of transactions.)

		Transaction			Holding Period (Days)		Acquiring Cost ($000)	
	Insurer	N	Mean	Max.	Mean	Max	Mean	Max
Preferred Stocks								
Public Utilities	5	12	2.40	4	137.1	272	1,804	7,845
Banks, Trust & Insurance	6	10	1.67	3	133.1	316	803	3,501
Industrial & Miscellaneous	26	63	2.42	10	80.6	317	1,210	10,990
Total - Preferred Stocks	33	86	2.61	15	93.7	317	1,246	10,990
Common Stocks								
Public Utilities	57	132	2.32	17	106.2	329	158	3,663
Banks, Trust & Insurance	81	296	3.65	35	104.1	343	276	14,861
Industrial & Miscellaneous	238	3,940	16.55	288	95.3	362	386	147,127
Total - Common Stocks	252	4,369	17.34	294	96.3	362	372	147,127
Total – Stocks	257	4,455	17.33	294	96.2	362	389	147,127

Table 3. Logistic Regression of Short-Term Equity Transactions
(Total number of insurers used in the regressions is 687 insurers)

	Insurers with Transaction with					
	Any Stock (N = 257)[a]		Common Stock Only (N = 252)[a]		Preferred Stock Only (N = 33)[a]	
Intercept	-7.93 (1.553)	***	-8.05 (1.564)	***	-12.75 (2.993)	***
Organization Structure (Stock = 1)	-0.00833 (0.200)		0.00716 (0.201)		0.1706 (0.416)	
Log of Total Assets, $_{t-1}$	0.4012 (0.083)	***	0.3836 (0.082)	***	0.4872 (0.142)	***
Cash to Total Assets, $_{t-1}$	-2.7913 (0.641)	***	-2.84 (0.651)	***	-1.0721 (1.460)	
Invested Assets to Total Assets, $_{t-1}$	1.5845 (0.796)	**	1.8365 (0.816)	**	1.9659 (2.006)	
Surplus to Total Assets, $_{t-1}$	-0.4302 (0.536)		-0.471 (0.539)		-0.3416 (1.147)	
RBC to Total Assets, $_{t-1}$	0.1696 (0.350)		0.3884 (0.360)		-0.5356 (0.699)	
Net Realized Capital Gain to Invested Assets, $_{t-1}$	14.5631 (4.232)	***	14.6042 (4.218)	***	14.5763 (5.963)	**
Return on Assets, $_{t-1}$	-1.432 (1.494)		-1.4225 (1.499)		-3.235 (3.439)	
Net Premium Written, Auto Insurance	0.1215 (0.423)		0.0489 (0.426)		-0.3494 (0.948)	
Net Premium Written, Personal Insurance	0.00622 (0.359)		-0.0426 (0.361)		0.7426 (0.822)	
Net Premium Written, Liability Insurance, $_{t-1}$	-0.252 (0.289)		-0.2901 (0.290)		0.303 (0.646)	
Net Premium Written, Property Insurance, $_{t-1}$	-0.3 (0.411)		-0.2395 (0.412)		0.1091 (1.047)	
Chi-Square						
Likelihood Ratio	155.62		155.14		33.78	
Wald Test	100.72		99.73		29.07	

Note [a] The N refers to the number of insurers who engage in short-term equity trading, and the insurers with a transaction is coded 1, otherwise 0, for the binomial dependent variable.
Figures in parenthesis are standard errors. Statistical significance at the 1, 5, and 10 percent levels is denoted by ***, **, and *, respectively.

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The "Sell in May and Go Away" Effect: Prevalent or Mythical Anomaly

Yuli Su and Gloria Lu

Abstract

The purpose of this study is to empirically examine the "Sell in May and Go Away" Effect over the period ranging from 1970 to 2010. This paper examines 50 worldwide markets and finds that the Sell in May Effect is more evident in developed than in emerging markets. The Sell in May effect does have a stronger presence in Europe and in a number of countries that were former colonies or under direct influence of European countries, which may lead these emerging markets to be more highly correlated to developed markets. Sub-periods results show that the Sell in May effect is non-stationary. It is found that the strong presence of the Sell in May effect in Europe during the period of 1990-1999 is less apparent during the most recent sub-period of 2000-2010.

I. Introduction

The study of calendar anomalies persists despite Fama's (1970) discussion on the subject of efficient capital markets. Evidence of calendar anomalies challenges the weak-form of the Efficient Market Hypothesis (EMH), in which the market is efficient in historical price information and cannot predict future market movements. Camps on both sides continue to debate the question posed by the title of Lakonishok and Smidt's (1988) article "Are Seasonal Anomalies Real?". Lakonishok and Smidt's (1988) examine the characteristics of the U.S. Dow Jones Industrial over a ninety-year time span and conclude that anomalous returns indeed exist for the turn of the week, month, and even year. Malkiel (2003) counter-argues that "the general problem with these predictable patterns or anomalies, however, is that they are *not* dependable from period to period. Wall Street traders now joke that the 'January effect' is more likely to occur on the previous Thanksgiving. … They do not appear to offer arbitrage opportunities that would enable investors to make excess risk adjusted returns." The spate of research on well-known anomalies such as the January effect and holiday effect has also incurred valid critiques of data mining or data snooping. Nevertheless, calendar anomalies have withstood decades of academic interest and investigation. These studies persist to examine whether or not such market anomalies still exist; and if they do, what are the potential explanations underlying these "anomalies". One calendar anomaly, the Halloween Indicator (or "Sell in May and Go Away" effect), has received some academic attention, but not in the magnitude of other anomalies, rendering it ripe for further analysis.

The "Sell in May and Go Away" Effect, also popularly known as the Halloween Effect or Halloween Indicator, posits that stock returns are significantly lower during the six-month period from May through October (the pre-Halloween period) than the other half of the year from November through April (the post-Halloween period). This finding implies that investors will be able to earn abnormal profits by selling stocks in May, going away during the pre-Halloween

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period, purchasing stocks in November and investing during the post-Halloween period. Since the documentation of the "Sell in May and Go Away" effect (simplified as the Sell in May effect in this study) by Bouman and Jacobsen (2002), several studies (Lucey and Zhao (2006); Maberly and Pierce (2004); and Ciccone and Etebari (2007)) tried to refute the existence and/or statisticalsignificance of the Sell in May effect for the U.S. market by accounting for outliers or adopting a more stringent testing methodology. Furthermore, studies such as Cao and Wei (2005), Jacobsen and Marquering (2008) and Doeswikj (2008) investigate the presence of the Sell in May effect from the viewpoint of behavior finance.

In this study, we re-examine the Sell in May effect by expanding the variety of sampling countries and the length of the testing periods. Our empirical results support Bouman and Jacobsen (2002) in that 28 of 50 worldwide markets – as opposed to 20 of the 37 markets in their study – show evidence of a statistically significant Sell in May effect. When the January effect is accounted for, 22 countries (14 countries in Bouman and Jacobsen (2002)) show a significant Sell in May effect. We find that the Sell in May effect appears more in developed than in emerging markets. The Sell in May effect does have a strong presence in Europe and in a number of countries that were former colonies or under direct influence of European countries, which may lead these emerging markets to be more highly correlated to developed markets.

While Bouman and Jacobsen (2002) do not test this apparent anomaly over sub-periods, Maberly and Pierce (2003) report that in the case of Japan, the Sell in May anomaly appears to have faded since the mid-1980s. To investigate the stationarity of the anomaly, our paper examines all 50 worldwide markets broken into sub-periods. Our sub-period results show that the Sell in May effect is non-stationary. It is found that the strong presence in Europe during the period of 1990-1999 is less apparent during the most recent sub-period of 2000-2010. Nevertheless, the effect does not appear to have occurred during any particular sub-period or range of years. As a result, it suggests greater difficulty in exploiting this "anomaly".

This study begins with a literature review in Section II, followed by discussion of methodology and data description in Section III. Empirical results are discussed in Section IV, with a concluding Section V.

II. Literature Review

The "Sell in May and Go Away" Effect, also popularly known as the Halloween Effect or Halloween Indicator, posits that stock returns are significantly lower during the six-month period from May through October (the pre-Halloween period) than the other half of the year from November through April (the post-Halloween period). Such market anomaly appears to attract the general public investors and economists' attention more than that of the financial analysts, practitioners, and academics. Indeed, references to the Sell in May effect as an "old Wall Street adage" appear in mainstream news outlets as if the anomaly is a certainty, and hence is precluded from any questions of its veracity in worldwide stock markets (Twin, 2007). On the other hand, numerous academic studies on other calendar effects, such as the January effect, Turn of the Month effect, and Holiday effect have rendered these effects both significant to academics and practitioners. These empirical evidences reveal unmistakable messages about calendar anomalies—namely, that a calendar effect introduces an arbitrage opportunity based solely on timing, be it a certain day of the week or a certain month of the year.

Bouman and Jacobsen (2002) strongly endorse the existence of the Halloween Indicator, as they find the effect in 20 of the 37 countries over a 28-year period (1970-1998).[1] Their study documents that the strongest and most significant presence of the effect is found in the cases of European countries. When a more stringent regression is adopted to adjust for the January effect, the Sell in May effect still exhibits for 14 of 20 countries.[2] By design, this model specification tends to underestimate the Sell in May effect. Hence, they conclude that the Sell in May effect is not the January effect in disguise. Finally, comparing the profitability of the Halloween strategy with that of the annual buy-and-hold strategy, they report that the Halloween strategy outperforms the buy-and-hold strategy except for Hong Kong and South Africa.

Bouman and Jacobsen (2002) also conduct cross-sectional analysis in an attempt to determine the potential drivers of the Sell in May effect. They find that the Sell in May effect seems to be unrelated to interest rate levels due to the observation that interest rates are not significantly higher during the pre-Halloween period. Yet, trading volume is found higher during the post-Halloween period. Furthermore, the finding of lower pre-Halloween returns in both of the Northern and Southern hemisphere countries suggests that the effect is not vacation-driven. Otherwise, one could expect to observe lower post-Halloween returns for the Southern hemisphere countries where the summer vacation period coincides with the post-Halloween period. The Sell in May effect is not news-driven because there is no evidence that more negative news is reported in the pre-Halloween period than in the post-Halloween period. Finally, they also report that the effect is not sector-specific.

Studying the Russian Trading System Stock Exchange (RTS) over a ten-year period from 1995 to 2006, Reichling and Moskalenko (2007) document that the optimal time to enter the RTS market was at the end of September and the optimal time to exit was May, thus illustrating the Sell In May effect. However, the ultimate conclusion drawn from their study is that the Sell in May strategy inconsistently exists. As a result, the Sell in May strategy providing premium returns in one year does not guarantee premium returns in any subsequent period. Therefore, the Sell in May Strategy may prove only to be an old Wall Street saying and nothing more.

Inquiries challenging the results found in Bouman and Jacobsen (2002) have also been performed by Maberly and Pierce (2003) in a sub-period study on the Japanese and U.S. markets as well as by Maberly and Pierce (2004) on an additional test of the anomaly's robustness. These two studies provide evidence that the use of alternative models and the exclusion of outliers could reduce the presence of the Sell in May effect. Studying Nikkei 225 Index from 1970 to 2003, Maberly and Pierce (2003) report a Sell in May effect in the Japanese stock market. The effect persists even when the January effect and the outliers issues are addressed using the regression models with dummy variables. However, they also find that the Sell in May effect is only present in Japan's stock market in the period prior to the introduction of Nikkei 225 index futures in September 1986, but the effect essentially disappears after the Japan stock market became more internationalized in the 1980s. Furthermore, conceding that in bull market

[1] MSCI reinvestment indices are used in their study.

[2] The Sell in May Dummy is assigned a value of 1 from the period of November through April except for January.

years the Nikkei 225 index provided higher returns during the post-Halloween period, but did not in the 13 bear market years (40% of the 34-year dataset), Maberly and Pierce (2003) characterize the Sell in May effect as one that "cannot be profitably exploited" (p.17).

Maberly and Pierce (2004) adopt their robust methodology to test the Sell in May effect using the value-weighted CRSP index returns from 1970-1998 as well as the S&P 500 futures from April 1982 to April 2003. Again, the authors document that a Sell in May effect is initially present in the U.S. market. However, the effect vanishes after adjusting for outliers, particularly October 1987 (stock market crash) and August 1998 (the collapse of Long-Term Capital Management hedge fund). Similarly, Ciccone and Etebari (2007) argue that the Halloween Effect is strong, but that "If January, September, and October returns are excluded, the superior November to April performance virtually vanishes" (p. 5). In other words, these studies recommend that the Sell in May effect is not stationary and can easily be caused by special economic events.

Nevertheless, recent articles such as Doeswijk (2008) argues that half of the Sell in May effect is due to market-timing and half is due to true seasonality while Jacobsen and Marquering (2008) suggest that the Sell in May effect is not caused by seasonal affective disorder (SAD), but rather remains a "puzzle".[3] As a results, the verdict on the existence of the Sell in May effect remains open to further analysis.

III. Data and Methodology

a. Data

This study employs the monthly continuously compounded stock returns of the value-weighted MSCI (Morgan Stanley Capital International) market indices (denominated in local currencies) for 50 countries. Data between January 1970 and September 2010 are collected for 18 developed countries (namely, Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States). Due to data accessibility, the remaining 32 countries' returns data sets cover different periods with start dates ranging from January 1982 to January 1995. These remaining countries represent all countries, especially emerging markets, available as MSCI reinvestment indices.[4]

In order to investigate the stationarity of the Sell in May Effect, the whole sampling period is then divided into sub-periods. For the 18 aforementioned countries, data is analyzed as a whole sampling period from January 1970 to September 2010 as well as four sub-periods with the first three sub-periods demarcated into ten-year periods (N = 120) and a fourth period covering the period of January 2000 to September 2010 (N = 129). The whole sampling period for the remaining 32 countries is also divided, but only covers the last two sub-periods.[5]

[3] Cao and Wei (2005) propose that attribute seasonal affective disorder or temperature effects on investors' moods as the cause for less optimal returns during the period from May through October.

[4] This study extends Bouman and Jacobsen's (2002) sample data set of January 1970-August 1998 with an additional twelve years of data.

[5] Two countries (Finland and New Zealand) contain data from January 1982 to September 2010 and fifteen countries (Argentina, Brazil, Chile, Greece, Indonesia, Ireland, Jordan, Korea, Malaysia, Mexico, Philippines, Portugal, Taiwan, Thailand, and Turkey) contain data from January 1988 to September 2010. The sub-period analysis for these seventeen countries only covers the period from January 1990 to September 2010.

b. Methodology

Analogous to the research model used by Maberly and Pierce (2003 and 2004), a simple regression with dummy variables analysis is adopted to test for the existence of a Sell in May effect. The regression equation is as follows:

$$\begin{aligned} R_t &= \mu + \alpha_1 S_t + \varepsilon_t \\ \textit{where } S &= 1 \text{ if } t \text{ falls in the 6-month period between November and April,} \\ &= 0 \text{ otherwise} \\ \varepsilon &\sim N(0,1) \end{aligned} \qquad (1)$$

The dependent variable, R_t, represents the continuously compounded monthly returns for the value-weighted MSCI index. Monthly returns are calculated using the natural logarithm of the price relative, or $R_t = \ln(\text{Index}_t / \text{Index}_{t-1})$. When dummy variables are excluded, equation (1) simply becomes the random walk model. The dummy variable S_t takes on the value 1 if month *t* falls in the post-Halloween period (between November and April) and 0 otherwise. The coefficient, μ, represents the monthly mean return over the pre-Halloween periods while $\mu + \alpha_1$ represents the monthly mean return over the post-Halloween periods. A positively significant α_1 suggests that monthly mean returns are larger over the post-Halloween period, and hence potential evidence of the Sell in May effect.

Given several studies (such as Bouman and Jacobsen (2002), Maberly and Pierce (2003 and 2004), and Ciccone and Etebari (2007)) have suspected the Sell in May effect occurs merely as a consequence of a strong January effect, it is important to distinguish these two effects. To test whether the Sell in May effect is itself a distinct anomaly, Equation (1) is modified by inserting a second dummy variable, J_t ,which is set equal to 1 whenever month *t* is January and 0 otherwise:

$$\begin{aligned} R_t &= \mu + \alpha_1 S_t + \alpha_2 J_t + \varepsilon_t \\ \textit{where } S &= 1 \text{ if } t \text{ falls in the 6-month period between November and April,} \\ &= 0 \text{ otherwise} \\ J &= 1 \text{ if } t = \text{January,} \\ &= 0 \text{ otherwise} \\ \varepsilon &\sim N(0,1) \end{aligned} \qquad (2)$$

Under equation (2), μ is the monthly mean return for the months of May, June, July, August, September, and October whereas $\mu + \alpha_1$ measures the monthly mean return for the months of November, December, February, March, and April. Finally, $\mu + \alpha_1 + \alpha_2$ represents the monthly mean return for the month of January.

Under this model, a significantly positive α_1 combined with an insignificant α_2 provides evidence of a Sell in May effect but no January effect. On the contrary, an insignificantly α_1

Ten countries (China, Colombia, India, Israel, Pakistan, Peru, Poland, South Africa, Sri Lanka, Venezuela) contain data from January 1993 to September 2010 which is divided into sub-period 3 (1993.01-2000.12) and sub-period 4 (2001.01-2010.09). Five countries (Czech Rep, Egypt, Hungary, Morocco, and Russia contain data from January 1995 to September 2010 which is divided into sub-period 3 (1995.01-2000.12) and sub-period 4 (2001.01-2010.09).

together with a significantly positive α_2 suggests the existence of only a January effect. If α_1 and α_2 are both significantly positive, both the Sell in May and January effects are present simultaneously. In short, if the Sell in May effect remains robust in the regression estimation of equation (2), then the coefficients of the Sell in May effect dummy (α_1) will be statistically significant even with the presence of the January dummy.

IV. Empirical Results

a. Empirical Results for the Whole Sampling Period

Figures1 and 2 report the average returns in the pre-Halloween (May-October) and the post-Halloween (November-April) periods for developed markets and emerging markets, respectively. The returns of the eighteen countries charted in Figure 1 encompass the entire dataset period of January 1970 to September 2010. It is evident that the Sell in May effect exists for developed countries. For all 18 developed countries, the returns during the post-Halloween periods are positive and higher than those in the pre-Halloween periods. In fact, 12 out of the 18 countries (67%) report negative average returns in the pre-Halloween period.

Figure 2 plots the shorter data series in our sample including many of the emerging markets. With the exception of China and Sri Lanka, positive returns are observed in post-Halloween periods. Different from the results of developed countries, only 15 out of the 32 emerging markets (47%) report negative average returns in the pre-Halloween period. Specifically, the positive pre-Halloween returns are more evident in the Latin American markets. Nevertheless, it can be clearly seen that, except for the case of China, Sir Lanka and Venezuela, post-Halloween returns still outperform pre-Halloween returns.

Tables I and II report the summary statistics and estimation results from equations (1) and (2) performed on the whole sampling period for developed markets and emerging markets, respectively. Results for equation (1) are similar to those reported in Bouman and Jacobsen (2002) in that 28 of the 50 countries exhibit a statistically significant Sell in May Effect at the 10% level.[6] Specifically, 15 of the 18 developed countries reported in Table I and 13 of the 32 emerging countries reported in Table II demonstrate a significant Sell in May effect.

To isolate the possible January effect masked in the Sell in May effect, the January effect dummy is included in Equation (2). As shown in Tables I and II, the Sell in May effect disappears for 7 of the 28 country markets with the inclusion of the January effect dummy in Equation (2). Specifically, adding the January Dummy results in an insignificant Sell in May effect in the cases of Norway (from Table I) as well as the cases of Colombia, Egypt, Finland, Greece, Hungary and Portugal (from Table II). Interestingly, Russian reports a significant Sell in May effect after the January Dummy is included. In general, although adjusting for the January effect seems to reduce the Sell in May effect, the observation that 22 countries still exhibit a significant Sell in May effect in Equation (2) supports the contention that the Sell in May effect is not completely the January effect in disguise.

Judging from the entire data sets evaluated in Tables I and II, the Sell in May effect

[6] 13 of those 28 countries remain significant at the 1% level

indeed appears to exist, chiefly in European, North American (Canada and United States only), Southeast Asian and Greater Australasian / Asian-Pacific markets. It is also present in Morocco and South Africa, two of the three African markets in this study (the third is Egypt). It is clear, however, that the emerging markets of Latin American markets—encompassing all of South America as well as Mexico in North America—do not exhibit the Sell in May effect. Brazil is the noteworthy Latin market exception that displays the Sell in May effect at the 10% level.

Given that the Western (European and North American) markets demonstrate a strong presence of the effect, it may be inferred that the remaining non-Western markets exhibiting the similar effect are either more highly correlated with Western markets or share a past via their former Western colonial or imperialistic heads of state. For example, Japan and Taiwan both exhibit a significant Sell in May effect and are easily recognized as integral players in modern world market economies with their prowess in manufacturing and technology development. Southeast Asian countries exhibiting the effect in Equation (2) include former Dutch colony Indonesia, and former British colonies Malaysia and Singapore. Additionally, former British colony South Africa and heavily French-influenced Morocco also exhibit the Sell in May effect. However, other former British colonies in Asia not exhibiting any Sell in May effect at all include Hong Kong, India, Pakistan, and Sri Lanka (Ceylon).

b. Empirical Results for Sub-periods

To test the robustness of the Sell in May effect, the data set is divided into four sub-periods for the 18 developed countries. The first three sub-periods are equal in length at ten years and cover the periods of January 1970 to December 1979, January 1980 to December 1989, and January 1990 to December 1999. The fourth sub-period rounds out the remaining years of the entire dataset in our sample, covering ten years and nine months, and spans January 2000 to September 2010. Table III presents the sub-period regression results for these eighteen countries.[7]

Under each country panel and four sub-periods in Table III, Equation (1) corresponds to the Sell in May effect and Equation (2) corresponds to the Sell in May effect with a January effect combined. Recall that 14 of the 18 countries report a significant Sell in May effect with a January effect adjustment for the whole sampling period as shown in Table I. Sub-period results reported in Table III reveal an apparent non-stationarity of the Sell in May effect over time across different countries. Examining the empirical results from Equation (2), several observations are noted. First, the Sell in May effect seems to be more evident in the 3rd sub-period given significant α_1's are found for 10 countries. Second, the Sell in May effect is more persistent in Austria, Belgium and Japan as the significant coefficients are reported for 3 out of the 4 sub-periods. However, no country in our sample exhibits the Sell in May effect consistently throughout the 4 sub-periods. Third, Canada and the United States, which display a significant Sell in May effect in Table I, do not reveal any presence of a significant Sell in May effect for any of the four sub-periods. Finally, similar to Maberly and Pierce (2003), our results in Table III show that Japan has a significant presence of the Sell in May effect in the first two sub-periods of 1970-1979 and 1980-1989, but not in the third sub-period of 1990-2000. Maberly and Pierce (2003) present that Japan exhibits the Sell in May effect for the period of January 1970-December 1986, but no such effect in the second period of January 1987-December 2003.

[7] To save space, the estimates of intercept coefficients are eliminated in the Table. The results are available on request from the authors.

They assert that the internationalization of the Japanese financial markets in 1985-86 demarcates the time in which the Sell in May effect essentially disappeared from the Japanese markets.

Table IV presents the regression results of Equations (1) and (2) for the 3rd and the 4th sub-periods of the remaining 32 countries with shorter data series. Ten countries report a significant Sell in May effect sporadically. Similar to the results found in Table III, the Sell in May effect is non-stationary over different sub-periods. Among the 8 countries reporting significant Sell in May effect in Table II, only 2 countries (Ireland and Morocco) exhibit a significant Sell in May effect in both sub-periods. Three countries (Malaysia, South Africa and Taiwan) and Indonesia report a significant Sell in May effect in the 3rd and the 4th sub-period, respectively. Brazil and Russia do not exhibit a significant Sell in May effect in neither of the two sub-periods.

In sum, Tables III and IV provide evidence that the Sell in May effect indeed appears to pervade many country markets, but without any definite worldwide patterns. The empirical evidence suggests the Sell in May effect is more evident among developed countries than emerging markets. Nevertheless, the observation that the strong presence in Europe during 1990s is less apparent during the most recent sub-period of 2000-2010 seems to be consistent with the old finance tenet that anomalies tend to disappear over time.

V. Conclusions

This study of 50 worldwide markets finds that the Sell in May effect is statistically significant in 28 of 50 worldwide markets. The fifty worldwide markets represent the majority of country market indices available from MSCI. Even with the adjustment for the January effect, 22 of the 50 worldwide markets continue to show a significant Sell in May effect. Sub-period analysis suggest that the Sell in May effect is non-stationary. Our results are consistent with those reported in previous studies that the Sell in May effect occurs in Japan over the long-run (Bouman and Jacobsen 2002) but disappears during the period between 1987 and 2003 (Maberly and Pierce 2003).

Given that data snooping is oft-cited as the force behind so-called market anomalies, the use of new data is frequently encouraged in an attempt to reduce the data mining bias. In this study, we extend Bouman and Jacobsen's (2002) data set with an additional twelve years of monthly returns. We also include more country indices in the sample. As evidenced by our empirical results, significant Sell in May effects still exist whether the analysis is conducted with longer sampling period or with wider choices of countries. Although we do not use different market indices as employed in other country-specific studies, most of their empirical results confirm that the Sell in May effect still appear over the long-term even if the national market indices are used.[8] Thus, the use of the MSCI data does not appear to factor as a source skewed in favor of harboring the presence of the Sell in May effect.

Regardless of what appears to drive the Sell in May effect, this study shows that the nature of the Sell in May anomaly proves robust in a general study of world markets over time.

[8] For example, Nikkei 225 index was used in Maberly and Pierce (2003) and the Russian Trading Stock Exchange (RTS) data was used in Reichling and Moskalenko (2007). In studies of the U.S. market for the Sell in May effect, Ciccone and Etebari (2007), Lucey and Zhao (2006) and Maberly and Pierce (2004) all used the Center for Research in Security Prices (CRSP) dataset.

At the same time, the impromptu appearance of the Sell in May effect suggests that the strategy might not be able to provide any true trading advantage or opportunity.

Table I. The Sell in May Effect: Whole Sampling Period Results for Developed Markets

This table reports the regression results of the Sell in May effect for the whole sampling period, from January 1970 to September 2010. Monthly returns are calculated using value-weighted MSCI reinvestment indices for 18 developed countries. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

				$R_t = \mu + \alpha_1 S_t + \varepsilon_t$ (1)		$R_t = \mu + \alpha_1 S_t + \alpha_2 J_t + \varepsilon_t$ (2)		
Country	**# of Obs.**	**Monthly Mean Returns (%)**	**Monthly Standard Deviation (%)**	**μ**	**α_1 Sell in May (No Jan. Effect)**	**μ**	**α_1 Sell in May with Jan. Effect**	**α_2 - Jan. Dummy**
Australia	489	0.46	5.86	0.001	0.010	0.001	0.008	0.003
				(0.10)	(1.59)	(0.10)	(1.42)	(0.31)
Austria	489	0.32	6.00	-0.006	0.019	-0.006	0.021	-0.012
				(-1.60)	(3.53)***	(-1.60)	(3.73)***	(-1.21)
Belgium	489	0.39	5.34	-0.006	0.020	-0.006	0.019	0.006
				(-1.85)*	(4.23)***	(-1.85)*	(3.82)***	(0.68)
Canada	489	0.57	4.98	0.001	0.011	0.001	0.010	0.004
				(0.11)	(2.37)**	(0.11)	(2.11)*	(0.48)
Denmark	489	0.74	5.20	0.005	0.005	0.005	0.000	0.025
				(1.48)	(1.07)	(1.49)	(0.18)	(2.78)***
France	489	0.52	5.91	-0.005	0.020	-0.005	0.020	0.002
				(-1.35)	(3.88)***	(-1.34)	(3.65)***	(0.16)
Germany	489	0.37	5.78	-0.004	0.015	-0.004	0.016	-0.006
				(-1.04)	(2.91)***	(-1.04)	(2.95)***	(-0.60)
Hong Kong	489	0.61	5.49	0.006	0.008	0.006	0.005	0.019
				(0.91)	(0.88)	(0.91)	(0.50)	(1.12)
Italy	489	0.40	6.78	-0.008	0.025	-0.008	0.021	0.022
				(-1.92)*	(4.08)***	(-1.93)*	(3.33)***	(1.90)*
Japan	489	0.34	5.41	-0.005	0.017	-0.005	0.017	-0.002
				(-1.43)	(3.41)***	(-1.43)	(3.32)***	(-0.21)
Netherlands	489	0.44	5.30	-0.004	0.018	-0.004	0.018	0.002
				(-1.34)	(3.78)***	(-1.34)	(3.52)***	(0.25)
Norway	489	0.63	7.45	-0.000	0.013	-0.000	0.010	0.020
				(-0.08)	(2.00)**	(-0.08)	(1.43)	(1.58)
Singapore	489	0.61	7.99	-0.002	0.016	-0.002	0.012	0.021
				(-0.43)	(2.22)**	(-0.44)	(1.65)*	(1.55)
Spain	489	0.58	5.88	-0.003	0.016	-0.003	0.015	0.005
				(-0.85)	(2.91)***	(-0.85)	(2.64)***	(0.45)
Sweden	489	0.90	6.54	-0.002	0.022	-0.002	0.021	0.009
				(-0.51)	(3.82)***	(-0.50)	(3.39)***	(0.83)
Switzerland	489	0.34	4.93	-0.000	0.010	-0.001	0.010	0.006
				(-0.15)	(2.20)**	(-0.15)	(1.88)*	(0.68)
United Kingdom	489	0.57	5.68	-0.002	0.017	-0.003	0.016	0.005
				(-0.77)	(3.35)***	(-0.77)	(3.04)***	(0.48)
United States	489	0.51	4.58	0.001	0.009	0.001	0.009	-0.0000
				(0.18)	(2.12)**	(0.18)	(2.03)**	(-0.04)

Table II. The Sell in May Effect: Whole Sampling Period Results for Emerging Markets

This table reports the regression results of the Sell in May effect for the whole sampling period, from January 1970 to September 2010. Monthly returns are calculated using value-weighted MSCI reinvestment indices for 32 emerging countries. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

				$R_t = \mu + \alpha_1 S_t + \varepsilon_t$ (1)		$R_t = \mu + \alpha_1 S_t + \alpha_2 J_t + \varepsilon_t$ (2)		
Country	**# of Obs.**	**Monthly Mean Returns (%)**	**Monthly Standard Deviation (%)**	**μ**	**α_1 Sell in May (No Jan. Effect)**	**μ**	**α_1 Sell in May with Jan. Effect**	**α_2 - Jan. Dummy**
Argentina	273	4.49	20.34	0.037	0.016	0.037	0.018	-0.007
				(2.13)**	(0.65)	(2.13)**	(0.65)	(-0.15)
Brazil	273	7.91	17.46	0.057	0.044	0.057	0.037	0.046
				(3.85)***	(2.10)**	(3.85)***	(1.65)*	(1.15)
Chile	273	1.48	6.21	0.011	0.008	0.011	0.006	0.015
				(2.05)**	(1.06)	(2.05)**	(0.70)	(1.02)
China	213	-0.11	10.61	-0.000	-0.003	-0.000	0.007	-0.062
				(-0.03)	(-0.23)	(-0.03)	(0.47)	(-2.27)*
Colombia	213	1.58	8.34	0.006	0.019	0.006	0.018	0.009
				(0.77)	(1.69)*	(0.77)	(1.48)	(0.41)
Czech	189	0.64	7.60	-0.000	0.013	-0.000	0.014	-0.003
Republic				(-0.03)	(1.22)	(-0.03)	(1.20)	(-0.14)
Egypt	189	1.38	9.27	0.000	0.027	0.000	0.018	0.056
				(0.03)	(2.04)*	(0.03)	(1.27)	(2.26)**
Finland	345	1.01	8.65	0.001	0.018	0.001	0.015	0.016
				(0.20)	(1.94)*	(0.20)	(1.57)	(0.91)
Greece	273	0.57	9.82	-0.005	0.022	-0.005	0.020	0.011
				(-0.58)	(1.82)*	(-0.58)	(1.58)	(0.50)
Hungary	189	1.36	10.02	0.000	0.027	0.000	0.024	0.020
				(0.01)	(1.87)*	(0.01)	(1.55)	(0.74)
India	213	1.03	8.29	0.007	0.006	0.007	0.008	-0.010
				(0.85)	(0.52)	(0.85)	(0.63)	(-0.47)
Indonesia	273	1.48	11.53	-0.002	0.033	-0.002	0.032	0.006
				(-0.23)	(2.34)**	(-0.23)	(2.16)**	(0.23)
Ireland	273	-0.01	6.51	-0.014	0.027	-0.014	0.024	0.018
				(-2.53)**	(3.54)***	(-2.53)**	(3.01***	(1.20)
Israel	213	0.56	6.69	-0.001	0.014	-0.001	0.014	-0.002
				(-0.18)	(1.48)	(-0.18)	(1.44)	(-0.09)
Jordan	273	0.37	5.36	-0.001	0.09	-0.001	0.005	0.024
				(-0.14)	(1.34)	(-0.14)	(0.67)	(2.00)**
Korea	273	0.65	9.04	-0.003	0.018	-0.003	0.013	0.027
				(-0.36)	(1.62)	(-0.36)	(1.15)	(1.31)
Malaysia	273	0.64	7.76	-0.003	0.019	-0.003	0.019	0.001
				(-0.50)	(2.04)**	(-0.50)	(1.93)*	(0.05)

Table II. Continued

Country	# of Obs.	Monthly Mean Returns (%)	Monthly Standard Deviation (%)	$R_t = \mu + \alpha_1 S_t + \varepsilon_t$ (1) μ	$R_t = \mu + \alpha_1 S_t + \varepsilon_t$ (1) α_1 Sell in May (No Jan. Effect)	$R_t = \mu + \alpha_1 S_t + \alpha_2 J_t + \varepsilon_t$ (2) μ	$R_t = \mu + \alpha_1 S_t + \alpha_2 J_t + \varepsilon_t$ (2) α_1 Sell in May with Jan. Effect	$R_t = \mu + \alpha_1 S_t + \alpha_2 J_t + \varepsilon_t$ (2) α_2 - Jan. Dummy
Mexico	273	2.10	7.97	0.015	0.012	0.015	0.013	-0.009
				(2.25)**	(1.19)	(2.24)**	(1.29)	(-0.50)
Morocco	189	0.75	5.15	-0.006	0.027	-0.006	0.025	0.012
				(-1.20)	(3.77)***	(-1.20)	(3.31)***	(0.90)
New Zealand	345	0.32	6.35	0.001	0.005	0.001	0.006	-0.002
				(0.14)	(0.76)	(0.14)	(0.77)	(-0.15)
Poland	213	1.36	12.29	0.004	0.019	0.004	0.015	0.020
				(0.37)	(1.10)	(0.37)	(0.86)	(0.63)
Pakistan	213	0.64	11.03	-0.005	0.019	-0.005	0.014	0.032
				(-0.44)	(1.22)	(-0.44)	(0.83)	(1.08)
Peru	213	1.58	9.43	0.010	0.012	0.010	0.015	-0.019
				(1.07)	(0.95)	(1.07)	(1.14)	(-0.77)
Philippines	273	0.79	8.32	0.002	0.012	0.002	0.009	0.017
				(0.24)	(1.14)	(0.24)	(0.81)	(0.90)
Portugal	273	0.13	6.04	-0.006	0.014	-0.006	0.012	0.015
				(-1.14)	(1.97)*	(-1.14)	(1.55)	(1.07)
Russia	189	1.07	16.81	-0.008	0.038	-0.008	0.047	-0.053
				(-0.47)	(1.56)	(-0.47)	(1.83)*	(-1.15)
South Africa	213	0.96	6.08	0.001	0.017	0.001	0.018	-0.001
				(0.23)	(2.01)**	(0.23)	(2.08)**	(-0.54)
Sri Lanka	183	0.71	9.81	0.034	-0.020	0.034	-0.014	-0.035
				(1.09)	(-0.46)	(1.09)	(-0.31)	(-0.44)
Taiwan	273	0.45	10.18	-0.015	0.039	-0.015	0.037	0.008
				(-1.79)*	(3.18)***	(-1.78)*	(2.92)***	(0.34)
Thailand	273	0.57	10.57	-0.005	0.020	-0.005	0.015	0.033
				(-0.55)	(1.57)	(-0.55)	(1.08)	(1.37)
Turkey	273	3.36	14.89	0.020	0.027	0.020	0.021	0.035
				(1.60)	(1.48)	(1.60)	(1.10)	(1.02)
Venezuela	180	1.78	11.34	0.024	-0.006	0.024	-0.002	-0.022
				(1.85)*	(-0.33)	(1.85)*	(-0.13)	(-0.63)

Table III. The Sell in May Effect: Sub-Period Results for Developed Markets

This table reports the regression results of the Sell in May effect, performed on 18 developed markets during four sub-periods: Jan. 1970 to Dec. 1979, Jan. 1980 to Dec. 1989, Jan. 1990 to Dec. 1999, and Jan. 2000 to Sep. 2010. There are 120 observations each for the first three periods, and 129 observations for the last period. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. To reserve space, the estimates of coefficient μ are not reported.

	Sub-period 1: January 1970 - December 1979		**Sub-period 2: January 1980 – December 1989**		**Sub-period 3: January 1990 – December 1999**		**Sub-period 4: January 2000 – September 2010**	
	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)
Australia								
α_1	0.011	0.007	0.008	0.006	0.012	0.012	0.003	0.006
	(0.92)	(0.55)	(0.56)	(0.42)	(1.64)	(1.59)	(0.37)	(0.82)
α_2		0.026		0.010		-0.002		-0.020
		(1.11)		(0.37)		(-0.11)		(-1.52)
Austria								
α_1	0.003	0.002	0.014	0.024	0.034	0.031	0.024	0.027
	(0.69)	(0.48)	(1.37)	(2.20)**	(2.64)***	(2.31)**	(1.91)*	(2.01)**
α_2		0.005		-0.055		0.016		-0.015
		(0.59)		(-2.82)***		(0.66)		(-0.62)
Belgium								
α_1	0.025	0.018	0.023	0.023	0.022	0.021	0.011	0.015
	(3.95)***	(2.84)***	(2.20)**	(2.05)**	(2.73)***	(2.45)**	(0.95)	(1.25)
α_2		0.043		0.002		0.007		-0.024
		(3.76)***		(0.12)		(0.46)		(-1.10)
Canada								
α_1	0.013	0.010	0.013	0.011	0.008	0.008	0.009	0.010
	(1.45)	(1.05)	(1.24)	(1.03)	(1.03)	(1.01)	(0.99)	(1.12)
α_2		0.019		0.010		-0.002		-0.010
		(1.13)		(0.50)		(-0.11)		(-0.59)
Denmark								
α_1	0.001	-0.006	-0.001	-0.005	0.013	0.007	0.008	0.007
	(0.03)	(-0.79)	(-0.05)	(-0.48)	(1.32)	(0.68)	(0.74)	(0.68)
α_2		0.038		0.026		0.035		0.001
		(2.71)***		(1.41)		(1.96)*		(0.07)
France								
α_1	0.015	0.009	0.027	0.025	0.030	0.030	0.011	0.016
	(1.34)	(0.81)	(2.31)**	(2.07)**	(3.09)***	(2.93)***	(1.12)	(1.64)
α_2		0.033		0.010		0.000		-0.033
		(1.59)		(0.44)		(0.02)		(-1.83)*
Germany								
α_1	0.015	0.009	0.006	0.011	0.025	0.024	0.014	0.020
	(1.98)**	(1.18)	(0.52)	(0.97)	(2.41)**	(2.17)**	(1.19)	(1.59)
α_2		0.034		-0.032		0.008		-0.033
		(2.48)**		(-1.59)		(0.40)		(-1.49)
Hong Kong								
α_1	-0.005	-0.017	0.027	0.017	0.002	0.008	0.007	0.011
	(-0.19)	(-0.68)	(1.40)	(0.85)	(0.13)	(0.46)	(0.62)	(0.87)
α_2		0.075		0.059		-0.034		-0.020
		(1.65)		(1.63)		(-1.11)		(-0.90)
Italy								
α_1	0.016	0.011	0.026	0.018	0.044	0.040	0.012	0.016
	(1.43)	(0.91)	(1.91)*	(1.24)	(3.52)***	(3.01)***	(1.24)	(1.55)
α_2		0.034		0.052		0.028		-0.023
		(1.56)		(2.03)**		(1.16)		(-1.21)

Table III. Continued

	Sub-period 1: January 1970 - December 1979		**Sub-period 2: January 1980 – December 1989**		**Sub-period 3: January 1990 – December 1999**		**Sub-period 4: January 2000 – September 2010**	
	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)
Japan								
α_1	0.018	0.016	0.023	0.021	0.008	0.008	0.017	0.022
	(2.09)**	(1.75)*	(2.83)***	(2.51)**	(0.64)	(0.61)	(1.85)*	(2.26)**
α_2		0.014		0.009		-0.001		-0.028
		(0.81)		(0.60)		(-0.02)		(-1.59)
Netherlands								
α_1	0.025	0.019	0.015	0.011	0.021	0.024	0.011	0.016
	(2.98)***	(2.22)**	(1.47)	(1.06)	(2.60)**	(2.73)***	(1.03)	(1.46)
α_2		0.035		0.022		-0.013		-0.031
		(2.25)**		(1.14)		(-0.85)		(-1.54)
Norway								
α_1	0.005	-0.004	0.009	0.001	0.026	0.022	0.015	0.021
	(0.34)	(-0.29)	(0.57)	(0.05)	(2.06)**	(1.72)*	(1.17)	(1.56)
α_2		0.054		0.047		0.019		-0.034
		(2.06)**		(1.66)*		(0.79)		(-1.44)
Singapore								
α_1	0.010	-0.006	0.023	0.015	0.024	0.029	0.008	0.012
	(0.54)	(-0.34)	(1.50)	(0.93)	(1.86)*	(2.18)**	(0.70)	(0.95)
α_2		0.094		0.049		-0.032		-0.021
		(2.88)***		(1.70)*		(-1.33)		(-0.94)
Spain								
α_1	0.016	0.016	0.012	0.005	0.030	0.028	0.006	0.011
	(1.83)*	(1.68)*	(1.02)	(0.44)	(2.50)**	(2.21)**	(0.55)	(1.03)
α_2		0.004		0.039		0.012		-0.032
		(0.21)		(1.82)*		(0.52)		(-1.61)
Sweden								
α_1	0.025	0.021	0.019	0.017	0.025	0.022	0.020	0.023
	(3.01)***	(2.36)**	(1.65)	(1.37)	(1.95)*	(1.64)	(1.54)	(1.73)*
α_2		0.028		0.014		0.018		-0.021
		(1.77)*		(0.65)		(0.74)		(-0.86)
Switzerland								
α_1	0.015	0.005	0.003	0.005	0.017	0.017	0.004	0.008
	(1.63)	(0.57)	(0.31)	(0.52)	(1.83)*	(1.68)*	(0.51)	(0.98)
α_2		0.058		-0.013		0.004		-0.023
		(3.50)***		(-0.76)		(0.20)		(-1.59)
United Kingdom								
α_1	0.029	0.023	0.022	0.016	0.012	0.013	0.006	0.014
	(2.06)**	(1.56)	(2.17)**	(1.50)	(1.61)	(1.63)	(0.73)	(1.71)*
α_2		0.036		0.038		-0.005		-0.046
		(1.38)		(1.96)*		(-0.33)		(-3.21)***
United States								
α_1	0.012	0.011	0.007	0.003	0.011	0.011	0.006	0.010
	(1.41)	(1.28)	(0.75)	(0.28)	(1.51)	(1.45)	(0.71)	(1.15)
α_2		0.003		0.024		-0.001		-0.025
		(0.21)		(1.44)		(-0.06)		(-1.54)

Table IV. The Sell in May Effect: Sub-Period Results for Emerging Markets

This table reports the regression results of the Sell in May effect, performed on 32 emerging markets for the 3rd and the 4th sub-periods. Due to data availability, some countries do not contain data covering the full duration of the 3rd sub-period. In this case, the number of observations noted by "N" is the number of observations (months) available in the 3rd sub-period. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. To reserve space, the estimates of coefficient μ are not reported.

	Sub-period 3: January 1990 – December 1999		**Sub-period 4: January 2000 – September 2010**		**Sub-period 3: January 1990 – December 1999**		**Sub-period 4: January 2000 – September 2010**	
	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)
	Argentina				**Brazil**			
α_1	0.048	0.055	0.026	0.014	0.072	0.047	0.010	0.014
	(1.40)	(1.52)	(1.24)	(0.67)	(1.92)*	(1.20)	(0.78)	(1.03)
α_2		-0.040		0.066		0.153		-0.022
		(-0.62)		(1.69)*		(2.17)**		(-0.92)
	Chile				**China (N = 84)**			
α_1	0.013	0.010	-0.000	-0.002	-0.009	0.007	0.000	0.007
	(0.93	(0.71)	(-0.05)	(-0.22)	(-0.32)	(0.24)	(0.02)	(0.45)
α_2		0.015		0.008		-0.096		-0.041
		(0.57)		(0.55)		(-1.81)*		(-1.38)
	Colombia (N = 84)				**Czech Republic (N = 60)**			
α_1	0.032	0.034	0.011	0.007	0.005	0.011	0.017	0.015
	(1.65)	(1.68)*	(0.79)	(0.47)	(0.24)	(0.49)	(1.33)	(1.12)
α_2		-0.014		0.024		-0.035		0.011
		(-0.38)		(0.90)		(-0.87)		(0.46)
	Egypt (N = 60)				**Finland**			
α_1	0.033	0.023	0.025	0.015	0.027	0.019	0.011	0.016
	(1.63)	(1.08)	(1.42)	(0.85)	(1.61)	(1.10)	(0.67)	(0.86)
α_2		0.063		0.054		0.046		-0.024
		(1.65)		(1.67)*		(1.46)		(-0.73)
	Greece				**Hungary (N = 60)**			
α_1	0.057	0.050	0.004	0.004	0.052	0.045	0.015	0.013
	(3.09)**	(2.57)**	(0.25)	(0.27)	(1.62)	(1.33)	(1.03)	(0.85)
α_2		0.044		-0.003		0.042		0.011
		(1.27)		(-0.11)		(0.68)		(0.40)
	India (N = 84)				**Indonesia**			
α_1	0.008	0.007	0.005	0.008	0.044	0.037	0.027	0.029
	(0.44)	(0.36)	(0.31)	(0.52)	(2.02)**	(1.61)	(1.76)*	(1.82)*
α_2		0.006		-0.020		0.044		-0.014
		(0.18)		(-0.73)		(1.05)		(-0.49)
	Ireland				**Israel (N = 84)**			
α_1	0.032	0.027	0.024	0.025	0.018	0.018	0.011	0.011
	(3.19)***	(2.60)**	(1.91)*	(1.91)*	(1.25)	(1.16)	(0.90)	(0.90)
α_2		0.028		-0.007		0.002		-0.004
		(1.51)		(-0.32)		(0.07)		(-0.16)
	Jordan				**Korea**			
α_1	0.023	0.022	-0.000	-0.006	0.012	0.003	0.022	0.021
	(2.94)***	(2.64)***	(-0.02)	(-0.55)	(0.61)	(0.17)	(1.54)	(1.44)
α_2		0.008		0.035		0.049		0.002
		(0.51)		(1.71)*		(1.38)		(0.07)

Table IV. Continued

	Sub-period 3: January 1990 – December 1999		Sub-period 4: January 2000 – September 2010		Sub-period 3: January 1990 – December 1999		Sub-period 4: January 2000 – September 2010	
	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)	Eq. (1)	Eq. (2)
	Malaysia				**Mexico**			
α_1	0.025	0.033	0.011	0.004	0.016	0.020	0.012	0.013
	(1.37)	(1.75)*	(1.13)	(0.44)	(0.98)	(1.17)	(1.09)	(1.16)
α_2		-0.046		0.037		-0.024		-0.009
		(-1.34)		(2.10)**		(-0.78)		(-0.42)
	Morocco (N = 60)				**New Zealand**			
α_1	0.024	0.023	0.029	0.026	0.005	0.004	0.010	0.010
	(2.32)**	(2.05)**	(3.05)***	(2.65)***	(0.51)	(0.33)	(1.20)	(1.20)
α_2		0.009		0.014		0.010		-0.003
		(0.47)		(0.78)		(0.49)		(-0.21)
	Poland (N = 84)				**Pakistan (N = 84)**			
α_1	0.035	0.024	0.008	0.009	0.013	0.014	0.023	0.013
	(0.93)	(0.63)	(0.56)	(0.62)	(0.49)	(0.52)	(1.18)	(0.64)
α_2		0.064		-0.008		-0.010		0.059
		(0.91)		(-0.29)		(-0.19)		(1.58)
	Peru (N = 84)[a]				**Philippines**			
α_1	0.015	0.021	0.011	0.012	0.032	0.032	0.002	-0.004
	(0.68)	(0.92)	(0.66)	(0.70)	(1.85)*	(1.75)*	(0.14)	(-0.31)
α_2		-0.037		-0.007		0.001		0.034
		(-0.90)		(-0.23)		(0.02)		(1.45)
	Portugal				**Russia (N = 60)**			
α_1	0.024	0.019	0.012	0.013	0.066	0.088	0.025	0.028
	(2.14)**	(1.65)	(1.23)	(1.30)	(1.01)	(1.28)	(1.29)	(1.36)
α_2		0.028		-0.008		-0.132		-0.016
		(1.30)		(-0.44)		(-1.06)		(-0.44)
	South Africa (N = 84)				**Sri Lanka (N = 84)**			
α_1	0.034	0.038	0.005	0.006	0.011	0.013	-0.049	-0.040
	(2.44)**	(2.50)**	(0.50)	(0.53)	(0.53)	(0.60)	(-0.62)	(-0.48)
α_2		-0.016		-0.004		-0.013		-0.053
		(-0.58)		(-0.19)		(-0.31)		(-0.37)
	Taiwan				**Thailand**			
α_1	0.060	0.065	0.025	0.022	0.024	0.016	0.013	0.011
	(3.03)***	(3.11)***	(1.83)*	(1.53)	(1.03)	(0.65)	(0.86)	(0.70)
α_2		-0.029		0.018		0.049		0.011
		(-0.75)		(0.69)		(1.12)		(0.38)
	Turkey				**Venezuela (N = 84)**		**(N = 96)**	
α_1	0.006	0.049	0.009	0.010	-0.004	0.012	-0.008	-0.015
	(2.06)**	(1.61)	(0.42)	(0.42)	(-0.13)	(0.34)	(-0.39)	(-0.71)
α_2		0.065		-0.002		-0.095		0.042
		(1.18)		(-0.06)		(-1.56)		(1.12)

Figure 1: Pre-Halloween and Post-Halloween Returns – Developed Markets

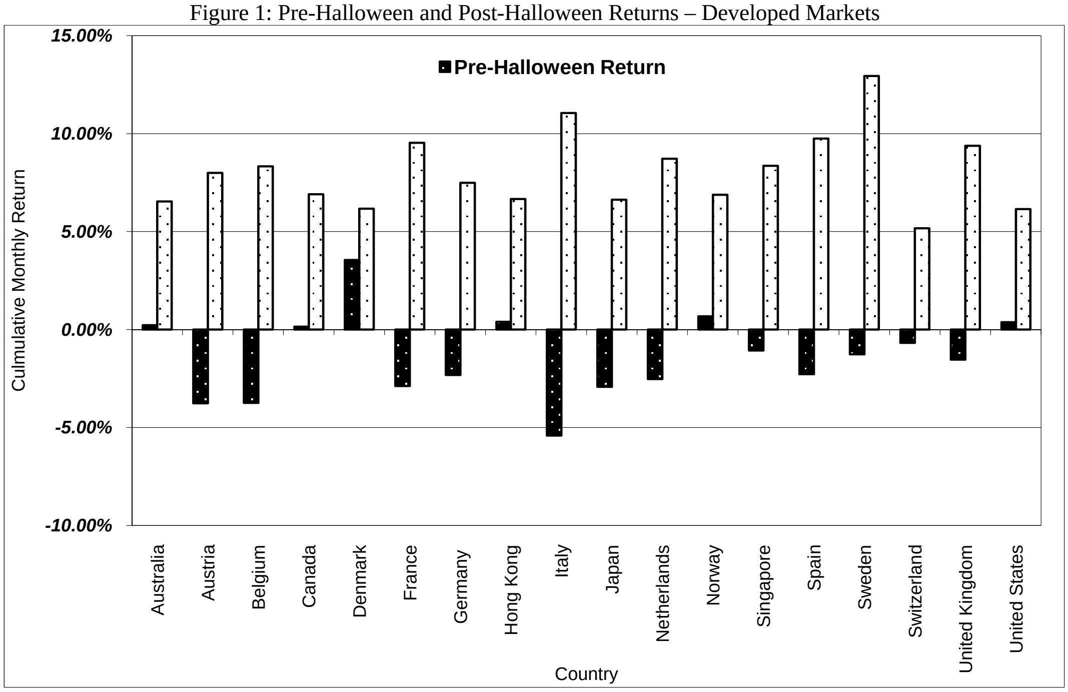
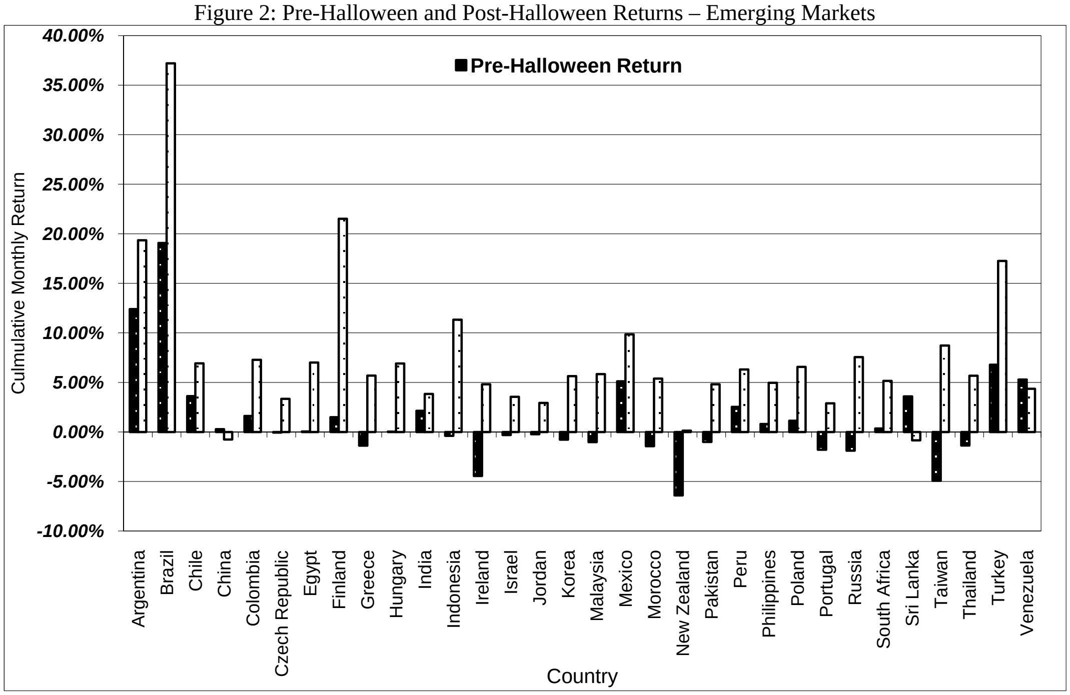


Figure 2: Pre-Halloween and Post-Halloween Returns – Emerging Markets



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Assessing Alternative Equal-Weight Asset Re-Balancing Rules

Albert E DePrince, Jr. and Pamela D. Morris

Abstract

This paper evaluates a hypothetical portfolio based on an equal-weight investment rule involving four asset classes: domestics, industrialized countries excluding the U.S., emerging market countries, and global bonds. Portfolio results using three alternative re-balancing rules are compared with a composite benchmark index. The simulation period runs from July 1996 through January 2010, which is dictated by the availability of data on the underlying asset classes. The equal-weight investment strategy is superior to investing the composite benchmark index in all three rules examined. The first involves no rebalancing over the simulation period. This provides the best performance versus the composite benchmark. The second rule collects and rebalances dividends according to the equal-weight investment rule. The third collects both dividends and capital gains and reallocates them among the four asset classes using the same equal-weight investment rule. Of these rules, there is a slight surrendering of return as one moves to more complex rebalancing rules. Additionally, the variability of portfolio return increases marginally as one moves from the baseline rule through the two rebalancing rules. Thus, a good case could be made to following a fixed investment rule and allowing the market to rebalance the portfolio.

I. Introduction

Specialized asset allocation mutual fund portfolios have proliferated in recent years, and these come in two general forms: (1) risk-based or strategic allocation funds and (2) life-cycle or target retirement date funds. As interest in asset allocation funds developed, their structure changed. Managers shifted from investment in a large number of domestics and foreign stocks and bonds to fund-of-funds. More and more strategic allocation funds are now taking on a fund-of-fund structure, whereas target retirement date funds are typically a fund-of-funds structure. The funds within the fund-of-funds structure are various cap-weighted indexes designed to provide a return consistent with the risk level of each life cycle fund.

At the same time, investment decisions have been complicated by the explosive growth of exchange-traded funds. Making sense of the maze of alternatives should be forefront in investment decisions. Admittedly, there is presently any number of vehicles available to investors that substitute the expertise of professional managers for the vagaries of individual choices. Target retirement year mutual funds have become a popular vehicle, along with various strategic asset allocation funds. These fund-of-fund vehicles dominate fund flows today.

Additionally, assorted weighting schemes have emerged as alternatives to broad market indexes. These include equal weight indexes and fundamental weight indexes (Arnott, Hsu, and

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Moore, 2005; Siegel, 2005, and Wood and Evans, 2003). Some (Hsu, 2004) even argued that traditional cap-weighted indexes were suboptimal. Of these, the equal weight index has a higher turnover rate than cap-weighted indexes (S&P, 2009), due to its quarterly rebalancing. This makes equal-weight indexes a potentially high-cost alternative to the customary cap-weighted index.

Though it has returns superior to its cap-weighted cousins, there has been only limited introduction of this asset class into either mutual fund families or exchange-traded funds (ETFs). Nonetheless, the equal-weight index is an intriguing innovation, and the equal-weight notion embedded in the index can potentially lend itself to an asset allocation model which is the subject of this paper.

This study looks to a variant of this theme in which cash flows are distributed among cap-weighted asset classes on an equal-weight basis. As such, it addresses the questions as to whether a fix-allocation rule can provide returns superior to a benchmark index or a composite benchmark index. If so, this can provide a low cost vehicle to generate either the risk-based or the life-cycle asset allocation funds. The possibility of a low-cost equal-weight rebalancing alternatives to more complex fund-of fund structure is intriguing to an industry beset by rising expense ratios in recent years.

To addresses this question, the paper first provides a background on the asset allocation funds and the alternative indexes, followed by a description of the baseline equal-investment rule and the two extensions of the rule. These extensions deal with asset rebalancing among the indexes during the simulation horizon. The data are discussed, along with the data smoothing methodology. The investment rule is simulated over a 13 ½ year period (July 1996 through January 2010) for the baseline rule and the two extensions. Implications of the findings for both individual investors and fund-of-funds managers are discussed. Shortcomings are noted, and the study ends with a look to the future, including both a sense of how fund-of-funds might expand in the future.

II. Background on Asset Allocation Funds

Investors, whether individual or institutional, must make portfolio allocation decisions. Defining the stock, bond, and cash or money market composition of a portfolio is making a strategic allocation decision (Blake, Lehmann, and Timmermann, 1999). Strategic asset allocation decisions account for 94% of the total return differential in pension funds that are institutionally managed (Bogle, 1994, p. 235). Financial analysts, researchers, and fund directors interested in enhancing portfolio returns and diversifying risk have developed and investigated various asset allocation funds (Indjic, 2002). In their development, focus is placed on the needs and characteristics of the investor in order to determine asset inclusion and weights. In order to meet investor's demand, hybrid funds have evolved into two broad investment strategies, (1) risk-based funds and (2) life-cycles funds. The risk-based funds are broadly called strategic asset allocation funds and typically carry a risk profile of conservative, moderate, or aggressive. Life-cycle funds are the target retirement date funds.

An important aspect to consider when making allocation decisions is the investor’s investment horizon, which is highly dependent on age and life expectancy of the investor

(Poterba, 2001). Rational investors are assumed to be increasingly interested in protecting against principal loss as the term of their investment horizon becomes shorter; yet many investors appear to become relatively more risky over time by failing to reduce their portfolio risk as they age (Ameriks & Zeldes, 2001). These investors' allocation strategies are not necessarily irrational but can be attributed to inertia (Rugh, 2003). Target-date funds solve this inertia problem by altering the allocations as the investor approaches retirement or the funds target date. Target-date funds meet the needs of investors, who without them are perceived as irrational due to their failure to rebalance and/or modify their portfolio allocations.

At their simplest level, risks-based asset allocation funds are balanced. More recent entrants are the asset allocation funds with gradients of risk — conservative, moderate, or aggressive. Each has a mix between stocks and bonds. All must be periodically rebalanced as market valuations of the assets fluctuate. Also, asset allocation mix of those with gradients of risk will alter the mix funds geared toward obtaining the highest returns attempting to time the market varying mix of either individual stock and bonds or the underlying funds in a fund-of-funds structure in an attempt to provide a management enhanced yield. Where funds are composed of individual stocks and bonds, asset selection is actively managed. In response to expenses as well as the evolution of the asset allocation regimes, risk-based allocation funds with gradients of risk are shifting to a fund-of-funds structure. The target-date funds are typically fund-of-funds structures.

As such, the expenses associated with these asset allocation funds are higher than those associated with index funds. As of December 31, 2009, the average net expense ratio for all asset allocation funds was 1.28 percent (Principia). This represented all share classes and a total of 1447 funds. Of these share classes, 643 were fund-of-fund structures with an average net expense ratio of 1.14 percent. This compares to a net expense ratio of 0.11 percent for the 100 least expensive index funds and 0.22 percent for the next 100 least expensive. Admittedly, the industry has developed some expense index funds. The next 718 index funds have an average net expense ratio of 1.20 percent.

III. Research Objective and Methodology

This study presents alternative fixed-rule allocation schemes that seek exposure to all segments of the U.S. equity market and a broad exposure to the international (developed and emerging market) equity market, and a global bond exposure.

The approach developed and tested in this paper uses a fund-of-funds approach. This can be used either at the asset manager level in a specialized fund-of-funds or on a “do-it-yourself” portfolio for individual investors. The advantage it has over existing strategic allocation models is the fact that all the underlying funds are index funds or ETFs, and hence have lower expense ratios than actively managed funds. Hence, it is cost-effective compared with existing products.

The study begins with the notion that a separate exposure to all segments of the global market in a systematic manner is preferred to investment in the market as a whole using a broad cap-weighted index such as the MSCI All Country World Index. A similar philosophy underscores existing strategic asset allocation models.

To that end, this study develops a fund-of-funds with a broad domestic exposure (captured by the Wilshire 5000), an exposure to industrialized countries (MSCI EAFE Index), an emerging market exposure (MSCI EM Index), and a global bond exposure (Barclays Capital Global Bond Index).

At this point, exchange traded funds (ETFs) are available for these broad asset classes, and from a cost perspective, ETFs are low cost alternatives to mutual funds. The choice of underlying funds will influence the realized return due to the underlying expense ratios. This study uses index returns and does not get into the issue of the choice of underlying funds; the choice, however, will influence the real-world realized returns of the allocation strategies discussed below.

The process begins with a fund-of-funds in which the initial mix is based on a simple equal-weight weight rule, namely, 25 percent of the months investment will be made in each of the four asset classes. A set dollar amount is added to the portfolio at the end of each quarter and is allocated in accordance to the same 25 percent per asset category rule as the initial allocation.

Three alternative asset allocation schemes are then assessed. In the baseline, the quarterly investment of contributions follows the equal-weight rule, and dividends and capital gains reinvested in the asset class that generated the dividends and capital gains. No re-allocation will be made throughout the simulation horizon. This inertia assumption allows markets to reallocate the investments on an ongoing basis.

The baseline equal-weight investment strategy assumes that an equal cash contribution is made monthly into each of the asset classes. No reallocations are made. Thus, the equal weight refers to the contribution into each of the four asset classes. At the outset of the simulation period each of the four asset classes have an equal weight. Going forward, the market will effectively reallocate between the four asset classes as the market total return varies among the classes. The value of each asset class at any point in time may be denoted by

$$wilshire_t = wilshire_{t-1} \times (1 + r_{w,t}) + div_{w,t} \times wilshire_{t-1} + 1000$$

$$EAFE_t = EAFE_{t-1} \times (1 + r_{eafe,t}) + div_{eafe,t} \times EAFE_{t-1} + 1000$$

$$EM_t = EM_{t-1} \times (1 + r_{bond,t}) + div_{bond,t} \times BOND_{t-1} + 1000$$

$$BOND_t = BOND_{t-1} \times (1 + r_{bond,t}) \times BOND_{t-1} + 1000$$

$$portfolio_t = wilshire_t + EAFE_t + EM_t + BOND_t$$

This model assumes that the periodic contribution is made at the end of each period (monthly). Additionally, the dollar value of this period’s dividends is based on last period’s portfolio and the dividend contribution portion of this period’s total return.

The equal-weight investment rule rests on the assumption that over time, markets reallocate the portfolio, which may be superior to any attempt to capture rotation among asset classes. At its simplest level, this may be a test of the way most individuals make their monthly contributions into sponsored retirement plans, that is, a fixed dollar amount allocated among a preset choice of funds with little change in that investment strategy over time. Here, there is some evidence of investor inertia in terms of either the portfolio or the contributions (ICI).

The second scheme collects the capital gains at the end of each quarter and allocates them among the four asset classes on an equal weight (25 percent) basis. In this alternative, capital gains remain with the asset class that generated the capital gains. The third alternative collects the capital gains and the dividends at the end of each quarter and reallocates them based on the same equal-weight rule. This alternative may be denoted by

$$wilshire_t = wilshire_{t-1} \times (1 + r_{w,t}) + (div_{w,t} \times wilshire_{t-1} + div_{eafe,t} \times EAFE_{t-1} \\ div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1}) / 4 + 1000$$

$$EAFE_t = EAFE_{t-1} \times (1 + r_{eafe,t}) + (div_{w,t} \times wilshire_{t-1} + div_{eafe,t} \times EAFE_{t-1} \\ div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1}) / 4 + 1000$$

$$EM_t = EM_{t-1} \times (1 + r_{em,t}) + (div_{w,t} \times wilshire_{t-1} + div_{efea,t} \times EAFE_{t-1} \\ div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1}) / 4 + 1000$$

$$BOND_t = BOND_{t-1} \times (1 + r_{bond,t}) + (div_{w,t} \times wilshire_{t-1} + div_{eafe,t} \times EAFE_{t-1} \\ div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1}) / 4 + 1000$$

$$portfolio_t = wilshire_t + EAFE_t + EM_t + BOND_t$$

The third alternative collects the capital gains and the dividends at the end of each quarter and reallocates them based on the same equal-weight rule. This alternative may be denoted by

$$wilshire_t = (portfolio_{t-1} / 4) \times (1 + r_{w,t}) + (div_{w,t} \times wilshire_{t-1} + div_{eafe,t} \times EAFE_{t-1} \\ div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1}) / 4 + 1000$$

$$EAFE_t = (portfolio_{t-1} / 4) \times (1 + r_{eafe,t}) + (div_{w,t} \times wilshire_{t-1} + div_{eafe,t} \times EAFE_{t-1} \\ div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1}) / 4 + 1000$$

$$EM_t = (portfolio_{t-1} / 4) \times (1 + r_{em,t}) + (div_{w,t} \times wilshire_{t-1} + div_{efea,t} \times EAFE_{t-1} \\ div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1}) / 4 + 1000$$

$$BOND_t = (portfolio/4)_{t-1} \times (1 + r_{bond,t}) + (div_{w,t} \times wilshire_{t-1} + div_{eafe,t} \times EAFE_{t-1}$$
$$div_{em,t} \times EM_{t-1} + div_{bond,t} \times BOND_{t-1})/4 + 1000$$

$$portfolio_t = wilshire_t + EAFE_t + EM_t + BOND_t$$

This model is an outgrowth on an earlier model developed by DePrince and Morris (2007). The present study preserves their three rebalancing rules, while dealing with three shortcomings First, it was developed before the 2007-2009 financial crises, and thus does not capture extreme market movements. Second, most of the high dividend-paying stocks in the preliminary study were financials, and dividends have either been cut or eliminated in the last two years. Third and most important, the rebalancing rules were applied to six domestic styles (large cap value, large cap growth, mid-cap value, mid-cap growth, small cap growth, and small cap value), and as such, it lacked any international or fixed-income component.

IV. Benchmark

Results need to be compared with a benchmark index. Unfortunately, there are no recognized indices that combine stocks and bonds. In such cases, a composite benchmark is used. Here, the most reasonable composite is a 75 percent weight on the MSCI All Country World Index[1] and a 25 percent weight on the Barclays Capital Global Aggregate Bond Index.[2] Against this composite benchmark, the portfolios constructed above have a higher emerging markets weighting than the composite benchmark. Using these weights, the composite benchmark return over the 13 ½ year sample period is 3.76 percent.

V. Simulation Results

The simulation period used in this study extends from July 1996 through January 2010, which represents the longest common sample period for the four asset classes used in this study. In testing the equal-weight investment model, it is assumed that a total of $4000 is invested each month over this 13 ½ year period. Of this amount, an equal amount is invested each month in each of the four asset classes. As discussed earlier, two alternative investment rules are considered. Results are compared with a composite benchmark index.

a. Equal Monthly Investments in Four Asset Classes

The first stage (Model 1 in Table I) was an equal monthly investment of $1000 into each of the four asset classes. Dividends were reinvested in the investment category that generated the dividend. This produces a compound annual return of 8.1 percent over the 13 ½ year span. This performance is dominated by the performance of the emerging market sector and the bond asset

[1] The **MSCI ACWI (All Country World Index) Index** is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of developed and emerging markets. As of June 2009 the **MSCI ACWI** consisted of 45 country indices comprising 23 developed and 22 emerging market country indices. Seehttp://www.mscibarra.com/products/indices/international_equity_indices/definitions.html#WORLDThe total return of this index over the 13 ½ year sample period is 2.96 percent. This is based on data obtained at: http://www.mscibarra.com/products/indices/international_equity_indices/performance.html

[2] Unfortunately, information on this benchmark does not seem to be publically available. Thus, it was decided to use the Barclays Capital (U.S.) Aggregate Bond Index in its place. For purposes of calculating the composite return, the BlackRock Bond Index Fund, an Exchange-Traded Fund that tracks the Barclays Capital Aggregate Bond Index, is used in this study. So that the total return of the ETF is comparable to the total returns of the indexes, the ETF's 24 basis point expense ratio was added back into the net return to yield a gross return.

class. Though both the domestic and the EAFE portion of the portfolio lags behind the performance of the portfolio, the performance of the equal weight portfolio surpasses the benchmark return. This likely reflects two factors. The first is the overweight of the emerging market index in the portfolio. The second may well be the equal investment rule. A similar outcome was noted in DePrince and Morris (2007).

The asset mix (Table II) underwent considerable change over the simulation period. Low performance sectors (i.e., the domestic and the EAFE asset classes) fell beneath the original 25 percent mix, notwithstanding the equal periodic investments, while the asset weight of the high performing sectors rose above the 25 percent share. This market-based re-balancing is also a contributing factor to the superior performance of the fixed (equal) investment rule. The rise in the weight of high-performing asset classes reinforced subsequent high performance on the overall portfolio, Unfortunately, this will also contribute to an underperformance of the overall portfolio should a shift in asset class performance develop.

b. Reallocation of Dividends

The second stage (Model 2 in Table I) maintained the fixed equal monthly contribution but went on to aggregate each month's dividends. The aggregated dividends were then reallocated equally among each of the four asset classes. Here, the compound annual return slipped to 7.9 percent. The loss in performance is likely attributed to the reallocation of the coupon payments in the aggregate bond index to asset classes whose performance is less than that of the sector generating the coupons (the aggregate bond class).

Asset class weights again shifted, but the fall in the shares of the lower performing asset classes was not as large. This reflects the reallocations of the dividends (and coupons) from the high performing asset classes.

c. Reallocation of Dividends and Capital Gains

The third stage took the methodology of the second stage and went on to collect the capital gains each month. The aggregate capital gains, along with the aggregated dividends, were then reallocated equally among the four asset classes. The 13 ½ years compound annual return dips to 7.8 percent, which is still over twice the return on the benchmark composite index. Here reallocation of capital gains from high capital gains to low capital gains generating asset classes probably accounts for the slight diminution in performance compared with Models 1 and 2. Here, there is no change in the asset weights over the simulation period, reflecting the complete reallocation of both dividends and capital gains according to the equal investment rule.

VI. Rebalancing Rules and Variability of Portfolio Returns

The standard deviation of one-month portfolio returns is used as the measure of portfolio variability. These are reported in Table I. As can be seen, there is a slight increase in portfolio variability as one moves from Model 1 (fixed investment of monthly cash flows with no rebalancing of dividends or capital gains) through Model 3, which preserves the original 25 percent weight in each asset class. While the increase in returns variability may seem negligible as the asset rebalancing increases in complexity, it does suggest that the gains from such a complex rebalancing may not be worth the effort, particularly when execution costs are considered.

VII. Rebalancing Rules and Estimated Expense Ratios

Up to this point, expense ratios on the underlying funds are not considered, and the choice of funds will alter the performance outcome. To address this point, expense ratio from ETFs for each of the four asset classes were collected and combined using the average weights reported in Tables II. Expense ratios are reported in Table III for the selected iShares ETFs. Readers should note that the ETFs are large and each has a sizeable daily volume; hence, they have the liquidity necessary for periodic rebalancing. In reviewing these data, readers should also note that the iShares Russell 3000 ETF was used rather than the Wilshire 5000 Total Market Index ETF in calculating the expense ratio. This is because the Wilshire ETF has only recently been introduced, and as such, it lacks the size and liquidity needed for use in a fund structure with periodic rebalancing.

Table IV reports the effects of expense ratios on total returns. As can be seen, the effective expense ratio for Models 1 and 2 are equal and have the same effect of their respective total returns. In contrast, the effective expense ratio on Model 3 is a bit smaller, due mainly to a reduced weight on the emerging market ETF. As a result, on a net basis, the difference between Model 3 and Models 1 and 2 narrows slightly from that reported in Table II.

Finally, execution costs are involved whenever reallocations are considered. If done on a small scale, execution costs would be minimal. However, if re-allocation among separate index funds within a fund-of-funds complex is done on a large-scale basis, there will likely be execution effects. These would obviously alter the outcome from that reported in Table I, and estimating such effects are beyond the scope of this paper.

VIII. Looking Ahead

Several points need to be noted at this time. First, the world economy will likely continue the fast growth in emerging economies relative to the U.S. and Europe. As a result, shares of global GDP will begin to converge among the U.S. (represented by the Wilshire 5000), other developed countries (represented by MCSI-EAFE), and emerging economies (represented by MSCI-EM). Indeed some see the field leveling within the next 50 years (Teach, 2007). In a sense, the portfolios used in this study capture this convergence with the equal weights of the three geographic-based asset classes.

As convergence occurs, fund-of-funds will need to raise the relative share of the emerging market fund within the fund-of-funds structure. The simple world of one broad-based fund of the Vanguard model will likely give way to either one global fund (US, EAFE, and EM firms) or a three-fund combination (US, EAFE, and EM funds). However, results from this study will still likely hold. Simplicity of structure will likely provide returns equal to or better than more complicated structures after fees in the long-run.

Second, in response to the growing share of GDP in the emerging markets, the equity and bond markets in those regions will also grow, and with that growth there may well be an expansion of specialized regional funds. Already, emerging markets are showing signs of parsing itself into more specialized areas. For example, as asset values in the BRIC (Brazil, Russia, India, and China) area mature, some focus is shifting to GCC (Cooperation Council of the Arab States of the Gulf, composed of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United

Arab Emirates) and its broader cousin, MENA countries. The latter is composed of Middle East and North Africa countries. While still in the infant stage of development, funds composed of MENA countries are appearing. As examples, see Atlas (no date); Stensgaard (2008); and de Sa'Pinto (2007).

IX. Epilogue

The basic purpose of this paper was accomplished. Results show superiority of the equal-weight investment strategy in a market-encompassing an array of indexes over investment in a single market-wide index, with the best results involving no rebalancing. Interestingly, this suggests that individuals who have a fixed and roughly equal investment strategy in a limited number of index funds that encompass the entire equity market in their retirement packages may have stumbled onto an optimal strategy.

It is useful to note that while regular rebalancing of both dividends and capital gains (Model 3), to preserve the original equal-weight asset mix, comes at a slight cost compared with Model 1, the performance of Model 3 is still superior to the benchmark composite. This is important, since the complete re-balancing reduces the adverse effect of any rotation of performance among asset classes noted above. Thus, the slight surrender of performance may produce a reduced portfolio variance when such performance rotations occur. Finally, comparing results of this study and the earlier DePrince and Morris (2007) study, gains from rebalancing seem related to the time frame and the asset classes. As with the current study, the 2007 fixed rebalancing rule produced returns superior to a broad index in all three regimes. However, Unlike the present study, the 2007 study produced slightly better results for full rebalancing of dividends and capital gains. In any event, differences between the three rebalancing rules were minor as with the current study.

While results may be sample-period dependent, one conclusion seems to be clear. The fixed rebalancing rules provide returns superior to a composite index, and a strong case can be made for Model 1, i.e., fixed periodic investments while allowing the market to reallocate among asset classes.

TABLE I: Total Returns for Alternative Portfolio Simulations (July 1996—January 2010)

	Benchmark Return	Domestic Return	EAFE Return	EM Return	Aggregate Bond Return	Portfolio Return	Std Dev of Mthly Returns
Model 1*	3.76	2.27	4.05	11.80	11.08	8.12	3.85
Model 2**	3.76					7.94	4.01
Model 3***	3.76					7.81	4.06

Note: *Model 1:$1000 per fund per month no reallocation,**Model 2:$1000 per fund per month reallocation of dividends, and ***Model 3: $1000 per fund per month reallocation of dividends and accretions

TABLE II: Asset Weights

	Domestic		EAFE		EM		Aggregate Bond	
	Start	**End**	**Start**	**End**	**Start**	**End**	**Start**	**End**
Model 1	25.00	16.07	25.00	18.28	25.00	33.81	25.00	31.84
Model 2	25.00	18.66	25.00	19.65	25.00	34.96	25.00	26.74
Model 3	25.00	24.84	25.00	24.59	25.00	24.30	25.00	26.27

Table III: Expense Ratios on Underlying Funds

	ETF	**Ticker**	**Expense Ratio**	**Model Weights**		
				Model 1	Model 2	Model 3
Broad U.S. Market	iShares Russell 3000 Index	IWV	0.21	16.07	18.66	24.84
	Wilshire 5000 Total Market Index	WFVK	0.12			
EAFE	Ishares MSCI EAFE	EFA	0.35	18.28	19.65	24.59
Emerg. Mkt Index	Ishares MSCI Emerging Market Index	EEM	0.72	33.81	34.96	24.3
Broad Bond Index	iShares Barclays Capital Aggregate Bond Index	AGG	0.24	31.84	26.74	26.27

Table IV: Expense Ratios and Performance

	Gross Return	Weighted Expense Ratio	Net Return
Model 1	8.12	0.42	7.70
Model 2	7.94	0.42	7.52
Model 3	7.81	0.37	7.44

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Performance of DJIA Stocks Using Fundamental Indexation

Thomas M. Krueger and Mark A. Wrolstad

Abstract

During the decade beginning on December 31, 1999, an equal-weighted portfolio of the Dow Jones Industrial Average (DJIA) stocks outperformed the market capitalization and price-weighted portfolios, with ending values of $1,020, $731, and $777 on the $1,000 originally invested, respectively. The net income and free cash flows-weighted portfolios performed the best with identical ending values of $1,082. The portfolio with the lowest standard deviation measure of total risk was weighted on net income (14.26%) and the portfolio with the highest total risk was weighted on total assets (27.78%). All portfolios had their worst performance in 2008, while the best performance varied across portfolios but were limited to the years 2003, 2006 and 2009.

I. Introduction

Using eleven different weighting methods, we look at the performance of portfolios of DJIA stocks over the past decade. The financial literature contains information on a myriad of potential weighting strategies, of which we have chosen four different approaches for weighting portfolios. The first allocation strategy we will consider is price-weighting. The Dow Jones Industrial Average (DJIA) uses a price-weighting scheme to determine the index value. Among the DJIA's virtues are its longevity, wide dissemination, and ease of calculation. Most investments textbooks deride the Dow Jones Industrial Average because it is price-weighted instead of the assumed superior approach of being market capitalization-weighted (i.e., Gitman & Joehnk, 2008, 94-96, Reilly & Brown, 2003, 168).

A trillion dollar industry has developed around investing in indexes weighted upon market capitalization. The advantages often cited for being market capitalization-weighted include clearly identifying the investable opportunity set, revealing the average return for investors in a particular asset class, and the increasingly suspect assertion that this technique is mean-variance efficient (Arnott, 2005). Examples of market capitalization-weighting include the NASDAQ Composite, the NYSE Composite, the Russell 2000 Index, and a number of other international indexes. The best know market capitalization-weighted index has been the S&P 500 which became "float-weighted" in 1995. Float weighting uses only the number of shares (called "float") available for public trading rather than the traditional "number of shares outstanding". A major concern expressed by critics of market capitalization-weighting is that this approach tends to over-weight overpriced stocks and to under-weight underpriced stocks in the index. This happens because the market price of stocks can vary from their fundamental value for a variety of reasons often referred to as "market noise" (Carrel, 2006).This concern, of course, would also be relevant for the price-weighted DJIA.

A third alternative is to equally-weight securities in a portfolio. An example of this

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approach is the Value Line Index. An advantage to this approach is its lack of dependence upon market prices which can vary over time for a variety of reasons other than changing intrinsic M<value. However, McQuarrie (2008) found that his equal weighted S&P 500 portfolio index had over 200 bps higher volatility than either the cap-weighted S&P Index or the fundamental attribute-weighted Research Affiliates Fundamental 1000 Index (RAFI).

The fourth indexing alternative is to base the index upon fundamental factors of firms in order to avoid using the market value of the common stock (Estrada, 2008; Treynor, 2005). The motivation for discarding cap-weighting in favor of fundamental business metrics is the assumption that markets are not totally efficient (Estrada, 2008). The result of this approach is a portfolio that minimizes the return drag of over-weighting overpriced stocks and underweighting underpriced stocks that can be a significant problem with the approaches mentioned above. An example of this approach is the RAFI, which weights companies by factors such as book equity value, free cash flow, total cash dividends, and total sales. This report examines these four indexing approaches, including asset allocation based on a variety of fundamental factors

II. Literature Review

A large amount of research in the past decade has been devoted to helping profit-maximizing investors decide which of the above weighting approaches would help them achieve optimum returns with their investable funds. Arnott (2005) found that fundamental indexes outperformed the S&P 500 by approximately 2% of annual returns between 1962 and 2004. Fundamentals-weighted indexes also outperformed the equal-weighted S&P 500 and the CRSP universe, with lower risk. McQuarrie (2008) found that an equal-weight S&P 500 index outperformed the RAFI Composite with a 13.11% versus 12.47% geometric average return while the S&P 500 itself had a return of only 10.39%. Thus there does not seem to be agreement as to which of these approaches is the best one to obtain optimal investment results.

III. Research Method

This research contrasts portfolio performance arising from traditional allocation methods and a variety of fundamental factors to create portfolios of the DJIA companies in an effort to outperform the well-known index. Our research goes beyond price and shares outstanding to consider eight non-price portfolio-weighting variables. From the balance sheet, we allocate investment on the basis of total equity and total assets. From the income statement, we allocate investment on the basis of sales revenues, net income, and operating income (EBIT). From the cash flow statement, we allocate investment on the basis of cash flow from operations and free cash flow. Finally, checking the robustness of the RAFI dividend-weighted method, we allocate investment on the basis of dividends.

The thirty companies in the Dow Jones Industrial Average (DJIA) serve as the sample for this study. The initial sample is created on December 31, 1999. Table I presents a listing of the companies which were members of the Dow Jones Industrial Average during the decade. DJIA membership is quite stable. Over three fourths of the thirty companies in the DJIA are in the index for the entire ten-year sample period, which runs from 1999 through 2009.

Most of the membership volatility that occurs coincided with the recession in thelatter part of the sample period. To deal with membership changes, sample membership is updated on an annual basis. The replacement company is assumed to be in place for the whole year in which it replaces another company that is dropped out of the index. For instance, on March 8, 2004, Kodak and International Paper were replaced by Pfizer and Verizon. Year-end 2003 financial statement values for Pfizer and Verizon are used for portfolio allocation purposes in the year 2004. As a consequence, the values presented in this paper will vary slightly from those presented in the financial press for the DJIA.

Total returns are used in this research as the independent variable. Price and dividend data were obtained from finance.yahoo.com. Data used in the allocation process was primarily obtained from Morningstar.com. Missing data were obtained from the individual company financial statements. Eleven portfolios are created in total. Three of them are weighted upon the traditional allocation models of price, market value of outstanding common stock, and equal weighting. In most cases, the observed values of the allocation variables are positive in all periods. For example, firms always have positive price, sales, and total assets levels. When no dividends are paid, no allocation is made to the company on the basis of this metric. In instances where an independent variable is negative (i.e., net income), it was assumed that the portfolio shorted the weighting of this DJIA member.

IV. Results

a. Measures of Portfolio Return and Return Volatility

Returns and risk for portfolio based on the various portfolio allocation approaches are shown in Table II. Among the common valuation techniques, the equal-weighted portfolio is the only allocation technique with a positive average rate of return for the entire decade. The equal-weighted technique's arithmetic mean exceeds the value-weighted approach by 3.91 percent. The best allocation technique is free cash flow which earned 1.96 percent per year on average. The worst arithmetic mean portfolio performance is that of the value-weighted portfolio which dropped an average of 1.69percent per year.

The median return of the price-weighted portfolio was 1.83 percent worse than that of the value-weighted portfolio. Across the common valuation techniques, only the equal-weighted portfolio has a positive median. The highest median return is registered by the EBIT-weighted portfolio, at 4.72 percent. Meanwhile, the free cash flow-weighted portfolio is only slightly behind at 4.69 percent. The two lowest median returns are the price-weighted portfolio (-2.25%) and total assets-weighted portfolios (-1.80%).

When geometric returns of the common valuation techniques are considered, the value-weighted portfolio displays the worst performance at a negative 3.01 percent, as shown in Row 3 of Table II. As a consequence, the ending value of a $1000 investment on December 31, 1999 is only $731! The price-weighted portfolio is only slightly better with a geometric return of negative 2.49 percent and an ending value of $777. By contrast, the equal-weighted portfolio has a slightly positive geometric return of 0.2 percent and a gain of $20 for a $1000 initial investment. Across the eight attribute weighting schemes, net income and free cash flows provide the highest geometric mean returns. Their identical79 basis point annual gains result in a terminal value for their portfolios of $1,082. The total assets-weighted portfolio returns only 97 cents annually per dollar invested during the decade and have a terminal value of only $737.

Despite having relatively poor return performance, the value-weighted portfolio can claim to have a lower return variation than either the price-weighted or equal-weighted portfolios. Only the equal-weighted portfolio of the three common weighting schemes has a positive coefficient of variation. The coefficient of variation value of 9.39 suggests that investors experienced a nine percent level of total risk for every unit of return.

The two lowest levels of total risk are registered by the net income-weighted portfolio and the free cash flow-weighted portfolios. These two portfolios also have the lowest coefficients of variation, among those portfolios with positive values. At the other extreme, the largest standard deviations are registered by the total assets-weighted (27.78%) and equal-weighted portfolios (20.85%). The two worst coefficients of variation are posted by the operating income (EBIT)-weighted (33.4%) and the total asset-weighted portfolios (31.9%).

Given the fact that all eleven portfolios have the same thirty securities in them, we might expect the performance of the eleven portfolios in this study to be fairly similar. On an arithmetic means basis they are, with a range from only -1.69% to 2.22%. It is somewhat surprising that the different weighting approaches result in terminal portfolio values that range from $731 to $1082, a difference of $351 after 10 years. When incorporating differences in the standard deviation, we find that the coefficients of variation ran from 8.01 to 33.4, the highest being over four times larger than the lowest.

b. Analysis of Maximum and Minimum Returns

Perhaps one portfolio allocation technique works best in rising markets, while another works best in falling markets. In order to gain some insight into the difference in performance across the various markets, Panel A of Table III reports the best and worst returns for each allocation scheme and the year in which each was recorded. For ease of understanding, percentages are presented in ratio terms. Scanning across the “Best” column, one can see that the best performance among the common valuation techniques was registered by the equal-weighted portfolio with a 31 percent rate of return in 2009. Only the 41 percent return of the total assets-weighted portfolio (also in 2009) did better. At the other extreme, the lowest “Best” performance was 22 percent, which was earned by the EBIT-weighted, net income-weighted, and operating cash flow-weighted portfolios which all occurred in 2003. The years in which the best performance was registered occurred six times in 2003, three times in 2009, and twice in 2006. Both of the highest “Best” returns were earned in 2009, while the lowest “Best” returns were earned in 2003.

By comparison, the “Worst” performance for all eleven portfolios was registered in 2008. In 2008, returns ranged from a negative 19 percent to a negative 51 percent. The portfolio weighted on total assets lost slightly more than half of its value, while the portfolio weighted upon net income lost slightly less than one-fifth of its value. Across the three common weighting methods, the price-weighted method experienced the greatest percentage decline.

To provide additional insight into the performance of the various attribute allocation schemes, we looked at the performance of the best and worst security in each portfolio to see if any particular company played a major role in helping or hurting portfolio performance. Individual security performance is based on the weighting allocated to an individual DJIA member by the specified metric and the total return of that stock. These results are presented in the second panel of Table III. The largest single impact would have arisen from investing in Bank of America (BAC), which added thirty-three percent to the total assets-weighted portfolio return in 2009. In fact, Bank of America's 2009 performance had the greatest impact on the equal-weighted, total stockholders' equity-weighted, and total assets-weighted portfolios. The impact arising from Exxon Mobil's(XOM's) 2006 return is also the greatest for a specified index in three cases; sales-weighted, EBIT-weighted, and operating cash flow-weighted portfolios. If you also consider the impact of Altria(MO) in 2000 on the free cash flow-weighted and dividend-weighted portfolios, you will conclude that relatively few firms had the largest impacts across all eleven portfolios.

Attributed-weighted portfolios are also highly dependent upon a relatively small number of stocks when looking at the low side of their performance range. For instance, the losses of Microsoft in 2000 had the largest negative, single stock impact on the price-weighted and value-weighted portfolios when it dropped these portfolio returns by 4 percent and 13 percent, respectively. Exxon Mobil, ironically supplies both the largest positive impact (as mentioned in the last paragraph) and negative impact on the equal-weight weighted, sales-weighted, EBIT-weighted, net income-weighted, operating cash flows-weighted, and free cash flows-weighted portfolios.

c. Analysis of Correlations and Mean Differences

Additional analysis consisted of measuring pair-wise total return correlations across all eleven portfolios. Given the consistency of most returns and risk measures (exhibited in Table II), years with most extreme performance on a portfolio basis (Panel A of Table III), and individual component basis (Panel B of Table III), it is not surprising that a vast majority of correlations are above 0.94. There are only two correlation coefficients with values below 0.90, both of which are at the 0.87 level. One is the correlation between the returns of the value-weighted portfolio and total assets-weighted portfolio and the other is the value-weighted portfolio and the dividend-weighted portfolio correlation. Tests of correlation significance found that that the only pair-wise combination that is statistically significant at the 0.10 level of confidence is the value-weighted portfolio and free cash flow-weighted portfolio combination. Looking back at Table II, one can see that the value-weighted portfolio declined by 1.69 percent, while the free cash flow-weighted portfolio rose 1.96 percent, on average.

V. Conclusions

Assuming that financial markets are inefficiently pricing securities, a profit- maximizing investor would like to avoid over-priced stocks and allocate more money to under-priced securities. Unfortunately, this is not done reliably using the popular, price-weighted Dow Jones Industrial Average or other approaches that are based upon the market price of stocks. Some evidence was presented suggesting that firm fundamentals are better allocation criteria. However, high correlations tend to minimize the relative value of selecting information found in the financial statements.

The sample period chosen for this research has been an extremely volatile decade. There was the aftermath of the Dot-Com bubble, the 9/11terrorist attacks, the sub-prime mortgage crisis, and the election of a powerful coalition of left-of-center political leaders attempting to change the economic direction of this country. Extreme stock market highs and lows were all compressed into this one decade. Our study supports the findings of other studies that suggest that price-weighting and valuation-weighting methods may not lead to the optimal performance of a portfolio. Across the financial statements, over this period and based on financial statement information studied here, the cash flow statement appears to provide the most fertile ground for above average rates of return to the passive, long-term investor.. The average terminal value for portfolios based on cash flow statement values exceeded the income statement-based portfolios' average terminal value by $35 and the balance sheet-based portfolio's average terminal value by $180. Further research, across extended time periods or based on financial ratios, may shed additional light on security weighting techniques that magnify investor return.

Table I. Dow Jones Industrial Average Membership

Stock in DJIA for Entire Decade			
3M Company	Coca-Cola	Intel	Microsoft
Alcoa Incorporate	DuPont	International Business Machines	Procter & Gamble
American Express	Exxon Mobil	Johnson & Johnson	United Technologies
AT&T	General Electric	J.P. Morgan	Walmart
Boeing	Home Depot	McDonald's	Walt Disney
Caterpillar	Hewlett-Packard	Merck	
Changes in DJIA Membership			
On 4/8/04	Kodak & International Paper	Replaced by	Pfizer & Verizon
On 2/19/08	Altria & Honeywell	Replaced by	Bank America & Chevron
On 9/22/08	AIG	Replaced by	Kraft
On 6/8/2009	Citigroup & General Motors	Replaced by	Travelers & Cisco

Table II. Comparisons of Return and Risk Measures Across Various Allocation Methods

	Common Valuation Techniques			Income Statement Accounts			Balance Sheet Accounts		Cash Flow Statement Accounts		
	Price	Value	Equal	Sales	EBIT	Net Income	Total Stockholder Equity	Total Assets	Operating Cash Flows	Free Cash Flows	Dividend
Arithmetic Mean %	-0.29	-1.69	2.22	1.79	0.50	1.71	1.83	0.87	1.89	1.96	1.90
Median %	-2.25	-0.42	0.29	1.51	4.72	3.47	3.23	-1.80	3.24	4.69	1.32
Geometric Mean %	-2.49	-3.01	0.20	0.30	-0.87	0.79	-0.07	-3.00	0.59	0.79	-0.07
Value of $1000	$777	$731	1020	1030	917	1082	993	737	1060	1082	993
Standard Deviation %	21.30	16.9	20.85	18.02	16.71	14.26	20.19	27.78	16.65	15.69	20.45
Coefficient of Variation	-74.5	-10.0	9.39	10.1	33.4	8.3	11.0	31.9	8.81	8.01	10.8

Table III. Analysis of Maximum and Minimum Returns

Panel A: Index Performance: Annual Returns

	Common Valuation Techniques			Income Statement Accounts			Balance Sheet Accounts		Cash Flow Statement Accounts		
	Price	Value	Equal	Sales	EBIT	Net Income	Total Stockholder Equity	Total Assets	Operating Cash Flows	Free Cash Flows	Dividends
Best	0.26	0.29	0.31	0.27	0.22	0.22	0.28	0.41	0.22	0.22	0.29
Year	2003	2006	2009	2003	2003	2003	2003	2009	2003	2006	2009
Worst	-0.40	-0.29	-0.35	-0.28	-0.32	-0.19	-0.33	-0.51	-0.26	-0.27	-0.34
Year	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008	2008

Panel 2: Insights to Component Performance: Single Stock Contribution to Index

Function of company weighting by index metric x company's total return in specified year

	Price	Value	Equal	Sales	EBIT	NI	TSE	TA	OCF	FCF	DIV
Largest Contribution	MCD 0.03	IBM 0.05	BAC 0.04	XOM 0.06	XOM 0.07	GM 0.18 (short)	BAC 0.18	BAC 0.33	XOM 0.07	MO 0.10	MO 0.13
Year	2009	2001	2009	2006	2006	2007	2009	2009	2006	2000	2000
Lowest Contribution	MSFT -0.04	MSFT -0.13	XOM -0.03	XOM -0.08	XOM -0.13	XOM -0.06	BAC -0.09	C -0.19	XOM -0.07	XOM -0.08	HPQ -0.18
Year	2000	2000	2008	2001	2008	2001	2008	2008	2001	2001	2001

C: Citigroup; BAC: Bank of America; EK: Eastman Kodak; GM: General Motors; HPQ: Hewlett-Packard; IBM: International Business Machines; MCD: McDonald's; MO: Altria; MSFT: Microsoft, XOM: Exxon Mobil

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Commercial Real Estate Concentrations: Evidence on the Survival of Small Banks

Elisabeta Pana

Abstract

This study examines the survival of small banks with commercial real estate concentrations over the 2006-2009 period. Using data on 4646 banks, I document that commercial real estate loan concentrations increase the hazard of disappearance. The analysis of bank-specific factors reveals that bank capitalization, liquidity, and asset quality play a significant role on bank survival. I also find evidence that small banks in the Pacific Southwest and South Atlantic regions are less likely to survive as separate entities.

I. Introduction

It is often argued that the restructuring of the banking sector in the aftermath of a financial crisis eliminates excess capacity, strengthens surviving institutions, and restores the flow of capital from savers to borrowers. An important feature of the restructuring process is the regulatory intervention through capital infusions, purchases and assumption agreements, and liquidations (Santomero and Hoffman, 1998; Acharya and Yorulmazer, 2005).

During the 2007-2008 crisis, regulatory intervention provided capital for larger, politically connected banks but offered limited incentives to smaller banks to apply for government funds (Duchin and Sosyura, 2009; Li, 2010; Congressional Oversight Panel, 2010). The debate around bank capital infusions encompassed the distribution and the use of the funds, with members of the Congress arguing that federal funds should not be used for opportunistic acquisitions and Treasury officials saying that acquisitions of troubled banks would strengthen the entire sector. In his speech delivered at the Economic Club of New York, the Chairman of the Federal Reserve, Ben Bernanke acknowledged that challenges were especially high for "smaller regional and community banks that entered the crisis with high concentrations of CRE [commercial real estate] loans."

Using logistic regression analysis and a hazard model, I investigate the main determinants of small bank survival during the recent financial crisis. The sample of small banks is the ideal setting for this analysis, as it entails no significant government capital infusions. Aimed at strengthening the entire banking sector, capital infusions through the Trouble Asset Relief Program (TARP) stimulated the lending activity of the larger bank recipients (Li, 2010), but were considered unattractive by the smaller banks (Congressional Oversight Panel, 2010). Thus, after I rule out any significant external stimulus, I focus my analysis on lending activity of small banks and the relationship between the CRE loan concentration and banks' survival during and immediately after the crisis.

Although I do not examine the effectiveness of the regulatory supervision, my analysis contributes to the understanding that regulatory agencies identified the CRE-concentration problem in the banking sector in a timely manner. After controlling for different factors related to the bank survival, I document that small CRE-concentrated banks have a higher hazard of

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disappearance than the group of banks of similar size without CRE concentrations. Following Sinkey (1979) and Arena (2008), I posit that this study focuses on the near-term bank vulnerability, and not on medium-to-long-term vulnerabilities, which would require the identification and assessment of structural weaknesses affecting a bank's incentive to screen and monitor.

This paper is mainly related to two lines of literature. First, this study contributes to the literature on the impact of bank regulation and prudential supervision on lending activity (Peek and Rosengren, 1995; Berger, Kyle, and Scalise, 2001). Prior evidence suggests that the implementation of bank supervision and prudential regulation leads to a significant asset portfolio restructuring (Curry, Fissel, and Ramirez, 2006). The results support this argument and confirm that there are significant differences between the lending activities of the CRE-concentrated banks and those of the group of banks with no CRE concentration.

Second, this study contributes to the literature on financial and banking crises. Extant evidence indicates that bank crises have a negative impact on the real economy, especially on small businesses (Bernanke and Lown, 1991; Berger and Udell, 1996; Rajan and Zingales, 1998; Dell'Ariccia, Detragiache, and Rajan, 2008). The flow of credit from banks to borrowers is impeded in the event of failure, when valuable private information banks have collected about their customers is lost (Stiglitz and Weiss, 1981; Diamond, 1984; Boot, 2000; Fenn and Cole, 2008; Degryse, Masschelein, and Mitchell, 2010). This study adds to this evidence by showing that CRE-concentration had a negative impact on small bank survival during the recent crisis and implicitly on the availability of credit to the economy.

The remainder of this study is organized as follows. Next section presents an overview of the extant theoretical and empirical literature and develops the testable hypotheses. Section 3 describes the sample and presents the methodology. Section 4 presents the main results. A summary of the main findings concludes the study.

II. Literature review and hypothesis development

Over the last three decades, the banking sector has gone through a profound technological, legislative, and financial transformation and an unprecedented consolidation process (Harford, 2005). Banking consolidation has resulted in a polarized sector with large banks specialized in transaction-based lending at one end and small banks specialized in relationship lending at the other end (Berger, Kashyap, and Scalise, 1995; Yeager, 2004).

The economic slowdown of the 1980s had a severe impact on the banking sector and challenged the survival of small banks in a deregulated environment (Gup and Walter, 1989). Two distinguishing features helped small banks endure the difficult environment and emerge as strong performers in the 1990s (Bostic and Robinson, 2004). First, small banks have a higher ability to process soft information needed in the process of originating and monitoring loans (Cole, Goldberg, and White, 2004). Second, the established presence of small banks in niche-markets allows them to extract higher profit margins than those earned by large banks (Nakamura, 1994; Banerjee, Beseley, and Guinanne, 1994). However, the advantages that small banks have over larger banks have diminished over time because of changes in regulation. Bostic and Robinson (2004) show that the enforcement of the Community Reinvestment Act of 1977 altered the quality of niche-markets and increased competition in markets served by community banks. As a result, in order to maintain the same riskiness of the average borrower, community lenders originated fewer mortgages in counties where CRA agreements were in effect. In a similar vein, Calem (1994) posit that the acquisition wave triggered by the relaxation of in-state branching restrictions resulted in a reduction of the number of small banks.

The Riegle–Neal Interstate Banking and Branching Efficiency Act and the Graham–Leach–Bliley Act have removed the remaining consolidation hurdles and created the optimal conditions for a wider gap between the product and services in which large and small bank specialize. Although specialization in products and services does not increase the vulnerability of small banks to local economic shocks, it may affect their ability to survive a generalized and prolonged crisis (Yeager, 2004; Berger and Bouwman, 2009). The real estate market deterioration during the recent crisis has impaired the lending activity and reduced the ability of small banks to compete with larger banks. The mortgage-backed securities market failed to shield banks against real estate shocks and the accumulation of the risk based capital prior to the crisis proved insufficient (Lopez, 2007). With challenges quickly mounting in the banking sector, practitioners asked regulators to preserve the growth of good loans by adopting "a measured supervisory response specifically targeted at the institutions with poor risk management practices" (Igan and Pinheiro, 2009).

One group of banks with poor risk management practices has been identified immediately prior to the recent crisis through a regulatory screening process, known as the CRE-guidance. Implemented at the end of 2006, the guidance placed CRE-concentrated banks under enhanced supervisory scrutiny[1]. Although no lending limits are imposed by the guidance, CRE-concentrated banks are required to put into practice higher credit and risk management standards, and thus are likely to trim down the credit supply. With a reduced lending activity, small banks become less competitive and turn into vulnerable targets to merger and acquisitions attempts. The absorption of a CRE-concentrated bank though acquisition into a larger bank with a diversified loan portfolio eliminates the enhanced supervision and allows further growth in the CRE loan portfolio of the newly created bank. Empirical evidence supporting these arguments advances the hypothesis that the enforcement of borrower limits encouraged the consolidation of small banks (Peek and Rosengen, 1995). Similarly, small banks with balance sheet concentrations were more likely to fail during the U.K. crisis of the early 1990s (Logan, 2001). Based on these arguments, I hypothesize that during the recent crisis small CRE-concentrated banks altered their lending activity and faced a lower probability of survival and a higher hazard of disappearance than banks with similar size and no CRE concentration.

Next, I analyze other variables found significant in previous studies of bank mergers and acquisitions or failure and report their predicted sign on Table 1. Following recent empirical evidence, which suggests that the addition of macroeconomic variables does not improve the bank survival analysis (Arena, 2008; Cole and Wu, 2009), I restrict the list of covariates to bank-specific and regional variables.

Two alternative hypotheses on the relationship between capital adequacy and survival

[1] "Concentrations in Commercial Real Estate lending, Sound Risk management Practices," December, 2006, was issued by the Office of the Comptroller of the Currency, The Board of Governors of the Federal Reserve System, and the Federal Deposit Insurance Corporations.

probability have emerged in the literature (Demirguc-Kunt, 1989; Thomson, 1992; Cole and Gunther, 1998; Wheelock and Wilson, 2000; Logan, 2001; Hannan and Pilloff, 2007). A positive relationship between bank capitalization and the likelihood of being a target might be expected, if a bank has excess capital or has limited growth opportunities. In this case, banks are attractive targets for growth-oriented acquirers or for better-diversified acquirers (Hernando, Nieto, and Wall, 2009). In extreme situations, when the level of capitalization falls below a critical level, the supervisor might foster an acquisition by a well-capitalized bank. Alternatively, if high capitalization is a reflection of managerial efficiency, then better-capitalized banks are less attractive to potential buyers. Recent evidence by Berger and Bouwman (2009) shows that the capital helps small banks survive banking and market crises and that the manner in which a bank exits when it does not survive a crisis depends on the pre-crisis capital level. Finally, Hannan and Pilloff (2007) argue that taking over a poor-capitalized target enables acquirers to maximize the post-merger gains.

Another factor playing an important role on bank survival is liquidity. Several empirical studies find that higher levels of bank liquidity are associated with a higher probability of survival (Wheelock and Wilson, 2000; Fenn and Cole, 2008). Supporting evidence is also provided by a recent report issued by the Committee of European Banking Supervisors (CEBS), which stresses the importance of creating liquidity buffers to ensure bank survival[2]. Based on these arguments, I expect a negative relationship between bank liquidity and the hazard of disappearance or the probability of exit.

The inverse relationship between poor asset quality and survival has been extensively documented in the banking literature (Demirguc-Kunt, 1989; Whalen, 1991; Thomson, 1992; Cole and Gunther, 1995; Cole and Gunther, 1998). Oshinsky and Olin (2005) argue that among the factors that determine whether troubled banks recover, merge, survive as a problem bank, or eventually fail, the asset-quality variables are "statistically significant more often than other variables". In this study, I use the delinquency rate of commercial loans and the delinquency rate of residential loans as proxies of poor asset quality. A negative relationship is expected between poor asset quality and bank survival.

Bank size is considered one of the main factors affecting the probability of bank failure and the probability of being acquired. On one hand, acquirers may find small banks a more attractive acquisition because they can be easily integrated into acquirer's operations and, the acquisition process of a small target is less likely to be challenged by the competition authorities. DeYoung, Hunter and Udell (2004) and Gilbert (2007) show that asset size is important for the survival of small banks and argue that banks with assets less than $100 million need to be especially well run to survive the competition with larger banks. On the other hand, one might expect a negative relationship between size and the survival probability because the acquisition of a larger target provides the acquirer with economies of scale and market power sooner than through a series of small acquisitions (Hernando, Nieto, and Wall, 2008).

I also control for management's preference for risk by including the ratio of jumbo CDs to total assets, a variable commonly used in bank performance and survival studies (Fenn and

[2] Committee of European Banking Supervisors, "Interim Report on Liquidity Buffers and Survival Periods", March 2009

Cole, 1998, Maechler and McDill, 2006; Schaeck, 2008). For instance, Maechler and McDill (2006) show that riskier institutions fail to increase the volume of insured deposits to compensate the outflow of uninsured deposits – such as jumbo CDs. Schaeck (2008) concludes that banks that rely heavily on uninsured deposits are likely to fail faster due to their inability to substitute the uninsured deposits cash outflows with other types of funds.

Finally, I control for regional differences by including a dummy variable that takes the value of 1 for banks in the Pacific Southwest and the South Atlantic regions and 0 otherwise. As shown by Peek and Rosengen (1995) and Fenn and Cole (2008), controlling for regional differences is necessary because differences in the structure of the banking industry across different regions affect bank consolidation and failure patterns. Specifically, Fenn and Cole (2008) show that Southwestern banks accounted for at least one fourth of all U.S. bank failures in each year from 1987-92.

III. Sample and methodology

The sample of small banks is obtained from the Reports of Conditions and Income (Call Reports) database. The analysis is restricted to the sample of banks with total assets up to one billion dollars because it represents the group of banks with no significant capital injection during the TARP program[3]. I define commercial real estate (CRE) loans as loans secured by real estate for (i) construction, land development, and other land loans; (ii) multifamily residential properties; and (iii) non-farm,nonresidential properties. CRE loans are loans where cash flow from the real estate is the primary source of repayment.

The sample of small banks with CRE concentration is identified by applying the two-step screening process outlined by the CRE guidance. The first criterion identifies banks with aggregate CRE loans for construction, land development, and other land representing 100% or more of bank total capital. The second criterion identifies banks where aggregate CRE loans represent 300% or more of total capital and the CRE portfolios have increased 50% or more during the prior three-year period. I obtain a sample of 2323 small banks that violated at least one of the CRE lending concentrations criteria at the end of 2006. Each bank identified by the CRE Guidance criteria is next matched with a bank of similar size from the remaining population of banks. During the sample period, 564 banks were acquired or failed. The sample of 4082 surviving banks at the end of 2009 banks contains 1942 banks classified as CRE-concentrated and 2140 banks as non-CRE-concentrated.

Following Fenn and Cole (2008), I model bank exit using a logistic regression. I assume that $Exit^*{}_{it}$ is an unobservable index of the probability that bank *i* exits through failure or merger and acquisitions in year *t* and is a function of bank specific characteristics x_{it}.

$$Exit^*{}_{it} = b_t x_{it} + \mu_{it} \qquad (1)$$

where x_{it} is a vector of commercial real estate loan concentrations and control variables, b_t is a vector of parameter estimates for the independent variables and μ_{it} is a random disturbance term. The likelihood function for this model is:

[3] In a 2010 letter to Congressional leaders, Secretary of Treasury Timothy Geithner mentioned that future commitments of government funds will "provide capital to small and community banks, which are important sources for credit for small businesses." However, these capital injections fall outside our study period.

$$L = \prod_{Exit_{it}=0} [\Phi(-b_t x_{it})] \prod_{Exit_{it}=1} [1 - \Phi(-b_t x_{it})]$$

where:

$\Phi(-b_t x_{it}) = 1/[1 - exp(-b_t x_{it})]and1 - \Phi(-b_t x_{it}) = exp(-b_t x_{it})/[1 + exp(-b_t x_{it})]$

Shumway (2001) and Cole and Wu (2009) argue that hazard models are superior to static models in predicting bank bankruptcy or failure. Static models fail to correct for the length of period for which a bank is at risk of bankruptcy or failure and as a result, parameter estimates are biased and inconsistent. Thus, the second part of the analysis presents a model of the determinants of bank disappearance similar to the one used by Wheelock and Wilson (2000).

The model for the hazard of disappearance is based on the Cox (1972) proportional hazard model with time-varying covariates, where all disappearances (takeovers and failures) are treated as identical events. The hazard function of the probability that the ith community bank disappears through event k between time t and time t+1, is as follows:

$$\lambda_{k,i}\left(t \middle| x_{k,i}(t), b_k\right) = \bar{\lambda}_k(t) \exp(x_{k,i}\,(t)' b_k) \qquad (2)$$

where$x_{k,i}(t)$ represents a vector of covariates of the i^{th} bank at time t, $\bar{\lambda}_k(t)$denotes the baseline hazard, and b_k is a vector of coefficients to be estimated. Time is measured in calendar time elapsed since the first observation, on December 2006. If S_t is the set of banks in existence at the end of 2006 and $D_{k,t}$is the set of banks $d_{k,t}$that disappear through event k between t and t+1, then $\exp(x_{k,i}\,(t)' b_k)/\sum_{n \in S_t} \exp(x_{k,n}\,(t)' b_k)$ represents the contribution to the partial likelihood function of bank i which disappears through event k between t and t+1.The log-partial likelihood function is:

$$ln\big(L(b_k)\big) = \sum_{t=1}^{T} \left\{ \sum_{i \in D_{k,t}} x_{k,i}\,(t)' b_k - d_{k,t} \cdot ln \left[\sum_{n \in S_t} \exp(x_{k,n}\,(t)' b_k \right] \right\}$$

IV. Empirical results

Table 1 presents the definition for each dependent and independent variables. Table 2 presents the descriptive statistics for the independent variables for the group of CRE-concentrated banks and the group of banks without CRE-concentrated loan portfolio at the end of each year, from 2006 to 2009. I report that for each year during the sample period CRE-concentrated banks operate at a significantly lower equity ratio than the group of banks without CRE concentration. However, both liquidity measures—the 1-year GAP and the 1-year GAP best estimate—indicate a more cautious approach in liquidity management undertaken by CRE-concentrated banks. Although at the beginning of the sample period the delinquency rates for the two bank groups were similar, the delinquency growth rates for the CRE-concentrated banks outpaced the growth of the delinquency rates for non-CRE-concentrated banks, reaching a level of 7.8% for commercial real estate loans and 5.8% for residential estate at the end of 2009. I also note that commercial real estate concentrated banks relied more on non-insured deposits.

The logistic regression results in Table III show that banks identified as CRE-concentrated at the end of 2006 are more likely to exit through mergers, acquisitions, or failures, than non-CRE-concentrated banks. The coefficient of the *2006 CRE dummy* variable is positive and significant in all specifications. The results provide support to the arguments that bank loan portfolio concentrations result in bank exit through failure or acquisition (Peek and Rosengen, 1995; Fenn and Cole, 2008). The negative and significant coefficients of the *1-year GAP*, *1-Year GAP best estimate,* and the *Jumbo CDs* variables are consistent with the interpretation that lower liquidity and the ability to attract non-insured deposits facilitate bank survival during the first year of crisis. Although the sign of the coefficients remains unchanged, the lack of significance for the year 2009 indicates that the role played by liquidity and non-insured funds on bank survival diminishes over time. However, I find that asset quality plays an increasing role on small bank survival. Although the coefficients of the delinquency rate variables are not significant for the year 2006, I document that a higher commercial real estate delinquency rate increases the likelihood of a bank exiting through mergers, acquisitions, or failure in 2009. Finally, consistent with previous empirical evidence, I show that smaller banks were less likely to survive as separate entities during the crisis (DeYoung, Hunter, and Udell, 2004; Gilbert, 2007). This result is generally attributed to the ability of larger banks to garner benefits from the diversification of risk. However, in the year immediately following the crisis, size is unrelated to the probability of surviving as a separate entity.

Table IV reports the results of the hazard model estimation for the time-to-exit though mergers, acquisitions, or failure. I report the results for four equations, corresponding to two measures of CRE-concentrations and two measures of liquidity. In order to account for CRE-concentration, I include a dummy variable that identifies the group of banks with CRE-concentration at the end of 2006 and the group of banks matched by size. In a different specification, I include a time-varying covariate (CRE-concentration) which classifies each bank as CRE-concentrated or non-CRE-concentrated at the end of each quarter during the sample period. The two liquidity measures are the 1-year GAP and the 1-year GAP best estimate.

The results support the evidence that significant loan portfolio concentrations lead to bank exit through mergers, acquisitions, or failure (Peek and Rosengen, 1995; Logan, 2001). The coefficients of the two CRE-concentrations variables are positive and significant in all four equations. The results also indicate that banks with a higher equity ratio have a higher hazard of disappearance. The coefficients of the *Equity ratio* lend support to the argument advanced by Thomson (1992), that the positive relationship between bank capitalization and the hazard of disappearance is explained by the fact that “stronger banks are more aggressive in recognizing and reserving against emerging problems in their loan portfolios than are weaker banks.” The negative coefficients of the two variables for liquidity indicate that banks with a more aggressive liquidity management are more likely to survive as separate entities. Consistent with the asset quality hypothesis, I find that banks with higher commercial and residential delinquency rates are more likely to exit through mergers, acquisitions, or failure. I also document a signaling effect consistent with the assertion by Schaeck (2008) that a bank’s ability to attract and retain uninsured funds indicates that it is able to hide emerging problems in its asset portfolio. Thus, the regulator perceives it as less risky and sees no reason to intervene and take remedial action. The negative coefficient on *Size* is consistent with the interpretation that larger banks are less vulnerable than smaller banks. Finally, similar to the crisis of late 1980s and early 1990s, banks from the Pacific Southwest and the South Atlantic regions were less likely to survive as separate entities.

V. Concluding remarks

The empirical evidence on the impact of commercial real estate lending concentration on bank survival provides support for the need to control one the most important challenge in the post-crisis period.

This study documents that larger banks with better liquidity management and a higher ability to attract uninsured funds are more likely to survive as separate entities. Consistent with previous empirical evidence, I find that poor asset quality increases the hazard of disappearance. I also show that at the beginning of the recent financial crisis CRE-concentrated banks had lower delinquency rates than the group of banks of similar size without CRE-concentrations. However, higher growth rates during the crisis led to unprecedented levels of commercial and residential delinquencies at the end of year 2009. Using a time varying covariate for the CRE-concentration, I find strong evidence that banks with concentrated asset portfolios are less likely to survive as separate entities. The main findings provide support to recent regulatory initiatives to revisit the credit and risk management standards for the group of banks with CRE-concentrations.

Table I: Definition of variables

Variable	Predicted sign	Definition
Logit dependent Variable		The dependent variable takes the value of 1 for banks that exit and 0 otherwise
Hazard model dependent variable		The dependent variable is measured as the number of quarters the bank survives as an independent entity after December 2006.
2006 CRE dummy	+/-	A dummy variable that takes the value of 1 for CRE-concentrated banks at the end of 2006 and 0 otherwise.
CRE-concentration	+/-	A time covariate created as a set of dummy variables that identify CRE concentrated banks at the end of each quarter, from December 2006 to December 2009.
Equity ratio	+/-	The equity ratio is defined as equity as a percentage of total assets.
1-year GAP	-	The 1-year GAP variable is the difference between rate sensitive assets and rate sensitive liabilities. *Rate sensitive assets* = (federal funds sold) + (securities purchased under agreements to resell) + (trading assets) + (fixed and floating debt securities maturing or repricing within 12 months) + (fixed and floating loans maturing or repricing within 12 months); *Rate sensitive liabilities*= (federal funds purchased) + (securities sold under agreements to repurchase) + (bank's liability on acceptances executed and outstanding) + (trading liabilities) + (other borrowed money) + (demand notes issued to the U.S. Treasury) + (time and savings deposits) − (large long-term time deposits)
1-year GAP best estimate	-	The 1-year GAP best estimate is the 1-year GAP plus small longer-term deposits as a percentage of total assets.
Delinquency rates	+	Loans secured by real estate that are past due thirty days or more and still accruing interest, as well as those in nonaccrual status, expressed asa percentage of year-end loans (calculated separately for residential and commercial real estate)
Jumbo CDs	-	The Jumbo CDs variable is defined as Certificate of Deposits greater than $100,000 as a percentage of total assets
Region dummy	+	A dummy variable that takes the value of 1 for banks in the Pacific Southwest and the South Atlantic regions and 0 otherwise.
Size dummy	+/-	A dummy variable that takes the value of 1 for banks with total assets above $100,000,000 and 0 otherwise

Table II: Descriptive statistics

The variables are created using one-year lagged, end of the year data.Columns (1) present the mean and median (in the brackets) for all the variables calculated for non-CRE-concentrated banks. Columns (2) present the data for CRE-concentrated banks.

	2006		2007		2008		2009	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Equity ratio	0.1128	0.0958	0.1124	0.0995	0.1096	0.0934	0.1074	0.0887
	[0.1010]	[0.0895]	[0.1029]	[0.0913]	[0.1007]	[0.0886]	[0.1001]	[0.0879]
1-year GAP	-0.3358	-0.2592	-0.3456	-0.2934	-0.4065	-0.3716	-0.4323	-0.4206
	[-0.3510]	[0.2627]	[-0.3597]	[-0.2990]	[-0.4230]	[-0.3843]	[-0.4497]	[-0.4327]
1-year GAP best estimate	-0.2804	-0.2143	-0.2942	-0.2490	-0.3506	-0.3131	-0.3780	-0.3573
	[-0.2888]	[-0.2190]	[-0.3065]	[-0.2582]	[-0.3662]	[-0.3243]	[-0.3965]	[-0.3658]
Delinquency rate commercial	0.0221	0.0162	0.0282	0.0296	0.0408	0.0579	0.0462	0.0782
	[0.0075]	[0.082]	[0.0128]	[0.0181]	[0.0223]	[0.0370]	[0.0269]	[0.0542]
Delinquency rate residential	0.0251	0.0197	0.0306	0.0282	0.0346	0.0404	0.0382	0.0581
	[0.0151]	[0.0115]	[0.0217]	[0.0173]	[0.0225]	[0.0257]	[0.0268]	[0.0392]
Jumbo CD	0.1596	0.1934	0.1632	0.1822	0.1650	0.1821	0.1713	0.1943
	[0.1484]	[0.1798]	[0.1534]	[0.1700]	[0.1509]	[0.1698]	[0.1555]	[0.1841]
Nr. Observations	2323	2323	2051	2365	2036	2210	2140	1942

Table III: Logistic regressions

Logistic regression estimates of the probability of exit through mergers, acquisitions, or failure of small commercial banks during the 2006-2009 period; χ^2 appears in parentheses. The dependent variable takes the value of 1 for banks that exit and 0 otherwise. For each year, the probability of bank exit is estimated using Call Report data for December 31 of the preceding year. Call report data were obtained from the Federal Reserve Board's archival files. * Indicates significance at the 5.0% level. ** Indicates significance at the 1.0% level. ***Indicates significance at the 0.1% level.

	2007		2008		2009	
	(1)	(2)	(1)	(2)	(1)	(2)
2006 CRE dummy	1.076***	1.050***	0.679**	0.708**	0.959**	0.940**
	(12.188)	(11.665)	(4.374)	(4.777)	(6.032)	(5.847)
Equity ratio	-2.454	-2.470	1.360	1.888	2.605	2.100
	(0.215)	(0.221)	(0.094)	(0.187)	(0.253)	(0.172)
1-year GAP	-3.591***		-1.837*		-0.465	
	(16.426)		(3.550)		(0.149)	
1-year GAP best estimate		-3.568***		-2.357**		-0.156
		(0.221)		(5.886)		(0.019)
Delinquency rate commercial	-9.888	-9.432	1.074	1.252	5.368***	5.389***
	(2.213)	(2.040)	(0.114)	(0.158)	(10.655)	(10.812)
Delinquency rate residential	-4.171	-3.511	-0.152	0.008	1.162	1.208
	(0.427)	(0.312)	(0.001)	(0.001)	(0.188)	(0.269)
Jumbo CD	-5.492***	-5.520***	-0.912	-0.903	-0.985	-1.041
	(7.156)	(7.405)	(0.283)	(0.281)	(0.239)	(0.269)
Region dummy	-0.916	-0.905	0.853***	0.863***	-0.140	-0.142
	(2.299)	(2.243)	(7.090)	(7.240)	(0.105)	(0.107)
Size dummy	-1.249***	-1.275***	-0.827***	-0.858***	-0.005	0.001
	(17.718)	(18.315)	(6.715)	(7.223)	(0.001)	(0.000)
Accuracy ratio	73.3	72.8	62.2	59.1	64.6	64.9
Likelihood Ratio (χ^2)	57.66	57.07	17.39	19.84	22.35	22.21
Number of surviving banks	4570		4343		4184	

Table IV: Survival analysis

Hazard model estimates for banks exit through mergers, acquisitions, or failure of small commercial banks during the 2006-2009 period; standard errorsappear in parentheses. The dependent variable is the number of quarters between the end of 2006 and the bank exit through mergers, acquisitions, or failure. * Indicates significance at the 5.0% level. ** Indicates significance at the 1.0% level. ***Indicates significance at the 0.1% level.

	(1)	(2)	(3)	(4)
2006 CRE dummy	0.864***		0.852***	
	(0.090)		(0.098)	
CRE-concentration		0.874***		0.860***
		(0.100)		(0.100)
Equity ratio	3.575***	3.612***	3.239***	3.251***
	(1.139)	(1.127)	(1.125)	(1.111)
1-year GAP	-1.252***	-1.282***		
	(0.295)	(0.297)		
1-year GAP best estimate			-1.159***	-1.184***
			(0.287)	(0.288)
Delinquency rate commercial	5.308***	5.423***	5.324***	5.449***
	(0.426)	(0.420)	(0.422)	(0.417)
Delinquency rate residential	2.388***	2.337***	2.485***	2.427***
	(0.492)	(0.494)	(0.491)	(0.493)
Jumbo CD	-1.756***	-1.800***	-1.874***	-1.916***
	(0.535)	(0.537)	(0.532)	(0.534)
Region dummy	0.403***	0.384***	0.405***	0.386***
	(0.102)	(0.102)	(0.102)	(0.102)
Size dummy	-0.366***	-0.367***	-0.368***	-0.367***
	(0.098)	(0.098)	(0.098)	(0.098)
Likelihood Ratio (χ^2)	288.93	300.52	299.27	285.26

Does The Ruling to Break Up Microsoft Add Value to Its Competitors and Other High Tech Companies?

Yewmun Yip and Cathy Ye Lou

Abstract

In this study, we examine the impact of the announcements of the ruling to break up Microsoft into two independent companies on the market values of Microsoft, Microsoft's competitors and other firms operating in computer related industry. Our empirical results show that the stock price of Microsoft declined substantially on the day when the Department of Justice proposed to break up the company. In addition, significant negative abnormal returns are also observed for Microsoft's competitors and other firms operating in the computer industry. This result contradicts the belief that a stricter enforcement of the antitrust laws will benefit Microsoft's competitors. Although significant negative abnormal returns are also observed on the final hearing day, the abnormal negative returns on the ruling day is not statistically significant. This is perhaps an indication that the market has already factored in a high likelihood that the judge will rule to break up Microsoft as a remedy.

I. Introduction

The study by Bittlingmayer and Hazlett (2000) [hereafter refers to as BH] examines the impact of a series of antitrust actions taken against Microsoft by the Department of Justice [DOJ] on the market value of Microsoft and firms operating in the computer-related industry. Of the 54 antitrust related announcements they examined for the period from 1991 to 1997, 29 are identified to be pro-antitrust enforcement. Their results show that pro-antitrust enforcement actions taken by the DOJ have resulted in a statistically significant decline in the stock prices of Microsoft and firms operating in the computer industry. On the other hand, stock prices react positively to the news on the setbacks of the DOJ's enforcement actions. Since the market reacts negatively to the news of stricter enforcement of the antitrust laws and positively to the news of a setback or a more lax in the enforcement of the laws, the empirical findings provided by BH (2000) contradict the argument that the business practices of Microsoft are anti-competitive and/or the enforcement of antitrust policy increases efficiency.

The aim of this paper is to extend the BH (2000) study to include the proposal by the DOJ to breakup Microsoft and the ruling by the federal judge to break it up. Our study examines the stock price reactions of Microsoft, its competitors and other firms operating in the high-tech industry on three announcement dates, namely, (i) April 24, 2000, the day on which the DOJ and 19 states announces their intention to file a lawsuit to break up Microsoft; (ii) May 25, 2000, the first trading day after the last hearing day, and (iii) June 8, 2000, the first trading day after the ruling made by Judge Thomas Penfield Jackson to breakup Microsoft into two independent companies.

We expect a stronger reaction on April 24, 2000, the first time the DOJ suggested that the appropriate anti-trust remedy is to breakup Microsoft. The reaction to subsequent pro-antitrust enforcement announcements can used to assess the initial market perception of the likelihood that the judge will rule in favor of the DOJ. If the reactions to subsequent pro-antitrust

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announcements are weakly negative or positive, it is perhaps an indication that the market has initially perceives that it is highly likely that the judge will rule in favor of DOJ to breakup Microsoft.

In this study, we also examine whether competitor firms and non-competing firms react differently to the announcements. One would expect that the ruling to break up Microsoft to be beneficial to Microsoft's competitor firms since some its competitors, namely, Sun Microsystems, Oracle, IBM, Netscape, and Novell have lobbied strongly for strict antitrust enforcement against Microsoft (Economides, 2001).

Our results show that the stock price of Microsoft declines substantially on the announcement of the proposal by the Department of Justice to break up Microsoft. In addition, significant negative abnormal returns are also observed for Microsoft's competitors and other firms in the computer industry. Similar to the findings of BH (2000), our result contradicts the belief that a stricter enforcement of the antitrust laws will benefit Microsoft's competitors. Although significant negative abnormal returns are also observed on the last hearing day, the stock market reaction to the ruling to split up Microsoft is not statistically significant. This is perhaps an indication that the market has already anticipated on the last day of hearing that the judge will rule to breakup Microsoft into the two independent companies.

II. Antitrust Law Suit Against Microsoft

The 1995 consent decree, which Microsoft agreed to, explicitly prohibits contractual bundling but it does allow Microsoft to incorporate additional functions and features into its existing products, particularly, its Windows operating system. However, in October 1997, the DOJ sued Microsoft for violating the 1995 consent decree in that Microsoft required PC makers to install Microsoft's web browser, the Internet Explorer [IE], as the default browser. In December 1997, a preliminary injunction was issued by Judge Thomas Penfield Jackson, the presiding federal judge, to stop Microsoft from bundling its web browser with its Windows operating system. However, in May 1998, the DC Circuit Court of Appeals voided the preliminary injunction, and later it ruled that Microsoft did not violate the 1995 consent decree.

The DOJ's antitrust case against Microsoft began in court in December 1998, and a year later, in December 1999, Judge Jackson found that **harm** was done to consumers in view of Microsoft's monopoly power in the personal computer operating system market and its practice of bundling of IE with its operating system as being anti-competition (Brinkley and Lohr, 2000).

On April 24, 2000, 19 states and the DOJ together proposed that the appropriate remedy to their antitrust case against Microsoft is to split Microsoft's operating system from its application software, such as Office suite and IE, and they also sought immediate curb on the company's current practice of bundling. It is the first official announcement demanding the breakup of Microsoft since the beginning of the battle between the DOJ and Microsoft in 1998. On April 28, 2000, the DOJ together with the 19 states officially filed their proposal demanding to split Microsoft into two as a punishment for violating the antitrust laws.

On May 24, 2000**,** after the market closed, the result of last scheduled hearing was released. Judge Jackson, the presiding judge for the case, appeared to be moving swiftly and leaning towards a breakup of the company. In after-hours trading, the stock price of Microsoft fell to near its 52-week low.

On June 7, 2000**,** after the market closed, Judge Jackson rules that Microsoft should be split in two: one to make and sell operating systems for personal computers, such as Windows; and another firm to make and market Microsoft's other software and online businesses. The two companies can do business with each other so long as outside companies are not disadvantaged. Jackson's order and final ruling also include restrictions on Microsoft's corporate behavior. These remedies include publishing the source code used by programmers to design software applications for Windows. Other behavioral remedies regulate Microsoft's relations with computer makers and software companies. The conduct remedies are scheduled to go into effect in 90 days but the breakup order can be stayed pending future court appeal. After the release of the ruling, Microsoft announced its plans to file its appeal and a motion to stay the order, and Microsoft is confident that the ruling will be overturned.

Although the antitrust case against Microsoft has further developments, this study focuses only on the initial proposal to break up Microsoft, and we only examine the event window from April 24, 2000 to June 8, 2000.

III. Data definition and sources

Our sample firms are chosen using Hoover's online. A sample of 37 competitor firms and a sample of 26 non-competing high tech companies are identified. Tables I and II provide a list of competitor and non-competitor companies, respectively. From the tables, we noticed that on average, the competitor firms have substantially higher beta and also larger market capitalization.

We employ an event study approach (Fama et al., 1969 and Hilmer and Yu, 1979) to examine the market reaction to the ruling on Microsoft, and we have selected an event window from April 11, 2000 to June 20, 2000. To allow for any leakage of information and delayed reaction, the event window starts 8 days before April 24, 2000, the day on which the breakup of Microsoft is proposed and 8 days after the ruling to break up Microsoft on June 8, 2000. In order to compute the abnormal returns, we collect another 60 days of returns prior to our event period for estimating the betas of the firms. The daily stock prices and dividend information for all companies are gathered from Yahoo! Finance's website.

The parameters of the market model, alpha (α_i) and beta (β_i), are estimated for each security *i* over a period of 60 days prior to the event period using the S&P 500 index as the market index. Similar to the procedure used by Brown and Warner (1980), these parameters are then used to calculate the expected returns over the event window. The abnormal returns (AR_t) for each firm are obtained by computing the difference between the observed returns and the expected returns for each day. The cumulative abnormal return (CAR_t) for day *t* for each stock is then computed.

IV. Empirical Results

Table III presents the market-model adjusted abnormal return for Microsoft, the average abnormal return for Microsoft's competitors and Microsoft's non-competing high tech firms. On

April 24, 2000, the day on which the proposal to split Microsoft into two is announced, the stock price of Microsoft declines by 15.14% on a risk-adjusted basis. Statistically significant reactions are also observed for both the competitor and non-competing high tech firms, and their abnormal returns are -5.50% and -3.76%, respectively.

From Figures I, we observe that after the first event day, Microsoft stock price bounces back slightly. Surprisingly, on April 28, 2000, the day on which the DOJ and 19 states filed their proposed punishment to split Microsoft into two, Microsoft's share price shows a slight positive reaction, and both its competitor firms and non-competing high tech firms show a significant positive reaction to the news. However, thereafter, the stock prices of the two groups trend downward to the lowest point around May 25th 2000, the first trading day after the final hearing.

On May 24, 2000 after the close of the market, Judge Jackson ended the hearing on the proposal to breakup Microsoft, and the indication was that the judge was leaning towards splitting Microsoft into two firms. The next day on May 25, 2000, Microsoft stock price declines by 4.73% on a risk-adjusted basis. The average abnormal returns for competitor firms and non-competing high teach firms are -1.92% and -2.14%, respectively, and they are statistically significant at 10% and 5% level, respectively. The cumulative abnormal return up till May 25, 2000 is about -19% for Microsoft whereas both competitor firms as well as non-competing high tech firms show a loss of approximately 38% and 26%, respectively. In other words, the other high tech firms seem to suffer bigger losses than Microsoft due to the actions taken by DOJ.

On the third event day, June 8, 2000,the first trading day after the ruling to split Microsoft, both Microsoft and its competitor firms reacted negatively to the news, albeit statistically not significant. On the other hand, the non-competitor firms show a positive average abnormal return of 0.98%. On the day after event day, the share price of Microsoft rebounded, and both its competitor and the non-competing high tech firms also show a positive but statistically insignificant reaction.

To make sure that the results we obtained are not an artifact of the risk adjustment process, we also perform a similar analysis using market-adjusted returns. Since similar results are obtained and to conserve space, the results using market-adjusted returns are not reported.

V. Conclusions

Similar to the findings by BH (2000), our results show that DOJ's proposal to break up Microsoft into two independent firms harms not only Microsoft but also firms operating in the computer related industry. At the lowest point, both its competitor`s firms and non-competing high tech firms suffer, on average, a loss of value of about 38% and 26%, respectively, on risk-adjusted basis. Furthermore, we find that the reaction is the strongest on the first day on which the government announces its intention to breakup Microsoft. Our findings, similar to those of BH (2000), contradict the common believe that Microsoft's market dominance in the operating system as well as its business practices of bundling have harm not only the consumers but also its competitors. In fact, the market reacts negatively to the remedy as proposed by the DOJ and the 19 participating states.

Table I.List of Competitor Firms and Their Descriptive Statistics

Type of Firm	Ticker	Name	Beta	Market Capitalization (in billion $s on 3/5/01)
Operating system	SUNW	Sun Microsystem	1.40	61.00
	CORL	Corel	0.39	0.15
	NOVL	Novell	2.78	1.64
	RHAT	Red Hat	1.14	0.84
	BEOS	Be	0.37	0.06
	SCOC	Santa Cruz Operation	0.48	0.05
Database system	ORCL	Oracle	1.75	86.50
	BORL	Inprise	0.50	0.40
	SYBS	Sybase	0.98	1.39
Computer hardware and Software	AAPL	Apple Computer	1.73	7.48
	HP	Hewlett-Packard	0.81	2.52
	IBM	IBM	0.38	156.90
Application software	ADBE	Adobe	1.71	8.67
	ERTS	Electronic Arts	1.70	0.07
	RNWK	Real Network	1.80	1.06
	BVSN	Broad Vision	1.17	1.51
	IFMX	Informedix	0.53	1.28
	INTU	Intuit	1.97	6.30
	SYMC	Symantec	0.61	3.30
	LBRT	Liberate Techonology	1.14	0.83
	MACR	Macromedia	0.65	0.96
	PRGY	Prodigy	1.00	0.19
Internet service and content provider	YHOO	Yahoo!	1.58	8.39
	AOL	AOL	1.08	156.90
Wireless software	T	AT&T	0.67	84.00
	3COM	3Com	1.60	2.01
	QCOM	Qualcomm	1.87	42.00
Average			1.18	23.57

Table II. List of Non-Competing High Tech Firms and Their Descriptive Statistics

Type of Firm	Ticker	Name	Beta	Market Capitalization (in billion $s on 3/5/01)
Computer hardware	DELL	Dell Computer	0.94	67.00
	CPQ	Compaq computer	0.46	32.90
	GTW	Gateway Computer	0.84	5.40
Networking software	BEAS	BEA systems Inc.	0.69	13.07
	CCRD	Concord Communications	0.34	0.13
	LGTO	Legato System	1.05	1.15
Networking device	CSCO	Cisco Systems	1.33	143.70
	CRDS	Crossroads Systems	0.36	0.15
	CMNT	Computer Network Tech	0.49	0.42
	SNWL	Sonicwall	0.35	0.75
	ZOOM	Zoom Technologies	-0.40	0.02
Telecom – Internet service provider	MFNX	Metromedia Fiber Network	0.85	2.74
	EXDS	Exodus Communications	0.91	5.60
	DSLN	DSL Net	0.66	0.07
	NPNT	Northpoint Communication	0.38	0.01
Data storage	ADIC	Advanced Digital Information Co.	0.50	0.84
	AXC	Ampex corporation	0.71	0.02
	EMC	EMC Corp.	1.05	79.00
	NTAP	Network Appliance	1.65	7.30
Media –Internet and online content providers	BOUT	About.com	0.80	0.47
	CNET	CNET Networks	1.10	1.23
	WOMN	Woman.com	0.22	0.01
	VERT	VerticalNet	0.18	0.15
Average			0.67	11.13

Table III. Risk-Adjusted Abnormal Returns

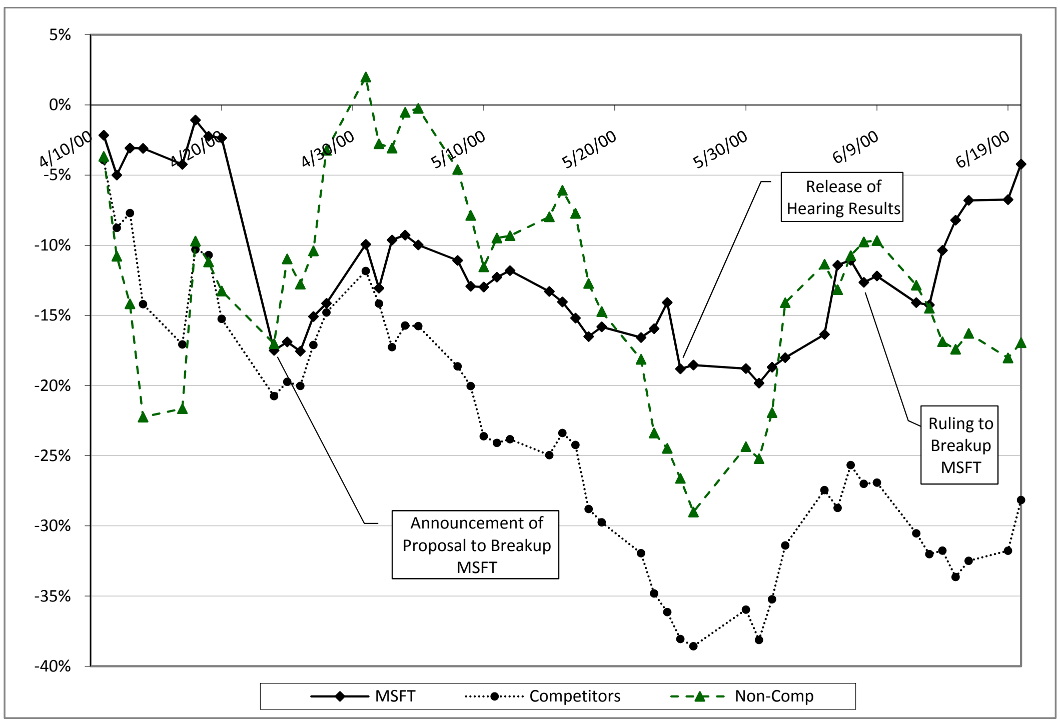
For each of the 37 stocks that make up the group of competitors and the 26 stocks for the non-competitor group, the daily risk-adjusted returns are estimated using the market model where the S&P 500 Index is used as the market portfolio. The market-model-adjusted abnormal returns are calculated as: $AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt})$. The event window is from April 11, 2000 to June 20, 2000. The *AR* reported in the table is the mean for each group, and the reported t-statistic is to test if the mean is different from zero. Highlighted in bold are the dates on which major announcements relating to the ruling to break up Microsoft are reported.

Date	MSFT	Competitors		Non-Competitors	
	AR	AR	T-Test	AR	T-Test
04/11/00	-2.16%	-3.94%	-4.49	-3.67%	-2.66
04/12/00	-2.84%	-4.83%	-4.90	-7.11%	-9.70
04/13/00	1.92%	1.06%	1.02	-3.39%	-2.20
04/14/00	-0.02%	-6.50%	-3.00	-8.07%	-3.41
04/17/00	-1.14%	-2.86%	-1.59	0.60%	0.23
04/18/00	3.16%	6.76%	3.66	11.94%	5.29
04/19/00	-1.16%	-0.40%	-0.30	-1.49%	-1.15
04/20/00	-0.12%	-4.54%	-2.47	-2.07%	-1.08
04/24/00	**-15.14%**	**-5.50%**	**-4.78**	**-3.76%**	**-2.21**
04/25/00	0.61%	1.02%	1.14	6.04%	3.06
04/26/00	-0.67%	-0.30%	-0.27	-1.80%	-1.09
04/27/00	2.47%	2.92%	2.16	2.37%	1.65
04/28/00	**0.94%**	**2.31%**	**2.43**	**7.16%**	**3.66**
05/01/00	4.20%	2.96%	2.20	5.23%	2.12
05/18/00	-1.32%	-4.56%	-4.20	-5.00%	-4.48
05/19/00	0.69%	-0.95%	-1.24	-2.00%	-2.69
05/22/00	-0.76%	-2.20%	-2.85	-3.40%	-4.56
05/23/00	0.63%	-2.87%	-3.16	-5.25%	-4.78
05/24/00	1.86%	-1.33%	-0.80	-1.09%	-0.71
05/25/00	**-4.73%**	**-1.92%**	**-1.90**	**-2.14%**	**-2.27**
05/26/00	0.28%	-0.51%	-0.46	-2.40%	-1.77
05/30/00	-0.25%	2.61%	3.41	4.66%	2.52
05/31/00	-1.04%	-2.16%	-1.92	-0.85%	-0.74
06/01/00	1.14%	2.90%	3.51	3.28%	2.48
06/02/00	0.67%	3.84%	3.49	7.84%	4.89
06/05/00	1.66%	3.94%	2.32	2.74%	2.11
06/06/00	4.94%	-1.26%	-1.34	-1.82%	-1.36
06/07/00	0.35%	3.05%	2.56	2.43%	2.36
06/08/00	**-1.58%**	**-1.33%**	**-1.37**	**0.98%**	**1.18**
06/09/00	0.45%	0.09%	0.12	0.09%	0.14
06/12/00	-1.90%	-3.62%	-3.14	-3.18%	-3.78
06/13/00	-0.17%	-1.48%	-2.57	-1.64%	-1.29
06/14/00	3.89%	0.25%	0.21	-2.38%	-2.62
06/15/00	2.16%	-1.88%	-1.66	-0.54%	-0.43
06/16/00	1.41%	1.15%	1.48	1.13%	0.93
06/19/00	0.05%	0.73%	0.90	-1.74%	-0.79
06/20/00	2.53%	3.61%	3.10	1.08%	0.85

Note: In order to display the data in a page, data from 05/02/2000 to 05/18/2000 are omitted but will be furnished upon request.

Figure I. Cumulative Abnormal Returns for Microsoft, and Average Cumulative Abnormal Returns for Competitor and Non-Competitor Firms.

For each of the 37 stocks that make up the group of competitors and the 26 stocks for the non-competitor group, the daily risk-adjusted returns are estimated using the market model where the S&P 500 Index is used as the market portfolio. The market-model-adjusted abnormal returns are calculated as: $AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt})$. The cumulative abnormal return (CAR_t) for day t for each group is then computed as: $CAR_t = \sum_{k=1} AR_k$. The event window is from April 11, 2000 to June 20, 2000. The solid line shows the cumulative abnormal returns for Microsoft, the dotted line for competitors, and the dashes for non-competitors.



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The Day of the Week Effect in the U.S. Stock Market

Hossein Varamini and Bingye Mu

Abstract

This paper tests the efficiency of the U.S. stock market by examining the day-of-the-week effect for the average daily returns of the S&P 500 Index for a recent sample period and during the financial meltdown of 2008. The result of the pair-wise comparison of equal means show that the t-values for all pairs of daily returns are insignificant. The study then uses dummy variables to examine the day-of-the-week effect of the stock market by testing for equality of the mean returns across all trading days of the week. The empirical results of the study show that the individual t-values for the dummy variables and the F-value are insignificant for both time periods, signifying the absence of the day-of-the-week effect. The study concludes that there are no statistical differences among the daily returns of the S&P 500 Index for recent sample periods and provides additional support for the efficient market hypothesis.

I. Introduction

Investors have been trying for decades to find patterns in the stock market to increase their risk-adjusted rate of return. While some investors believe that the stock market is unpredictable, others are convinced that there are patterns in stock price movements that could be exploited to earn abnormal return. The claim of the random price changes in the equity market is best represented by the Efficient Market Hypothesis (EMH). This hypothesis has been one of the most common, and controversial, subjects in the field of finance. If the EMH is correct, the stock market appears to be unpredictable, thus the investing game is fair. However, in the absence of the efficient market, investors could take advantage of this inefficiency and make abnormal profits. In such cases, the market could exhibit some anomalies such as the "January effect" and the "weekend effect". Seasonal and the day-of-the-week patterns have also provided examples of anomalies in the U.S. stock market.

A number of researchers have tested the efficient market hypothesis for equity markets. The overall results provide mixed signals about the existence of anomalies in the stock market. Furthermore, there is a lack of studies to test the efficiency of the U.S. equity market during the recent years and during the financial crisis in 2008. Therefore, the purpose of this paper is to examine the day-of-the-week effect of the U.S. stock market by comparing the average daily returns of the S&P 500 index in recent years and during the 2008 financial meltdown.

This paper will present the Review of Literature in the next part. Part III of the paper will present the methodology and the data for this research. In Part IV, the paper reports the results of the research. The last section of the paper provides the conclusions and offers suggestions for further studies.

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II. Literature Review

a. Efficient Market Hypothesis

The idea of the EMH has been around for a long time. One of the pioneers in the field, Eugene F. Fama, was the first person who wrote a definitive paper on the efficient market hypothesis in 1970. Fama's idea essentially follows the concept of the Random Walk Theory, where the stock prices move randomly and investors cannot predict the future pattern of stock returns on a consistent basis. Although, as stated by Jargic, Podobnik and Kolanovic (2005), the adjustment of price to arrival of information is imperfect, price movement is still unpredictable. Therefore, investors have no way of predicting the random nature of the market movements.

The efficient market hypothesis was widely accepted by scholars and many investors about a generation ago. Following Fama's studies, many researchers have published papers on randomness of stock price movements to demonstrate the efficiency of stock markets (Jarrett and Kyper, 2006). For example, in 1973, Burton G. Malkiel published the first edition of *A Random Walk down Wall Street*. In 1978, Michael C. Jensen famously wrote: "I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the efficient market hypothesis". He claims that the EMH has been tested and, with a few exceptions, found consistent support for this hypothesis.

Contrary to supporting evidence, there are other studies arguing against the efficient market hypothesis. For instance, Andrew W. Lo and A. Craig MacKinlay (1988) strongly rejected the Random Walk Theory for weekly stock market returns using the variance-ratio test. In 1999, Lo and MacKinlay published a book, *A Non-Random Walk down Wall Street*, to provide counterarguments against the efficient market hypothesis.

Supporters of market inefficiencies provide evidence of permanent variations in stock markets. Controversies arise when evidence strongly suggests that there are specific trends within the stock market that could be predicted ahead of time. Advocates of the efficient market hypothesis argue that the predictability resulted from rational pricing in expected returns in an efficient market. In contrast, opponents believe that the predictability reflects irrational investors in a speculative market (Russel and Torbey, 2002).

Some analysts argue that the issue of market efficiency comes down to whether or not investors are rational. John Maynard Keynes pictures the stock market as a 'casino' guided by 'animal spirit'. He argues that investors are guided by short-run speculative motives rather than having long-term perspectives that are rational (Russel and Torbey, 2002). An article by Mike Clowes (2005) asks "If the market is efficient, and investors act rationally, why do so many investors still seek active management returns? And why do market bubbles occur?" According to recent studies by Andrew Lo, Harris & Harris Group investors are often irrational, "exhibiting predictable and financially ruinous behavior". Warren Buffett has also argued against the efficient market hypothesis. Buffett once said that "I'd be a bum in the street with a tin cup if markets were efficient" (Glassman, 2007).

b. Stock Market Anomalies

If the EMH holds, how do we explain many of the anomalies in the market? The irregularities of the markets include the January effect, the weekend effect, the day-of-the-week effect, the seasonal/holiday effect, etc. (Russel and Torbey, 2002). The January effect indicates that small-capitalization stocks tend to yield higher rates of return in January than in any other month of the year. A research study by Haug and Hirschey (2006) refers to data from the New York Stock Exchange Index during the year of 1904 to 1974 and calculates the average stock market return. The research concludes that the average return during the month of January was 3.48 percent whereas the monthly return during the other 11 months of the year was only 0.42 percent. Therefore, returns in January were more than eight times higher than returns for a typical month of the year. Furthermore, as Shell (2004) reports "the January effect has occurred 70% of the time since 1926". After many years of intensive study, as Haug and Hirschey (2006) claim, the January effect becomes a compelling evidence of market inefficiency.

A study by Rozeff and Kinney (1976) used the data from 1904-1974 to show that the NYSE stock returns were 8 times higher than returns for a typical month. In a more recent study, Haug and Hirschey (2006) used the value-weighted returns from 1802-2004 and equal-weighted returns from 1927-2004 to test the January effect. They found a persistent January effect on small-cap stocks even for the period after the passage of the 1986 Tax Reform Act. They concluded that the January effect is a serious challenge to the efficient market hypothesis.

The other common anomaly in the stock market is the day-of-the-week effect that implies that the distribution of stock returns varies according to the day of the week. A number of researchers have tested the day-of-the-week effect in various exchanges, across many securities and for different indices. Most of the studies such as Cross (1973), French (1980), Rogalski (1984), Harris (1986), and Berument and Kiymaz (2001) have used the data for the U.S. and have shown negative returns on Mondays and positive returns on Fridays.

The available literature shows that stock market anomalies exist in markets outside of the United States as well. In a study by Gultekin and Gulfekin (1983), the January returns were exceptionally large in 15 out of 16 countries. In another study, Jaffee and Westerfield (1985) found significant negative returns for Mondays for several countries whereas the mean returns for Tuesdays were significantly positive. According to Berument and Kiymaz's study (2001), the highest volatility occurs on Mondays for Germany and Japan, on Fridays for Canada and the United States, and on Thursdays for the United Kingdom. Aggarwal and Rivoli's paper (1989) tested the January effect and the day-of-the-week effect in equity markets for four emerging economies. The results support the existence of both anomalies in the equity markets for the period under study. The day-of-the-week effect was also tested by Tsangarakis (2007) for the Athens stock exchange for the period of 1981 to 2002. He has concluded that the day-of-the-week effect was not a dominant phenomenon in his study.

Agrawal and Tandon (1994) have conducted a comprehensive study to examine five seasonal patterns in stock markets of eighteen countries from 1971 to 1987. The results of their study for the day-of-the-week effect show that Friday returns are large and significantly positive for almost all of the eighteen countries. They found negative returns on Mondays for thirteen countries. In comparison, their study showed negative returns on Tuesdays in twelve countries. Their overall findings cast some doubt on validity of the efficient market hypothesis.

Despite the existence of numerous studies about the existence of different anomalies in equity markets, there are other studies that have raised questions about the implications of such findings for investment purposes. Schwert (2002), for example, has conducted a number of tests about several common anomalies in the stock market and claims that the anomalies are more apparent than real. He concludes that even if the anomalies existed, the activities of practitioners who implement strategies to take advantage of such inefficiencies would cause the anomalies to disappear.

III. Methodology and Data

In order to test the efficient market hypothesis for the U.S. stock market in recent years, this study uses two sample periods for the S&P 500 Index from Yahoo Finance to test the day-of-the-week effect. The first sample is daily data from 08/25/2008 to 12/05/2008. This period is isolated mainly because it covers the period of high volatility of the recent financial meltdown in the U.S. stock market. The other sample includes daily information from 08/01/2003 to 08/22/2008. This five-year range data provides a longer time to avoid the focus only on abnormal changes in the market during the recent financial crisis. The information collected contains the closing prices of the S&P 500 Index for each day that the market was open. The actual number of trading days for the shorter sample ranged from 58 to 62 days. For the longer sample size, the number of observations for each trading day was from 1250 to 1268 days. The rate of return for each day was computed by assuming that we are buying stocks at the closing price on Friday and selling them at the closing price on Monday, etc. The computed rate of return for each day does not include any dividends payment.

The first step is to use the t-test to examine the equality of means of daily returns for both sample periods. The next step is to use dummy variables in a regression model to test for equality of all means. To do this task, this study follows the methodology used by Agrawal and Tandon (1994) and Aggarwal and Rivoli (1989), among others, to estimate the following equation:

$$R_t = \beta_1 D_{1t} M + \beta_2 D_{2t} Tu + \beta_3 D_{3t} W + \beta_4 D_{4t} Th + \beta_5 D_{5t} F + \mu_t$$

Where R_t is the average daily return for the S&P 500 index and beta coefficients represent the mean returns for Monday through Friday. The dummy variables indicate the day of the week on which the return is observed. For example, if day t is Monday, $D_{1t} = 1$ and zero otherwise, etc. Finally, μ_t is the error term with zero expectations.

If the estimated coefficients of β_1, β_2, β_3, β_4, and β_5 are statistically insignificant, the F-statistic measuring the joint effects of the dummy variables is also expected to be insignificant, then there is no evidence to support the day-of-the-week effect. In that case, the efficient market hypothesis is supported. On the other hand, if the F-statistic is significant, it implies that there is a day-of-the-week effect and investors could earn abnormal returns on certain days of the week.

IV. Empirical Results

In order to test the null hypothesis of equal pair of means, a t-test was performed. The t-values show whether or not the means for all of two-day combinations are different from each other. The results are reported in Table 1 for both sample periods under study. As the findings indicate, there is no difference between the means of daily returns for any pairs of days, either during the fall of 2008 or for the 2003-2008 time periods. Given the results of the t-test, we could conclude that the average stock returns on any possible pairs of days are equal. These findings are supportive of the efficient market hypothesis, implying that investors are not able to earn an abnormal rate of return on any particular day of the week.

The next section of the study implements five dummy variables in a multiple regression function to test for equality of daily means for each day of the week for both sample periods. The results of the regression analysis, as reported in Table 2, show that the coefficients of the dummy variables for every day of the week, for both sample periods, are statistically insignificant. The computed F-statistics measuring the joint significance of the dummy variables for the shorter time period is 1.42 whereas the F-value for the 2003-2008 samples is only 1.17. The coefficient of determination is 8.9% and less than 1% respectively for the two samples in this study. Therefore, the results of the study show that the null hypothesis of equal rates of return across days of the week cannot be rejected; hence, this study does not find any evidence to support the day-of-the-week effect in the U.S. stock market for the recent five years or during the 2008 financial meltdown. This finding provides another piece of evidence in support of the efficient market hypothesis.

V. Conclusions

The main purpose of this paper is to compare the average daily returns in the U.S. stock market for a recent sample period and during the financial meltdown in 2008 to examine the efficiency of the stock market using the day-of-the-week effect. To determine if the average daily returns are statistically equal, the study first performs a pair-wise comparison of daily means. The results show that the t-values for all pairs of daily returns are insignificant. The study then uses dummy variables to test for the day-of-the-effect of the stock market by testing for the equality of means across all of the trading days of the week. The empirical results of the study show that the individual t-values for the dummy variables and the F-value are insignificant for both samples signifying the absence of the day-of-the-week anomaly. The conclusion of the study indicates that there are no statistical differences among the daily returns of the S&P 500 Index and it provides support for the efficient market hypothesis.

The results of this study are consistent with findings of a number of other studies to support the efficient market hypothesis, but they are in contrast with other findings where the evidence showed the existence of some anomalies such as the day-of-the-week-effect. The differences in such results could be due to the use of different market indexes or different time periods for the studies. It is also likely that the existence of anomalies has provided knowledgeable investors some opportunities to earn abnormal profits for a limited time, but once these anomalies are publicized, abnormal profitable opportunities may disappear. Such arbitrage actions make the market even more efficient

Future studies could identify some of the specific reasons for the anomalies, whenever they exist. One specific area of research is to examine the role of advances in technology and in communication of information across countries on market efficiency. Another area of future research is to investigate the effect of stock indexes and the growth of Exchange Traded Funds (ETFs) on efficiency of the stock markets.

TABLE 1

Test for Pair-wise Equality of Means

	Fall 2008 (N1*)	2003-2008 (N2**)
Pair-wise trading days	t-values	t-values
Monday & Tuesday	0.35	0.23
Monday & Wednesday	1.64	-.08
Monday & Thursday	0.84	0.57
Monday & Friday	0.50	0.31
Tuesday & Wednesday	1.08	-0.47
Tuesday & Thursday	0.72	0.48
Tuesday & Friday	0.21	0.10
Wednesday & Thursday	-1.15	1.06
Wednesday & Friday	-1.15	0.57
Thursday & Friday	-0.62	-0.34

N1* = # of observations = 58 to 62 trading days for Sample 1
N2** = # of observations = 1250 to 1268 trading days for Sample 2

TABLE 2

Results of the Regression Model with Dummy Variables to Test Equal Means

$$R_t = \beta_1 D_{1t} M + \beta_2 D_{2t} Tu + \beta_3 D_{3t} W + \beta_4 D_{4t} Th + \beta_5 D_{5t} F + \mu_t$$

Panel A: Shorter Sample (Fall 2008):

	β_1	β_2	β_3	β_4	β_5
Coefficients	-0.012	0.002	-0.03	-0.004	-0.006
t-values	(-0.70)	(0.12)	(-1.05)	(-0.27)	(-0.85)
$R^2 = .089$		$F = 1.42$		$N = 63$	

Panel B: Longer Sample (2003-2008):

	β_1	β_2	β_3	β_4	β_5
Coefficients	0.0003	-0.0006	0.0003	.0009	.0007
t-values	(0.417)	(-0.800)	(0.423)	(1.30)	(0.921)
$R^2 = 0.003$		$F = 1.175$		$N = 1266$	

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Public University Retirement Systems in the Midwest: An Overview

Stanley R. Adamson and James Philpot

Abstract

This paper examines the recent financial experience of public university defined benefit retirement plans in several Midwestern states. Generally, funding percentages have declined over the past ten years. In some instances, the decrease in funding level has been on the order of thirty percentage points. Little significant change in average plan asset allocation is seen over the past four years.

I. Introduction

Arguably the biggest changes in the past few decades in the field of retirement planning is the nearly universal switch of private, corporate employers from providing their employees defined benefit pension plans to providing instead some sort of defined contribution retirement plan. In the early to middle twentieth century, those workers whose employers offered a retirement plan tended to stay with employers for a whole career, and as a result looked forward to a stable, known retirement income. Because life expectancies were shorter than now, and because inflation rates and investment rates of return were more stable than now, companies were fairly easily able to guarantee their employees this income, which was a contract obligation of the firm and was based on an employee's tenure, age, and average salary.

In recent years, many privately-held corporations have gone to 401(k) plans or other defined contribution plans as their primary means for providing retirement benefits to their employees. While these plans are less fiscally demanding on the employer, the investment, inflation and superannuation risks are shifted directly from the employer to the employee. As a result, many of our citizens may find themselves ill-prepared for retirement. Until very recently, the conventional wisdom has been that if a worker wanted the protections of a defined benefit pension plan, the best place to work is in the government. This notion has its roots in the fact that governments are not under a profit-maximization constraint and have revenues based on taxing authority which, in theory, leads to stability in cash flows. Many university professors across the country are covered under various defined benefit pension plans for state employees.

Recently, many state and local public employee defined benefit pension plans have received attention due to their poor financial position. For example, the Colorado Public Employees' Retirement Association, which provides a defined benefit pension plan for that state's employees, has recently reported that it had assets of $29.5 billion in July 2009, while the present value of its liabilities was $57 billion. Colorado took aggressive measures in an attempt to remedy this shortfall, passing legislation increasing the retirement age and years of service requirements of retirees, increasing required contributions by both employer agencies and employees, and reducing cost of living adjustments for pensioners (Wojick, 2010). Clearly, employees who seek government or state agency employment in an attempt to avoid retirement

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risks still face some of those risks. The question then becomes "are these plans sustainable over the long-run?"

In the United States, corporate sector workers who are participants in a "qualified retirement plan" enjoy considerable protections through the federal Employee Retirement Income Security Act (ERISA). ERISA protections include requirements for coverage, eligibility, vesting, fiduciary duty, and against prohibited transactions. For defined benefit plans in particular, ERISA establishes a funding requirement. That is, employers are annually required to contribute the actuarially determined amount of benefits earned by employees. Further, if the present value of liabilities of the plan is greater than the plan assets, the plan is required by ERISA to increase annual employer contributions to overcome the deficit. Finally, ERISA requires that private, corporate defined benefit plans insure employee benefits with the Pension Benefit Guarantee Corporation (PBGC). ERISA does not apply to public employee pensions.

This paper makes a preliminary examination of a number of public university retirement systems in the Midwest States in an effort to determine the financial health and viability of the individual systems, as well as the trend in each state. Such results should be of interest to the tens of thousands of state employees who are or will be directly impacted by such plans.

II. University Retirement Plans in the Midwest

We examine the retirement plans in the Midwest region of the United States as defined by the U.S. Census Bureau. This statistical region includes Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota. These plans may vary considerably with regard to benefit structure and funding levels as one looks from state to state. At least for university faculty employees, several of the states have recognized the advantages (at least to the employer) of a defined contribution system. Indiana, Michigan, Minnesota, and Nebraska have defined contribution plans as their primary retirement benefit, some of these having switched from a defined benefit plan in the past decade. Some states, like Iowa, have more than one system, and participation varies by institution. Wisconsin has a hybrid plan, which combines features of defined benefit and defined contribution plans. We analyze defined contributions in the remaining states: Missouri, Illinois, Kansas, North Dakota, South Dakota, and Ohio.

Those universities that still offer defined benefit plans are not immune to problems similar to those in Colorado. Under a defined benefit pension plan, the investment risk is borne by the employer. Thus, if investment returns fall short as they have several times in the first decade of the twenty-first century, employers may find themselves having to contribute vast sums of money to make the plan financially stable. A case in point is the Kansas Public Employees Retirement System (KPERS). According to a report released in September 2009 by the Center for Applied Economics at the Kansas School of Business, the pension fund is headed for bankruptcy. This was the case even before the current recession because of structural problems in the plan. However, the current recession has exacerbated the problem. The report concludes that "KPERS is bankrupt under current operating assumptions". Furthermore the report found that when utilizing the market value of assets, the total unfunded actuarial liabilities of the plan have more than doubled from $4.8 billion to $10.25 billion within the last year.

III. Midwest Defined Benefit Plans

We examine reported assets, liabilities and investments of the defined benefit plans in the six Midwest defined benefit states. Data are collected from the published annual reports issued by each plan. Government pension plan financial statements are subject to standards set by the Government Accounting Standards Board (GASB); thus, to the extent that any corporate financial statements are comparable, the annual reports of these pension funds are comparable. However, like corporate accounting, government pension accounting statements are not perfectly comparable (states may use different fiscal years or use different allowable accounting treatments), so inferences must be made with caution.

One of the most critical measurements used to determine the financial health of a defined benefit pension plan is the percentage of liabilities funded by each plan. Unfunded liabilities are representative of the debt obligation to cover future and current benefit payouts that are greater than the current assets of the plan. A plan that has enough assets to cover current and future benefit obligations is said to be "fully-funded". Many pension experts believe that a defined benefit pension plan is in excellent shape if it has a funding level of 80% or more (that is to say the plan has assets to cover 80% of all current and future obligations).

Table I shows funding percentages for six Midwestern states' public university retirement plans over the years 2000 to 2009. Over that time period, all plans showed a downward trend in funding levels, with some seeing critical decreases in funding percentage. Four states, Illinois, Kansas, North Dakota and Ohio, each saw their funding percentages drop by at least thirty percentage points. Of those four, only North Dakota continues to meet the 80% level. Two plans, Missouri and South Dakota, also decreasing their funding levels, have avoided the massive declines of the other four. In fact, both of these states continue to meet the 80% benchmark.

It is interesting to note the plans' decline during the 2008-2009 fiscal year. Most state retirement plans use a fiscal year ending in June. Thus the 2008-2009 fiscal year would contain the critical stock market decline of 2008. Every one of the states saw its funding percentage drop from 2008 to 2009, undoubtedly in response to the decimation of equity prices in that time period. The average decline across the six states over this period was 8.5 percent. While alarming, these results compared favorably when looking at state plans of all types across the nation which lost an average of twenty percentage points (Diamond, 2010). Two states in particular, Kansas and Ohio, saw very large declines (12 and 19 percentage points, respectively) in funding percentages in that year. The other states saw much more modest decreases.

The extreme nature of the losses of the Kansas and Ohio plans, in response to the 2008 stock market decline is hard to explain, particularly given the asset allocation of the six plans. Table II shows asset allocation percentages for these six state plans for the fiscal years ended in 2006 thru 2009, as well as the year-end total assets of those plans. At year end 2008, Kansas and Ohio had less exposure to domestic equity than at least two of the other states (South Dakota reports domestic and international equities as one class). Kansas and Ohio had exposure to international equities that was comparable to the other states. The time period was also a difficult time for mortgage-backed bonds, and it may be possible that these two states were holding this type of debt, categorized as fixed income.

Also, Table II shows a significant decline in total plan assets for each of the six states. As a percentage of 2008 assets, the plans lost an average of 24.1 percent with even the best performing state plan losing 22.5 percent. It was a brutal year for these plans as well as state plans across the country that lost an average of 21.4% in plan assets (Diamond, 2010).

Most of the states made few significant adjustments to their asset allocations between fiscal years 2008 and 2009. On average, across the six states, equity holdings (domestic and international) declined slightly (less than 2 percent). In fact, despite the major decline in domestic equity values over this period, four of the states slightly increased their allocation percentages in domestic equities. Two states that implemented significant changes in asset allocations were Missouri and North Dakota. Missouri decreased its cash and equivalents and significantly increased its alternative investments. North Dakota significantly increased its position in fixed income securities. These limited changes in asset mixes may indicate resolve to remain with a long-term strategy through limited re-balancing.

IV. Conclusions

While several public retirement plans in the Midwest have changed to defined contribution, the financial state of the remaining defined benefit plans leaves the participants effectively bearing risk due to the low funding levels and the absence of PBGC insurance. There is considerable disparity in the funding levels among the plans, as well as the past decade's funding trend. As states suffer from shortfalls in revenue throughout the country, it is indeed tempting to shift from the defined benefit plan to defined contribution plans for state university employees. State legislatures across the Midwest and the entire country have much to consider with regard to the future funding of these defined benefit plans as state revenues have declined significantly. The funding of state services hangs in the balance.

While this report should help in assessing the financial well-being of university employees with regard to the adequacy of their primary retirement plan, other research should be done with regard to the additional sources of retirement funds available to U.S. retirees. This is a major concern for all Americans in that an elderly person without adequate financial resources puts a burden on the entire society in which he or she lives. Such information will help policy makers determine the best course of action for the future.

Table I
Liability funding percentage of selected Midwest university defined benefit retirement plans, 2000-2009

Year	Illinois	Kansas	Missouri	N. Dakota	Ohio	S. Dakota
2000	88.20%	89.00%	84.90%	115.10%	92.00%	96.00%
2001	72.10%	88.00%	93.50%	110.60%	91.20%	96.40%
2002	58.90%	85.00%	92.50%	104.20%	77.40%	96.70%
2003	53.90%	78.00%	87.90%	98.10%	74.20%	97.20%
2004	66.00%	75.00%	82.00%	94.00%	74.80%	97.70%
2005	65.60%	70.00%	82.30%	90.80%	72.80%	96.60%
2006	65.40%	69.00%	82.80%	86.80%	75.00%	96.70%
2007	68.40%	69.00%	84.30%	93.40%	82.20%	97.10%
2008	58.50%	71.00%	83.40%	92.60%	79.10%	97.20%
2009	54.30%	59.00%	80.70%	85.10%	60.00%	91.80%
Average	65.13%	75.30%	85.43%	97.07%	77.87%	96.34%
Median	65.50%	73.00%	83.85%	93.70%	76.20%	96.70%
Minimum	53.90%	59.00%	80.70%	85.10%	60.00%	91.80%
Maximum	88.20%	89.00%	93.50%	115.10%	92.00%	97.70%

Source: States' respective pension plan annual reports.

Table II
Asset allocation percentages of selected Midwest university defined benefit retirement plans, 2006-2009

Asset Class 2009	Illinois	Kansas	Missouri	N. Dakota	Ohio	S. Dakota	Average
Domestic Equities	35.00%	27.67%	20.40%	32.40%	31.75%	52.90%	33.35%
International Equities	26.00%	21.98%	21.00%	12.10%	20.95%	*	20.41%
Fixed Income	23.00%	30.81%	23.20%	44.00%	20.10%	24.10%	27.54%
Real Estate	5.00%	6.16%	6.20%	5.70%	12.83%	8.50%	7.40%
Cash & Short-term Investments	2.00%	9.77%	0.90%	0.60%	8.65%	0.30%	3.70%
Alternative Investments	9.00%	3.61%	28.30%	5.20%	5.72%	14.20%	11.01%
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
Total Assets	$11.6B	$10.2B	$6.2B	$1.3B	$54.7B	$5.6B	
Asset Class 2008							
Domestic Equities	39.50%	29.14%	22.20%	37.70%	33.35%	49.80%	35.28%
International Equities	23.50%	22.58%	19.80%	13.90%	21.50%	*	20.26%
Fixed Income	26.00%	34.63%	23.10%	35.70%	20.90%	19.60%	26.66%
Real Estate	6.00%	3.60%	6.20%	6.70%	12.57%	13.00%	8.01%
Cash & Short-term Investments	1.00%	7.07%	9.00%	0.50%	6.69%	1.30%	4.26%
Alternative Investments	4.00%	2.98%	19.70%	5.50%	4.99%	16.30%	8.91%
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
Total Assets	$15.2B	$13.2B	$8.0B	$1.8B	$72.6B	$7.3B	

* Domestic and international equities combined.

Source: States' respective pension plan annual reports.

Table II, continued

Asset Class 2007	Illinois	Kansas	Missouri	N. Dakota	Ohio	S. Dakota	Average
Domestic Equities	41.50%	30.60%	29.20%	41.00%	37.82%	53.50%	38.94%
International Equities	23.50%	24.60%	22.40%	16.30%	22.33%	*	21.83%
Fixed Income	21.00%	28.50%	28.30%	31.40%	22.00%	24.10%	25.88%
Real Estate	6.00%	7.10%	5.40%	5.90%	10.71%	8.50%	7.27%
Cash & Short-term Investments	0.00%	6.20%	0.00%	1.00%	3.71%	0.30%	1.87%
Alternative Investments	8.00%	3.00%	14.70%	4.40%	3.43%	13.60%	7.86%
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
Total Assets	$16.0B	$14.2B	$8.1B	$1.9B	$79.6B	$8.2B	
Asset Class 2006							
Domestic Equities	42.00%	32.00%	28.50%	41.00%	39.30%	56.90%	39.95%
International Equities	23.50%	25.10%	23.10%	14.60%	22.75%	*	21.81%
Fixed Income	22.00%	23.50%	29.00%	33.30%	22.70%	16.50%	24.50%
Real Estate	6.00%	7.50%	4.90%	6.00%	10.51%	6.40%	6.89%
Cash & Short-term Investments	0.00%	8.30%	0.00%	1.00%	1.87%	8.30%	3.25%
Alternative Investments	6.50%	3.60%	14.50%	4.10%	2.87%	11.90%	7.25%
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	
Total Assets	$14.2B	$13.4B	$7.0B	$1.6B	$67.4B	$6.8B	

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How is the High-Tech Bubble Affecting Company Performance?

Cheng-Huei Chiao, Robert Kao, and Michael Russell

Abstract

This study analyzes key financial ratios' variations and helps us understand company financial performance on both high-tech and non-high-tech companies before and after the impact of the high-tech bubble. The composite index of the ranked profitability, assets utilization, liquidity, debt utilization, price to earnings, and market to book value are generated by company level first. The price ratios of high-tech and non-high tech companies are evaluated by a non-linear regression method for the periods before and after the bubble. The outcomes of various ratios are tested by statistical significance for each industry in these time periods. The results show that the high-tech companies have reached a higher efficiency level and the non-high-tech companies have suffered relatively more on profitability level after the high-tech bubble. A significantly lowered return on equity indicates that the high-tech companies have reduced their product unit cost and profit margins. As for the effect of the size of the company, the large high-tech companies have weakened the profit gaining power, but the small high-tech companies have remained profitable after the effect.

I. Introduction

In the 1990s, a record-setting rise in stock valuations of high-tech companies occurred. Many venture capitalists moved in quickly and tried to mitigate the risk by starting as competitors and letting the market decide which stocks would prosper. Besides the low interest rates in 1998–1999 that helped increase the start-up capital amounts on high-tech industries, many aggressive high-tech businesses have relied on joining network effects. These companies were operating at a sustained net loss and tried to build their market shares first. They expected to build enough brand awareness and to turn it into a profitable mode for their services later. Many investors eagerly put more of their new wealth into high-tech companies' securities (Spector, 2000). A bubble in the high-tech sector began to form when speculators noticed the fast rise in its stock value. They anticipated the value would rise even further, rather than because the share was undervalued. Penman (2001) warned that such a bubble could affect consumers from having unreasonable expectations of likely returns and make misguided consumption decisions.

The Federal Reserve Bank (2009) had tried to slow the fast pace booming economy by raising interest rates six times throughout 1999 and early 2000. The overheating market began to show sign of cooling down. The high-tech bubble finally burst on March 10, 2000, when the NASDAQ Composite Index peaked at 5048, which was more than doubled its value from the year before. One possible cause for the collapse of the high-tech companies' stocks was directly involving the massive sell-off of multi-billion dollar orders from their major leading stocks. This huge sell-off resulted in almost four percentage points lower in the NASDAQ opening on Monday, March 13. This triggered a chain reaction of selling off investors' funds and

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institutions' liquidation. Eventually, the NASDAQ lost roughly nine percent of its points and fell to its lowest at 4580 on March 15 (Yahoo! Finance).

The accelerated business spending in preparation for the switchover of Y2K may also contribute to the collapse of the bubble. Businesses' spending on all the equipment they needed for some time had declined quickly when the New Year had passed without any incidents. In addition, the poor results of Internet retailers toward the end of 1999 may have been related to the bursting of the bubble. By 2001, the bubble was deflating even further. A majority of the high-tech companies ceased trading after exhausting their venture capital and without making any net profit. Many high-tech companies were either acquired by other companies or liquidated by creditors (Lowenstein, 2004).

Ever since, the high-tech companies have reshaped the aftermath economy and reflected on their financial positions. In response, many investors have recalibrated their investment strategies. Thereby, we examine key financial ratios with composite ranking indexes before and after the bubble to help us understand the structural changes of all major companies. Furthermore, the high-tech and non-high-tech companies were separated and cross-sectioned for insightful evaluations. The different company sizes are another important factor of the bubble's impact.

The high P/E ratios of the 1990s are now seen as more to do with the quality of prices rather than the quality of earnings after the high-tech bubble (Penman 2002). Glaum and Friedrich (2006) found that today the high-tech companies rely much more on the discounted cash flow analysis method than in the late 1990s, when valuation was largely based on multiples. In line with this, they reported that analysts have changed their focus from revenue-oriented measures towards an assessment of profitability and cash flow generation. Penman and Zhang's research (2004) stated that the P/E ratio has been tracked to analyze sustainability or persistence of earnings. They used the P/E ratio for the amount paid for a dollar of current earnings. This paper specifies and estimates a model that employs financial statement information to indicate the probability of sustainable earnings. Penman and Zhang (2004) indicated that stock returns can be predicted when the market's P/E ratio differs from that indicated by their models. Fama and French (2000) used a simple partial adjustment model with a uniform rate of mean reversion and found that mean reversion is faster when profitability is below its mean and when it is further from its mean in either direction. They concluded that the mean reversion in profitability produced predictable variation in earnings.

Nissim and Penman (2001) also applied a standard profitability analysis in the forecasting payoffs to equities. Their analysis of current financial statements provides historical benchmarks for forecasting, typical values for financial ratios, along with their cross-sectional variation and correlation. In order to view the forecasts, they used the time series behavior of many of the ratios and their typical "long-run, steady-state" levels were documented. Berger and Udell (1998) summarized the empirical findings on collateral and concluded that riskier firms are more likely to pledge collateral. Empirical evidence suggested that there was a negative relationship between a firm's leverage and its intangible assets. The lack of collateral assets held by high-tech firms limited their access to debt financing.

The findings of this study show that the high-tech companies have reduced their proportion of sales to outweigh the reduced product unit cost. In general, the non-high-tech companies have more impact on profitability after the bubble. The high-tech companies have a higher efficiency level than non-high-tech companies after the effect of the crush. The larger high-tech companies have reduced their short-term debt and the small high-tech companies have reduced their inventories after the bubble. The large high-tech companies have reduced the profit gaining power after the bubble, but the small high-tech companies are still maintaining profitability. Also the non-high-tech companies have turned around faster than the high-tech companies after the bubble.

II. Data Structure

Carpenter and Petersen (2002) examined 2,400 publicly traded U. S. high-tech companies over a period from 1981 to 1988 and concluded that most of the small high-tech firms obtained little debt. They also pointed out new equity financing was exceedingly important and permitted a substantial increase in firm size. The data for our study comes from two major sources. It consists of all firms in the intersection of (a) the Center for Research in Security Prices (CRSP) files, and (b) the merged COMPUSTAT annual files of income-statement and balance-sheet data, also maintained by CRSP (Fama and French 1992). We obtained price data from CRSP, and corporate financial ratios data from COMPUSTAT. All 52,895 companies from this database were evaluated.

For the comparative study of financial ratios changes during the high-tech stock market bubble and its aftermath, we separate our data for the period of 1993-2007 into two seven-year segments. The first covers 1993-1999, while the second 2001-2007. In this analysis, we repeat the steps in the main procedure that we have developed for the financial ratios and firms. We compare the results for the two time periods and outline the findings as stated below.

We then identify firms that were in the top 10-percentile of stock price total returns in the period from 1/1/1998 through 3/31/2000. These firms were then tracked by the first three digits of their SIC codes. We then calculate the proportion of the firms in the top 10-percentile group within each three-digit SIC code and identify eleven SIC groups that are within one percentile or less of the concentration of firms as observed in the top 10% group under the binomial probability model. The descriptions of the eleven SIC groups, which we call “high-tech” or “high-growth” sector, are provided in Appendix I.

From the list, we see that a vast majority of the firms are in the industries closely related to Internet, telecommunication, computer, or biomedical products. The proportion of firms in the so-called “high-tech” sector comprises 27% of all firms in our sample for the period 1/1998 – 3/2000. The high-tech companies before and after the high-tech bubble include 9.480 companies or 18.93 percent of the total. The non-high-tech companies before and after the high-tech bubble include 43,415 companies or 82.08 percent of the total. We construct the analysis as described in the following sections for the two seven-year periods and, within each period, for high-tech and non-high-tech firms separately. Hence, we have a total of 2 x 2 = 4 sets of results.

III. The Model and the Estimation Procedure

a. Definition of Ratios:

Soliman (2008) used a common form of financial statement analysis, or DuPont analysis, for profit margin and asset turnover ratios to measure accounting information. He indicated that the DuPont components represent an incremental and viable form of information about the operating characteristics of a firm. In this study, we group each set of ratios into two to four individual ratios as components. We then have analyzed and interoperated each set of ratios by our proposed methodologies and models. Listed below are the individual ratios within each set, with their definitions.

1) Profitability Ratios:[1]
   Gross Profit Margin Ratio (PM): Gross Profit / Sales
   Return on Assets Ratio (ROA): Net Income / Assets
   Return on Equity Ratio (ROE): Net Income / Stockholder's Equity
2) Assets Utilization Ratios:
   Receivables Turnover Ratio (RT): Sales / Receivables
   Inventory Turnover Ratio (IT): Sales / Inventory
   Fixed Assets Turnover Ratio (FAT): Sales / Property, Plant, and Equipment
   Total Assets Turnover Ratio (TATO): Sales / Assets
3) Liquidity Ratios:
   Current Ratio (CR): Current Assets / Current Liabilities
   Quick Ratio (QR): (Current Assets – Inventories) / Current Liabilities
   Net Working Capital to Total Assets Ratio (NWTA): (Current Assets – Current Liabilities) / Assets
4) Debt Utilization Ratios:
   Long-term Debt to Equity Ratio (LTDE): Long-term Debt / Stockholder's Equity
   Total Debt to Total Assets Ratio (TDTA): (Assets – Stockholder's Equity) / Assets
5) Price Ratios:
   Price to Earnings Ratio (PE): Stock Price / Earning Per Share

Market to Book Value Ratio (MB): (Market Price × Common Shares Outstanding) / Stockholder's Equity

b. Methodology

The composite index of the ranked profitability, assets utilization, liquidity, and debt utilization ratios has been used for the companies in each industry; each company also has been grouped as a high-tech or non-high-tech company. For comparison purposes between industries, we rank each financial ratio instead of using direct ratio of each company, allowing the different nature and characteristics of each industry to be neutralized and cross-examined in the analysis. First, we create nine equivalent partitions, then group and rank each company in each industry, assigning each company a rank from one through nine. Second, we group those financial ratios into four categories: profitability, assets utilization, liquidity, and debt utilization. The procedure

[1] Cash flow is not included in this study because it is not like financial ratios that have been standardized and is not comparable among different firms. In the profitability ratios, gross profit and net income are close to the cash flow concept. The coefficients of the Profitability Ratios in the regression model showed the largest coefficients comparing to others ratios. In the standard finance theory, it implies that one of the key factors influencing stock prices is the expectation of cash flow.

for ranking composite index for four indices is presented as below.

$$\sum_{i=1}^{n}[Rank(Ratio_{it})]/n\,,\ \ t = 1, 2, 3\ldots ; \qquad (1)$$

where $Rank(Ratio_{it})$ represents the ranking of the financial ratios i at year t.

Third, the nonlinear regression method has been applied in terms of price earning and market to book value ratios for both high-tech and non-high-tech companies. Bates and Watts (1988) provided practical introductions to the nonlinear regression with many examples. Seber and Wild (1989) also developed a more extensive treatment of nonlinear regression methodology. In Soliman's (2007) study, he found that the DuPont analysis was a useful tool of financial statement analysis and applied a linear regression to analyze the DuPont decomposition of a firm's return on net operating assets that had been derived from a theoretical and parsimonious framework of valuation and relates to the operational aspects of the firm. We further adopt the nonlinear regression method for analyzing these grouped financial composite indices in this study. The squared terms represent the accelerated effects of impacts from the composite indices. They are used to test the financial structure change before and after the high-tech bubble occurred in the year 2000. The models are presented below.

$$Y_i = \alpha_i + \sum_{j=1}^{4}\beta_j \times Ratiosrank_j + \sum_{j=1}^{4}\gamma_j \times (Ratiosrank_j)^2\ ,\quad i = 1 \text{ and } 2; \qquad (2)$$

where Y_i represents the market to book value ratios and price to earning ratios for all companies, high-tech, and non-high-tech companies. $Ratiosrank_j$ represents the composite indices of profitability ratios, the composite indices of assets utilization ratios, the composite indices of liquidity ratios, and the composite indices of debt utilization ratios. α_i , β_j , and γ_j represent the coefficients with the corresponding ratios for all companies, high-tech, and non-high-tech companies.

The results of each coefficient in the non-linear regression method would then represent an important effect on the magnitude of each financial ratio in the category. Each coefficient can be used for the comparison between and across the industries. We have examined the variance inflation factor in the regression model for the multi-co linearity problem. The result confirms that the multi-co linearity problem between industry groups is not significant in the model. It is mainly contributed by the composite index ratios used in this study that would prevent the multi-co linearity problem in the estimations. The coefficients of the regression can then generate a meaningful outcome to reflect the ratio variances before and after the bubble.

IV. Empirical Results

a. High-Tech Industries

In Table I Panel A and B, we observe that the significant decline of return on equity from 0.1488 to 0.1395 indicated that the high-tech companies reduced their product unit cost and profits. They have reduced their proportion of sales to outweigh the reduced product unit cost.

Among the mean ratios of assets utilization, RT and IT have increased from 5.5457 to 6.2911 and 14.3448 to 16.2810 after the high-tech bubble, respectively. It again shows the decrease of sales, receivables, and inventory among the high-tech companies after the bubble.

Among the mean ratios of liquidity, we identify that NWTA has declined from 0.4154 to 0.3777 after the effect of the bubble. It shows that the short-term liabilities and current assets have declined; however, the long-term liabilities have increased in the aftermath. When observing debt utilization ratio means, the long-term debts of those high-tech companies have increased some from 0.1641 to 0.1755, but the short-term debts have declined slightly from 0.3585 to 0.3523 after the year 2000.

The price to earnings ratios have increased from 19.5788 to 21.9535 after the bubble and it is shown that the short-term earning per share has declined some. Similarly, the market-to-book value ratios have declined from 3.6101 to 3.3224 after the bubble, and the long-term equity has declined but at an insignificant rate.

Other ratios have shown the larger volatility and higher risk because of their higher standard deviations after the bubble. Also, the ROE, IT, and PE show the wider minimum and maximum values range after the bubble. They are confirmed that the profitability, sales, and short-term earning have become more volatile and higher risk after the bubble.

b. Non-High-Tech industries

In Table I Panel C and D, we observe that after the bubble, the significant higher of ROE mean ratios, comparing 0.1426 with 0.1395, indicate that the non-high-tech companies have less profit than high-tech companies; however, non-high-tech companies have higher liability than high-tech companies, i.e. CR and QR mean ratios are lower in non-high-tech companies. Also, the insignificant sales changes prove that the non-high-tech short-term liability has been declining after the period of the bubble. In general, the non-high-tech companies have more impact on profitability after the bubble.

Among the mean ratios of assets utilization, the significant lower of RT, comparing 5.5107 to 6.2911, has indicated a small increase of receivables after the high-tech bubble. The increase of IT from 13.3245 to 20.8291 mean ratios explains that there is a small increase of sales and receivables. The decline of both FAT and TATO, reducing from 3.6805 to 3.5892 and from 0.8425 to 0.7606 respectively, has indicated a small decline of sales.

As for the liquidity ratios, the decline of CR from 2.3722 to 2.3148 describe that the short-term current liabilities and assets have declined after the bubble. However, the increase of QR from 1.6842 to 1.7227 and decrease of NWTA from 0.1721 to 0.1500 have shown the decrease of inventories.

When we observe debt utilization ratios, the increase of LTDE and TDTAIT from 0.3890 to 0.4186 and from 0.5391 to 0.5408, respectively, shows that the increase of long-term debt and short-term debt have increased modestly after the bubble, respectively.

Both PE and MB ratios have increased from 14.2151 to 16.0375 and 2.3298 to 2.4271, respectively after the bubble. The significant increase of MB has shown a small increase in price and equity after the bubble. The higher standard deviations of other ratios have shown that the profitability, sales, and long-term equity have higher volatility and risk after the year 2000.

c. Financial Ratios

Table II Panel A and B provides a comparison of means and slopes for all companies before and after the high-tech bubble burst. When we cross examine the high-tech and non-high-tech companies, mean values of profitability ratios have shown similar impacts on PM ratios. However, the high-tech companies have reduced more costs than the non-high-tech companies. In terms of ROA and ROE, the high-tech companies have had more impact after the bubble than the non-high-tech companies.

As for the trends or slopes of the profitability ranks, the high-tech companies' PM ratios did not show much difference after the bubble. However, their ROA and ROE ratios had shown significant difference after the bubble. This phenomenon indicates that the proportion of net income among high-tech companies has grown more than their assets and equities. The trend has shown a strong recovery after the bubble. When we observe the non-high-tech companies, all three ratios - PM, ROA, and ROE - have had stronger recoveries. The slopes of ROA and ROE ratios have especially had stronger outcomes than the high-tech companies.

Mean values of FAT and TATO ratios showed the different management among the high-tech and non-high-tech companies after the bubble. It means that the high-tech companies have a higher efficiency level than non-high-tech companies after the effect of the crash.

From the trends or slopes standpoint, RT ratios show that the high-tech companies' receivables have increased and then remain stable after the bubble. However, the non-high-tech companies remain at about the same level of receivables at the beginning but relieve some later on. The IT ratios showed that the high-tech companies' inventories were high before the bubble. The inventories had improved some in the first two years, but they were built up again after that. As for the non-high-tech companies, the level of inventories was lower than the high-tech companies had at the beginning and reduced afterward.

After the bubble, the trend of FAT ratios dropped to the bottom and rose up again thereafter. The high-tech companies had higher TATO ratios than the non-high-tech companies, but they declined after the bubble. In general, the non-high-tech companies have a lower declining rate or they are more mature than the high-tech companies.

The mean values of liquidity ratios show that the non-high-tech companies have lowered risk but they have a more difficult time obtaining the capital than the high-tech companies. The high-tech companies' mean ratios have reduced more than non-high-tech companies.

The non-high-tech companies' trends of CR and QR ratios have increased slightly after the bubble. The high-tech companies are more stable but there was not a significant change in their trends. Regarding the trend of NWTA, the high-tech companies have reduced slightly and then remain stable after the bubble. Their ratios were quite stable before and after the bubble.

The mean values of LTDE and TDTA ratios for the non-high-tech companies are higher than the high-tech companies both before and after the bubble. The mean values of LTDE indicate that the high-tech companies have increased their debt significantly. Both categories of companies have changed the LTDE after the bubble. From the slopes of debt utilization ratios, we observe that the non-high-tech companies are more cautious in borrowing the capital than the high-tech companies.

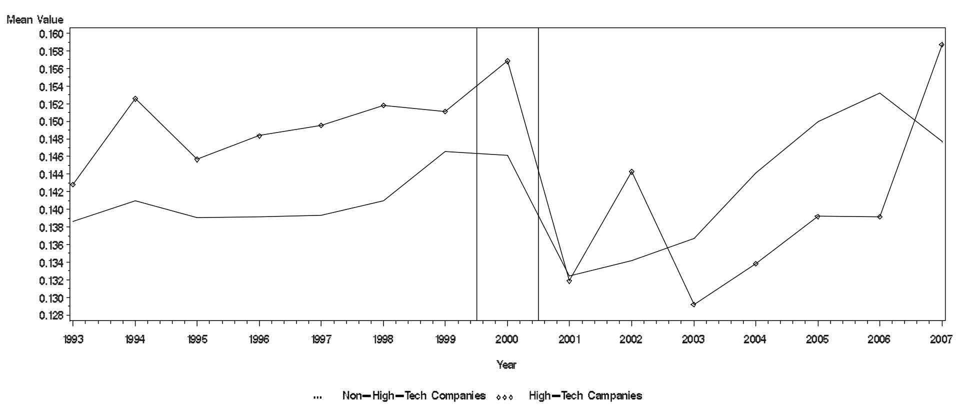
High-tech companies' mean values of PE and MB were higher than non-high-tech companies'. Non-high-tech companies had more significant changes after the bubble. The price reduced more than earnings per share in terms of magnitudes after the bubble.

In terms of the slopes of PE and MB ratios, the high-tech companies were higher but not significantly so in terms of statistics tests aftermath. For non-high-tech companies' PE, the slopes of its ratios were not significant. The capital had been transferred from the non-high-tech to the high-tech companies. The higher trend of MB showed that in the long-run people still like to invest the high-tech companies' securities. After the bubble, the gaps of slopes of MB between high-tech and non-high-tech companies have been shrinking. Investors have emphasized more on fundamental analysis after the bubble.

V. Graphic Results

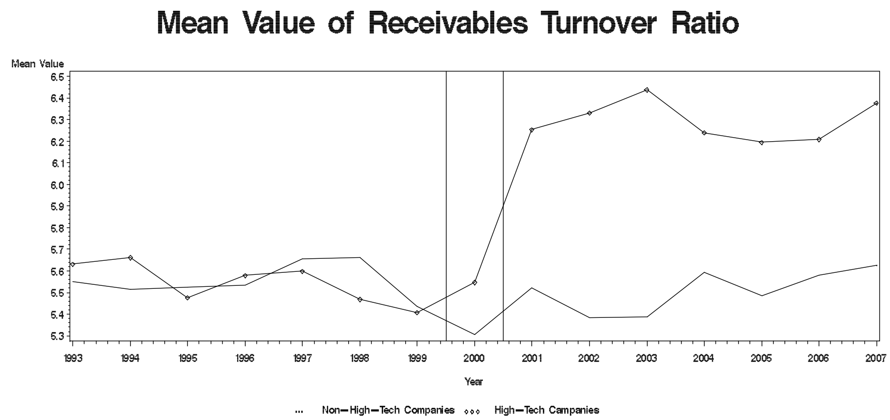
Mean values of return on equity ratios have shown the pattern change after the bubble in Graph 1. The high-tech ratios were higher than the non-high-tech ratios before the bubble, but revealed the mixed results after the year 2000. The ratios became random between two categories.

Graph 1 – Mean Value of Return on Equity Ratios

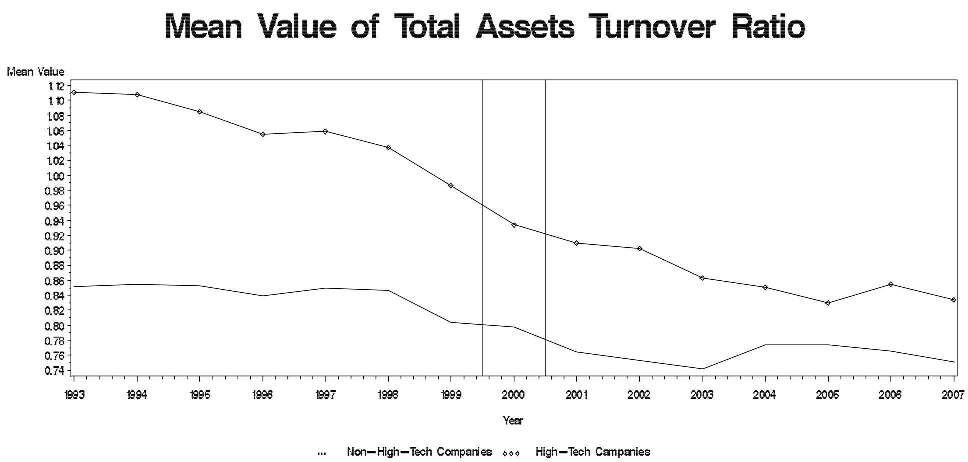


However, the mean value of receivable turnover rates had an opposite phenomenon before and after the bubble. In Graph 2, the high-tech and the non-high-tech rates were mixed before the bubble. The high-tech became much higher than the non-high-tech after the year 2000.

Trends of the mean value of gross profits and inventory turnover ratios for high-tech and non-high-tech companies have indicated continuous upward trends in the study period before and after the high-tech bubble. In those ratios, the high-tech companies' financial ratios were higher than the non-high-tech companies. Trends of return on assets ratios, fixed-asset turnover ratios, and price-earning ratios have shown larger fluctuations after the high-tech bubble in the study period. Their high-tech companies' financial ratios were higher than the non-high-tech ones.



Total assets turnover ratios have been declining throughout the entire period as shown in Graph 3. Dividend-to-price and total-debt-to-total-assets ratios have shown the opposite results - the non-high-tech companies' ratios were higher than the high-tech ones.



VI. Size-Effect

The market capitalization may be an important factor in influencing companies' performances before and after the high-tech bubble. Table III tabulates the means and slope for the small and large companies before and after the high-tech bubble.

In profitability rakings, large high-tech companies usually have a higher profit than small companies. Large high-tech companies have reduced the profit gaining power after the bubble, but the small high-tech companies are still profitable. Small high-tech companies' ROA and ROE have reduced slightly, but the large companies' slopes have changed more significantly after the bubble.

As for the assets utilization ratio ranking, the small high-tech companies were more sensitive than large high-tech companies after the bubble. Similar outcomes have been observed for non-high-tech companies. The high-tech and non-high-tech companies have more impact in terms of slope on the ratios than small companies after the bubble.

In the category of liquidity ratio ranking, we observed higher mean values in the non-high-tech companies. Both small and large NWTA mean values have changed after the bubble, indicating that the larger high-tech companies have reduced their short-term debt and the small high-tech companies have reduced inventory after the bubble.

The results showed that large high-tech and non-high-tech companies had larger debt utilization ratios after the bubble. The size-effect of debt utilization did not show a clear impact on the high-tech companies. In terms of long-term debt, the large non-high-tech companies were more conservative after the bubble and reduced long-term debt substantially. However, the small non-high-tech companies had less ability to reduce the long-term debt.

The large high-tech and non-high-tech companies had higher mean values of the price to earning ratio rankings because of their awareness and reputation even after the bubble. The earnings had reduced more than prices on large high-tech and non-high tech companies' aftermath.

VII. Structure Change Before and After High-Tech Bubble Burst

Table IV provides price ratios information about the non-linear regression of the structure change before and after the high-tech bubble. Overall, models include the independent variables of ranks in profits, assets, liquidities, and debts for all sample companies, both high-tech and non-high-tech.

The Chow test is also used in this time series analysis to test for the presence of a structural change. In this financial evaluation, the Chow test value is used to determine whether the independent variables have different impacts on different subgroups of all companies. The results of market to book value's Model 1 and Model 2 showed that F-value of the Chow Test was 6.69 and P-value was less than 0.0001, indicating that before and after the high-tech bubble, all companies' financial ratios have significantly changed. Asset and debt indices have become significant after the high-tech bubble occurred. However, the squared terms became insignificant for all samples.

When observing the market to book value of high-tech companies, we found that the profit index was the only one showing significant differences. The liquidity index became insignificant after the bubble. All four factors remained significant for non-high-tech companies.

We further examined price-equity ratio and found that the liquidity index had become insignificant for all companies after the bubble. For the high-tech companies, profit and debt indices remained significant while squared terms profit and asset indices also remained significant after the bubble.

For the price to equity ratio on non-high-tech companies, profit and debt indices remained significant after the bubble. However, the liquidity index became insignificant after the bubble. The squared terms of profit and debt indices remained or became significant afterward, but not on asset and liquidity indices.

In the short-term effect, the results showed that price to earning ratios have reduced first and then increased later after the bubble. High-tech companies had more profit impact than non-high-tech companies in the aftermath. The coefficients after the bubble have become higher than before, showing that the investors have weighted profitability ratios as more important than other factors for their investments.

In general, the squared terms of profitability ratios were higher on the non-high-tech companies than on the high-tech companies. This indicated that the non-high-tech companies have turned around faster than the high-tech companies after the bubble. Investors have used the profitability ratios on non-high-tech companies' investment more frequently than before the bubble.

The positive correlations between asset utilization ratio and profitability ratio have turned to a negative correlation after the bubble. It means that the reduction of inventory, receivables, and sale of assets would shrink the liability. With the reduced liability, asset utilization ratios will reduce too. Investors would have a perception of the performance of the company. Since these coefficients had relatively small values, the effects of assets utilization were not as important as the previous one.

When observing the liquidity ratio composite rankings, we found that many companies have structured the way they deal with the debt much better after the bubble. Investors have paid more attention to this issue after the event. However, the high-tech companies have not had significant influence either before or after the bubble.

The outcomes of debt ratio composite rankings have shown that the negative correlation coefficients become even larger after the bubble. This can be observed on the non-high-tech companies. The coefficient of high-tech companies has changed the sign from positive to negative after the bubble. In other words, investors have paid more attention to the debt-ratios after the bubble.

Market to book value ratios would show the companies' long-term outcomes. The profitability composite ratio ranking has shown the largest change among the coefficients: the ratios have become larger after the bubble. The high-growth companies will have high profit rankings and such high-growth stocks will have high MB ratios. After the bubble, the profit was more sensitive to the investors, and decisions of investors have become more reasonable and sensitive.

In the market to book value ratios, the asset composite ratio ranking had a larger coefficient after the bubble in the first-degree term. However, the coefficient of the squared term became insignificant, showing that investors became more normative. This effect has been observed among the non-high-tech investors.

The liquidity ratio composite ranking in the market to book ratio would show the short-term effect of companies' performances. After the bubble, the coefficients of the liquidity have become less significant. The squared term has shown this outcome even more clearly.

The negative coefficients of debt ratio composite ranking in this model have shown more significant outcomes. In the long run, the increase of debt will increase the tax field effect, decrease weighted average cost of capital, and increase after-tax profit. The coefficients were more significant for the non-high-tech companies than the high-tech companies.

VIII. Conclusion

The results showed that the insignificant sales changes proved that the non-high-tech short-term liability has been declining after the period of the bubble. In general, the non-high-tech companies have more impact on profitability after the bubble. The profitability, sales, and long-term equity have higher volatility and risk after the year 2000. We observed that the non-high-tech companies are more conservative than the high-tech companies.

The high-tech companies have reduced more cost than the non-high-tech companies. This phenomenon indicated that the proportion of net income among high-tech companies has grown more than their assets and equities. The trend has shown a strong recovery after the bubble. The high-tech companies have a higher efficiency level than non-high-tech companies after the effect of the high-tech bubble. On the whole, the non-high-tech companies had a lower declining rate or they were more mature than the high-tech companies.

The size-effect analysis showed that large high-tech companies have reduced the profit gaining power after the bubble, but the small high-tech companies were still profitable. The study indicated that the larger high-tech companies have reduced their short-term debt and the small high-tech companies have reduced their inventories after the bubble. In terms of long-term debt, the large non-high-tech companies were more cautious after the bubble and reduced long-term debt substantially. However, the small non-high-tech companies had less ability to reduce long-term debt. The earnings have reduced more than the prices on large high-tech and non-high tech companies after the bubble.

The regression results indicated that the non-high-tech companies have turned around faster than the high-tech companies after the bubble. Investors have used the profitability ratios on non-high-tech companies' investment more frequently than before the bubble. Many companies have structured the way they can deal with the debt much better after the bubble. Investors have paid more attention to this issue after the event. However, the high-tech companies have not had significant influence either before or after the bubble. Investors also have paid more attention to the debt-ratios after the bubble. The large high-tech and non-high-tech companies had higher price to earning ratio rankings because of their awareness and reputation even after the bubble. The earnings have reduced more than the prices in both large high-tech and large non-high tech companies' aftermath. Generally, aftermath companies have changed most of their focus from revenue-oriented measures to profitability assessment, asset utilization, and debt burden.

Table I: Descriptive Statistics

This table displays the descriptive statistics of the most important financial ratios in our database. PM is Gross Profit Margin Ratio, ROA is Return on Assets Ratio, ROE is Return on Equity Ratio, RT is Receivables Turnover Ratio, IT is Inventory Turnover Ratio, FAT is Fixed Assets Turnover Ratio, TATO is Total Assets Turnover Ratio, CR is Current Ratio, QR is Quick Ratio, NWTA is Net Working Capital to Total Assets Ratio, LTDE is Long-term Debt to Equity ratio, TDTA is Total Debt to Total Assets Ratio, PE is Price to Earnings Ratio, and MB is Market to Book Value Ratio.

Panel A: Pre-High-Tech Bubble Burst (High-Tech Companies)

Ratios	Mean	Std. Dev.	Min.	Max.
PM	0.4838	0.0132	0.4668	0.5061
ROA	0.0880	0.0020	0.0840	0.0900
ROE	0.1488	0.0035	0.1428	0.1526
RT	5.5457	0.0957	5.4063	5.6612
IT	14.3448	0.8439	13.3110	15.6627
FAT	4.3471	0.0970	4.1852	4.4657
TATO	1.0630	0.0437	0.9864	1.1110
CR	3.3514	0.1087	3.2344	3.4995
QR	2.7372	0.1136	2.5571	2.8769
NWTA	0.4154	0.0156	0.3954	0.4340
LTDE	0.1641	0.0123	0.1460	0.1772
TDTA	0.3585	0.0102	0.3399	0.3707
PE	19.5788	2.1353	16.4452	23.4005
MB	3.6101	0.4389	3.0899	4.4486

Panel B: Post-High-Tech Bubble Burst (High-Tech Companies)

Ratios	Mean	Std. Dev.	Min.	Max.
PM	0.5247	0.0133	0.4994	0.5391
ROA	0.0800	0.0040	0.0747	0.0871
ROE	0.1395	0.0099	0.1292	0.1587
RT	6.2911	0.0917	6.1946	6.4372
IT	16.2810	1.2553	13.8298	17.8516
FAT	3.9644	0.1682	3.7540	4.2418
TATO	0.8635	0.0312	0.8300	0.9096
CR	3.4062	0.1107	3.3361	3.6493
QR	2.9207	0.0721	2.8225	3.0494
NWTA	0.3777	0.0140	0.3663	0.4072
LTDE	0.1755	0.0062	0.1664	0.1840
TDTA	0.3523	0.0080	0.3400	0.3640
PE	21.9535	3.3542	16.6970	25.7231
MB	3.3224	0.3087	2.7023	3.6757

Table I (Continued): Descriptive Statistics

Ratios	Mean	Std. Dev.	Min.	Max.
Panel C: Pre-High-Tech Bubble Burst (Non-High-Tech Companies)				
PM	0.3751	0.0061	0.3692	0.3854
ROA	0.0542	0.0012	0.0520	0.0555
ROE	0.1407	0.0028	0.1386	0.1466
RT	5.5540	0.0806	5.4356	5.6631
IT	18.5897	1.4111	16.0606	20.5927
FAT	3.6805	0.0237	3.6383	3.7071
TATO	0.8425	0.0178	0.8040	0.8551
CR	2.3722	0.0818	2.2174	2.4546
QR	1.6842	0.0756	1.5558	1.7705
NWTA	0.1721	0.0108	0.1488	0.1807
LTDE	0.3890	0.0327	0.3537	0.4459
TDTA	0.5391	0.0096	0.5303	0.5580
PE	14.2151	1.7301	12.1056	17.3068
MB	2.3298	0.1119	2.1945	2.4984
Panel D: Post-High-Tech Bubble Burst (Non-High-Tech Companies)				
Ratios	Mean	Std. Dev.	Min.	Max.
PM	0.4133	0.0182	0.3895	0.4353
ROA	0.0542	0.0054	0.0475	0.0605
ROE	0.1426	0.0082	0.1324	0.1532
RT	5.5107	0.0972	5.3835	5.6249
IT	20.6928	0.3979	20.1497	21.3603
FAT	3.5892	0.1439	3.4132	3.7371
TATO	0.7606	0.0121	0.7415	0.7738
CR	2.3148	0.0750	2.1968	2.3979
QR	1.7227	0.1015	1.5634	1.8306
NWTA	0.1500	0.0107	0.1370	0.1603
LTDE	0.4186	0.0230	0.3940	0.4460
TDTA	0.5408	0.0095	0.5293	0.5530
PE	16.0375	1.5795	13.7018	17.7537
MB	2.4273	0.2669	1.9837	2.6669

Table II: Comparison of Means and Slopes Before and After the High-Tech Bubble Burst (HTB) for All Companies

T-statistics are calculated by using a pooled difference of means test, F-statistics are for a Chow test
* Significant at the 10 percent level (two-tailed)
** Significant at the 5 percent level (two-tailed)
*** Significant at the 1 percent level (two-tailed)

Panel A: High-Tech Companies						
Ratios	Mean			Slope		
Successive Quarter	Pre-HTB	Post-HTB	*t*-statistic for difference	Pre-HTB	Post-HTB	*F*-statistic for difference
PM	0.4838	0.5247	5.77***	0.0057	0.0028	0.79
ROA	0.0880	0.0800	-4.71***	0.0003	0.0010	7.08**
ROE	0.1488	0.1395	-2.36***	0.0010	0.0029	5.89**
RT	5.5457	6.2911	14.88***	-0.0335	-0.0041	39.04***
IT	14.3448	16.2810	3.39***	0.3645	0.1397	0.38
FAT	4.3471	3.9644	-5.21***	-0.0122	0.0710	22.51***
TATO	1.0630	0.8635	-9.83***	-0.0194	-0.0126	9.06***
CR	3.3514	3.4062	0.93	-0.0015	-0.0302	1.45
QR	2.7372	2.9207	3.61***	0.0256	-0.0121	1.83
NWTA	0.4154	0.3777	-4.76***	-0.0026	-0.0046	0.30
LTDE	0.1641	0.1755	2.18**	0.0027	-0.0002	0.63
TDTA	0.3585	0.3523	-1.26	0.0002	0.0029	2.15
PE	19.5788	21.9535	1.58	0.6053	0.3635	0.15
MB	3.6101	3.3224	-1.42	0.1608	0.0154	4.94**
Panel B: Non-High-Tech Companies						
Ratios	Mean			Slope		
Successive Quarter	Pre-HTB	Post-HTB	*t*-statistic for difference	Pre-HTB	Post-HTB	*F*-statistic for difference
PM	0.3751	0.4133	5.25***	0.0001	-0.0017	3.35*
ROA	0.0542	0.0542	0.00	-0.0002	0.0023	17.77***
ROE	0.1407	0.1426	0.59	0.0009	0.0035	14.25***
RT	5.5540	5.5107	-0.91	0.0029	0.0285	2.00
IT	18.5897	20.6928	3.80***	0.5955	0.1191	6.95**
FAT	3.6805	3.5892	-1.66	-0.0035	0.0611	28.67***
TATO	0.8425	0.7606	-10.07***	-0.0058	0.0007	8.83***
CR	2.3722	2.3148	-1.37	-0.0266	0.0335	12.19***
QR	1.6842	1.7227	0.80	-0.0224	0.0458	14.29***
NWTA	0.1721	0.1500	-3.84***	-0.0038	0.0045	16.91***
LTDE	0.3890	0.4186	1.96*	0.0137	-0.0100	25.67***
TDTA	0.5391	0.5408	0.34	0.0028	-0.0042	9.38***
PE	14.2151	16.0375	2.06**	0.0191	0.3491	0.27
MB	2.2783	2.4273	1.19	0.0079	0.0855	1.31

Table III: Comparison of Means and Slopes Before and After the High-Tech Bubble Burst for Small Size Companies

Stocks listed in NYSE, AMEX, and NASDAQ that have the required CRSP-COMPUSTST data are then allocated to three size portfolios based on the NYSE deciles breakpoints, divided at the 3rd and the 7th deciles breakpoint.
T-statistics are calculated by using a pooled difference of means test, F-statistics are for a Chow test
* Significant at the 10 percent level (two-tailed)
** Significant at the 5 percent level (two-tailed)
*** Significant at the 1 percent level (two-tailed)

Panel A: High-Tech Companies						
Ratios	Mean			Slope		
Successive Quarter	Pre-HTB	Post-HTB	*t*-statistic for difference	Pre-HTB	Post-HTB	*F*-statistic for difference
PM	0.4692	0.5049	4.66***	0.0038	0.0038	0.06
ROA	0.0827	0.0768	-2.90***	-0.0005	0.0010	2.66
ROE	0.1344	0.1257	-2.18**	-0.0011	0.0019	2.08
RT	5.5076	6.2628	8.10***	-0.0658	-0.0213	9.04***
IT	13.3245	15.1098	2.95***	0.2790	0.2603	0.04
FAT	4.5936	4.2729	-3.82***	-0.0198	0.0853	24.09***
TATO	1.1153	0.9275	-9.22***	-0.0139	-0.0184	5.23**
CR	3.5297	3.6410	1.53	-0.0122	-0.0059	0.56
QR	2.8105	3.0753	3.95***	0.0015	0.0239	0.74
NWTA	0.4439	0.4154	-3.21***	-0.0037	-0.0022	0.09
LTDE	0.1432	0.1351	-1.04	0.0041	-0.0027	2.06
TDTA	0.3412	0.3273	-2.56***	0.0014	0.0008	1.54
PE	17.2877	20.3411	1.90	0.1608	0.7778	0.80
MB	2.8958	2.8122	-0.45	-0.0384	0.0954	1.38
Panel B: Non-High-Tech Companies						
Ratios	Mean			Slope		
Successive Quarter	Pre-HTB	Post-HTB	*t*-statistic for difference	Pre-HTB	Post-HTB	*F*-statistic for difference
PM	0.4248	0.3764	5.46***	-0.0005	-0.0022	3.99*
ROA	0.0487	0.0516	-1.59	-0.0005	0.0018	15.10***
ROE	0.1237	0.1289	-2.46**	-0.0010	0.0016	6.90**
RT	5.0268	5.3145	-4.61***	0.0056	0.0209	3.71*
IT	20.8291	18.5461	3.55***	0.5947	0.3747	3.47*
FAT	3.8818	4.0387	-2.03**	-0.0026	0.0892	54.08***
TATO	0.7423	0.8566	-10.97***	-0.0068	0.0009	10.14***
CR	2.6549	2.6208	0.58	-0.0216	0.0597	16.59***
QR	1.9767	1.8616	1.67	-0.0248	0.0737	22.51***
NWTA	0.1705	0.1951	-3.46***	-0.0037	0.0057	11.86***
LTDE	0.3935	0.3538	2.43**	0.0142	-0.0112	23.00***
TDTA	0.5280	0.5243	0.54	0.0024	-0.0064	9.39***
PE	15.6431	13.2423	2.28**	-0.0952	0.6067	0.97
MB	2.0731	1.9229	0.99	-0.0493	0.0984	2.44

Table III (continued): Comparison of Means and Slopes Before and After the High-Tech Bubble Burst for Large Size Companies

Panel A: High-Tech Companies						
Ratios	Mean			Slope		
Successive Quarter	Pre-HTB	Post-HTB	*t*-statistic for difference	Pre-HTB	Post-HTB	*F*-statistic for difference
PM	0.5384	0.5834	5.27***	0.0066	0.0031	0.64
ROA	0.1045	0.0916	-2.62***	0.0020	0.0036	8.22***
ROE	0.2076	0.1902	-1.55	0.0031	0.0084	5.27**
RT	5.6722	6.5466	7.24***	0.0471	0.0887	1.53
IT	17.4568	19.8505	2.19**	0.8714	-0.1692	2.74
FAT	3.1078	3.1143	0.04	0.1349	0.0821	7.41**
TATO	0.9177	0.7235	-8.18***	-0.0165	0.0010	5.17**
CR	2.2727	2.5458	2.04**	0.0979	-0.0443	3.33*
QR	1.9437	2.2611	2.21**	0.1207	-0.0409	4.44**
NWTA	0.2631	0.2638	0.04	0.0153	-0.0039	5.28**
LTDE	0.2503	0.2580	0.51	-0.0073	-0.0034	1.32
TDTA	0.4562	0.4307	-1.92*	-0.0102	0.0018	2.31
PE	26.3107	26.3043	0.00	0.6053	0.3635	10.31***
MB	5.2460	4.7670	-1.13	0.4418	-0.1387	21.15***
Panel B: Non-High-Tech Companies						
Ratios	Means			Slope		
Successive Quarter	Pre-HTB	Post-HTB	*t*-statistic for difference	Pre-HTB	Post-HTB	*F*-statistic for difference
PM	0.4004	0.3824	4.30***	0.0015	-0.0002	1.19
ROA	0.0631	0.0568	1.73	0.0002	0.0043	36.65***
ROE	0.1935	0.1813	1.64	0.0042	0.0074	16.93***
RT	6.3768	6.0036	2.93***	-0.0792	0.0946	9.62***
IT	19.8493	18.1190	2.88***	0.4491	-0.4490	17.27***
FAT	3.0299	2.5781	8.36***	0.0258	0.0352	2.27
TATO	0.7274	0.7455	-1.50	-0.0101	0.0047	5.74**
CR	1.5238	1.4826	1.98*	-0.0038	0.0115	1.20
QR	1.1171	1.0043	5.10***	0.0030	0.0164	1.34
NWTA	0.0794	0.0755	1.20	-0.0013	0.0032	15.02***
LTDE	0.5045	0.5285	-1.58	0.0072	-0.0160	35.02***
TDTA	0.5961	0.6095	-3.02***	0.0017	-0.0046	20.48***
PE	17.2553	17.2773	-0.02	0.7016	-0.5092	5.07**
MB	3.3618	3.2904	0.41	0.1806	0.0380	10.57***

Table IV: Structure Change Before and After the High-Tech Bubble Burst

The market to book value ratio is the dependent variables in the panel A. Models 1 and 2 represent the entire sample companies before and after high-tech bubble, respectively, for all 52,895 companies. Models 3 and 4 represent the high-tech companies only before and after high-tech bubble, respectively, for 9.480 companies or 18.93 percent of the total. Models 5 and 6 represent the non-high-tech companies before and after high-tech bubble for 43,415 companies or 82.08 percent of the total.

Panel A: Regression for Market to Book Value Ratio

	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	1.437***	0.941***	1.342***	0.959***	1.425***	0.897***
	(12.87)	(7.23)	(5.13)	(3.23)	(11.45)	(6.16)
Profit rank	0.437***	0.609***	0.349***	0.512***	0.458***	0.637***
	(14.62)	(17.44)	(5.80)	(7.22)	(13.25)	(15.85)
Asset rank	0.057	0.131***	0.009	0.109	0.075*	0.147***
	(1.47)	(2.92)	(0.11)	(1.12)	(1.74)	(2.90)
Liquids rank	-0.109***	-0.056**	-0.124**	0.010	-0.108***	-0.087***
	(-4.55)	(-2.03)	(-2.46)	(0.18)	(-3.91)	(-2.71)
Debt rank	-0.033	-0.178***	0.012	-0.146*	-0.039	-0.172***
	(-1.21)	(-5.69)	(0.19)	(-1.93)	(-1.32)	(-5.02)
Profit rank^2	0.025***	0.010**	0.031***	0.022***	0.024***	0.007
	(6.86)	(2.41)	(4.25)	(2.61)	(5.74)	(1.40)
Asset rank^2	0.010**	0.004	0.017*	-0.005	0.007	0.006
	(2.05)	(0.68)	(1.65)	(-0.45)	(1.36)	(0.90)
Liquids rank^2	0.007**	0.001	0.021***	-0.003	0.003	0.003
	(2.37)	(0.19)	(3.38)	(-0.38)	(0.88)	(0.76)
Debt rank^2	0.019***	0.038***	0.015**	0.039***	0.020***	0.036***
	(6.00)	(10.66)	(2.06)	(4.77)	(5.82)	(9.06)
Adjusted R^2	24.26%	30.63%	22.81%	30.04%	25.15%	31.10%
N	30,864	22,031	5,525	3,955	25,339	18,076
F Value-Chow Test	6.69***		5.18***		5.25***	
P Value-Chow Test	<.0001		<.0001		<.0001	

Panel B: Regression for Price to Earnings Ratio

	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	8.258***	8.518***	7.309***	7.873***	8.508***	8.618***
	(70.58)	(60.82)	(27.46)	(25.86)	(64.69)	(54.17)
Profit rank	-1.307***	-1.168***	-1.373***	-1.201***	-1.293***	-1.155***
	(-41.71)	(-31.13)	(-22.41)	(-16.53)	(-35.40)	(-26.27)
Asset rank	-0.045	-0.069	0.075	0.100	-0.074	-0.107*
	(-1.10)	(-1.42)	(0.87)	(1.00)	(-1.61)	(-1.93)
Liquids rank	-0.088***	0.011	-0.039	0.071	-0.117***	-0.016
	(-3.49)	(0.37)	(-0.76)	(1.24)	(-4.03)	(-0.45)

Debt rank	-0.070** (-2.48)	-0.308*** (-9.14)	0.115* (1.74)	-0.130* (-1.69)	-0.115*** (-3.64)	-0.336*** (-8.94)
Profit rank^2	0.105*** (27.93)	0.081*** (18.02)	0.112*** (15.23)	0.075*** (8.53)	0.104*** (23.63)	0.084*** (15.84)
Asset rank^2	-0.016*** (-3.19)	-0.013** (-2.27)	-0.028*** (-2.69)	-0.038*** (-3.14)	-0.013** (-2.28)	-0.007 (-1.03)
Liquids rank^2	0.010*** (3.17)	-0.002 (-0.50)	0.020*** (3.23)	0.001 (0.13)	0.008*** (2.33)	-0.002 (-0.39)
Debtrank^2	-0.008** (-2.31)	0.017*** (4.50)	-0.027*** (-3.67)	0.000 (-0.05)	-0.001 (-0.38)	0.021*** (4.74)
Adjusted R^2	16.48%	19.55%	19.76%	26.37%	15.95%	17.39%
N	30,864	22,031	5,525	3,955	25,339	18,076
F Value-Chow Test	5.41		6.29		7.76	
P Value-Chow Test	<.0001		<.0001		<.0001	

Appendix I

Industries Identified as High-Growth High-Tech Companies During 1/1/1998 – 3/31/2000

Industry Group **283**: Drugs
- 2833 Medicinal Chemicals and Botanical Products
- 2834 Pharmaceutical Preparations
- 2835 In Vitro and In Vivo Diagnostic Substances
- 2836 Biological Products, Except Diagnostic Substances

Industry Group **357**: Computer and Office Equipment
- 3571 Electronic Computers
- 3572 Computer Storage Devices
- 3575 Computer Terminals
- 3577 Computer Peripheral Equipment, Not Elsewhere Classified
- 3578 Calculating and Accounting Machines, Except Electronic Computers
- 3579 Office Machines, Not Elsewhere Classified

Industry Group **366**: Communications Equipment
- 3661 Telephone and Telegraph Apparatus
- 3663 Radio and Television Broadcasting and Communications Equipment
- 3669 Communications Equipment, Not Elsewhere Classified

Industry Group **367**: Electronic Components and Accessories
- 3671 Electron Tubes
- 3672 Printed Circuit Boards
- 3674 Semiconductors and Related Devices
- 3675 Electronic Capacitors

• 3676 Electronic Resistors
• 3677 Electronic Coils, Transformers, and Other Inductors
• 3678 Electronic Connectors
• 3679 Electronic Components, Not Elsewhere Classified

Industry Group **382**: Laboratory Apparatus and Analytical, Optical, Measuring, and Controlling Instruments
• 3821 Laboratory Apparatus and Furniture
• 3822 Automatic Controls for Regulating Residential and Commercial Environments and Appliances
• 3823 Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products
• 3824 Totalizing Fluid Meters and Counting Devices
• 3825 Instruments for Measuring and Testing of Electricity and Electrical Signals
• 3826 Laboratory Analytical Instruments
• 3827 Optical Instruments and Lenses
• 3829 Measuring and Controlling Devices, Not Elsewhere Classified

Industry Group **481**: Telephone Communications
• 4812 Radiotelephone Communications
• 4813 Telephone Communications, Except Radiotelephone

Industry Group **573**: Radio, Television, Consumer Electronics, and Music Stores
• 5731 Radio, Television, and Consumer Electronics Stores
• 5734 Computer and Computer Software Stores
• 5735 Record and Prerecorded Tape Stores
• 5736 Musical Instrument Stores

Industry Group **737**: Computer Programming, Data Processing, And Other Computer Related Services
• 7371 Computer Programming Services
• 7372 Prepackaged Software
• 7373 Computer Integrated Systems Design
• 7374 Computer Processing and Data Preparation and Processing Services
• 7375 Information Retrieval Services
• 7376 Computer Facilities Management Services
• 7377 Computer Rental and Leasing
• 7378 Computer Maintenance and Repair
• 7379 Computer Related Services, Not Elsewhere Classified

Industry Group **873**: Research, Development, and Testing Services
• 8731 Commercial Physical and Biological Research
• 8732 Commercial Economic, Sociological, and Educational Research
• 8733 Noncommercial Research Organizations
• 8734 Testing Laboratories

Industry Group **355**: Special Industry Machinery, Except Metalworking
• 3552 Textile Machinery
• 3553 Woodworking Machinery
• 3554 Paper Industries Machinery
• 3555 Printing Trades Machinery and Equipment
• 3556 Food Products Machinery
• 3559 Special Industry Machinery, Not Elsewhere Classified

Industry Group **365**: Household Audio and Video Equipment, And Audio
• 3651 Household Audio and Video Equipment
• 3652 Phonograph Records and Prerecorded Audio Tapes and Disks

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Islamic Banks and the Global Financial Crisis of 2007-09: An Assessment

Jamshed Y. Uppal and Inayat U. Mangla

Abstract

We examine the experience of the *Islamic* banks with respect to the global financial crisis of 2007-09 (GFC) and find that these were not immune from the ravages of the GFC. In particular, our analysis of the banking sector in Malaysia shows that the Islamic banks were adversely affected by it to a greater extend then were the conventional banks. Post-December 2008, the capital adequacy ratios for these banks were significantly lower, the loan loss ratios significantly higher, and their total loss reserves and secondary liquidity positions deteriorated.

I. Introduction - Islamic Banking

Islamic banking (IB) has developed remarkably over the last four decades, and is in practice in more than 60 countries with varying estimate of $800-$1000 billion in deposits. Standard & Poors estimates that it could expand to $4 trillion of assets in the next decade (Economist, 2008). As *Riba* (interest) is forbidden in Islam, it is implied that all debt contracts are excluded. Thus, the emphasis of IB is on engineering various profit and loss sharing (PLS) contracts where a fixed rate of interest is replaced with a variable rate of return based on real economic activities (Mangla and Uppal, 1988 and 1990). Thus the IB is intended to be an equity based system where equity capital is provided by the investors, who receive no fixed interest on their funds but a dividend out of the bank's profit (Bashir, 2001).

In the wake of the global financial crisis (GFC) of 2007-09, some scholars have suggested that Islamic finance may be an attractive option for investors as conventional finance faces challenges arising from the U.S. sub-prime lending crisis and recession concerns (Apps, 2008). In a recent statement by the Vatican (Middle East Online, 2009) it was suggested that banks should look at the rules of Islamic finance to restore confidence amongst their clients which has been lost during the current global economic crisis. In view of the recent exposé of the unethical and scandalous conduct of some in the banking and mortgage industry, the Vatican's statement has resounded in varied circles. Following the recent surge of interest in the IB, "those who have been in Islamic banking for a long time now feel vindicated" (Ambah, 2008). Some welcome the integration of ethics and values into finance as a positive development, especially in the light of recent U.S. business corruption scandals. "Many investors reportedly consider IB to be more reliable than conventional financing, given the recent global credit crisis and fears of economic recession," (Apps, 2008). The proponents of Islamic banking argue that profit-sharing contracts, being equity based, are superior financial instruments to debt in particular because of the risk-sharing nature of equity investment (Askari and Mirakhor (2009). Because of this participatory risk relationship, the financial institution may not be exposed to credit risk associated with conventional lending but, however, be more exposed to the risks associated with the performance as well as volatility in the value of underlying assets.

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More recently, the default and restructuring of the Islamic bonds (*sukuks*) notably issued by some of the property developers in Dubai have dampened the euphoric outlook on the Islamic finance. A recent Economist editorial notes that, "The problem of speculative, casino-like Western banks contrasted nicely with the emphasis that *sharia*-compliant finance places on an ethical, risk-sharing approach. But risk-sharing looks much less appealing when issues are , risk-sharing approach. But risk-sharing looks much less appealing when issues are defaulting" (Economist, 2010). The recent experience has forced the creditors to reevaluate risks associated with Islamic finance, in particular, risks associated with enforceability of the collateral and interpretation of *sharia*, and has adversely impacted the liquidity of the *sukuk* market.

"As Islamic finance activities grow in the United States, critics raise concerns about the related capital adequacy and system risks," (Ilias, 2008). It is, thus, worthwhile to examine how the Islamic banks have actually fared in the global financial crisis (GFC) period. In this paper we examine the experience of the Islamic banks with respect to the extent of the stress on their asset/liabilities and capital from the impact of the GFC. Our analysis is based on (i) survey of recent studies on this subject, (ii) examination of recent banking performance data from Pakistan, and (iii) empirical analysis of the relative performance of Islamic banks in Malaysia.

II. Unique Risks in Islamic Banking

A number of studies have pointed out pitfalls and risks associated with the Islamic banking; see, for example, Aggarwal and Yousef (2000), Kuran (2004) and Metwally (1997). Bacha (2004) argues that the ability of depositors to switch between the two banking systems inevitably exposes Islamic banks to interest rate risk. A report by Price-Waterhouse-Cooper (2008) notes that, "Risk management has not been uppermost on the Islamic banking sector's agenda in recent years." Another unique risk in Islamic Banking arises due to differences of interpretation between *sharia* scholars about what is permissible and what isn't (Modi, 2007). A recent study (Uppal and Mangla, 2010) pointed out that over the year 2006-2007 the Islamic banks seem to have increased their equity holdings, a period coinciding with the beginning of the global financial crisis. The Islamic banks have also moved into real estate and consumer financing over this period which are relatively new products in the emerging markets. The risks associated with these may not be yet fully quantifiable for a lack of adequate data history.

III. Some Recent Evidence

A few studies to-date have compared the performance of Islamic banks vis-à-vis the conventional banks during the global financial crisis (GFC). A recent IMF report (IMF, 2009) poses the question, "How Did They Fare?" with respect to the Islamic banks in the Gulf Cooperation Council (GCC) region. The report notes that although unlike conventional banks, Islamic banks are not permitted to have any direct exposure to financial derivatives or structured securities, the conventional banks in the region also had little exposure of from such securities. The main difference in risk exposures arose due to Islamic banks' greater exposure to the risky real estate and construction sectors, especially in the United Arab Emirates and Qatar (Exhibit 1). The IMF report further notes that GCC banks' profitability fell substantially in 2008 and in the first half of 2009 (Exhibit 1), with a largely similar overall impact on Islamic and conventional banks. Islamic banks were less affected by the initial impact of the global crisis, while there was a stronger first-round effect on conventional banks through mark-to-market valuations on securities in 2008. However, for the first half of 2009, there has been slightly larger decline in profitability for Islamic banks compared to conventional banks, as the second-round effects of the crisis on the real economy, especially real estate, unfolded. In particular, Islamic banks in the United Arab Emirates and Qatar have been affected as they had a considerably higher exposure to the real estate and construction sectors. The IMF report however, holds its judgment till more information becomes available and the banks post additional provisions for 2009.

Exhibit 1: Selected Indicators for GCC Islamic Banks and the Banking System

	Saudi Arabia		Kuwait		United Arab Emirates		Bahrain		Qatar		GCC Average	
(Percent; 2008)	IBs	All	IBs	All	IBs	All	IBs	All	IBs	All	IBs	All
Capital adequacy ratio	22.1	16.0	21.7	16.0	12.8	13.3	24.5	18.1	17.9	15.6	19.8	15.7
Change in profitability (2007–08)	2.0	(11.8)	(42.7)	(70.1)	0.7	7.9	18.8	(4.6)	4.5	21.7	(6.6)	(13.9)
Change in profitability (H1 2009–H1 2008)	2.9	(11.9)	(71.9)	(65.3)	(34.2)	(19.5)	(46.5)	(33.7)	-	5.1	(29.0)	(23.5)
Change in profitability (2008 and H1 2009 compared with 2007)	4.3	(7.2)	(49.7)	(65.8)	(0.8)	10.0	8.2	(3.2)	2.8	25.4	(8.8)	(10.2)
Return on assets	3.7	2.1	1.6	3.2	1.7	2.2	2.6	1.3	6.6	2.6	3.2	2.3
Exposure to real estate & construction (as % of total loans)	5.6	7.3	22.1	31.4	25.7	12.9	11.3	26.2	38.3	18.4	20.6	19.2

Source: IMF, Regional Economic Outlook: Middle East and Central Asia, Washington D.C., 2009

The Islamic International Rating Agency (IIRA) conducted a survey of selected Islamic commercial banks' liquidity indicators for 2007/2008. The IIRA assessment shows that these banks had a strong liquidity position at the end of 2007 with liquid assets constituting 46.9 percent of total liabilities. The report concludes that, on average, the impact of the global crisis on the liquid assets in 2008 remained limited as reflected in a relatively modest downward adjustment of the liquid assets to total liabilities ratio. However, there were noticeable declines in the liquidity position for Bahrain Islamic Bank and Dubai Islamic Bank. On the other hand, Al Baraka and Meezan banks have seen their liquid assets increase over 2007-08. A report by International Financial Services (IFSL, 2010) notes that, "Islamic banks have not been immune to the effects of the financial crisis and downturn: some have suffered a higher rate of non-performing loans than conventional banks, mainly due to their exposure to falling real estate markets. Revenue and profitability has suffered in both 2008 and 2009 and liquidity is a significant restraint for some banks."

IV. Recent Evidence from Pakistan

Another exercise at evaluating the performance of Islamic banks has been State Bank of Pakistan's Financial Stability Report for 2009. Based on the first-half year data for 2009, the report notes that, "In sharp contrast to the conventional banking industry which has already weathered the worst of the storm in 2008, the impact of the slowdown in the economy has manifested itself more visibly on IBI's financial position in 2009." Further, it notes a marked slowdown in the asset and deposit growth, and deterioration in the asset quality in the first half of the year "as indicated by the rising non-performing financing (NPF) and increase in both the NPFs to Financing and Net NPFs to Net Financing ratios. There was an obvious impact of these developments on profitability, as evidenced by the decline in both RoA and RoE."

When we analyze more recent data on the banking sector in Pakistan, the impact of the global financial crisis (GFC) is quite noticeable. Exhibit 2 compares key indicators for the banking sector. The recent quarterly data over 2009 reveals that the Islamic banks have not been immune to the impact of the global financial crisis. The growth in assets, financing and deposits starting from a small base had been phenomenal over the period 2003-08; each category increased respectively 21, 18 and 25 folds, registering an annual compounded rate of growth of 84%, 79% and 91% respectively. The year 2009 data shows a significant slowdown from the historical growth rates. However, Islamic banking institutions' (IBI) growth rates remained higher than that of the conventional banks, thus increasing their market share from 4.9% to 5.3%.

Exhibit 2: Highlights of the Pakistani Banks - Quarter Dec 2008 – Sep 2009

(in percent)		**Dec-08**	**Mar-09**	**Jun-09**	**Sep-09**
Asset (growth)	IBI's	10.1	0.7	12.4	3.3
	All Banks	8.8	1.6	6.0	0.3
Financing/Loans (growth)	IBI's	1.8	(5.9)	3.0	(4.7)
	All Banks	18.3	(5.6)	5.0	(1.8)
Deposits (growth)	IBI's	17.7	2.3	15.5	2.8
	All Banks	9.4	-	8.2	(1.7)
Investment (growth)	IBI's	4.7	16.1	9.3	20.8
	All Banks	(15.4)	20.0	8.5	13.1
Equity (growth)	IBI's	10.1	1.8	6.8	3.1
	All Banks	3.4	1.5	4.7	3.0
NPFs to total financing	IBI's	2.3	4.5	5.0	6.5
	All Banks	10.5	11.5	11.5	12.4
Net NPFs to net financing	IBI's	0.8	2.3	2.4	3.0
	All Banks	3.4	3.9	3.7	4.1
ROA (after tax)	IBI's	0.8	0.8	0.8	0.7
	All Banks	1.2	1.8	1.7	1.6
Advances to Deposit Ratio	IBI's	75.5	71.7	69.6	69.6
	All Banks	71.7	66.0	58.9	54.6
Share of IBI's in total Banking Assets		4.9	4.8	5.1	5.3

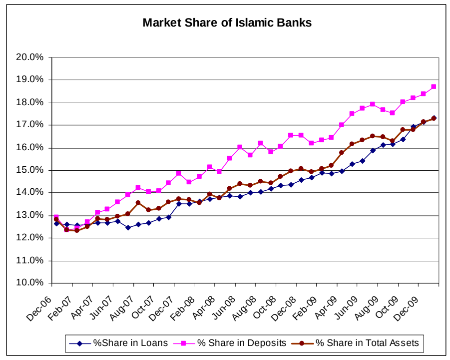
Source: State Bank of Pakistan, 2009

The asset structure of the IBI's saw significant increase in investments and inter-bank lending, while their financing portfolio contracted. Notable is the increase in investments of 21 percent in September 2009 which resulted from large placement of Government of Pakistan *Ijara Sukuk* of Rs 14.4 billion. However, deposits of the Islamic banks increased, despite a decline in deposit base of the banking system. The liquidity position of IBIs improved over the period, as the amount of financing declined and the deposit base increased, thus lowering the Financing to Deposits ratio (FDR). However, the FDR ratios for the whole banking sector also improved. There was a notable increase in the Non-Performing Financing (NPF) during the year 2009. The NPF as a percentage of Total Financing increased from 2.3% to 6.5% for the IBI's, almost a threefold jump, in comparison the NPL to Total Loan ratio increase from 10.5% to 12.4% for all banks. However, the IBIs were able to maintain their profitability, though with slight deceleration during the 2009. The Islamic banks saw a marginal decline in ROA attributable to a shift in the mix of earning asset towards low-return assets.

Evidence from Malaysia

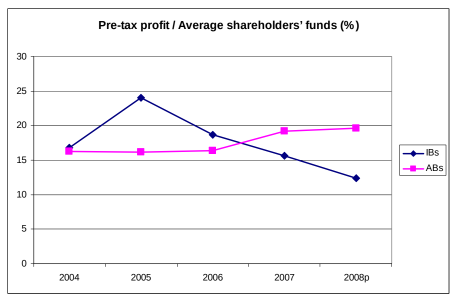
To look into the comparative performance of the Islamic bank we examine the banking sector in Malaysia in detail. There are several advantages in taking up the Malaysian case. First, more detailed and more recent data is available on Islamic banks on monthly basis since 2006. Second, the country has not experienced a collapsing real estate market as has been the case in the UAE, or a near collapsing economy as in the case of Pakistan. Third, the Malaysian central bank enjoys best reputation among regulator around the globe. It is expected that the requirements for loss provisions would be strongly enforced and regulatory fore-bearance would be minimum. Finally, the Islamic banking in Malaysia is the oldest and the largest in the world, and is supported by a large, liquid and active secondary Islamic securities market, particularly in sukus. Comparative balance sheet data on monthly basis is available at the web-site of the Malaysian central bank, Bank Negara Malaysia, which we utilize in this study.

Figure 1: Malaysian Islamic Banks -Growth



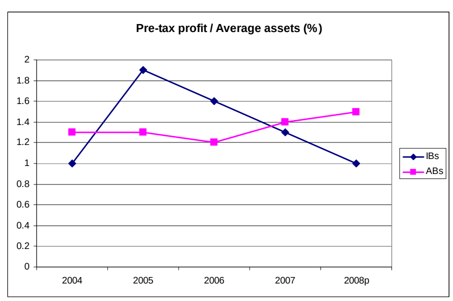
Growth, Market Share and Profitability: Malaysia had a head start in Islamic banking with establishment of the first Islamic bank, Bank Islam Malaysia Berhad (BIMB), which commenced operations on 1 July 1983. The IB's have experienced a remarkable rate of growth since then. Figure 1 shows the share of Islamic banks in the total banking sector in Malaysia, with respect to total assets, loans and deposits. The data shows continuing gains in the market share for the Islamic banks over the 2006-2010 period. Its share in the banking assets increased from 12.8% in December 2006 to 17.3% in January 2010. There is a slight slowdown in the sector growth, though it is expected as the asset base increases over time.

Figure 2: Malaysian Banks-Return on Equity



Despite the increasing market share the Islamic banks have been falling behind in profitability. The Returns on Assets are graphed in Figure 2 and the Returns on Equity in Figure 3 for the period 2004-2008. (The data on the profits of the banks is only available on annual basis up to year 2008).The Islamic banks show a consistent decline in profitability as measured by ROA or ROE. On the other hand, the profitability of the overall banking sector seems to have improved the year 2008.

Figure 3: Malaysian Banks - Return on Assets



Empirical Tests: In order to examine how the global financial crisis impacted the Islamic banking sector in Malaysia, we study the following six indicators for these banks relative to the overall banking sector:

1) *Risk Weighted Capital Ratio* = Capital Base / Total Risk Weighted Assets.

2) *Core Capital Ratio* = Tier-1 Capital or Core Capital / Total Risk Weighted Assets.
3) *Non-Performing Loans (Financing) Ratio* = Net Non-performing Loans/Net Total Loans.
4) *Total Provisions Ratio* = Total provisions / Net Non-Performing Financing.
5) *Cash Reserves Ratio* calculated as Cash & Reserves / Short Term Liabilities = Cash, Deposits Placed and Reverse Repos divided by Deposits, Amounts Due To, and Miscellaneous Borrowings.
6) *Liquid Assets Ratio* calculated as Liquid Assets / Short Term Liabilities = Cash, Deposits Placed and Reverse Repos, Amounts Due From, and Negotiable Instruments of Deposit Held divided by Deposits, Amounts Due To, and Miscellaneous Borrowings.

In order to compare the above listed bank indicators for the Islamic banks vs. the overall banking sector we run a series of linear regressions based on the following two models:

$$IB\_RATIO_{i,t} = \alpha_i + \beta_i AB\_RATIO_{i,t} + \varepsilon_{i,t} \quad \text{... (1)}$$

$$IB\_RATIO_{i,t} = \alpha_i + \beta_i AB\_RATIO_{i,t} + \delta.D + \varepsilon_{i,t} \quad \text{... (2)}$$

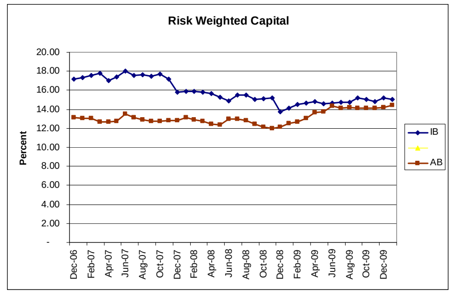
Where $IB\_RATIO_{i,t}$ and $AB\_RATIO_{i,t}$ refer to each of the six *i* ratios as listed above for the Islamic banks and all banks respectively for the month *t*, and D is a dummy variable which takes value of zero before December 2008 and of one from that month onwards. As the Islamic banking statistics are included in the overall banking sector data, there is a possibility of inducing spurious correlation between the dependent and the independent variable. This does not, however, pose a serious issue as our focus here is not on parameter estimation but on their stability, particularly of the constant. The methodology is to estimate model (1) and test it for stability of parameters across the sample period using *Chow's Break Point Test*. Two test statistics are used for the Chow test; F-statistics has an exact finite sample F-distribution, if the errors are *iid* normal random variables, and log likelihood statistic which has an asymptotic χ^2 distribution with DF=(m-1)/k, where k is the number of parameters and m is the number of sub-samples. Break point is specified as December 2008 to capture the impact of the global financial crisis. In the second model a dummy variable is included (December 2008) to capture the improvement or deterioration in the relative ratios for the two groups of banks. The choice of the break point is suggested by the clustering of a series of adverse financial events in October 2008; December 2008 being the end of the typical accounting year is a logical choice. Our results are, however, robust as to the selection of a different break point between July 2009 and March 2010.

Results from estimation of models (1) and (2) are reported in Table I which is split into two panels A and B presenting results from model 1 and 2 respectively, and six sub-sections each pertaining to one of the six performance indicators listed above. In each of the seven sub-sections of Table I, IB_RATIOi for Islamic banks is the dependent variable and AB_RATIOi for all banks is the independent variable. The empirical results are discussed below.

Capital adequacy: Figure 4 shows the risk-weighted capital ratios (under Basel II) for the Malaysian Islamic banks and the overall banking sector. The IBs started with a higher capital ratio of 17.14% in December 2006 which dropped to 15% by January 2010. Noticeable drops occurred at the end of year 2007 and 2008. On the other hand the banks as a whole improved their capital ratio from 13.11% to 14.42% over this period. The capital ratios of two types of banking institutions seem to converge over the period.

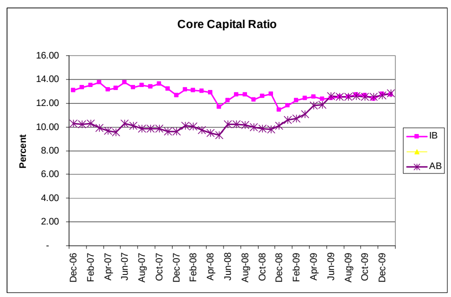
Results from regression of all-banks' risk-weighted capital ratio (AB_RWC) on Islamic banks risk-weighted capital ratio (IB_RWC) are presented in panel A and B of Table I.a respectively for models 1 and 2. As the results in panel A show, the regression is not statistically significant, prob(F-statistic = 0.2096), and the Chow test statistics strongly reject the null hypothesis of no structural change over the period. When we include a dummy variable, the coefficient of the dummy variable is highly significant (panel B) and there is a dramatic improvement in the regression statistics indicated by higher values for the adjusted R^2, F-statistics, and lower values for the Akaike and Schwarz Information Criteria. The negative value of dummy's estimated coefficient implies that the Islamic banks' core capital ratio deteriorated in the second period.

Figure 4: Malaysian Banks – Risk Weighted Capital



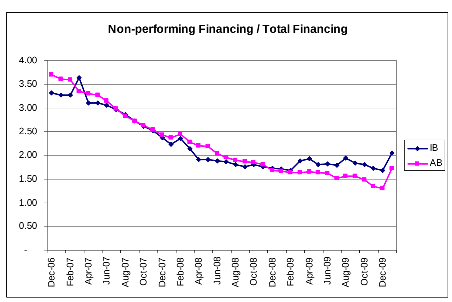
A similar picture is presented with respect to the core capital ratios for the Islamic banks and the overall banking sector in Malaysia in Figure 5. The IBs' capital ratio was more favorable than the overall banking sector, but the conventional banking ratios seem to have improved over time, converging towards the end of the period. Regression results support the observation. The Chow test rejects parameter stability and comparing regression results in the panel A and B of the Table I.b the model with the dummy variable is highly significant. The dummy variable coefficient is negative and highly significant, indicating that the core capital ratio of the Islamic banks deteriorated over the sample period.

Figure 5: Malaysian Banks - Core Capital



Non-Performing Loans: Figure 6 depicts non-performing financing or loans (NPF or NPL) for the Islamic banks and the overall banking sector. The movement over time of the ratio of NPF (or NPL) to total financing (or loans) seems to be almost identical until March 2009 when the Islamic banks NPF ratio seems to experience a sudden increase. After that the IBs non-performing portfolio seems to continue to deteriorate, which reflects a belated impact of the global financial crisis which affected the Islamic banks in secondary aftershocks to the overall economy of developing countries and impacted consumers spending and credit and the real estate markets. Since IBs were over-exposed in consumer credit and real estate lending, the GFC's impact is registered at a later stage in the economic crisis cycle.

Figure 6: Malaysian Banks - Non-performing Loans

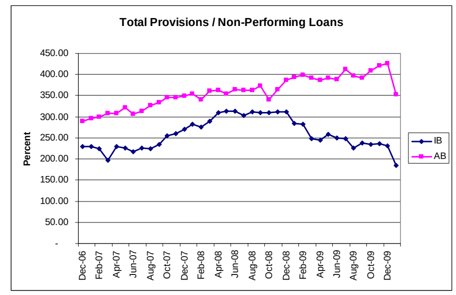


The regression results for non-performing loan ratio are reported in section 3 of Table I.

The Chow test strongly rejects the null hypothesis of no structural change, and the regression statistics improve substantially when we include the dummy variable, as indicated by the higher values of adjusted R^2 and lower values for Akaike and Schwarz information criterion. The statistically significant and positive coefficient of the dummy variable indicates that the NPL ratio increased for the Islamic banks post-December 2008.

Loan Loss Provisions: Figure 7 shows the total loan loss provisions as a percentage of the total non-performing portfolios for the Islamic banks and the industry. The figure depicts that the overall banking sector has been better covered reflecting a more conservative provisioning against credit risk than the Islamic banking sector. It appears that towards the end of the year 2008 the provisioning position of the Islamic banks deteriorated noticeably. At the end of 2009, Islamic banks' total provisions were about two times the size of their non-performing portfolio. On the other hand the overall banking sector's total provisions were about four times as the size of their non-performing loan portfolio.

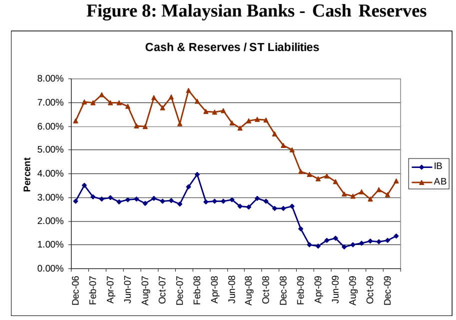
Figure 7: Malaysian Banks-Loss Provisions



The empirical tests indicate that the Islamic banks decreased their total loan loss provisions compared to the sample of all banks. Table I.d shows that the Chow test strongly rejects parameter stability in a regression of Islamic banks' total loan loss provision ratio on the ratio for all banks. The coefficient on the dummy variable is negative and statistically significant.

Liquidity: It appears that the liquidity position of both the Islamic as well as the conventional banks has been adversely affected during the global financial crisis period. As Figure 8 shows, the overall banking systems liquidity seems to have started deteriorating in October 2008, while the Islamic bank liquidity started sliding in February 2009. The lagged effect on the IB is consistent with the idea that these banks were impacted by the deteriorating consumer credit and real estate markets, in a second round of repercussion from the GFC. In January 2010 the liquidity ratio was about 60% and 50% of its level in December 2006 for the Islamic banks and all banks respectively.

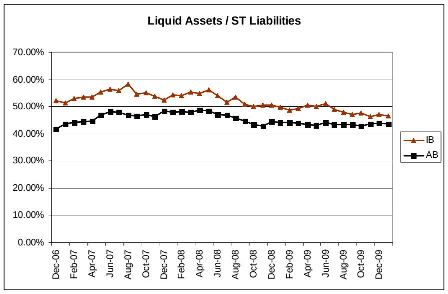
Figure 8: Malaysian Banks - Cash Reserves



The empirical tests using cash reserve ratio are reported in section 'e' of Table I. Although the chow test rejects parameter stability at the conventional level of 10% significance, the coefficient of the dummy variable is insignificant. The cash reserve ratio which reflects bank's primary liquidity reserve does not seem to have been impacted by the financial crisis.

However, the impact of the financial crisis is more pronounced when we include secondary reserves and examine a broader measure of liquidity, ratio of liquid assets to short-term liabilities; see Figure 9. It should be noted that Islamic banks rely substantially on a liquid market for *sukuks*, Islamic bonds, which was particularly affected by the unfolding of the global financial crisis. Our empirical test rejects the stability of the regression parameters (Table I.f, panel A) and the dummy variable is highly significant and of negative sign. It indicates that the liquidity position of the Islamic banks deteriorated relative to the total banking sector in the post December 2008 period.

Figure 9: Malaysian Banks - Liquid Assets



V. Summary and Conclusion

The global financial crisis has revealed the risks in the Islamic banking, and brought home the realization that all financial institutions operate in one global economy and cannot be isolated from the shocks arising in another sector or another country. It appears that though the Islamic banks were not directly impacted by the repercussions of the global financial crisis in its initial phase, the banks did experience the after-shocks of the GFC transmitted through indirect channels, through its impact on the global trade, economies and financial markets throughout the world. The Islamic banks were particularly exposed to the consumer and the real estate financing. According to an estimate around 20 percent of all financing by Islamic banks is backed by real estate (Standard & Poor's, 2009). As such, the Islamic banks had *indirect exposure* to excessive leverage in the real estate sector. The assets of Islamic banks in GCC region was less diversified and thereby the banks were more vulnerable. In addition, the Islamic banks invested in the equities of both listed and unlisted companies, which exposed them to the risk of severe correction in stock markets, as has been the case during the financial crisis. As a result of the global credit crunch, the *sukuk* market liquidity also evaporated and subjected the Islamic banks to liquidity pressures.

Our empirical analysis of the banking sector in Malaysia shows that not only the Islamic banks in the country were not immune from the ravages of the global financial crisis, but, as revealed by a number of commonly used performance indicators, were also adversely affected by it to a greater extend then were the conventional banks. There is empirical evidence that in the post-December 2008 period the capital adequacy ratios for the Islamic banks were significantly lower, the loan loss ratios were significantly higher, and there was deterioration in their total loss reserves and secondary liquidity positions.

In drawing lessons from the GFC experience we could also take note of the conclusion of the State Bank of Pakistan report (SBP, 2009) that, "The view that IFIs are inherently safe because of the prohibition on the use of structured finance vehicles is countered by the argument that Islamic finance is still not a mature industry, that there would have been attempts to introduce *shariah*-compliant securitization instruments if the crisis hadn't occurred when it did, and that IFIs are prone to risks specific to the nature of their operations." Sacirbey (2010) summarizes that, "Speculation was an across the board failing and Islamic banking fared less dramatically only because it had not been allowed to employ excessive leverage which had magnified the problem in more traditional financial institutions."

Table I: Results from Estimation of Models 1 and 2

Section: I.a	**Dependent Variable IB_RWC, Islamic Banks' Risk Weighted Capital Ratio**						
Panel A: Variable	Coeff.	t-Stat.	Prob.	**Panel B**: Variable	Coeff.	t-Stat	Prob.
AB_RWC	-0.3806	-1.2775	0.2096	AB_RWC	0.7614	2.9494	0.0056
				DUMMY	-2.4548	-6.8612	0.0000
Constant	20.8033	5.3163	0.0000	Constant	6.7287	2.0358	0.0494
Regression Statistics							
Adj. R-squared	0.0168			Adj. R-squared	0.5688		
Durbin-Watson	0.1608			Durbin-Watson	0.2944		
Akaike Info Crit.	3.2997			Akaike Info Crit.	2.5000		
Schwarz Crit.	3.3859			Schwarz Crit.	2.6293		
F-statistic	1.6319		0.2096	F-statistic	25.3986		0.0000
Chow Breakpoint Test: 2008:12							
F-statistic	28.6109		0.0000				
Log likelihood ratio	37.5034		0.0000				
Section: I.b	**Dependent Variable IB_CORE, Islamic Banks Core Capital Ratio**						
Panel A: Variable	Coeff.	t-Stat.	Prob.	**Panel B**: Variable	Coeff.	t-Stat	Prob.
AB_CORE	-0.1331	-1.7370	0.0909	AB_CORE	0.3648	3.1976	0.0029
				DUMMY	-1.3616	-5.0968	0.0000
Constant	14.2140	17.3044	0.0000	Constant	9.4099	8.2953	0.0000
Regression Statistics							
Adj. R-squared	0.0517			Adj. R-squared	0.4401		
Durbin-Watson	0.6873			Durbin-Watson	0.6538		
Akaike Info Crit.	1.6337			Akaike Info Crit.	1.1312		
Schwarz Crit.	1.7199			Schwarz Crit.	1.2604		
F-statistic	3.0173		0.0909	F-statistic	15.5442		0.0000
Chow Breakpoint Test: 2008:12							
F-statistic	12.8805		0.0001				
Log likelihood ratio	21.4317		0.0000				
Section: I.c	**Dependent Variable IB_NPF, Islamic Banks' Non-performing Financing Ratio**						
Panel A: Variable	Coeff.	t-Stat.	Prob.	**Panel B**: Variable	Coeff.	t-Stat	Prob.
AB_NPL	0.7949	20.6313	0.0000	AB_NPL	0.9398	20.7282	0.0000
				DUMMY	0.2914	4.4195	0.0001
Constant	0.4753	5.2703	0.0000	Constant	0.0442	0.3625	0.7192
Regression Statistics							
Adj. R-squared	0.9199			Adj. R-squared	0.9471		
Durbin-Watson	0.7360			Durbin-Watson	1.2721		
Akaike Info Crit.	-0.6956			Akaike Info Crit.	-1.0864		
Schwarz Crit.	-0.6094			Schwarz Crit.	-0.9571		
F-statistic	425.6489		0.0000	F-statistic	332.1488		0.0000
Chow Breakpoint Test: 2008:12							
F-statistic	12.4347		0.0001				
Log likelihood ratio	20.8605		0.0000				

Table I continued

Section: I.d	**Dependent Variable IB_TP, Islamic Banks' Total Provision Ratio**						
Panel A: Variable	Coeff.	t-Stat.	Prob.	**Panel B**: Variable	Coeff.	t-Stat	Prob.
AB_TP	0.2668	1.6736	0.1029	AB_TP	1.1282	6.1472	0.0000
				DUMMY	-82.9007	-5.9793	0.0000
Constant	162.8315	2.8336	0.0075	Constant	-115.5889	-1.8633	0.0708
Regression Statistics							
Adj. R-squared	0.0464			Adj. R-squared	0.5148		
Durbin-Watson	0.1480			Durbin-Watson	0.6644		
Akaike Info Crit.	10.0453			Akaike Info Crit.	9.3941		
Schwarz Crit.	10.1315			Schwarz Crit.	9.5234		
F-statistic	2.8011		0.1029	F-statistic	20.6288		0.0000
Chow Breakpoint Test: 2008:12							
F-statistic	24.2072		0.0000				
Log likelihood ratio	33.6452		0.0000				
Section: I.e	**Dependent Variable IB_CR, Islamic Banks' Cash Reserve Ratio**						
Panel A: Variable	Coeff.	t-Stat.	Prob.	**Panel B**: Variable	Coeff.	t-Stat	Prob.
AB_CR	0.5414	17.9498	0.0000	AB_CR	0.5269	6.4934	0.0000
				DUMMY	-0.0005	-0.1931	0.8480
Constant	-0.0065	-3.7219	0.0007	Constant	-0.0055	-1.0132	0.3179
Regression Statistics							
Adj. R-squared	0.8967			Adj. R-squared	0.8939		
Durbin-Watson	1.4290			Durbin-Watson	1.4227		
Akaike info Crit.	-8.8704			Akaike Info Crit.	-8.8188		
Schwarz Crit.	-8.7842			Schwarz Crit.	-8.6895		
F-statistic	322.1937		0.0000	F-statistic	156.8075		0.0000
Chow Breakpoint Test: 2008:12							
F-statistic	2.5544		0.0926				
Log likelihood ratio	5.31952		0.0700				
Section: I.F	**Dependent Variable IB_LA, Islamic Banks' Liquid Assets Ratio**						
Panel A: Variable	Coeff.	t-Stat.	Prob.	**Panel B**: Variable	Coeff.	t-Stat	Prob.
AB_LA	1.1765	7.2888	0.0000	AB_LA	0.6979	4.5287	0.0001
				DUMMY	-0.0329	-5.1733	0.0000
Constant	-0.0135	-0.1840	0.8551	Constant	0.2153	3.0232	0.0047
Regression Statistics							
Adj. R-squared	0.5849			Adj. R-squared	0.7580		
Durbin-Watson	0.6983			Durbin-Watson	1.0465		
Akaike Info Crit.	-4.9519			Akaike Info Crit.	-5.4672		
Schwarz Crit.	-4.8657			Schwarz Crit.	-5.3379		
F-statistic	53.1270		0.0000	F-statistic	58.9547		0.0000
Prob(F-statistic)							
Chow Breakpoint Test: 2008:12							
F-statistic	13.1343		0.0001				
Log likelihood ratio	21.7531		0.0000				

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Credit Risk Determinants of commercial bank: A Look from Texas Commercial Banking Industry

Abdus Samad

Abstract

This paper examines and estimates the credit risk of commercial banks from Texas banking industry and finds that dominants factors influencing the credit risk of commercial banks are (i) bank's expectation towards higher ROA and ROE (ii) larger ratio of long term loans in bank assets portfolio, LTERMTA and (iii) bank size, LNTA. Regulatory capital requirement, REGCP, Real estate loans as a percentage of total loans (RESLL) and total assets (REALTA) are not significant factors.

The paper suggests some policy prescription to improve the credit risk management of commercial banks.

I. Introduction

It is well known in the banking market that banks deal with asymmetric information. Given economic condition and asymmetric information (faced by all banks), it is observed that some banks fail and some banks excel others. Some banks default rates are higher than that of others. These differences in bank performance are believed to be located in banks internal factors since all banks face the same economic conditions. The internal factors are those factors which are within the control of bank management. There are wide ranges of internal variables that may affect banks asymmetric performances. Banks attitude towards earning, decision towards the allocation of funds in asset and loan portfolio, leverage consideration, and the regulatory condition are, among others, believed to be important factors affecting bank credit risk. The difference in the structure and composition of loan portfolio might be a potential candidate for the difference in loan performance.

Since banks deal borrowers with asymmetric information, moral hazard and adverse selection is unavoidable in the credit markets. Given this asymmetric information, credit risk has been the major risk in the past and will remain the critical risk in the future for the commercial banks. Credit risk refers to the nonpayment of loans by borrowers. Since a majority of a bank's assets are in the form of loans, credit risk is the major risk for a bank. Credit risk is mainly a function of the quality of the bank's loan portfolio which can be associated with three main factors: (i) insider transaction called fraud risk. (ii)

Foreign risk, and (iii) normal domestic risk also known as nonfraud/nonforegin risk. Fraud type risk, usually takes the form of concentration of credits to friends, relatives and/or business associates of the bank's top manager, becomes an important source of current and past bank failures. In the U.S. history, three of the largest *de jure* bank failures—United States National Bank of San Diego in 1973, Franklin National Bank in New York in 1974, and United American Banks of Knoxville in 1983—are due to some kind of insider or fraud type of transaction (Sinkey 1992, pp. 402). However, it is hard to detect and difficult to get data.

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Given that most bankers are honest and have no foreign loan risk, commercial banks' major credit risk is the non-fraud, non foreign or normal domestic risk. This normal domestic risk is attributable to several factors such as inefficient bank management, less diversification of loan portfolio, advancement of large amount of risky loans, high equity multiplier, and lower volume of risk based capital. The structure and composition of loan portfolio that might cause the difference in credit risk from bank to bank. These are bank's internal factors because they are within the control of bank. However, which of these internal factors are statically significant for the credit risk is yet unknown to bank managements, policy makers, and bank creditors.

In the past, credit risk is one of the main risks that dangerously affected banks' viability. This was evidenced from the 1977 financial crisis The deep recession of the 21st century trigged by the failure of large financial institutions in the U.S.A. motivates financial economists to examine bank internal factors influencing credit risk. Such a critical issue as the bank credit risk deserves special attention from the financial economists. Both external and internal factors have important impact of bank credit performance. Since external factors such as economic recession, wars, law suits etc are beyond the bank management control, bank internal factors deserve analytical attention. Bank internal factors are factors which are available form the balance sheet and income statement of banks. Pantalone and Marjorie (1987) report that bank internal factors continue to be the significant factor contributing to at least one third of the bank failure

However, which of bank internal factors are significant in influencing credit risk have not been explored quantitatively and it deserve examination and exploration. This paper is motivated to provide answer in the context of Texas banking. Texas banking system provides wide variety of banks and has one of the largest numbers of total banks, over 600, in 2001.

By examining the relationship between banks' internal factors and credit risk, this paper aims to contribute to the existing literature in two important ways: (1) Identify the internal factors that are statistically significant in influencing the credit risk of bank. The identification of these factors can minimize bank's credit risk and losses (2) Determination of these factors is important valuable information for bank management, bank regulator, and bank creditors in improving the risk management of commercial banks.

This paper is organized as: A short survey of literature review is provided in Section II. Data and Methodology are outlined in Section III. Section IV provides empirical results, policy prescription. Conclusion is provided in Section V.

1I. Literature Review

There are numerous studies relating to bank failures. Henage, (1995, Beaver, (1966), and Cates, (1985) examined bank failures. There are only a few studies involved in bank credit risk. Brewer, Jackson, and Mondschean (1996) studied commercial bank risk factors. They found that fixed rate mortgage loans, investment in service, and real estate loans are significant and negatively related to credit risk. The higher the fixed rate mortgage loans and real estate loans the lower the credit risk. However, non-fixed rate mortgage loan is found to be positively related to credit risk and is significant. Berger and DeYoung (1997) found that lagged risk-weighted asset is significant and positively related to risk measured by non-performance loan (NPL) as a percentage of total loans. They reasoned that a relatively risky loan portfolio would result in higher NPLs. They also found that banks with relatively low capital face higher NPL i.e. the higher the equity multiplier (EM), the higher NPL. Fisher, Gueyine, and Ortiz (2000) found that loan loss provision, LLP, as a percentage of total loans are positively related to credit risk and bank size is negatively related to credit risk. That is, the larger the bank sizes the lower the credit risk for banks. Ross (1996) used loan loss provision (LLP) as a measure for credit risk. Angbazo, Mei, and Sounders (1998) examined the determinants of required credit spreads on highly leveraged transaction (HLT) and found "a positive HLT loan sensitivity to changes in the corporate bond market" (p. 1249). Shrieves(1992) investigated the relationship between the observed changes in risk and capital of large sample banks and found a positive relationship between them. Samad and Hassan (2000) measured equity multiplier (EM) as an index for bank risk. Pantalone and Marjorie (1987) identified several internal factors causing bank failure. These factors, among the most important, were: high equity multiplier, commercial and industrial loans to total loans and total loan to total assets

III. Data and Methodology

Data of all 680 banks operating in Texas in 2005 are obtained from the wave site: WWW.FDIC.GOV. Year 2005 is selected for the reason that year 2005 was considered as benchmark year because banking performance bubble begins to decline from 2005.

In order for determining the key risk factors influencing the credit risk of commercial bank and their predictive power, multivariable regression model is applied to two measures of credit default risk NPL and LLP. White (1980) procedure is used to ensure that the coefficients are heteroskedastic. The model is estimated from the set of following equations:

$$NPL = \lambda_0 + \lambda_1 ROA + \lambda_2\ LTERMTA + \lambda_3\ RESLSTA + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (1)$$

$$NPL = \lambda_0 + \lambda_1 ROA + \lambda_2\ LTERMTA + \lambda_3\ RESLL + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (2)$$

$$NPL = \lambda_0 + \lambda_1 ROE + \lambda_2\ LTERMTA + \lambda_3\ RESLSTA + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (3)$$

$$NPL = \lambda_0 + \lambda_1 ROE + \lambda_2\ LTERMTA + \lambda_3\ RESLL + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (4)$$

$$LLP = \lambda_0 + \lambda_1 ROA + \lambda_2\ LTERMTA + \lambda_3\ RESLSTA + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (5)$$

$$LLP = \lambda_0 + \lambda_1 ROA + \lambda_2\ LTERMTA + \lambda_3\ RESLL + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (6)$$

$$LLP = \lambda_0 + \lambda_1 ROE + \lambda_2\ LTERMTA + \lambda_3\ RESLSTA + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (7)$$

$$LLP = \lambda_0 + \lambda_1 ROE + \lambda_2\ LTERMTA + \lambda_3\ RESLL + \lambda_4 COMLN + \lambda_5 REGCP + \lambda_6 EQM + \lambda_7 LNTA + \varepsilon_I \quad (8)$$

Dependent variables:

Based on the survey of related literature to risk management, this paper selects two measures of loan default risk. (i) Non performance loan (NPL) and (ii) Loan loss provision (LLP).

Non-performance loans (NPL) are defined as loans that are past due 90 day. Non-performance loans are represented by a set of two variables—90 day past due (NPL). The 90 day past due (90PD) is considered the actual credit loss. Loan loss provision (LLP) is, on the other hand, subjective and also used as a proxy for loan loss/default.
As both of these variables show positively, weak correlation (0.16) between them, both of them are used separately as regresand. NPL and LLP variables are transformed into natural log to correct for non-linearity

Independent variables:

A set of seven independent variables are considered in this paper for examining credit risk. These variables are obtained from individual bank balance sheet and income statements and classified under six predictive groups.

Group A: Management expectation/attitude. A bank management which expects a very high rate of return is prone to higher credit risk than a bank with which expect a lower rate of return. The banks that expect to have a low rate of return are a risk-averse. The higher the propensity of risk taking, the higher the return on asset (ROA) or return on equity (ROE) and the greater the credit risk and vice versa. In order to expect a higher rate of return bank management must have larger portfolio of risky loans. Both these variables are expected to be positively related to NPL and LLP. That is,

$\frac{\partial NPL}{\partial ROA} > 0 \quad \frac{\partial NPL}{\partial ROE} > 0$, and

Group B: Risky loan: The higher the amount of risky loan, the higher the default risk for a bank. Real estate loans, whether collaterized or not, are considered risky loans due income loss or volatility of property value. There are various measures of default risk. Real estate loans in the portfolio of total loans, RESLL, or REALTA, real estate loans in the portfolio of total asset are both risky loans. RESLL is the amount of residential properties loans plus non-residential properties loans plus real estate loans plus construction loans plus consumption credit loans as a percentage of total loans. LTERMTA is the amount of long term, (total loans- earning investment) as a percentage of total assets. Since the correlation matrix, provided in Table 1, shows that both REALTA and RESLL show strong positive correlation (0.98), RALTA and RESLL are not used in the same equation as an independent variable.
It is expected that

$$\frac{\delta NPL/LLP}{\delta RESLL/REALTA} > 0$$

Another important measure of credit risk is the ratio of long term loan in asset portfolio, LTERMTA. Long term loan are more risky than the short term loan as the probability of long term loan payment prediction is more uncertain and may be affected by a host external factors such as recession, price uncertainty, etc. The higher the amount of long term loans as a percentage of total assets, the higher the default risk for a commercial risk. LTERMTA, long term loan as a percentage of total assets, is determined by subtracting cash and income earning investment from the total asset and dividing by total assets. It is expected that real estate loans, (RESLL and REALTA) and the long term loans, LTERMTA may be linearly dependent. The correlation matrix, in Table 1, shows that LTERMTA has a very weak correlation with RESLL and REALTA, 0.09 and 0.11, respectively. It is expected that

$$\frac{\delta NPL/LLP}{\delta LTERMTA} > 0$$

Table 1 Correlation Matrix

	LTERMTA	RESLL	REALTA
LTERMTA	1.000	0.0936	0.1184
RESLL	0.0936	1.000	0.9820
REALTA	0.1184	0.9820	1.000

Group C. Loan diversification: A bank loan diversification tends to reduce its default risk. A geographic restriction for the advancement of loan is a manifest of less diversification. Commercial loans are considered as non-diversified loans. COMLN, the amount of commercial and industrial loans as a percentage of total loans represents less loan diversification. The higher the ratio the lower the loan diversification and the greater the default risk. Penn Square Bank, which closed in 1982, suffered from a lack of diversification. “Its loan portfolio had a heavy concentration of consumer and industrial loans (e.g. 71% in 1980) mainly in energy related areas”. Sinkey (1992, p. 540). It is thus expected that

$$\frac{\partial NPL}{\partial COMLN} > o \, .$$

Group D. Risk Based capital: The link between capital and credit risk can be described in the way that bank capital has the ability to absorb losses due to default by banks’ customers. Based on Basle Agreement, the amount of total regulatory capital, known as Tier 1, is required to be 4% of the total risk based assets. The presumption is that the higher the ratio of Tier 1 capital as a percentage of total assets (REGCP), the lower the credit risk. The higher the REGCP, the lower the credit risk for a bank. $\frac{\partial NPL}{\partial REGCP} < 0$,

Group E. Leverage factor: When a bank generates a large amount of total assets with a low amount equity capital, the bank, in general, exposes to high default risk. A bank with a small equity capital is more vulnerable to economic or industry specific down turn that causes a portion of bank’s loan portfolio to default. Equity multiplier, EQM, is the amount of equity capital as a percentage of total assets. It is expected that, $\frac{\partial NPL}{\partial EQM} > 0$

Group F. The size of bank is an important factor for credit risk. Usually, the larger the bank size, the higher the propensity of risk taking and the higher the credit risk. Small bank is less aggressive to risky loans. LNTA is the log of total assets. This variable is transformed into natural log to correct for non-linearity. It is expected that, $\frac{\partial NPL}{\partial LNTA} > 0$.

IV. Empirical Results

Empirical findings are provided in Table 2 and Table 3.

Table 2
Regression Result with non-performance loan (NPL) as a dependent variable[1]

EQ	Regressor	Coefficients	T-stats	R^2	F-statistic	Prob(F-statistics	DW
1	ROA	-0.027	-0.68				
	LTERMTA	0.0000006	1.97**				
	REALTA	0.005	1.06				
	COMLN	0.002	0.93				
	REGCP	.0001	0.97				
	EQM	0.0000065					
	LNTA	-0.0008	-3.09*				
				0.02	2.21	0.03	1.9
2	ROA	-0.023	0.-66				
	LTERMTA	0.0000004	1.96**				
	RESLL	0.0004	0.1.06				
	COMLN	0.002	0.96				
	REGCP	0.0001	0.87				
	EQM	0.0000041	-0.27				
	LNTA	-0.0008	-2.99				
3	ROE	-0.003	-0.72				
	LTERMTA	0.000005	2.4*				
	REALTA	0.005	1.06				
	COMLN	0.002	0.92				
	REGCP	0.0001	0.55				
	EQM	0.0001	1.52				
	LNTA	-0.0008	-3.32*				
				0.02	2.26	0.02	1.89
4	ROE	-0.003	-0.72				
	LTERMTA	0.0000041	2.78*				
	RESLL	0.0005	1.06				
	COMLN	0.003	0.99				
	REGCP	0.0001	0.71				

[1] Differences between equations 1 and 2 are the inclusion of REALTA and RESLL with ROA common and differences between equations 3 and 4 are the inclusion of REALTA and RESLL with ROE common.

	EQM LNTA	-0.0000068 -0.0008	0.050 -3.14*	0.03	2.54	0.01	1.88

* Significant at 1% level of significance,** Significant at 5% level of significance
** *Significance at 10% level of significance

Table 2 shows that the major determinants of credit risk, measured in NPL, are LTERMTA, long term loans as a percentage of total assets and bank size measured in terms of total assets, LNTA. T-statistics for both variables show s that they are statistically significant in four equations.

Management attitude measured in ROA and ROE and variables such as equity multiplier, EQM and real estate loans, RESLL, REALTA as a percentage of total loans and total assets are not significant in any of the four equations.

In all four equations the sign for long term loans, LTERMTA, is consistent as expected in the model. The higher the ratio of LTERMTA, the higher the default risk of loans.

Large bank measured in terms of total assets can have more diversification of loans in its asset portfolio and thereby can reduce the credit risk of banks. This is reflected in the coefficient for LNTA. The coefficient of LNTA, is negative and significant indicating that NPL of large banks assets is negatively related to bank size.

Signs for ROE, ROA, and EQM are not consistent and are not significant. Signs for REGCP, REALTA and RESLL are consistent but significant in all equations.
The R^2 of all the regression are between .02 and .04 and the F-statistics of these regressions are significant as supported by the p-value. This suggests that the overall explanatory power of all models is satisfactory.

The high value, close to 2, of Durbin Watson (DW) supports that there is no multicolinearity.

Table 3
Regression Result with loan loss provision (LLP) as a dependent variable[2]

Eq	Regressor	Coefficients	T-stats	R^2	F-statistic	Prob(F-statistics	DW
1	ROA LTERMTA REALTA COMLN REGCP EQM LNTA	0.12 -0.000004 0.01 0.006 0.001 0.0003 -0.0002	2.61** 0.88 0.98 2.41** 0.76 0.14 1.67***	0.06	7.99	0.0000	1.98
2	ROA	0.11	2.70**				

[2] Differences between equations 1 and 2 are the inclusion of REALTA and RESLL with ROA common and differences between equations 3 and 4 are the inclusion of REALTA and RESLL with ROE common.

	LTERMTA	-0.000005	-0.79				
	RESLL	0.0000004	0.60				
	COMLN	0.006	2.47**				
	REGCP	0.0001	0.70				
	EQM	0.002	0.14				
	LNTA	-0.002	-1.67				
				0.08	7.98	0.0000	1.98
3	ROE	0.0000005	2.76**				
	LTERMTA	0.00000022	0.72				
	REALTA	0.001	0.97				
	COMLN	0.005	2.25**				
	REGCP	0.0003	0.24				
	EQM	0.0001	0.74				
	LNTA	-0.0003	-1.90**				
				0.09	8.89	0.0000	1.89
4	ROE	0.001	2.77*				
	LTERMTA	0.000003	0.45				
	RESLL	0.000004	0.67				
	COMLN	0.006	2.27**				
	REGCP	0.0003	0.76				
	EQM	0.0001	0.57				
	LNTA	-0.0003	-1.84***				
				0.09	8.79	0.0000	1.89

* Significant at 1% level of significance,** Significant at 5% level of significance
** *Significance at 10% level of significance

When loan loss provision is considered for measuring credit loss/default, Table 3 shows that factors influencing the credit losses are: (i) management return attitude i.e. ROA and ROE, (ii) COML, commercial loans and (iii) LNTA,bank size measured in total assets. T-statistics for both variables show s that they are statistically significant in four equations.

Large bank measured in terms of total assets can have more diversification of loans in its asset portfolio and thereby can reduce the credit risk of banks. This is reflected in the coefficient sign for LNTA. The coefficient of LNTA, is negative and significant indicating that NPL of large banks assets is negatively related to bank size.

Signs for ROA and ROE are positive, as expected, and significant at the level of Bank attitude towards higher expected return is commensurate with higher risk and consequently bank must face higher default risk. Since ROA and ROE are positively and significantly related to NPL and LLP, it suggests that bank management should pursue a policy of moderate return for its asset and equity. A policy of higher rate of return jeopardizes the sound allocation of bank's loan portfolio.

The sign for COMLN is positive and and significant but contrary to the expectation of model. This might be due to difference in the composition of commercial loans.

Sign for the coefficient of regulatory capital REGCP, EQM and real estate loans, RESLL and REALTA as a percentage of total loans and total assets are consistent as per the expectation of model but not significant.

The F-statistics for all four regressions are significant. This suggests that the overall power of the model is satisfactory. The high value of Durbin Watson (DW), in all equations, supports that there is no multi-collinearity.

V. Conclusions

The paper builds up models for examining factors influencing the credit risk of the commercial bank and estimated the model with the data of 600 commercial banks from Texas. When default risk is measured in non performance loans, NPL, the dominant internal factors influencing the credit risk are: LTERMTA, long term loans as a percentage of total assets and bank size measured in terms of total assets, LNTA. The higher the ratio of long term loan in the portfolio of total assets, the higher the credit risk for commercial banks.

When credit risk is measured in loan loss provision, LLP, the major internal factors affecting credit risk are: management return attitude i.e. ROA and ROE, (ii) COML, commercial loans and (iii) LNTA, bank size measured in total assets.

The paper provides two policy prescriptions. (i)A bank management should pursue a policy of moderate return for its asset and equity. A policy of higher rate of return jeopardizes the sound allocation of bank's loan portfolio. (ii) Since long term loans are positively related to credit risk, bank should have smaller percentage of long term loans in the portfolio of total assets.

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Economic Integration and Portfolio Diversification: An Empirical Examination of ASEAN Markets

G. N. Naidu and Askar Choudhury

Abstract

In this paper, we examine the potential gain achievable through international diversification using two different approaches to portfolio construction. We build portfolios in the Association of Southeast Asian Nations (ASEAN) stock markets for Japanese, German, and British investors respectively. Two sets of portfolios are constructed using two different approaches: a) Correlation based approach and b) Country Beta based approach proposed by Naidu and Choudhury (2006). Overall, our results show that Naidu-Choudhury approach (country-beta based) is a comparable alternative to Markowitz approach (correlation based) for all the three investors based on Sharpe's performance measure for the time period considered. Moreover, our results indicate that Naidu-Choudhury approach holds a promise as an alternative method to create internationally diversified portfolios.

I. Introduction and Background

Trade agreements, bilateral and multilateral, among nations have been around for several decades. However, a new wave of Trade blocs began with the signing of North American Free Trade Agreement. The European nations started their efforts to create Single Market. Some Asian nations started laying ground work to form trade associations of their own. Association of Southeast Asian Nations (ASEAN) was formed in 1984 with 5 members. The membership grew over the next 15 years to ten. Meanwhile, a much broader Trade Association, Asia Pacific Economic Co-operation (APEC) was formed. APEC has 21 member nations with the U.S.A. as one of its members. The purpose of all these trade associations is to enhance the trade and investment flows among the member nations and thereby achieve regional prosperity, peace and stability. The functioning of these trade associations vary from a rigid rule -based system to a flexible/loose affiliation. APEC and ASEAN are the groups with flexible affiliations. This is in direct contrast with the North American Free Trade Agreement (NAFTA) or the European Union (EU).

Economic literature is full of studies revealing the benefits of trade blocs for its members as well as the outsiders of the bloc. The most recent study by Francois and Wignaraja (2008) is an example of such studies. In their study, Francois and Wignaraja tested global input-output structural model on data for ASEAN, ASEAN +3, ASEAN +3+India. While the ASEAN group is widely recognized regional trade bloc, the other two expanded groups include the potential new members for a much broader trade bloc. A trade bloc is no longer perceived as a trade "fortress". Instead, it is widely viewed as a way to unleash the economic synergies among nations. Simply put, it is one way to make the economic landscape flat. Accumulated evidence points to the fact that economic benefits accrue to the member nations without ill-effects on non-

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members of a trade bloc. As the trade bloc fosters economic prosperity and income growth for its members, savings accumulation and capital formation follow. This paves the way for capital markets development. The purpose of this paper is to examine the risk-return tradeoffs prevailing in the capital markets of member nations of ASEAN bloc. First, this paper examines the correlation structure of stock returns from the ASEAN group of countries. By examining the correlation structure, we can see if benefits of portfolio diversification accrue to investors in ASEAN region. Further, this paper applies a new method of constructing portfolios of investments within the trade bloc to show that investors may still improve their return performance by diversifying within the trade bloc. Market imperfections continue to persist even after trade bloc's formation. Political differences, institutional rigidities, differences in economic philosophy, and inefficiencies of capital markets are some of the reasons for the delay in achieving economic harmonization. True economic integration among the member nations takes a long time to develop. In the mean time investors can find opportunities to diversify their portfolios within the region that they are quite familiar and knowledgeable about.

The paper is organized as follows. Data and methodology are described in the next section. Descriptive statistics for stock market returns appear in Table 1. Correlation matrix of stock returns and country betas are presented in Table 2 and Table 3 respectively. Section III provides portfolio diversification scheme. Section IV presents Country beta estimates for several Asian countries in the study. This section also constructs portfolios using country betas as guide. After we constructed country-beta based portfolios, they were compared with the portfolios generated by Markowitz's portfolios as to their risk adjusted performance. Such a comparison helps us observe if country beta approach to build internationally diversified portfolios is comparable to the Markowitz's correlation-based method.

II. Research Methodologies

Data for this study were obtained from Global Financial Data, Inc., Source OECD, IMF statistics, and Yahoo-Finance. The data covers the period, 1995-2007. ASEAN group has a list of 10 countries. Some of these countries such as Laos, Cambodia, Myanmar don't have stock exchanges. The potential for expansion of the trade group towards east may include Japan, Korea and China (ASEAN+3). Some are of the opinion that India may also be the member of the expanded group. So, we included these countries as well in our research. The daily data for all the stock market indices of the countries (ASEAN+3+India) in the region were obtained. Daily returns were computed and then the daily returns were annualized using standard method suggested in investment text books. Daily exchange rate changes were found to be random and therefore, exchange rate effect was not considered in estimation of daily stock returns. Furthermore, the research aim here is to discern portfolio diversification benefits. Effects of informational leads and lags on stock prices were not taken into account, since informational efficiency is not the primary intention of this paper. Descriptive statistics of equity return series appear in Table 1. Since, the correlation structure of returns has been one of the bases for judging the diversification (risk reduction) potential, we have estimated the correlation structure of annualized daily stock returns among the Asian equity markets and presented in Table 2. As pointed out in the next section of this paper, for certain markets the correlation structure does not give us adequate picture of diversification potential when global diversification is sought. Therefore, another approach as suggested by Shapiro (2003) and demonstrated by Naidu and Choudhury (2006) is also used in this study. The country beta approach has a greater potential for global diversification of portfolios. Therefore, we estimated country betas for all the Asian stock markets in the sample by taking the Japanese investor's perspective.

III. Theoretical Setting

The idea that the smaller the degree of correlation the greater the benefit of diversification was popularized by Harry Markowitz (1959). This idea of risk reduction using the correlation structure of returns determines the extent of benefits derived through diversification. However, Sharpe's theory of capital market equilibrium that introduced the concept of beta has a potential for diversification as well. The beta of an asset reflects the variability of its return relative to the variability of market's return. Thus beta is a relative risk measure. An individual asset's beta is calculated relative to a specific market index, such as S&P500.

All national equity markets together create the global capital market environment. Therefore, if we aggregate all the national equity markets we will have a huge world (global) equity market. Each national equity market has its own degree of volatility. However, the volatility relative to each other market will be different. In the same way an equity market's volatility relative to an index of world equity market will be different. Just as one can estimate the risk (beta) of an asset relative to a market index, one can also estimate the risk (beta) of a national equity market relative to world equity market index. This risk estimate of a national equity market is termed as country beta. Thus, a country's beta is the measure of its market's sensitivity to world market variability. Bekaert and Harvey (1997) concluded that market volatility is a function of the openness of its economy. Therefore, a country's beta is indicative of integrator. The smaller the beta, the more segmented is the country's market and hence better will be the gains from diversification. Consequently, international diversification pushes out the efficient frontier further by allowing investors simultaneously to reduce their risk and increase their expected return. Similarly, we can also study the sensitivity of a given equity market to the movements of another equity market of our interest. For example, if we want to know how sensitive the Korean equity market is relative to the movements in Japanese equity market, we can examine this relationship by estimating country beta for Korea with respect to the Japanese equity market. Shapiro (2003) demonstrated this methodology in his book (p.517). A country's market beta is estimated as follows:

Market beta for country, i with respect to Japan

= [Correlation of market, i with Japanese market] X
[Std. Devn. of market, i / Std.Devn. of Japanese Market.]

$\beta_i = \rho_{i,J} \left(\frac{\sigma_i}{\sigma_J} \right)$ where $\rho_{i,J}$ = Correlation coefficient between i^{th} market returns and Japanese market returns

σ_i = Standard deviation of i^{th} market returns

σ_J = Standard deviation of Japanese market returns

A small beta value for a country implies a higher unsystematic risk in that market. Therefore, a smaller country beta offers greater potential for the benefits of diversification. On the contrary, a higher value for a country's beta implies smaller potential for gains from diversification.

Markowitz (1959) theorized that the smaller the degree of correlation the greater is the benefits of diversification. However, this theory looks too simple when it comes to global diversification.

In a global market, it is possible for a pair of countries to have the same degree of correlation with a third country and yet have different values for individual market risk. For example,

$$\rho_{J,US} = 0.25 \quad \sigma_J = 28.8\% \quad \beta_J = 0.40$$

$$\rho_{K,US} = 0.25 \quad \sigma_K = 35.5\% \quad \beta_K = 0.50$$

In this example, the difference in individual standard deviations produced different country betas. That means even though Japan and Korea had the same degree of correlation (0.25) with the U. S. market, their country betas imply that Japanese market offers better gains from diversification than the Korean market does. This example demonstrates that gains from diversification can be estimated better by using country betas rather than the simple correlation coefficients.

By generalizing this theory we can develop the following equation:

Market beta for country i with respect to World Market
= [Correlation of market, i with World Market] X
[Std.Devn. of market, i / Std.Devn. of World Market.]

$$\beta_i = \rho_{i,w}\left(\frac{\sigma_i}{\sigma_w}\right)$$

where $\rho_{i,W}$ = Correlation coefficient between ith market returns and World Market returns

σ_i = Standard deviation of ith market returns

σ_W = Standard deviation of World Market returns

IV. Portfolio Diversification and Performance Index

One way to estimate the benefits of portfolio diversification is to consider the expected return and standard deviation of return for a portfolio consisting of a fraction invested in the host country and the remaining fraction invested in several other countries (or markets).

The expected return of a portfolio is calculated as,

$$\mu_p = W'\mu$$

and the variance of the portfolio is calculated as,

$$V_p = W'\Sigma W$$

where, W is the vector of portfolio weights (or percentages) for different markets, μ is the mean vector of returns of markets in the portfolio, and Σ is the variance-covariance matrix. For example, the mean and variance of a portfolio with only two markets (assets) can be written as,

$$V_p = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\sigma_{12}\sigma_1\sigma_2 \quad .$$

$$\mu_p = w_1\mu_1 + w_2\mu_2$$

Where, μ_1 = average return of market-1, μ_2 = average return of market-2, σ_1 = standard deviation of return of market-1, σ_2 = standard deviation of return of market-2, $\sigma_1\sigma_2$ = covariance of returns between market-1 and market-2.

To evaluate the performance of a portfolio, both return and risk should be incorporated into the performance measure. William Sharpe (1966) developed a composite (risk-adjusted) measure of portfolio performance called the reward-to-variability ratio (RVAR). This measure is also known as Sharpe's Performance Index (PI), which can be defined as,

$$PI_p = \frac{\mu_p - r}{\sigma_p} .$$

Where, σ_p = standard deviation of p^{th} portfolio return, μ_p = average return of p^{th} portfolio, r = risk-free rate for this period. Therefore, the higher the values of the index better the performance of that portfolio on risk-adjusted basis.

The coefficient of variation (CV), which measures relative variability, can also be used to measure the standardized risk with respect to the mean and can be considered as risk-reward ratio of a portfolio's performance. Coefficient of variation of a portfolio is defined as,

$$CV_p = \frac{\sigma_p}{\mu_p} x100 .$$

Therefore, the smaller the CV the better is the performance of that portfolio. Thus, a portfolio is considered to be more diversified if the CV is smaller in value and may be a better measure for diversification, since the coefficient of variation is independent of the unit of measurement. Coefficient of variation is essentially a mirror reflection of Sharpe's Index. Hence, an investor's objective is to construct a portfolio with a relatively lower coefficient of variation or higher Sharpe's Index.

V. Diversification Scheme

In this paper, we have constructed portfolios for the purpose of diversification in the ASEAN stock markets for Japanese, German, and British investors respectively. First, we identify the opportunity for portfolio diversification using country beta as the criterion instead of the correlation coefficient for selecting the country to invest. For example, a Japanese investor may look at the remaining nine countries stock markets and select the country with the smallest beta to invest first. The country with the next highest beta could be the second investment to add to the portfolio. Following this process the investor will allocate funds to the markets in an ascending order of the country's beta value --- the smallest beta country will be the first chosen and the highest beta country will be chosen the last. In the process of portfolio allocation, some basic rules are arbitrarily set. First, an equal allocation to each single foreign market is set at 10% of the total funds. Second, the size of the portfolio is arbitrarily set to include only four assets. So a Japanese investor will have 70% of the funds invested in Japan stock market and 30% outside of Japan. Following this procedure, the Japanese investor will have three portfolios (four-assets each) as shown in Exhibit-2. Similarly, three portfolios are constructed for the German investor and three for the British investor. In total, we have nine portfolios constructed. The risk-return characteristics of these portfolios are estimated for the period, 1995-2007. We hope to demonstrate that country beta based approach to portfolio diversification offers a new way to build globally diversified portfolios. We have built similar portfolios using correlation coefficient (Markowitz approach) as a selection criterion (see, Exhibit-1) for the purpose of comparison.

VII. Empirical Results

The data in this study covers the period, 1995-2007. The daily data for all the stock market indices of the countries considered in this paper were obtained. Daily returns were computed and then the daily returns were annualized. Since, the correlation structure of returns has been one of the bases for judging the diversification (risk reduction) potential. We have estimated the correlation structure of annualized daily stock returns among the equity markets and presented in Table I, along with mean and standard deviation. As mentioned earlier in the paper, for certain markets the correlation structure does not give us adequate picture of diversification potential when global diversification is sought. In this context Naidu and Choudhury (2006)'s country beta approach may be desirable for global diversification. Therefore, we implemented their country beta approach in this study for all ASEAN stock markets by taking three different investors' perspectives. First, a set of betas was estimated by taking the Japanese market's perspective. Then a second set of betas were estimated from the German perspective. We, then, estimated a third set of country betas from the British perspective. These country betas are reported in Table III.

The beta estimates that are used in this paper to construct portfolios are explained and discussed in great detail by Naidu and Choudhury (2006). As described earlier in the methodology section, a set of nine portfolios are created using Markowitz approach. This set of portfolios appears in Exhibit 1. Similarly, we have created another set of nine portfolios using country beta as the basis of selection using Naidu-Choudhury approach. This second set of portfolios is presented in Exhibit 2. As can be seen from these two exhibits, the least correlated country (asset) portfolio (in exhibit 1) and the lowest-beta portfolio (in exhibit 2) are exactly identical in composition. Therefore, the country composition of first portfolio is exactly same irrespective of the underlying creation approach differences. Furthermore, the first portfolio constructed at the lowest risk level is same in composition regardless of the investors' home market. The portfolio composition changes, however, as the correlation and the beta levels ascend. For example, the portfolio-2 for Japanese investor in Exhibit 1 and that in Exhibit 2 have a slightly different composition. The portfolio-3 for German and British investors in Exhibit 1 and that in Exhibit 2 have little more divergence in composition. Thus, at the second or third level of screening, using correlation as selection basis produced a portfolio that is different in composition than that produced by the country beta as the selection criterion.

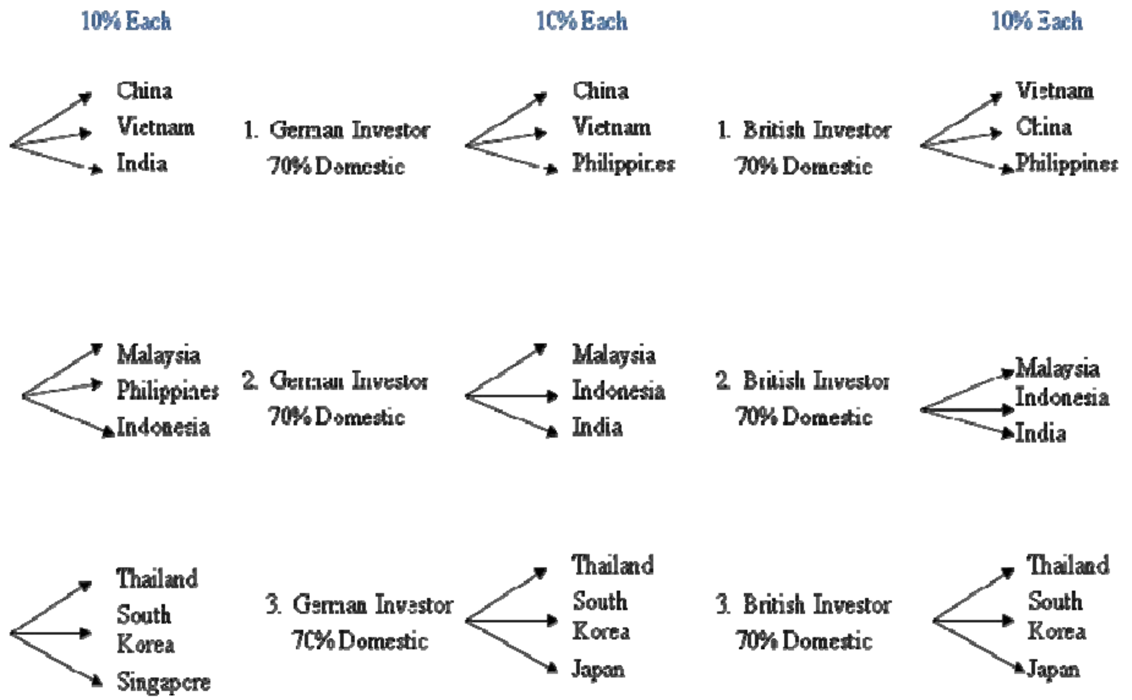
Mean, standard deviation, coefficient of variation (CV), and Sharpe's Index for all nine portfolios constructed using the correlation-based (Markowitz) screening criterion is presented in Table IV and the results are somewhat disappointing. Sharpe's Index values are all negative implying that all the nine portfolios constructed using Markowitz approach underperformed the risk-free assets (short-term government debt) in their respective home markets. The degree of underperformance varied greatly among the nine portfolios. The first set of portfolios delivered a better risk-adjusted performance than the other sets as measured by coefficient of variation. In other words, the markets in China, and Vietnam consistently offered the best diversification potential for the Japanese, German, and British investors alike. These investors would have been better off; however, had they invested in the short-term government debt instruments (risk-free assets). A plausible explanation is in order. It appears that the markets for risky assets did not adequately compensate the risk takers. Stock markets suffered two major crises (Asian financial crisis/contagion and the dot.com bubble burst) during this study period. Risk premiums were not adequate for the levels of risk the investors took during this time period.

Table V displays the mean, standard deviation, coefficient of variation (CV), and Sharpe's Index for all nine portfolios constructed using the country beta as the basis for screening. These portfolios constructed using country beta approach also produced negative values of Sharpe's Index of similar kind. In other words, the country beta based method of constructing portfolios did not produce any superior performance compared to Markowitz method. However, this provides investors an alternative tool to construct diversified portfolios across international markets and may produce different (perhaps favorable) results at different trade bloc in different time periods.

V. Conclusion

In a world of less integrated capital markets, international portfolio diversification is advocated to earn higher returns with lower risk. Markowitz approach to domestic diversification was extended to global diversification by Levy and Sarnat (1970) and Solnik (1974) and many others followed afterwards. However, not much attention has been given toward the investigation of relative risk measure (beta) for potential diversification gain in international arena. This paper implements a method of portfolio construction on the basis of country beta criterion proposed by Naidu and Choudhury (2006). In this paper, portfolios are constructed using both Naidu-Choudhury (beta) approach and Markowitz (correlation) approach for three different markets (Japan, Germany, and Britain). Then the performance of these portfolios has been measured using both Coefficient of Variation and Sharpe's Index. The analysis reveals that Naidu-Choudhury approach produces portfolios comparable to those produced by Markowitz approach. Another interesting finding is that, although the two different approaches produce portfolios with slightly different composition of markets, but the composition of markets stay same for the best diversified portfolio for each of the home markets considered in this paper. In other words, Naidu-Choudhury method and Markowitz method produced essentially same optimal portfolio.

Exhibit-1 [Correlation Based]



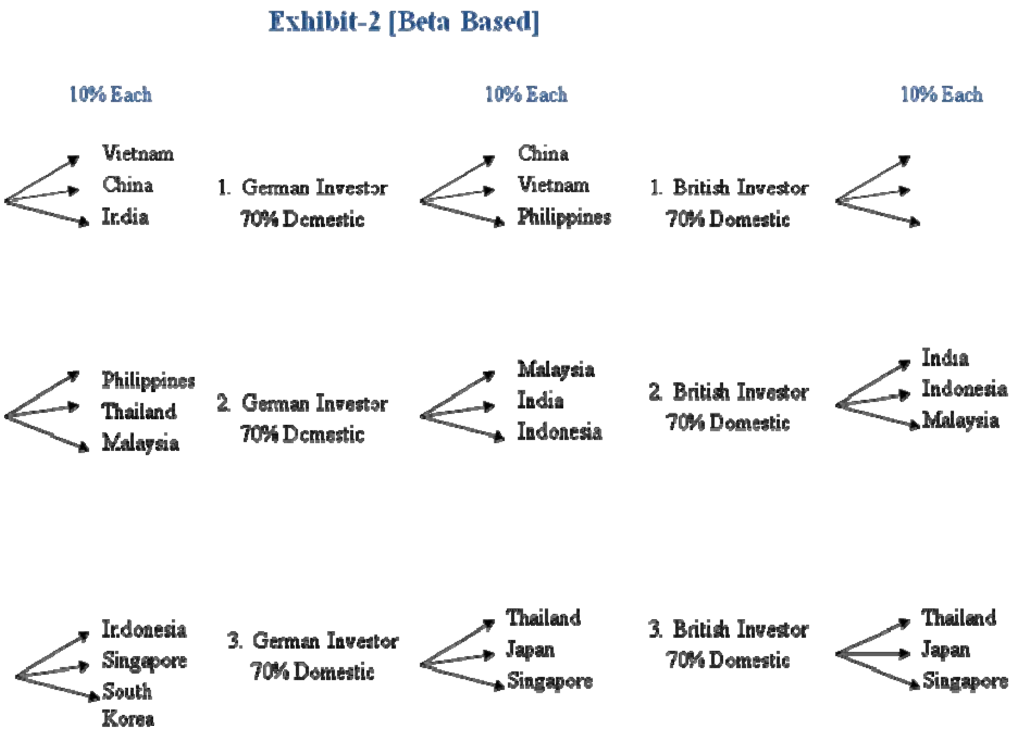


Exhibit-2 [Beta Based]
10% Each
10% Each
10% Each
Vietnam
China
India
1. German Investor
70% Domestic
China
Vietnam
Philippines
1. British Investor
70% Domestic
Philippines
Thailand
Malaysia
2. German Investor
70% Domestic
Malaysia
India
Indonesia
2. British Investor
70% Domestic
India
Indonesia
Malaysia
Indonesia
Singapore
South Korea
3. German Investor
70% Domestic
Thailand
Japan
Singapore
3. British Investor
70% Domestic
Thailand
Japan
Singapore

TABLE I
Correlations, Means, and Standard Deviations of Annualized Daily Stock Market Returns (1995-2007)

Country	Japan (Correlations)	Germany (Correlations)	England (Correlations)	N	Mean	Std Dev
China	0.031	-0.015	-0.013	3152	2.964	30.630
India	0.179	0.126	0.176	3206	2.134	19.502
Indonesia	0.209	0.125	0.145	3197	2.478	24.252
Japan	1	0.223	0.262	3203	1.099	17.242
Malaysia	0.190	0.093	0.142	3206	1.731	25.751
Philippines	0.194	0.085	0.116	3221	1.510	20.790
Singapore	0.370	0.271	0.320	3258	1.071	14.686
South Korea	0.368	0.193	0.246	2580	3.244	27.372
Thailand	0.213	0.157	0.187	3188	1.662	22.656
Vietnam	0.036	-0.008	-0.042	1629	2.893	21.718
USA	0.098	0.507	0.433	3273	1.119	13.056
England	0.262	0.722	1	3290	0.849	11.707
France	0.242	0.790	0.812	3293	1.490	16.496
Germany	0.223	1	0.722	3327	1.682	17.902

TABLE II

Correlations Matrix of Annualized Daily Stock Market Returns (1995-2007)

Country	China	India	Indonesia	Japan	Malaysia	Philippines	Singapore	South Korea	Thailand	Vietnam	USA	England	France	Germany
China	1.000	0.047	0.021	0.031	0.023	0.014	0.044	0.029	0.023	0.015	-0.032	-0.014	-0.018	-0.016
India	0.047	1.000	0.195	0.179	0.103	0.114	0.249	0.239	0.175	-0.013	0.043	0.176	0.159	0.126
Indonesia	0.021	0.195	1.000	0.209	0.222	0.315	0.450	0.192	0.385	0.018	0.023	0.145	0.114	0.125
Japan	0.031	0.179	0.209	1.000	0.190	0.195	0.370	0.368	0.213	0.037	0.098	0.263	0.242	0.223
Malaysia	0.023	0.103	0.222	0.190	1.000	0.152	0.339	0.180	0.266	0.016	0.001	0.142	0.087	0.094
Philippines	0.014	0.114	0.315	0.195	0.152	1.000	0.308	0.203	0.274	0.037	0.030	0.116	0.073	0.085
Singapore	0.044	0.249	0.450	0.370	0.339	0.308	1.000	0.367	0.444	0.008	0.124	0.320	0.281	0.271
South Korea	0.029	0.239	0.192	0.368	0.180	0.203	0.367	1.000	0.322	0.024	0.090	0.246	0.213	0.193
Thailand	0.023	0.175	0.385	0.213	0.266	0.274	0.444	0.322	1.000	-0.013	0.050	0.187	0.155	0.157
Vietnam	0.015	-0.013	0.018	0.037	0.016	0.037	0.008	0.024	-0.013	1.000	-0.036	-0.042	-0.021	-0.009
USA	-0.032	0.043	0.023	0.098	0.001	0.030	0.124	0.090	0.050	-0.036	1.000	0.434	0.459	0.508
England	-0.014	0.176	0.145	0.263	0.142	0.116	0.320	0.246	0.187	-0.042	0.434	1.000	0.813	0.723
France	-0.018	0.159	0.114	0.242	0.087	0.073	0.281	0.213	0.155	-0.021	0.459	0.813	1.000	0.790
Germany	-0.016	0.126	0.125	0.223	0.094	0.085	0.271	0.193	0.157	-0.009	0.508	0.723	0.790	1.000

TABLE III

Country Betas of Annualized Daily Stock Market Returns (1995-2007)

Country	Japan	Germany	England
China	0.056	-0.026	-0.035
India	0.203	0.137	0.293
Indonesia	0.294	0.169	0.300
Japan	1	0.215	0.386
Malaysia	0.284	0.135	0.313
Philippines	0.234	0.099	0.206
Singapore	0.315	0.222	0.401
South Korea	0.584	0.295	0.575
Thailand	0.279	0.1987	0.362
Vietnam	0.045	-0.011	-0.077
USA	0.074	0.370	0.483
England	0.178	0.472	1
France	0.231	0.728	1.145
Germany	0.232	1	1.105

TABLE – IV
Portfolios created using country correlations in ascending order.

Portfolios	MEAN	Standard Deviation	Coefficient of Variation (CV) %	Sharpe's Index	Portfolio of four countries and their % allocation			
Japanese Investor -1	1.56858	13.29047	847.2923	-0.18746	Japan-70%	China -10%	Vietnam-10%	India-10%
Japanese Investor -2	1.34139	14.27915	1064.503	-0.19039	Japan -70%	Malaysia -10%	Philippines-10%	Indonesia-10%
Japanese Investor -3	1.36724	14.8283	1084.537	-0.1816	Japan -70%	Thailand -10%	South Korea-10%	Singapore -10%
German Investor -1	1.91486	13.37034	698.2412	-0.16044	German-70%	China -10%	Vietnam -10%	Philippines -10%
German Investor -2	1.81242	14.09285	777.5688	-0.15948	German-70%	Malaysia -10%	Indonesia -10%	India -10%
German Investor -3	1.77873	14.65789	824.0652	-0.15563	German-70%	Thailand -10%	South Korea -10%	Japan - 10%
British Investor -1	1.33115	9.373297	704.1479	-0.29113	British-70%	Vietnam -10%	China -10%	Philippines -10%
British Investor -2	1.22871	10.30713	838.8517	-0.27469	British-70%	Malaysia -10%	Indonesia 10%	India -10%
British Investor -3	1.19502	10.8791	910.367	-0.26335	British-70%	Thailand -10%	South Korea -10%	Japan - 10%

Note: Coefficient of Variation (CV) = (Standard Deviation / Mean) x 100.
Sharpe's Performance Index (PI) = (average return – risk-free rate) / standard deviation of returns.

TABLE – V
Portfolios created using country betas in ascending order.

Portfolios	MEAN	Standard Deviation	Coefficient of Variation (CV) %	Sharpe's Index	Portfolio of four countries and their % allocation			
Japanese Investor -1	1.56858	13.29047	847.2923	-0.18746	Japan-70%	Vietnam -10%	China - 10%	India-10%
Japanese Investor -2	1.25987	14.2305	1129.519	-0.19677	Japan - 70%	Philippines -10%	Thailand -10%	Malaysia - 10%
Japanese Investor -3	1.44876	14.842	1024.459	-0.17594	Japan - 70%	Indonesia -10%	Singapore -10%	South Korea - 10%
German Investor -1	1.91486	13.37034	698.2412	-0.16044	German-70%	China - 10%	Vietnam -10%	Philippines -10%
German Investor -2	1.81242	14.09285	777.5688	-0.15948	German-70%	Malaysia -10%	India - 10%	Indonesia -10%
German Investor -3	1.56133	14.22377	910.9984	-0.17567	German-70%	Thailand -10%	Japan - 10%	Singapore -10%
British Investor -1	1.33115	9.373297	704.1479	-0.29113	British-70%	Vietnam -10%	China - 10%	Philippines -10%
British Investor -2	1.22871	10.30713	838.8517	-0.27469	British-70%	India - 10%	Indonesia 10%	Malaysia -10%
British Investor -3	0.97763	10.29434	1052.986	-0.29942	British-70%	Thailand -10%	Japan - 10%	Singapore -10%

Note: Coefficient of Variation (CV) = (Standard Deviation / Mean) x 100.
Sharpe's Performance Index (PI) = (average return – risk-free rate) / standard deviation of returns.

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