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THE IMPACT OF SBA LENDING ACTIVITY ON MICROPOLITAN STATISTICAL AREAS IN THE U.S. SOUTHEAST

Bienvenido S. Cortes, Pittsburg State University
Zheng Yao Ooi, Pittsburg State University

ABSTRACT

This study examines the economic impact of Small Business Administration (SBA) guaranteed lending activity on the 12 states comprising the Southeast region (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia) for the 1990-2015 period. Past studies find that the effect of Small Business Administration loans on regional economic performance, particularly in low-income areas, is positive but negligible. The study adds to the literature by focusing on a government-defined geographic unit called the micropolitan statistical area (which consists of at least one county with an urban core population of 10,000-50,000). The objective is to measure and evaluate the effect of Small Business Administration loans on various indicators of micropolitan area economic activity (gross regional product, employment, and income growth), while also controlling for other determinants of local economic growth. The study applies fixed effects regression model on a cross-section of 153 micropolitan areas for three subperiods in 1990-2015. It finds that micropolitan area economic growth in the Southeast region is dependent on Small Business Administration -guaranteed lending, industrial composition, human capital, and demographic factors.

JEL: R11, O16

KEYWORDS: Micropolitan Statistical Area, SBA, Fixed Effects

INTRODUCTION

The Southeast region of the USA, as defined in this study, consists of twelve states: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. It is a highly diverse group of economies, which has experienced rapid population growth over the past decades due to migration to the "Sunbelt" states and yet at the same time ranks at the bottom half of all states in terms of median household income and has the highest poverty rate compared to other regions (US Department of Commerce, 2016). The problems of low incomes and poverty are more acute when one considers the areas "outside the metropolitan statistical areas," that is, the micropolitan statistical areas and rural counties. The Office of Management and Budget (OMB) defines a micropolitan statistical area as a geographical area composed of an urban core with a population of 10,000 to 49,999. There are 153 micropolitan areas in the Southeast region. In 2015, the largest micropolitan area in the region in terms of population is Tupelo, MS, with approximately 141,000. The smallest micropolitan area is Maysville, KY, with a little over 17,000 population. The average population in 2015 for the 153 micropolitan areas is nearly 55,000. The micropolitan population grew significantly in the 1990s especially for the states of Florida, Georgia, North Carolina, and Tennessee. However, population growth in the region has been declining since then (see Table 1).

Table 1: Average Population Growth Rates of Southeast Micropolitan Areas

STATE	1990-2000	2000-2010	2010-2015
Alabama	0.68	0.37	0.12
Arkansas	0.80	0.10	-0.14
Florida	2.45	0.69	0.31
Georgia	1.60	1.00	0.28
Kentucky	0.99	0.58	0.46
Louisiana	-0.01	0.14	0.16
Mississippi	0.58	-0.09	-0.04
North Carolina	1.48	0.97	0.55
South Carolina	1.09	0.47	0.14
Tennessee	1.71	0.91	0.54
Virginia	-0.02	-0.29	-0.46
West Virginia	-0.21	0.11	-0.04

This table shows the population growth rates of the Southeast micropolitan areas for three time periods: 1990-2000, 2000-2010, and 2010-2015. Source: Woods & Poole Economics and authors' calculations.

In terms of real per capita income for 2015, the Southeast region's micropolitan areas exhibit wide variation. The micro area with the highest per capita income is Key West, FL, with $65,229, while the area with the lowest income level is Arcadia, also located in Florida, with $19, 869. The mean income for all 153 micro areas in 2015 is $30,623. As Table 2 shows, the average growth rates of real per capita income for three time periods for the Southeast micropolitan areas have been trending downward for half of the states.

Table 2: Per Capita Income Growth Rates in Southeast Micropolitan Areas

Average Growth Rates of Per Capita Income (%)	Number of Micro Areas	1990-2000	2000-2010	2010-2015
Alabama	9	2.22	1.50	1.04
Arkansas	14	2.16	1.52	1.72
Florida	7	1.02	1.09	0.73
Georgia	24	2.34	0.39	1.37
Kentucky	15	2.83	0.92	1.65
Louisiana	9	2.51	3.31	1.29
Mississippi	18	2.91	1.93	1.54
North Carolina	24	2.72	0.59	1.07
South Carolina	7	2.68	0.85	1.16
Tennessee	16	2.65	0.55	1.52
Virginia	4	1.40	1.73	0.59
West Virginia	6	2.55	2.05	1.15

This table shows the number of micropolitan areas in the Southeast region and their per capita income growth rates for three time periods: 1990-2000, 2000-2010, and 2010-2015. Source: Woods & Poole Economics and authors' calculations.

Similarly, Table 3 indicates that employment growth rates in the Southeast micropolitan areas also exhibited variability across states and time periods. Generally, employment was positive during the 1990s, turned negative during the 2000s, and slightly improved during the 2010-15 period.

Table 3: Employment Growth Rates in Southeast Micropolitan Areas

Average Growth Rates of Employment (%)	1990-2000	2000-2010	2010-2015
Alabama	0.96	-0.29	0.68
Arkansas	1.60	-0.30	0.28
Florida	2.69	0.37	1.30
Georgia	2.18	-0.41	1.30
Kentucky	2.01	-0.29	0.99
Louisiana	0.98	0.37	0.63
Mississippi	1.71	-0.36	1.06
North Carolina	1.70	-0.38	0.97
South Carolina	1.23	-0.56	1.04
Tennessee	2.04	-0.67	1.14
Virginia	0.01	-0.72	-0.30
West Virginia	1.09	0.06	0.22

This table shows the employment growth rates of the Southeast micropolitan areas for three time periods: 1990-2000, 2000-2010, and 2010-2015. Source: Woods & Poole Economics and authors' calculations.

The main objective of this study is to analyze the economic performance of micropolitan statistical areas in the Southeast region for the period 1990-2015. It identifies and empirically measures the impact of various growth determinants including industrial structure, demographics, and market factors. The key variable of interest, however, is credit availability or access, as represented by Small Business Administration (SBA) lending, specifically, the SBA 7(a) loan guarantee program for small businesses. In 2015, the Georgia micropolitan areas received the largest amount of SBA 7(a) loans ($47 million) relative to other Southeastern states, while micropolitan areas in Louisiana only accounted for $2.5 million in loans (Table 4).

Table 4: Real SBA Loans in Southeast Micropolitan Areas, 2015

Micro Areas in SE Region	Total Real SBA
State	(in $)
Alabama	6,030,567
Arkansas	15,311,994
Florida	15,973,408
Georgia	46,965,690
Kentucky	10,392,187
Louisiana	2,467,526
Mississippi	17,868,240
North Carolina	27,683,834
South Carolina	9,730,764
Tennessee	10,410,422
Virginia	3,991,867
West Virginia	3,283,035

This table shows the SBA 2015 total loans for the micropolitan areas in the 12 states of the Southeast region. Source: SBA and authors' calculations.

The next section discusses the recent literature which forms the basis for this study, followed by the model specification, variables, and data. Analysis of the empirical tests and results, and then conclusions and recommendations will round off the discussion.

LITERATURE REVIEW

The study of micropolitan areas, a government-defined geographic entity somewhere between a rural area and a metropolitan area, has received attention in the literature recently. Even before the official OMB designation, Glavac *et al.* (1998) and Vias *et al*. (2002) have examined these areas and their characteristics primarily because these places not only provided the peace and quiet of a rural setting but also the amenities associated with larger urban/metropolitan cities. In their 2015 study, Cortes, Davidsson, and McKinnis provide a detailed analysis of the regional distribution and diversity of the country's 536 micropolitan areas, their population and income growth rates, and the volatility of their economic growth. Following earlier studies by Davidsson and Rickman (2011) and Cortes *et al.* (2013), Cortes and colleagues find that the economic vitality of micropolitan areas is correlated with the industry structure, location, and government policy. In terms of the Southeast region, Nzaku and Bukenya (2005) determine that the economic growth (in terms of income, employment, and population) of non-metropolitan counties not only depends on sectoral composition and fiscal factors but also on the amenities available in these areas (natural and recreational amenities, low crime rates). The importance of quality of life factors associated with location, housing, and favorable regulatory environment in micropolitan areas is further examined and evidenced in Davidsson and Cortes (forthcoming).

The present study contributes to the micropolitan area growth literature by investigating the impact of credit to small businesses. Specifically, it looks at the role of government loan programs, in this case, Small Business Administration (SBA) lending activity, in promoting business and overall economic growth in micropolitan areas. Earlier studies by Craig and others (2006, 2007, 2008, 2009), Shaffer and Collender (2009), and Hancock and Wilcox (1998) show that SBA-guaranteed loans have a positive and significant effect on local economic activity especially in low-income areas or counties. This study extends the previous literature with some differences. First, it uses more recent data and focuses on the impact of SBA 7(a) lending activity during the 1990-2015 period. Second, it applies a fixed effects panel regression model with micropolitan area economic growth (i.e., as measured by real gross regional product, employment rate, and real personal income per capita) as the dependent variable. Third, the analysis only covers the micropolitan areas of the Southeast US region.

DATA AND METHODOLOGY

The theoretical framework of this study derives from Bruce *et al.* (2009) with some differences. First, this study applies the growth model to the micropolitan area level rather than the state-level. Second, SBA lending activity is the main key variable of interest; unlike Bruce *et al.* (2009) who include government loan guarantee program as a dummy non-tax variable, this study uses real SBA data. Third, this study employs more industry variables to account for differentiated sectoral effects. Lastly, unlike Bruce and others, more demographic variables are considered in the estimating equation. Following Bruce *et al.* (2009), the general model estimated here takes the following form:

$$\begin{aligned} GR = \beta_0 + \beta_1 INITIAL + \beta_2 SBA + \beta_3 DEP + \beta_4 FARM + \beta_5 MFTG + \beta_6 RETAIL + \beta_7 CONST \\ + \beta_8 GOVT + \beta_9 SERV + \beta_{10} WAGE + \beta_{11} UR + \beta_{12} HOUSING + \beta_{13} POPDENSITY \\ + \beta_{14} AGE + \beta_{15} EDUC + \beta_{16} WHITE + \beta_{17} BLACK + \beta_{18} HISP + \beta_{19} Time1990 \\ + \beta_{20} Time2000 + \varepsilon \end{aligned} \tag{1}$$

where GR is the micropolitan area economic growth rate (as measured by real gross regional product, employment rate, or per capita personal income); INITIAL is the beginning of the period real value of gross regional product, income, or employment; SBA is real per capita SBA 7(a) loans; DEP is bank deposits per capita; FARM, MFTG, RETAIL, CONST, GOVT, and SERV are the shares of total micropolitan area employment accounted by the farm, manufacturing, retail trade, construction, local government, and professional services sectors, respectively; WAGE is real wage per capita; UR is unemployment rate; HOUSING is housing units per square mile; POPDENSITY is population per square mile; AGE is the median age of population; EDUC is the percent of area population with a college degree; WHITE, BLACK, and HISP are the percent of population that is Caucasian, African-American, and Hispanic, respectively; Time1990 and Time2000 account for time fixed effects; and ε is the error term.

The model is applied to a balanced panel data consisting of 153 Southeast micropolitan areas for three time periods: 1990-2000, 2000-2010, and 2010-2015. The dependent variable is defined as the average annual percentage rate (of real gross regional product, employment rate, or real per capita income) for each of the three sub-periods. To avoid the issue of endogeneity, all explanatory variables are initial values for each of the three time periods. The key variable of interest, SBA-approved loan data, is provided by the Small Business Administration. Demand deposit data are gathered from the FDIC's Summary of Deposits. Housing data are from the U.S. Census Bureau. All other variables are taken from the Woods & Poole (2016) database. Descriptive statistics of the variables of the model are available upon request from the authors. Following standard growth models, the beginning value (INITIAL) for gross regional product, employment, or total personal income per capita is added to account for the "convergence hypothesis," which states that richer areas will grow more slowly than poorer areas (Bruce *et al.*, 2009: 244). Thus, the *a priori* or expected sign of the estimated coefficient for INITIAL is negative. SBA 7(a) guaranteed loans and bank deposits in the micropolitan area represent credit access as well as the degree of financial market competition, following Craig and others; a positive sign is hypothesized for both financial variables. To proxy for the area's market size or demand conditions, population density is employed. Housing density is a proxy variable for amenities. Real wage per capita indicates input price effect while the unemployment rate reflects the general economic health of the area. The last variables are control factors representing local economic conditions including industrial composition and demographics. The six industry employment shares measure the effect of industrial composition on micropolitan area growth; the *a priori* expectation is ambiguous. Finally, AGE, EDUC, WHITE, BLACK, and HISP variables represent demographic characteristics.

EMPIRICAL RESULTS

The panel data set consists of 153 micropolitan areas and three time periods, amounting to 459 observations. Preliminary tests indicate that the panel estimating equation has significant fixed effects for both cross-sections and time periods. The model is estimated using a feasible Generalized Least Squares regression with fixed cross-section effects; time dummy variables for 1990-2000 period and 2000-2010 period are also included in the model. The EViews statistical package is used in the study. The results of estimating the model using three different dependent variables are shown in Table 5 below.

Confirming earlier studies by Craig *et al.* (2006, 2007, 2008, 2009) and Cortes (2010), the findings in Table 5 show that the key variable of interest, SBA-guaranteed lending, has a positive and significant impact on GRP/output and employment growth in the micropolitan areas of the Southeastern states, but no differential effect on per capita personal income. The level of bank deposits has similar effects, although the absolute sizes of the estimated coefficients are very small. The convergence hypothesis is supported for GRP and income, but not employment. The main contributing determinant of micropolitan area growth is industry structure, consistent with earlier studies of micropolitan areas by Cortes *et al.* (2013, 2015) and Davidsson and Rickman (2011).

Table 5: Pooled Regression of the General Model with Fixed Effects

Variable	Model 1 Gross Regional Product Is Dependent	Model 2 Employment Rate Is Dependent	Model 3 Personal Income Is Dependent
Constant	4.33	-1.45	1.77
	(1.68)*	(-0.68)	(2.60)***
Initial Level	-0.00045	0.009	-0.0002
	(-5.24)***	(1.68)*	(-9.86)***
SBA per capita	0.009	0.014	0.003
	(1.96)**	(4.19)***	(1.13)
Bank deposits	0.0000007	0.0000006	0.0000004
	(2.92)***	(3.05)***	(3.38)***
Farm share	-0.09	0.08	0.08
	(-3.80)***	(4.96)***	(8.63)***
Manufacturing share	-0.02	-0.03	-0.004
	(-2.51)**	(-4.03)***	(-0.97)
Retail trade	-0.03	0.09	0.02
	(-0.88)	(3.21)***	(1.30)
Construction	-0.004	0.145	0.02
	(-0.12)	(5.67)***	(1.17)
Local government	-0.02	0.02	0.003
	(-1.01)	(2.42)**	(0.49)
Professional services	0.242	0.02	0.08
	(3.88)***	(0.42)	(2.91)***
Wages	-0.00008	-0.00002	0.00004
	(-3.33)***	(-1.27)	(3.34)***
Unemployment rate	-0.06	-0.01	-0.04
	(-2.40)**	(-0.70)	(-2.70)***
Housing density	-0.009	-0.03	0.01
	(-0.95)	(-4.26)***	(1.86)*
Population density	0.002	0.01	-0.01
	(0.52)	(3.30)***	(-2.23)**
Age	-0.04	-0.01	0.06
	(-1.72)*	(-0.48)	(4.05)***
Education	0.04	0.04	0.03
	(2.10)**	(2.82)***	(3.25)***
White population	0.01	-0.0001	0.002
	(0.29)	(-0.01)	(0.70)
Black population	-0.01	-0.015	0.01
	(-0.44)	(-0.75)	(3.96)***
Hispanic population	-0.001	-0.001	-0.04
	(-0.03)	(-0.06)	(-6.50)***
Time1990	2.85	1.00	0.02
	(11.30)***	(4.57)**	(0.11)
Time2000	0.22	-1.17	-0.91
	(0.95)	(-6.27)***	(-6.17)***
Adjusted R-squared	0.70	0.76	0.78
F-statistic	55.17 (Prob<0.00)	73.48 (Prob<0.00)	80.85 (Prob<0.00)

*This table shows the regression estimates for three versions of the general model (1) above. Model version 1 has GRP as the dependent variable; Model version 2 has employment rate as dependent; Model version 3 has personal income as dependent. The first figure in each cell is the estimated regression coefficient. t-statistics are in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively.*

The magnitudes and overall statistical significance of the coefficients of industry share variables indicate the role and importance of existing and dominant sectors such as agriculture, retail trade, construction, and professional services. Also reflecting current national trends, the manufacturing share of total employment has a consistently negative impact on micropolitan economic performance during the period under study. Unemployment rate has the expected negative effect, but is only significant in explaining output and income growth. As an indicator of input cost, wage has the expected and significant indirect relationship with GRP; as a component of personal income, wage is significantly and positively correlated with income growth. Human capital has the expected positive effect on growth. An aging population has a negative influence on output and employment growth; however, older or more mature workers are associated with higher incomes. Racial composition, i.e., black and Hispanic population, is important only in the income equation.

Population density and housing density affect both employment and income growth, but in opposite directions. Finally, the statistically significant time dummy variables reflect the importance of period effects, i.e., employment and income growth conditions in the recent 2010-15 period are more improved compared to those of the previous 2000-2010 period.

SUMMARY AND CONCLUSIONS

The main objective of this study is to identify and empirically measure the differential effect of Small Business Administration 7(a) guaranteed loans on the economic growth of micropolitan statistical areas in the U.S. Southeast region. It gathers data on small business loans from the SBA for the period 1990-2015 as well as statistics on various economic variables from the Woods & Poole database, U.S. Census Bureau, and the FDIC. The study applies fixed effects regression technique on a balanced panel data set comprised of 153 Southeast micropolitan areas and three time periods, amounting to 459 observations. The regression results confirm the positive, albeit small, impact of SBA loans on output and employment growth. Thus, it is important for local government and the banking sector to continue to provide credit access and financial intermediation particularly to small area businesses. The findings also indicate the critical role of a diversified and changing industrial base (from farming and manufacturing to services) in promoting economic growth and development. Finally, the economic survival of non-metropolitan/micropolitan areas is dependent on its attributes and competitive advantages such as human capital and entrepreneurship, and attractive amenities such as housing, climate, outdoor recreation, and quality of life (Nzaku and Bukenya, 2005). In terms of shortcomings, the study does not account for geospatial effects and is limited by data availability due to the relatively recent government-determined definition of "micropolitan statistical areas." Directions for future research include the impact of SBA loans on all 536 micropolitan statistical areas in the country and a comparative study of other government loan programs such as the Community Reinvestment Act.

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BIOGRAPHY

Dr. Bienvenido S. Cortes is Associate Dean and MBA Director at Pittsburg State University. His main research interests are regional economic growth, financial development, and economic education. He can be contacted at the Kelce College of Business, Pittsburg State University, Pittsburg, KS 66762. Email: bcortes@pittstate.edu

Mr. Zheng Yao Ooi is an MBA student and graduate research assistant. His main research interests are economic growth, data analytics, and technology. He can be contacted at the Kelce College of Business, Pittsburg State University, Pittsburg, KS 66762. Email: zooi@gus.pittstate.edu

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VALUE CREATION IN BANKS AND INFORMATIONAL CONTRIBUTION OF VALUE EFFICIENCY

Lamia Bouattour Boulifa, DEFI, ESSECT
Slim Khouaja, ESSECT

ABSTRACT

This paper investigates the contribution of cost, profit and value efficiency in explaining bank performance for a sample of U.S. listed bank holding companies from 2004 to 2006. In the first stage of the analysis, we estimated efficiency scores and made a descriptive analysis. We found a strong correlation between profit and value efficiency scores although these two concepts are not necessarily associated with cost minimization objective. In the second stage, we measured bank performance using; first, stock return as an indicator of market sensitivity and second, EVA as shareholder value creation indicator. We used OLS and Panel regression models to assess the informational contribution of these efficiency concepts. Our results show that market indicators are not very sensitive to bank efficiency. Thus, shareholder value creation can better be explained by value efficiency rather than profit or cost efficiency.

JEL: G21, G32

KEYWORDS: Shareholder Value, Cost, Profit and Value Efficiency, Stochastic Frontier, EVA, Banking, Market Performance

INTRODUCTION

Banks play a central role in developing economic activity. This pushes the monetary authorities, regulators and stakeholders to bring interest in their performance. This subject, although widely treated for decades, is still relevant. Traditional measures of bank performance were generally based on the objective of cost minimization or/and profit maximization. Recently, many researches have focused on value creation objective. Latest researches demonstrate that the focus should be on creating value for shareholders. (Albouy, 2006; Vernimmen *et. al.* 2016; Koller *et al.,* 2010). In the present study, we try to add to this literature by providing evidence on the link between bank value efficiency and their performance. This paper focuses on two aspects. First, we consider the three concepts of efficiency namely, cost, profit and value efficiency. Second, we link these three concepts of efficiency with bank performance for a sample of U.S. listed bank holding companies from 2004 to 2006 to investigate which of these three concepts is more linked to bank performance. The rest of this paper is organized as follows. The first section presents literature review. Section two presents data and methodology. The next section discusses empirical results. The last section concludes.

LITERATURE REVIEW

The financial theory shows that the aim of a firm is to maximize its value, and to improve the welfare of all stakeholders (Jensen, 2001) and mainly for shareholders. (Koller *et al.,* 2010). Many researches show that EVA (Economic Value Added) can be a good measure of value creation for shareholders in banks (Uyemura *et. al.*, 1996 ; Fiordelisi and Molyneux, 2010). EVA joins the notion of residual income or economic benefit that has its origins in the work of Marshall (1890). It considers wealth creation after remuneration of all factors, including equity (Stern *et. al.* 2001, Ehrbar 2000; Koller *et. al.* 2010). By introducing some adjustments, EVA avoids problems related to the manipulation of accounting origins measures (Grant 2003). However, there is no consensus about the best performance measure and the techniques for its estimation. Inefficiency is defined as the difference between the performance of a firm and the best practice actually observed in the market. Many concepts of efficiency are used in bank literature. Cost efficiency considers that banks act in the objective of costs minimization, presuming an optimal capital structure. Several studies applied this approach to the banking sector in the United States (Mester 1996, Berger and Mester 1997). According to the profit efficiency concept, the banks are working with the objective of maximizing their profits. Berger and Mester (1997) consider that the profit efficiency concept is superior to the cost efficiency concept in evaluating bank performance since it considers inefficiency both on the output and on the input side. However, profit does not consider the risks that affect future production plans and the interest rate at which profit is discounted. The least risky production plan will be disadvantaged since it would be less profitable (Modigliani and Miller 1958, Berger and Mester 2003). So, the profit maximization hypothesis should be rejected.

The third concept concerns shareholder value efficiency. Fiordelisi and Molyneux (2006) and Fiordelisi (2007) were the first to develop this idea. Value efficiency frontier is based on the assumption that banks objective is to maximize value creation for shareholders. Few studies tried to join the two branches of literature linking bank efficiency to performance. They show that efficient banks should be more profitable, and so, generate more return for shareholders. These researches focused on listed banks trying to link stock returns to cost and/or profit efficiencies. Eisenbeis *et. al.,* 1999 estimated cost efficiency for U.S. banks and Beccalli *et. al.* (2006) focused on European banks. They found that changes in cost efficiency are reflected in changes in stock prices. Cost efficient banks are more performant than their inefficient counterparts. Kirkwood and Nahm (2006) estimated cost and profit efficiency for Australian banks and Liadaki and Gaganis (2010) for European banks.

They found that the stock return was positively linked to profit efficiency, but not to cost efficiency. Liadaki *et.al.* (2008) found a positive and statistically significant relationship between technical efficiency and stock return for Greek banks while scale efficiency was not significant. However, these studies did not take into consideration value creation and value efficiency. Gascón *et al.*, 2002 studied the relationship between value maximization and economic efficiency in eighteen countries (North America, Japan and Europe). They found that cost efficiency is consistent with value maximization. Fiordelisi (2007) introduced the EVA as a measure of value creation and he found that value efficiency scores explain value creation better than cost or profit efficiency for European banks. Nevertheless, it is worth mentioning that on the one hand, he integrated both listed and non-listed banks belonging to different financial systems and with different activities. Thus, it can be considered that the heterogeneity of the sample would accentuate heteroscedasticity problems. On the other hand, he has not tested the relationship between different measures of efficiency and market response. Indeed, in a context of efficient market, it would be reasonable to assume that the ablest banks to create value for their shareholders would realize the best return.

DATA AND METHODOLOGY

Our study concerns listed US bank holding companies, from 2004 to 2006. We choose this period, before the 2007-2008 financial crisis, to test the relevance of value efficiency concept in a stable period. The dataset is a combination of accounting data, collected from the FDIC web site, and market data collected from the Yahoo finance web site. Some more data, as deferred taxes, were collected directly on the annual report of each bank. Data on treasury bonds have been collected from the Board of Governors of the Federal Reserve System web site. We have excluded the multi-holding companies and banks that are not member of FDIC from the sample. Our final dataset consists of 278 to 293 banks each year. Financial data is annual, presented as at the 12/31 of every year. Following Berger and Mester (1997) and

Fiordelisi (2007), we use stochastic cost, alternative profit and alternative shareholder value efficiency approaches to estimate efficiency scores. The alternative profit and value functions provide estimations that do not depend on output prices. We use efficiency estimates to compare cost minimization, profit maximization and value maximization objectives. The cost efficiency frontier is estimated using the parametric approach SFA (Stochastic Frontier Approach) under the translog form. $\ln u_c$ and $\ln \varepsilon_c$ represent respectively the terms of inefficiency and random error. Where C is the total cost, standardized by z_2 (i.e. the financial capital) to control for heteroscedasticity, y_k are the output quantities (credits and securities), w_j are input prices (the cost of deposits and the salary by employee) and z_r are netput quantities (physical capital and financial capital). A control variable is used to consider the difference in market conditions, which is the part of nonperforming loans in the state to which the bank belongs (stnpl). $\ln u_c$ is inefficiency factor that is zero for the best-practice banks and positive for the others, increasing their cost, $\ln \varepsilon_c$ is a random error term with mean of zero.

$$\begin{aligned}\ln(C/z_2) = {} & \alpha + \sum_i \beta_i \ln(w_i) + \tfrac{1}{2}\sum_i\sum_j \beta_{ij}\ln(w_i)\ln(w_j) + \sum_k \gamma_k \ln(y_k/z_2) + \tfrac{1}{2}\sum_k\sum_m \gamma_{km}\ln(y_k/z_2)\ln(y_m/z_2) \\ & + \delta\ln(z_1/z_2) + \tfrac{1}{2}\delta_{ii}\ln(z_1/z_2)^2 + \sum_i\sum_k \eta_{ik}\ln(w_i)\ln(y_k/z_2) + \sum_i\sum_r \rho_{ir}\ln(w_i)\ln(z_r/z_2) \\ & + \sum_k \tau_k \ln(y_k/z_2)\ln(z_1/z_2) + \ln u_c + \ln\varepsilon_c\end{aligned} \quad (1)$$

The alternative profit efficiency frontier uses the same variables as those of cost efficiency frontier, except that the dependent variable is replaced by $\ln[(\pi/z_2) + |(\pi/z_2)^{\min}| + 1]$, where π is the bank profit,$|(\pi/z2)min| +1$ is the absolute value of the minimum of $(\pi/z2)$ for all the banks at the same year. So, $\theta t = |(\pi/z2)t_{\min}|+1$ is added to the dependent variable for each bank to calculate the log of positive numbers, since the minimum profit may be negative. So, for banks having the smallest value of $(\pi/z2)$ for a given year, the dependent variable is ln(1)=0. To estimate the value efficiency frontier, the dependent variable is replaced by $\ln[(\tau/z_2) + |(\tau/z_2)^{\min}| + 1]$, where τ is the economic value added, EVAbkg, estimated according to the recommendations of Fiordelisi (2007). For alternative profit function (respectively value function), the only other change concerns the term of composite error, that is replaced by $-\ln u_{a\pi} + \ln\varepsilon_{a\pi}$, (respectively $-\ln u_\tau + \ln\varepsilon_\tau$,) as the exogenous variables are the same for the cost function.Total cost (C) includes all financial and operating costs. Financial costs are mainly interest expenses. Operating costs correspond to labor and capital expenditure, i.e. personnel expenses and general operating expenses. Profit (π) is as reported in the bank financial statements. EVAbkg (τ) is calculated for each bank in the sample during the period t-1, t by using a procedure that incorporates banks features. Thus, EVAbkg is calculated as follows, according to Equation 2:

$$EVA_{bkg(t-1,t)} = NOPAT_{(t-1,t)} - (CI_{t-1} * E(R_i)_{(t-1,t)}) \quad (2)$$

Where the NOPAT is the net operating profit after tax, CI is the capital invested in the beginning of the period, namely equity capital, (Sironi, 2005 and Fordelisi, 2007). E(Ri) the estimated cost of the capital invested using the Capital Asset Pricing Model (Other studies used the shadow price of equity as the cost of capital (Hughes and Mester, 2013; Radić, 2015)). Some specific adjustments, developed by Fiordelisi (2007), are applied to NOPAT and to capital invested making accounting values as close as possible to economic values. Next, we report descriptive statistics to compare the three efficiency scores. We also report Spearman's rank correlation coefficients between different concepts and across time to test consistency of the different scores rankings. This coefficient is very important in detecting good and bad practices. It is more appropriate in testing correlations to stress banks classifications rather than efficiency scores. Finally, we examine which of these three efficiency concepts brings better informational contribution in explaining performance. To do so, we consider two measures of performance: stock return for a market approach and shareholder value creation for a mixed (financial and accounting) approach. The choice of market approach is justified by the hypothesis that in an efficient market, it would be reasonable to assume that the more efficient banks would have better return (Liadaki and Gaganis, 2010).

Mixed approach is justified by various studies that provide evidence that EVA is useful in evaluating shareholder value (Ferguson *et. al.*, 2005, Fiordelisi, 2007, Heffernan and Fu, 2010).The following model is estimated using the ordinary least squares approach for stacked data and the random effect panel data for more robustness in our results.

$$\psi_{i,t} = \varsigma + \alpha.TR + \beta_h X_{i,t} + \sum_j \delta_j Z_j + e_{i,t} \quad (3)$$

Where $\psi_{i,t}$ is the performance measure by bank i at time t (stock return (STRET) and the ratio of $EVA_{bkg,t}$ to capital invested in t-1 (EVACI)). TR expresses the trend, $X_{i,t}$ are the various efficiency variables (cost, alternative profit and shareholder value) for bank i at time t, introduced sequentially. To control differences in the regulatory environment and bank activities, Z_j (j = 1, ..., 5) is a set of five additional characteristics: OCCDIST is the Office of control of currency district, TRUST indicates if the bank is Trust Powers Granted, BVCAPR is the book value capital to asset ratio to control for differences in the solvency. ASSGR is the total asset growth rate as a measure of management quality. CONC is the concentration of assets held by the three largest banks in each state. It measures market structure. ς is constant and $e_{i,t}$ is the random error term for bank i at time t. We expect that the model incorporating value efficiency scores has the highest explanatory power in explaining bank performance.

RESULTS

Table 1 presents descriptive statistics of main variables on 12/31/2006. We present the mean, the standard deviation, the minimum and the maximum of each variable used in estimating the frontier efficiency scores and in the regression models. Profit and EVA can be negative. On average, mean value created τ is much lower than profit π and performance measured by stock return is higher than measured by the EVA to capital invested ratio.

Efficiency Scores Analysis

Table 2 presents estimation results for efficiency scores. The estimation results of cost efficiency and profit efficiency scores are broadly consistent with those generally obtained from empirical research for the U.S. market. We find that profit efficiency is lower than cost efficiency as in Berger and Mester (1997, 2003) and Bos and Schmiedel (2007). Value efficiency scores are much lower, around 62% on average, suggesting the difficulty for banks to create value for their shareholders. Value inefficiency is due to cost inefficiency, profit inefficiency in addition to bad risk management , implying loss in value (U.S. banks lose more than one-third of their potential to create value). In addition, value efficiency scores are more scattered than cost and profit efficiency scores. This result suggests the heterogeneity of bank behavior. All these results are consistent with those of Fiordelisi (2007) for the European banks, but different from those of Hughes *et. al.* (1996) who found a small dispersion in the efficiency scores.

Table 1 : Some Key Variables on 12/31/2006 (Thousand Dollars)

Variable	Label	Mean	Standard Deviation	Min	Max
C		101	245	4	2 988
π	Profit	24	51	(0)	497
τ		12	29	(7)	312
y1	Credits	1,203	2,603	38	26,000
y2	Securities	342	677	0,96	5 183
w1	Cost of deposits	2.36%	0.94%	0.20%	6.48%
w2	Salary per employee	56	14	21	141
z1	Physical capital	60	171	0,31	2 371
z2	Financial capital	161	312	2,88	2 943
stnpl	State nonperforming loans	0,623	0,283	0,150	3,080
EVACI	EVA to Capital invested ratio	6.22%	5.04%	-14.63%	24.84%
STRET	Stock Return	8.60%	16.84%	-22.51%	77.78%

This table presents descriptive statistics for all the variables used in estimating frontier models. In estimating efficiency scores, the dependent variables are Total cost (C), Profit (π), and Economic Value Added (τ) and the independent variables are Credits (y1), Securities (y2), Cost of deposits (w1),Salary per employee (w2), Physical capital (z1), Financial capital (z2) and State nonperforming loans (stnpl). In estimating the informational contributions of value efficiency the dependent variables are EVA to Capital invested ratio (EVACI) and Stock Return (STRET)

Table 2 : Efficiency Scores (Descriptive Statistics)

	Cost Efficiency			Profit Efficiency			Value Efficiency		
Period	**2004**	**2005**	**2006**	**2004**	**2005**	**2006**	**2004**	**2005**	**2006**
Number of observations	278	290	293	278	290	293	278	290	293
Mean	0.856	0.884	0.887	0.757	0.843	0.832	0.546	0.677	0.644
Standard deviation	0.069	0.053	0.063	0.237	0.121	0.118	0.578	0.267	0.270
Minimum	0.562	0.658	0.604	-1.757	-0.165	0.108	-6.663	-1.573	-0.735
Maximum	0.965	0.968	0.977	1.000	1.000	1.000	1.000	1.000	1.000

This table shows estimation results for cost, profit and value efficiency scores. Mean scores and standard deviation are presented for each year. The number of observations varies between 278 and 293 per year.

To test the robustness of the results, the efficiency scores are estimated with a few changes from the preferred approach: First, by removing randomly from the sample 10% of the observations; second, by changing the assumption about the distribution of inefficiency term. The Spearman correlation coefficients show the stability of bank ranking. The Student test for equality of means shows that the average efficiency scores have remained essentially the same, implying robustness in the estimation of efficiency scores.

Table 3 : Spearman's Rank Correlation Between Efficiency Concepts and Over Time

A	Cost vs Profit	Profit vs Value	Cost vs Value
2004	0.235*	0.844*	0.337*
2005	0.320*	0.796*	0.334*
2006	0.323*	0.818*	0.337*
B	**Cost Efficiency**	**Profit Efficiency**	**Value Efficiency**
2004-2005	0.83*	0.77*	0.72*
2005-2006	0.80*	0.80*	0.78*
2004-2006	0.69*	0.64*	0.60*

This table shows the Spearman correlation rank. Part A compares efficiency concept scores for each year. Part B compares efficiency scores for each concept over time. All the correlations are significant at the 1% level.

Table 3 presents results for spearman's rank correlation between different concepts (A) and over time (B). We find that cost/profit and cost/value efficiencies correlations are positive but not high (around 30%).

These results are in contradiction with those of Bos et al. (2009) who found a negative correlation and Pasiouras, et.al. (2009) who found a non-significant correlation. By cons, profit/value correlations are very important (about 80%), in contrast to the results of Fiordelisi (2007) for European banks (he even found a negative correlation in France for the years 2001 and 2002). Then, profit efficient banks are more likely to be value efficient. This result suggests that these two concepts can provide similar information. However, the profit or value maximization behaviors are not necessarily associated with cost minimization objective. Concerning spearman's rank correlation over time, we find a strong stability from one year to another, mainly for consecutive years, bringing credibility for efficiency scores estimates. These results are consistent with previous research (Eisenbeis et al,. 1999; Bauer et al,. 1998)

Informational Contributions of Value Efficiency

The correlation matrix shows no significant correlation between the explanatory variables to justify the removal of some. So, all the variables considered above are adopted in the models. The estimation results of equation (3) using stock return (STRET) as performance measure are presented in Table 4 for each efficiency concept with stacked cross-sectional data (regressions (1), (3) and (5) and panel data (regressions (2), (4) and (6)). The Hausman test allowed us to keep the random effects model.

Table 4 : Regression Results, Relationship Between Stock Return and Cost Efficiency, Profit Efficiency and Value Efficiency, Respectively, Stacked Data and Panel Data

		(1)	(2)	(3)	(4)	(5)	(6)
Coefficients	**Variables**	**Cost Efficiency Model, Stacked Data**	**Cost Efficiency Model, Panel Data**	**Profit Efficiency Model, Stacked Data**	**Profit Efficiency Model, Panel Data**	**Value Efficiency Model, Stacked Data**	**Value Efficiency Model, Panel Data**
β	Efficiency considered	0.227**	0.227**	0.132***	0.132***	0.063***	0.063***
		(0.101)	(0.101)	(0.037)	(0.037)	(0.016)	(0.016)
α	Tr	-0.033***	-0.033***	-0.034***	-0.034***	-0.032***	-0.032***
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
δ_1	Occdist==central	-0.062***	-0.062***	-0.050***	-0.050***	-0.046**	-0.046**
		(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)
δ_2	Occdist==midwest	0.075***	0.075***	0.070***	0.070***	0.071***	0.071***
		(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
δ_3	Occdist==northeast	-0.079***	-0.079***	-0.072***	-0.072***	-0.072***	-0.072***
		(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
δ_4	Trust	-0.018	-0.018	-0.026**	-0.026**	-0.025*	-0.025*
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
δ_5	Bvcapr	-0.728**	-0.728**	-0.656*	-0.656*	-0.606*	-0.606*
		(0.340)	(0.340)	(0.339)	(0.339)	(0.339)	(0.339)
δ_6	Assgr	0.151***	0.151***	0.177***	0.177***	0.161***	0.161***
		(0.038)	(0.038)	(0.037)	(0.037)	(0.037)	(0.037)
δ_7	Conc	-0.034	-0.034	-0.036	-0.036	-0.036	-0.036
		(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
ς	Constant	0.063	0.063	0.148***	0.148***	0.209***	0.209***
		(0.093)	(0.093)	(0.053)	(0.053)	(0.046)	(0.046)
	R^2	0.165	0.164	0.172	0.172	0.176	0.175
	Within		0.064		0.073		0.071
	Between		0.311		0.331		0.342
	R^2 adjusted	0.155		0.163		0.166	

*This table shows estimation results of equation 3 with stock return as dependent variable .In the models (1) and (2) β refers to cost efficiency coefficient. In the models (3) and (4) β refers to profit efficiency coefficient. In the models (5) and (6) β refers to value efficiency coefficient. The models (1), (3) and (5) use stacked data. The models (2), (4) and (6) use panel data .Standard deviations between parentheses. ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively.*

The results presented in Table 4 show no difference between stacked data and panel data providing some robustness for our results. In both cases and for the different efficiency concepts used, the coefficients for the different efficiency scores are positive and statistically significant at the 1% level for profit and value efficiencies and 5% for cost efficiency. More efficient banks are more able to have important stock return. These results are coherent with our assumptions and with those of Beccalli *et al.* (2006), Adenso-Díaz and Gascón (1997) and Eisenbeis *et al.* (1999) for cost efficiency, but they did not estimate profit efficiency. However, they are partially different from those of Liadaki and Gaganis (2010) who found a positive relationship between profit efficiency and market return while cost efficiency was not significant. No research to our knowledge tested the relationship between banks market return and their value efficiency. The examination of control variables shows that most of the coefficients (40 coefficients over a total of 48 for all the models) are statistically significant. Management quality and regulation affect the ability of banks to create value for their shareholders. Only concentration is not significant. Concerning the explanatory power of these different models, the coefficients of determination are very low and close, although the models of value efficiency and profit efficiency have the highest explanatory powers (adjusted R^2 = 16.6% and 16.3% respectively). Cost efficiency model has the lowest coefficients (adjusted R^2 = 15.5%). These results show that a mature stock market can be influenced by all aspects of bank efficiency (cost, profit and value efficiency) that provide to investors further long-term information (Liadaki and Gaganis, 2010). However, stock market does not favor one of these concepts (the difference in the explanatory powers seems not significant).

Table 5 : Regression Results, Relationship Between Shareholder Value Creation Ratio and Cost Efficiency, Profit Efficiency and Value Efficiency, Respectively, Stacked Data and Panel Data

		(1)	(2)	(3)	(4)	(5)	(6)
Coefficients	**Variables**	**Cost Efficiency Model, Stacked Data**	**Cost Efficiency Model, Panel Data**	**Profit Efficiency Model, Stacked Data**	**Profit Efficiency Model, Panel Data**	**Value Efficiency Model, Stacked Data**	**Value Efficiency Model, Panel Data**
β	Efficiency considered	0.288***	0.280***	0.198***	0.179***	0.093***	0.088***
		(0.025)	(0.028)	(0.007)	(0.008)	(0.003)	(0.003)
α	Tr	-0.004**	-0.005***	-0.006***	-0.006***	-0.004***	-0.004***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
δ_1	Occdist==central	-0.031***	-0.033***	-0.015***	-0.015***	-0.008**	-0.006
		(0.004)	(0.006)	(0.003)	(0.005)	(0.003)	(0.005)
δ_2	Occdist==midwest	0.027***	0.025***	0.018***	0.018***	0.020***	0.019***
		(0.004)	(0.006)	(0.003)	(0.004)	(0.003)	(0.005)
δ_3	Occdist==northeast	-0.012***	-0.012**	-0.001	-0.003	-0.001	-0.002
		(0.004)	(0.006)	(0.003)	(0.004)	(0.003)	(0.004)
δ_4	Trust	0.017***	0.016***	0.004	0.004	0.007***	0.005
		(0.003)	(0.005)	(0.002)	(0.003)	(0.002)	(0.003)
δ_5	Bvcapr	-0.505***	-0.231**	-0.399***	-0.259***	-0.330***	-0.139**
		(0.082)	(0.096)	(0.064)	(0.076)	(0.057)	(0.071)
δ_6	Assgr	0.075***	0.067***	0.110***	0.099***	0.085***	0.076***
		(0.009)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)
δ_7	Conc	0.003	-0.003	-0.000	-0.001	-0.000	-0.001
		(0.008)	(0.011)	(0.006)	(0.008)	(0.006)	(0.008)
ς	Constant	-0.150***	-0.162***	-0.064***	-0.059***	0.029***	0.017*
		(0.023)	(0.027)	(0.010)	(0.012)	(0.008)	(0.010)
	R^2	0.349	0.339	0.612	0.609	0.689	0.684
	Within		0.177		0.307		0.582
	Between		0.422		0.609		0.667
	R^2 adjusted	0.342		0.607		0.685	

*This table shows estimation results of equation 3 with shareholder value creation ratio as dependent variable .In the models (1) and (2) β refers to cost efficiency coefficient. In the models (3) and (4) β refers to profit efficiency coefficient. In the models (5) and (6) β refers to value efficiency coefficient. The models (1), (3) and (5) use stacked data. The models (2), (4) and (6) use panel data .Standard deviations between parentheses. ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively.*

To bring robustness to our results, we randomly remove 10% of the sample and run these models again. The results remain mainly unchanged regarding the sign and the significance of each explanatory variable. The results are therefore robust with respect to the sample selection. We also replace OCCDIST by FDICDBS (a geographical classification by the FDIC) as control variable. The results concerning the amplitude, the sign and the significance of explanatory variables remain essentially unchanged.

Table 5 presents the estimation results of equation (3) using shareholder value creation ratio (EVACI) as a dependent variable for each efficiency concept with stacked cross-sectional data (regressions (1), (3) and (5)) and panel data (regressions (2), (4) and (6)). The Hausman test allows us to keep the random effects model.As shown above, results obtained for these two specifications are very similar, providing robustness for our results. The coefficients for the different efficiency scores are positive and statistically significant at the 1% level for all models having a positive impact on the ability of banks to create value for their shareholders. These results are coherent with our assumptions. Examining control variables shows that, as for the previous model, only concentration variable is not significant.

Regarding the explanatory powers of the models, they are generally much higher than those with the stock return as dependent variable (R^2 about 16%) and those of Fiordelisi (2007) (R^2 adjusted 28.9% in the best case). For the two specifications, the results show that the model including value efficiency has the highest explanatory power (R^2 adjusted=68,5%), followed by the model including profit efficiency (R^2 adjusted =60,7%). The model including cost efficiency has the lowest explanatory power (R^2 adjusted = 34.2%). These results suggest that the value efficiency concept dominates the others in explaining value creation for shareholders. This finding can be explained by the global nature of value concept. Indeed; to create value, banks must control costs, make more profit and better manage their risk. These results are close to those obtained by Fiordelisi (2007) and Fiordelisi and Molyneux (2006) on European banks. We run the same robustness checks as for the previous models. Our results remain broadly the same.

CONCLUSION

This paper is the first to estimate U.S. listed banks value efficiency and to examine the link between their cost, profit and value efficiency and their performances. We used a sample of 293 listed banks, during the 2004-2006 period. The estimation of efficiency scores, controlling for macroeconomic and other regulatory characteristics, indicated very low value efficiency scores (62% on average), suggesting the difficulty for banks to create value for their shareholders in consistence with previous studies. Profit and cost efficiency scores were higher at around 85%. We found also that value and profit efficiency scores were strongly related suggesting that profit efficient banks were more likely to be value efficient.

In considering the relationship between these efficiency measures and stock return, our results indicated that all these concepts affected positively and significantly stock returns suggesting that all the efficiency concepts include useful but not sufficient information for investors (R^2 weak). None of these concepts dominate the others. Investors are not able to capture all the information relating to value creation in banks. So the stock returns do not accurately reflect bank performance. This can be explained by the presence of information asymmetry. Regarding the relationship between efficiency concepts and value creation measure for shareholders, we found a positive and significant influence. However, the contribution of value efficiency seemed to be most relevant, closely followed by profit efficiency. The cost measures were more limited. The value measure integrates simultaneously the notions of cost, income and risk. It is therefore of particular importance both as a direct measure of performance and as a concept of efficiency. Moreover, this measure faces less accounting distortions making it superior.

We suggest that banks should incorporate the objective of creating shareholder value in their strategy. This requires, for example, setting up a salary incentive system based on value creation. To study the effects of deregulation, management quality, failure, risk behavior, and so on, researchers can direct their works by integrating value efficiency concept.

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BIOGRAPHY

L. Bouattour has a PhD in business administration (Finance) from the University of Tunis, Tunisia. Dr. Bouattour is lecturer in the department of Accounting and finance at ESSEC, Tunis, Tunisia. Dr. Bouattour teaches financial management, financial analysis and accounting in undergraduate levels. Dr. Bouattour teaches also financial analysis and alternative finance at senior level. E-mail: lbouattour@yahoo.fr

S. Khouaja has a PhD in business administration (Quantitative Methods) from the University of Sousse, Tunisia. Dr. Khouaja is lecturer in the department of Economy and Quantitative Methods at ESSEC, Tunis, Tunisia. Dr. Khouaja teaches mathematics, statistics and econometrics in undergraduate levels. Dr. Khouaja teaches also advanced econometrics and Polling Theory at senior level. E-mail: slimkhouaja@gmail.com

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WHAT THREATENS TUNISIAN BANKING STABILITY? BAYESIAN MODEL VERSUS PANEL DATA ANALYSIS

Abdelaziz Hakimi, University of Jendouba
Khemais Zaghdoudi, University of Jendouba
Taha Zaghdoudi, University of Jendouba
Nesrine Djebali, University of Jendouba

ABSTRACT

This paper aims to investigate the main determinants of Tunisian bank stability. To achieve this goal; we have used a dataset of ten (10) Tunisian banks during the period 1990-2015. These banks are the most dynamic and the most involved in the financing of the economy. The econometric strategy used in this paper was based on two approaches. The first one performed the Bayesian Model Average (BMA) to detect the most important indicators influencing bank stability. The second one was based on panel data analysis involving random effect regression. Results of these two methods have indicated that Tunisian bank stability is more sensitive to capital adequacy ratio, liquidity risk and the interaction between credit risk and liquidity risk. The capital adequacy ratio is positively and highly significantly associated with the dependent variable (Z-Score). However, liquidity risk and interaction variables exert a negative and significant effect on bank stability. These results have important policy implications. Banks and policy makers should continue to strengthen the capital adequacy ratio since it significantly contributes to improving bank stability. However, they should pay attention to liquidity risk as the main determinant of bank instability.

JEL: C63, E44, G21, G28

KEYWORDS: Bank Stability, Bank Specifics, Industry Specifics, Macroeconomics, Bayesian Model, Panel Data, Tunisia

INTRODUCTION

Banks play a major role on the real economy. They are considered as the main sources involved in financing the economy. There is a long-debated issue involving the association between financial development and economic growth. This relation has been dealt with in several aspects: positive or negative relation, unidirectional or bidirectional causality, and complementary or substitution relationship. (King and Levine, 1993; Levine, 1997, 2005; Wachtel, 2001; Petkovski and Kjosevski,2014). Most empirical results of these studies have supported the positive association between financial development and banks with economic growth. They have reported that finance promotes growth. In some credit-based economies, the performance of the real economy depends on banking system performance. Also, the stability of each economy is more sensitive to banking system stability. Hence specific emphasis has been granted to the stability question. Academics, policymakers and international agencies have tried to respond to some of these principal questions: What enhances or threatens bank stability? Is bank stability ~~is~~ more sensitive to bank, industry or macroeconomic specifics?
Several studies have investigated the determinants of bank stability. Like determinants of bank performance, empirical results have shown that bank stability can be explained by bank specific characteristics (size, capital adequacy ratio, credit risk, liquidity risk), by industry specific characteristics (competition/concentration relationship) and by macroeconomic conditions (GDP growth, inflation rate).

A significant impact of bank specific characteristics on bank stability has been confirmed by Uhde and Heimeshoff (2009), Mirzaei et al.(2013), Laeven et al., (2014), Cooke and Koch (2014), Adusei (2015), and Köhler (2015). However, an important part of literature has shown that industry specific characteristics (competition/concentration relationship) can affect bank stability (Allen and Gale, 2004; Boyd and De Nicolò, 2005; Martinez-Miera and Repullo,2010; Beck et al., 2013).

Besides bank and industry specifics, the macroeconomic conditions in which the bank operates can affect bank stability (Calza et al., 2003; Athanasoglou et al., 2008; Adusei, 2015) The Tunisian banking system is considered as the main source of firm financing. For example, in 2015, the total credit provided by the financial sector as % of GDP is about 94.214%. It dominates economic financing since the financial market is underdeveloped. The number of listed companies in the Tunisian stock market covers only 78 firms with a market capitalization of 24% as share of GDP. Following the revolution of 2011, the Tunisian banking system has suffered from many weaknesses. The most important are insufficient liquidity, deterioration of the business environment and the increase of unpaid debts. All these risks have certainly threatened bank stability. The aim of this paper is to empirically analyze the main factors that threaten Tunisian bank stability. To this end, we have used a dataset of ten (10) Tunisian banks during the period 1990-2015. The econometric strategy used in this paper was based on two approaches; the Bayesian Model Average (BMA) and panel data analysis. Empirical results have shown that Tunisian bank stability is positively and significantly associated with the capital adequacy ratio. However, liquidity risk increases bank instability. This paper contributes to the existent literature in several ways. First, there are few papers that seek the determinants of Tunisian bank stability. Second, two econometric approaches have been used to detect these determinants. Third, in the literature and empirical analysis, we have tried to classify these possible determinants in three groups that cover bank specific characteristics, industry specific characteristics and macroeconomic conditions. The remainder of this paper is articulated as follows. Section 2 presents the literature review on the determinants of bank stability. An overview of bank stability credit risk and liquidity risk is given in section 3. Data and methodology are presented in section 4. Sections 5 and 6 respectively show results of the BMA model and panel data analysis. We conclude in section 7.

LITERATURE REVIEW AND HYPOTHESES

Banking literature is focused on three main topics that can influence bank survival. The concepts of performance, risk and stability are these topics investigated by bankers, researchers and policy makers. Over the past two decades, the worldwide banking system has experienced several periods of instability that were followed by banking crises and banking failures. Hence, banking stability has been perceived as a necessary pillar to bank performance and survival. Supervisory authorities and central banks have adopted prudential regulatory policy in order to have sound banking systems which are able to ensure the optimal allocation of capital resources. This is considered as a necessary condition to manage risks well and to prevent crises. Before reviewing the main determinants of bank stability, we will focus on the principal indicators used to measure financial and/or bank stability. According to Segoviano and Goodhart (2009), there is no such widely accepted measure for measuring either financial or banking stability. The most popular measure of bank stability is the Z-Score which captures the probability of the default of a banking system. The Z-score compares the capitalization and returns of a country's banking system with the volatility of those returns. The Z-Score is the inverse of the probability of insolvency. A higher Z-Score indicates higher stability and vice versa. Several studies carried out on bank stability have used this indicator (Demirgüç-Kunt and Huizinga, 2010; Anginer et al., 2014; Williams, 2014; Köhler,2015; Adusei,2015). The second indicator used to measure bank stability is distress dependence among banks. Based on this indicator, the analyze of distress risk, credit risk and probability of default should not be limited only to specific banks, but it should take in consideration the effect of this event on the entire banking system. The third indicator of bank stability is banking system multivariate density. This indicator includes both individual and joint asset value movements of the portfolios of banks. This measure captures the linear and non-linear distress dependencies among banks which is able to detect change throughout the economic cycle. This allows one to conclude that in a period of distress, dependence increases (Segoviano and Goodhart, 2009).

Several empirical studies have used the financial stress index as a measure of bank or financial stability. Financial stress indexes are widely used by policymakers as an instrument for monitoring financial stability. This index measures the current state of stress in the financial system by combining several indicators of stress into a single statistic (Bordo et al., 2001; Hanschel and Monnin, 2005; Illing and Liu, 2006;Puddu, 2008;Borio and Drehmann, 2009). Like bank performance, bank stability has been explained by bank specific characteristics (size, capital, liquidity, credit risk) industry specific characteristics (competition/concentration relationship) and macroeconomic conditions (GDP growth and inflation rate). As for bank characteristics, bank size can differently affect bank stability. Several studies have supported the positive relationship between bank size and bank stability. According to Uhde and Heimeshoff (2009), in a concentrated banking sector, large banks are not exposed to financial fragility. Large banks record high profit and avoid the possibilities of liquidity or macroeconomic shocks. Larger banks enjoy higher economies of scale and scope. They have the potential to diversify loan-portfolio risks (Mirzaei, Moore and Liu, 2013). Size promotes better diversification which reduces risks and allows banks to operate in a different market segment. Also, large banks may have a comparative advantage in market-based activities which require significant fixed costs and enjoy economies of scale (Laeven et al., 2014). Adusei (2015) investigated the effect of bank size and funding risk on bank stability. He used a dataset of 112 rural banks in Ghana over the period 2009Q1- 2013Q3. Results of fixed and random effects indicate that an increase in the size of a rural bank results in an increase in its stability.

To the contrary, other literature defends the negative association between size and bank stability. For example, Laeven et *al*. (2014) analyzed the relationship between bank size and bank stability using data from 52 countries. Results showed that on average larger banks create more risks than smaller banks. Based on a data set of the EU banking sector during the period 2001-2011, Köhler (2015) studied the impact of business models on bank stability. Major findings of this study indicate that large banks are less stable than smaller banks. The absence of a significant relation between size and bank stability is verified by Altaee, et *al*. (2013) in the Gulf Cooperation Council countries. They found that size does not exert any significant effect on bank stability.

Capital and liquidity are two necessary pillars to ensure the stability, persistence and survival of each bank. It is obvious that bank capital is perceived as one of the most important targets of micro- and macro-prudential banking regulation. Several contributions have reported that a better capitalized bank should be more profitable and more stable. Showing high level of capital adequacy ratios, banks tend to face lower funding costs and they are able to support unexpected losses (Abreu and Mendes, 2002; and García-Herrero et al., 2009). Also, Banks with sufficient capital can easily avoid the shocks that may precipitate crises (Thakor, 2014). Coval and Thakor (2005) argue that better capitalized banks have stronger screening incentives and monitoring incentives. Also, they can speed up the post-crisis recovery of the economy. To the contrary, Cooke and Koch (2014) reported that despite the large size, banks with low capital ratios slowed down the lending recovery after the subprime crisis. A part from the importance of capital for bank solvency and bank stability, liquidity received great attention especially after the 2008 international financial crisis. Traditional banking activities are based on liquidity. It is for this reason that banks with sufficient level of liquidity are seemed profitable, stable and have constantly maintained the trust and reputation of the customer, following the 2008 crisis. To the contrary, banks with a weak level of liquidity experienced instability and fragility which finished either by merger acquisition or by bank failure. The third bank specific characteristic that threatens bank stability is credit risk. Credit risk results when borrowers are unable to honor their commitments. Non-reimbursement is equivalent to a loss, which incontestably reduces profitability and stability. Credit risk measures differ from one study to another. The most useful measures are that of nonperforming loans (Miller and Noulas, 1997; Alper and

Anbar, 2011), loan loss provisions and reports of total credit to total assets (Hakimi et al., 2011; Hamdi et al, 2013). In a comparative analysis over the period 2006-2009, Rajhi and Hassairi (2013) suggested that credit risk decreases bank stability for the MENA region and South Asian countries. Using quarterly data (2009Q1–2013Q4) from the rural banking industry in Ghana, Adusei (2015) reported that credit risk exerts a negative but insignificant effect on bank stability measured by the Z-score. In this study, credit risk is measured by total loans to total assets. The increase of total credit normally leads to an increase in the interest margin as a necessary condition for bank stability. Bank activities are accounted for loan specialization, so it's not the growth of granted credit that threatens bank stability but its quality (Bad or good credit). From the development presented above, we can form the following hypothesis:

(H1): Bank specific characteristics affect bank stability.

With regard to industry specific characteristics, we will focus our interest on the competition and/or concentration stability relationship. Is a concentrated banking system more stable than a competitive banking sector? The link between competition and financial stability remains a widely debated and ambiguous issue, both among policymakers and academics. There are two parts of the literature regarding this subject. The first one supports the concentration-stability relation and the second one defends the competition- stability association. In a concentrated banking system, supervision and monitoring seem to be easier than in a competitive banking system. Good supervision and monitoring can avoid the probability of the occurrence of banking fragility and banking crises (Beck et al., 2013). In a competitive banking system, banks earn fewer informational rents from their relationship with borrowers. This ~~is~~ can reduce their incentives to properly screen borrowers. Also, it leads to bad credit decisions which increase the fragility risk (Allen and Gale, 2000; Allen and Gale, 2004).The positive association between bank competition and bank stability is confirmed by Boyd and De Nicolò (2005). These authors, less competition allows banks to charge higher interest rates for loans. This behavior increases the probability of default due to the borrowers' moral hazard. Along the same line of thought, Martinez-Miera and Repullo (2010) revealed a non-linear relationship between competition and banking risk. The competitive banking system may reduce the borrower's probability of default. Following this development, we can form the hypothesis:

H (2): Banking stability can be influenced by the competition/concentration level.

Banks operate in a macroeconomic environment, so macroeconomic conditions are considered as an important key for banking performance and banking stability. GDP growth and inflation are the two macro indicators most popularly used in empirical literature to explain the change of performance and stability. GDP is used to measure the overall health of the economy. However, inflation is used to measure macroeconomic stability. (Adusei, 2015).An economic slowdown can decline the quality of the loan, increasing nonperforming loans and provisions, thereby reducing bank profitability and threatening bank stability. However, an improvement in economic conditions leads to an increase of the solvency of borrowers which positively affects the profitability of banks (Athanasoglou et al., 2008; Calza et al., 2003).About the effect of inflation, Revel (1979) suggested that bank profitability and stability was dependent on the level of inflation. A high level of inflation results in an increase in operating costs and consequently a decrease of bank profitability. On the contrary, weak inflation decreases operating expenses which improve the level of performance. Generally, the effect of inflation on bank activities depends on whether inflation is fully anticipated or not. Using a sample of 112 rural banks in Ghana during the period 2009Q1 – 2013Q3, Adusei (2015) reported that macroeconomic conditions measured by inflation rate and GDP improve bank stability. Results show, that inflation is positively and statistically significant with the Z-Score suggesting that inflation supports rural bank stability. Also, findings indicate that GDP positively and significantly impacts bank stability. Following this development, we can put forward the third hypothesis:

H (3): Macroeconomic conditions can determine bank stability.

An Overview of Bank Stability, Credit Risk and Liquidity Risk in Tunisia

The stability of the financial system in general and the banking system in particular is considered as the main economic concern of any government. The bankruptcy of a large bank or several bank failures in any country causes a sudden contraction of the money supply and a failure of the payment system. Also, banking instability can lead to a loss of trust in the whole system. On the contrary, a stable banking system provides a sound security to depositors which positively affect the level of investment and economic growth. Consequently, the topic of financial and banking stability is considered greatly important for governments, policy makers and bankers. The Tunisian banking sector is composed of 29 institutions, including 11 listed banks, with a market capitalization of 8 billion dinars in 2015.The banking sector is the primary market force, accounting for 41% of total capitalization. There are three public banks with 38% of the total assets. These three banks are considered as the most involved in the financing of the economy. Following the revolution of 2011, the Tunisian banking system has suffered from many weaknesses. The most important have been insufficient liquidity, deterioration of the business environment and the increase of unpaid debts. All these risks have certainly threatened bank stability. In this article, we have analyzed the annual evolution of bank stability and the two main risks that can threaten this stability. Table 1 presents an annual average evolution of some basic indicators concerning Tunisian banking sector over the period 1990-2015. We focus on credit risk, liquidity risk and bank stability. Tunisian banks are still relying on credit activities and their functioning is also based on liquidity which threatens their stability.

Table 1: Annual Average Evolution of Bank Stability, Liquidity Risk and Credit Risk Over the Period 1990-2015

1990-2002				2003-2015			
Years	ZSCORE	LIQR	RCDR	Years	ZSCORE	LIQR	RCDR
1990	4.279	119.602	60.985	2003	7.773	108.791	73.219
1991	4.221	126.991	61.674	2004	7.209	105.220	71.674
1992	4.247	133.890	65.152	2005	7.377	102.766	70.408
1993	4.422	131.270	64.994	2006	7.397	94.444	69.301
1994	6.392	124.028	64.302	2007	7.476	168.582	74.440
1995	6.747	132.671	66.837	2008	7.408	187.745	75.443
1996	8.129	119.607	65.640	2009	7.714	191.462	77.016
1997	8.969	104.862	71.562	2010	7.074	106.364	85.805
1998	6.676	113.118	52.112	2011	6.514	102.417	82.691
1999	8.144	95.686	64.915	2012	6.487	109.576	85.718
2000	7.954	106.068	69.352	2013	9.938	107.348	85.347
2001	7.802	109.494	70.271	2014	9.498	101.049	83.344
2002	7.689	108.959	73.973	2015	9.543	103.088	79.414

Table 1 presents average annual evolution of Z-Score measured by ($\frac{E(ROA)+CAP}{\rho\ (ROA)}$) which reflects bank stability. Also, Table 1 indicates the main determinants which threaten or enhance this stability. The first determinant is credit risk measured by total credit to total assets and the second one is liquidity risk measured by total deposit to total credit. Statistics used in this table are drown from annual reports of the most involved Tunisian banks during the period 1990-2015.

The most remarkable observation from Table 1 and figure 1below is that there was an improvement in Tunisian banking stability during the period 1990-2015. On average, the Z-score increased from 4.279 % in 1990 to reach 9.543% in 2015. However, some fluctuations characterized the evolution of bank stability. The Z-Score recorded a downward trend during the period 2010-2012. Banking stability improvement can be explained by the sufficient capital adequacy ratio. Tunisian banks have respected the recommendation of the Basel Accords to reinforce the level of equity. For example, in 1996, following the calculations of the Cooke ratio, there was an increase in banking stability from 6.392% in 1995to8.129% in 1996.The stability of Tunisian banks recorded an up down trend during the two years 2011 and 2012. This decrease is due to the low level of return on assets registered during this period. It is worth recalling that in 2011 the Tunisian revolution caused disequilibrium in all sectors. During the period of the revolution, banking activities were in decline. The level of deposit ~~is~~ decreased and there was a weak level of trust and reputation toward banking establishments. Also, the level of credit granted was not sufficient. Consequently, the level of income seemed to have decreased.

Figure 1: Annual Evolution of Z-Score, Liquidity and Credit Risks

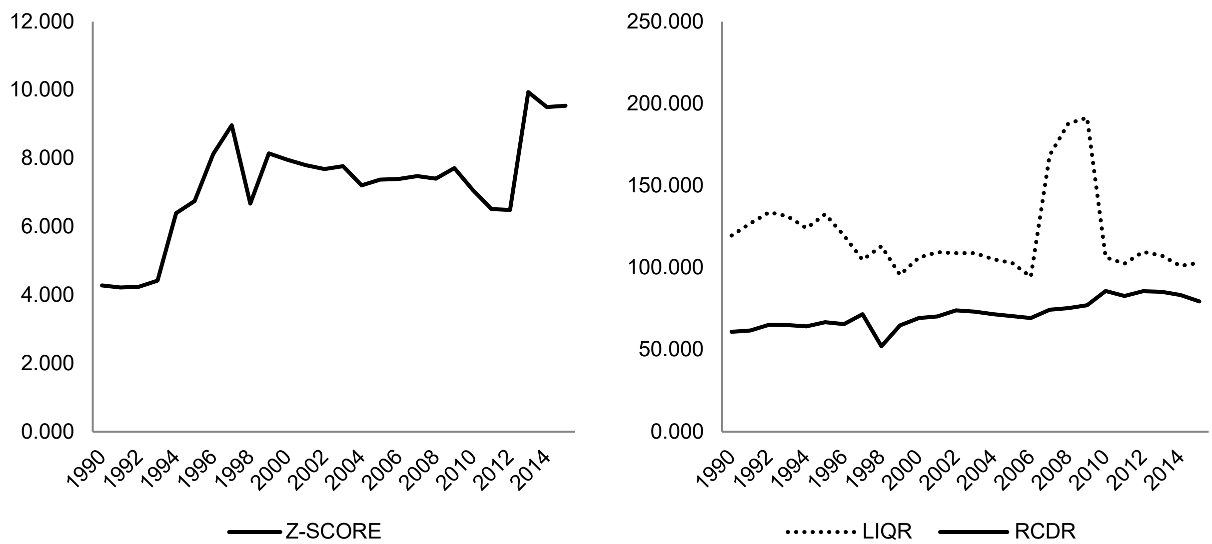

Figure 1 describes average annual evolution of bank stability measured by Z-Score ($\frac{E(ROA)+CAP}{\rho\ (ROA)}$), credit risk (total credit to total assets) and liquidity risk (total deposit to total credit). Values used in this figure are related to 10 Tunisian banks over the period 1990-2015.

The first risk to which a bank is exposed is credit risk. Table 1 and figure 1 indicate that the evolution of this risk was almost stable over the whole period. It increased from 60.98% in 1990 to reach 79.41% in 2015. Some worrying values were recorded in2010-2013. During this period, the level of credit risk was around 85%. As measured by total credit to total assets, the increase of this ratio is explained either by the increase of total granted credit or by the decrease of total assets. Generally, an increase in total credit leads to an increase in total assets, so we can eliminate the hypothesis that the decrease of total assets leads to an increase of credit risk. There is a weakness concerning this measure. Banking activities and banking performances are based on loan specialization. So, it is very important to be precise at what level and under what condition an amount of credit can be considered as risky. About liquidity risk evolution, it can be described in three phases. For the first one covering the period 1990-2006, liquidity risk decreased. It was around 120% in 1990 andbecame94.44% in 2006. During this period, Tunisian banks tried to adjust the level of deposit and the level of granted credit. From 2000 to 2005, the level of liquidity risk was around 100%. This means that deposits were nearly equal to the amount of credit. Even in 2006, on average, Tunisian banks recorded a liquidity risk lower than the unit. As measured by total credit to total deposit, the liquidity ratio recorded a level of 94.44%. This leads us to conclude that the total deposit was greater than the total credit.

The second phase covered the period 2007-2013.Duringthis period, there was an increase in the level of liquidity risk. For example, in 2008, liquidity risk recorded a high level compared to 2006; this risk doubled. It was 94.44% and became187.745%. The increase of this risk is not explained by the high level of credit. On the contrary, it can be justified by the weak level of deposit received by banks. The international financial crisis of 2008 was followed by a decrease in the level of trust of depositors toward banking institutions. Also, the reputation of these banks decreased and depositors were not motivated to keep their capital in banks. They were afraid of banking fragility and failure. For this reason, they preferred to withdraw and/or keep their capital outside of the banking establishment. Liquidity risk continued to record high levels reaching a high of 191.46% in 2009. However, in the third phase which began from 2010 to 2015, descriptive statistics indicate a satisfactory level of liquidity risk around 100%. We can consider that the granted credits were covered by the collected deposits. After analyzing our three based indicators, we aim in this paragraph to detect if there is any association between bank stability, credit risk and liquidity risk. Regarding figure 1, a reverse trend between liquidity risk and bank stability can be seen. For the evolution of credit risk, it seemed almost stable. An increase in the liquidity risk leads to a decrease in banking stability. We can conclude that Tunisian banking stability is more dependent on liquidity risk rather than credit risk.

DATA AND METHODOLOGY

To empirically analyze the main factors that threaten or enhance banking stability, we used in this study a sample of ten (10) Tunisian banks over the period 1990-2015. These banks are considered as the most dynamic and the most involved in the financing of the economy. So, the investigation of the stability of this sample is very important since they play a major role in promoting economic growth. We used annual data over the period 1990-2015.Variables used in the model are divided into two groups: some are internal that reflected bank specifics and others are external that are related to macroeconomic environment. As for bank characteristics, variables are collected from annual reports of each bank, however macroeconomic variables are drown from the World Development Indicators database (WDI).
In this paper we used two different econometric approaches. The first one is based on the Bayesian model average (BMA) which predicts the main indicators that determine bank stability either positively or negatively. The second involves panel data analysis. Using this method, we have tested our models *pre*-indicators selection based on the BMA model and the *post*-indicators selector. This was to compare results of these two approaches. In other words, is there a similarity between the results of BMA and panel data analysis?

Model Specification and Variable Definitions

With reference to previous studies related to bank stability, we presented the following econometric model. Like bank performance, bank stability can be explained by bank specific characteristics (Size, net interest margin, capital adequacy ratio, liquidity risk and credit risk), bank industry (banking concentration, banking crises) and the macroeconomic context (inflation and economic growth). The basic econometric model used in this study can be written as follows:

$$\begin{aligned} Z-SCORE_{i,t} \;&= \beta_0 + \beta_1\, SISE_{i,t} + \beta_2\, RCDR_{i.t} + +\beta_3\, CAP_{i,t} + \beta_4\, NIM_{i,t} + \beta_5\, LIQR_{i,t} + \beta_6\, IHH_{i,t} \\ &+ \beta_7\, LIQR * RCDR_{i,t} + \beta_8\, CRISE_{i,t} + \beta_9\, GDPG_{i,t} + \beta_{10}\, INF_{i.t} + \varepsilon_{i,t} \end{aligned}$$

Where;

(Z-SCORE) is the measure of bank stability. It is equal to $\frac{E(ROA)+CAP}{\rho\,(ROA)}$. A higher Z-score indicates that the bank is more stable (Laeven and Levine, 2009; Chalermchatvichien et al., 2014; Demirgüç-Kunt and Huizinga, 2010; Stiroh, 2004a, 2004b). *(NIM)*is the bank performance measured by the net interest margin which is equal to the ratio of interest margin to total assets. In a previous study, performance was measured by ROA (Curak et al., 2012; Adusei, 2015). In this study, we used the net interest margin to

avoid the problem of autocorrelation with the Z-Score measure. As this variable contains E (ROA) and ρ (ROA), *(LIQR)* is the liquidity risk measured by the ratio of total credit to total deposit (Fiordelisi and Mare, 2014; Rose and Hudgins, 2008).*(CRDR)* represents the credit risk which is measured by total credit to total assets (Curak et al., 2012; Adusei, 2015). *(LIQR*RCDR)* is the interaction between the two risks. We introduced this variable in our model to explore the combined effect of liquidity and credit risk. *(CAP)* is the capital adequacy ratio measured by the report of total equity to total assets (Adusei, 2015). *(SIZE)* represents the bank size which is measured by the Naperien logarithm of total assets. (Pasiouras and Kosmidou, 2007; Barros et al., 2007;Adusei, 2015).*(IHH)* is the Hirshmen Herfindahl index measured by the squared sum of the market share. In this study, we used total assets to calculate the market share. (CRISE) is a dummy variable which takes 0 before 2008 and 1 otherwise. Banks operate in an environment which is influenced by some macroeconomic indicators. For this reason, we introduced to our model *(GDP)* and *(INF)* as macroeconomic variables.GDP is used to measure the overall health of Tunisia's economy, and inflation is used to measure macroeconomic stability in Tunisia (Adusei 2015). This econometric model was tested within four (4) steps. In the first step, we only checked the effect of liquidity risk on bank stability. Banking activities are principally based on liquidity, consequently bank performance and/or (in) stability is dependent on the level of liquidity. The econometric model can be presented as follows:

$$Z-SCORE_{i,t} = \beta_0 + \beta_1 SISE_{i,t} + \beta_2 LIQR_{i.t} + \beta_3 CAP_{i,t} + \beta_4 NIM_{i,t} + \beta_5 IHH_{i,t} + \beta_6 CRISE_{i,t} + \beta_7 GDPG_{i,t} + \beta_8 INF_{i.t} + \varepsilon_{i,t} \quad \text{Model (1)}$$

In the second step, we only checked the effect of credit risk on bank stability. So, we eliminated the variable of liquidity risk. Credit risk can decrease bank performance and enhance the stability of the credit establishment. The second model can be written as follows:

$$Z-SCORE_{i,t} = \beta_0 + \beta_1 SISE_{i,t} + \beta_2 RCDR_{i.t} + \beta_3 CAP_{i,t} + \beta_4 NIM_{i,t} + \beta_5 IHH_{i,t} + \beta_6 CRISE_{i,t} + \beta_7 GDPG_{i,t} + \beta_8 INF_{i.t} + \varepsilon_{i,t} \quad \text{Model (2)}$$

We investigated the effect of the combined two risks in the third step. For this reason, we introduced an interactive variable which is LIQR*RCDR and we eliminated credit and liquidity risk. The third model is presented below:

$$Z-SCORE_{i,t} = \beta_0 + \beta_1 SISE_{i,t} + \beta_2 \mathrm{LIQR} * \mathrm{RCDR}_{i.t} + \beta_3 CAP_{i,t} + \beta_4 NIM_{i,t} + \beta_5 IHH_{i,t} + \beta_6 CRISE_{i,t} + \beta_7 GDPG_{i,t} + \beta_8 INF_{i.t} + \varepsilon_{i,t} \quad \text{Model (3)}$$

The fourth and the last step consisted of testing the model after the selection of principal indicators affecting bank stability. The selection of these indicators was done by the Bayesian Model Average. The fourth model is presented below:

$$Z-SCORE_{i,t} = \beta_0 + \beta_1 SISE_{i,t} + \beta_2 CAP_{i,t} + \beta_3 CRISE_{i,t} + \beta_4 CRISE_{i,t} + \beta_5 \mathrm{LIQR} * \mathrm{RCDR}_{i,t} + \varepsilon_{i,t} \quad \text{Model (4)}$$

<u>Bayesian Model Average (BMA) Regression</u>

We chose the BMA model to detect the most robust indicators affecting bank stability from among a panel of 10 potential variables. We considered the following linear regression model:

$$y = \alpha_i + X_i\beta_i + \varepsilon \sim (0, \sigma^2 I) \quad (5)$$

Where y represents bank stability, $\alpha_i$the constant, β_i the vector of coefficients and ε the error term. X_i, denotes a subset of all relevant explanatory variables available. In our case study they represent potential early warning indicators. The number k of potential explanatory variables gives 2^kpotential models. The index i is used to refer to a specific model of these 2^k models. The information from the models is then moderately distributed using the posterior probabilities of the model given by Bayes theorem:

$$p(M_i \mid y,X) \propto p(y \mid M_i,X)p(M_i) \qquad (6)$$

Where $p(M_i| y,X)$ is the posterior probability which is relative to the marginal probability of the model $p(y \mid M_i,X)$ multiplied by the apriori probabiliy of the model $p(M_i)$.The robustness of a variable in the explanation of the dependent variable can be captured by the probability that a given variable is included in the regression. To do this we calculated the posterior probability of inclusion (PPI), which is given by:

$$PIP= p(\beta_i \neq 0 \mid y)= \sum_{\beta_i} p(M_i| y) \qquad (7)$$

The PIP captures the indicator that can evaluate the robustness of the relationship of a potential explanatory variable with the dependent variable. Variables with a large PIP can be considered as robust determinants of the dependent variable, whereas variables with a low PIP seem not to be robustly related to the dependent variable. Moreover, it is impossible to go through all possible models if we have a very high number of potential explanatory variables. For this raison, we used the Monte Carlo Markov chain (MC^3) method of model comparison developed By Madigan and York (1995). The (MC^3) method is able to focus on the part of the model where there is a strong probability of posterior model. Hence, it can approximate the exact posterior probability in a more efficient way.

<u>Selection of Variables That Affect Bank Stability Via the Bayesian Model</u>

Figure 2 below helps us to detect the main variables that affect positively or negatively bank stability and this with reference to the color relative to each variable.

Figure 2 : Model Inclusion Based on Best 152 Models

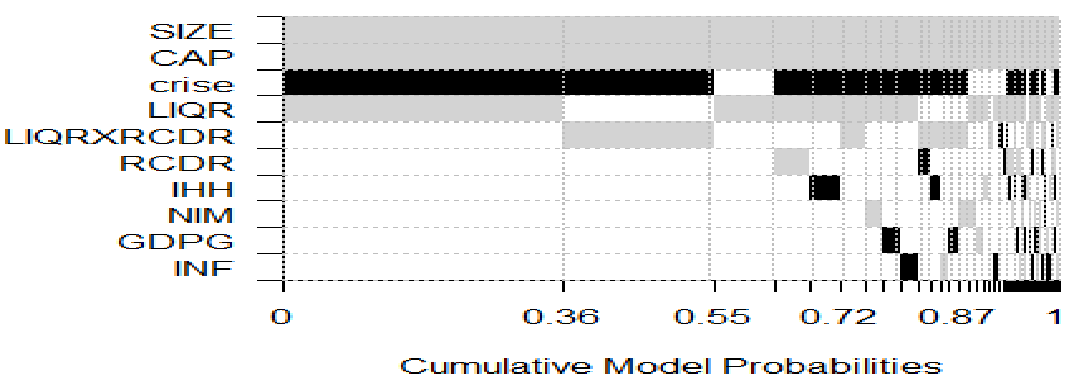

Figure 2 shows the 152 best models resulting from the Bayesian model. These models are ranked per their probabilities of posterior models. Subsequently, the best models are displayed on the left. Blue indicates a positive coefficient, while the colored indicates a negative coefficient. However, the white color indicates that the variable is not included in the respective model. It can be seen that a small part of the model includes variables that have a posterior inclusion probability (PIP) greater than 0.5.

Table 2 shows the results of the estimation of the Bayesian model, mainly the posterior probability included for each indicator, the posterior average, the standardized standard deviation and the posterior conditional sign.

Table 2 : Estimated Coefficients of BMA

	PIP	Post Mean	Post SD	Cond.Pos.Sign	Idx
SIZE	1.0000	5.6172	1.0763	1.0000	5
CAP	1.0000	84.245	14.920	1.0000	6
Crise	0.8492	-3.6183	2.0333	0.0000	7
LIQR	0.7120	4.7825	3.4496	1.0000	2
LIQRXRCDR	0.3407	2.3274	3.9053	0.9610	4
RCDR	0.0957	0.2463	2.3817	0.6676	3
IHH	0.0847	-3.7610	31.648	0.1752	8
GDPG	0.0698	0.2433	7.8971	0.2488	9
NIM	0.0647	1.3489	14.532	0.9835	1
INF	0.0580	-0.1737	9.3209	0.3792	10

Within a set often (10) explanatory variables, only four (4) variables have a posterior probability of inclusion greater than 0.5. These variables are the most important indicators of bank stability. These potential indicators are bank size (SIZE), capital adequacy ratio (CAP), crisis dummy variable (CRISE) and liquidity risk (LIQR).

The results of the BMA model show that the highest inclusion probability is recorded by bank size (SIZE). This variable shows a positive sign, consequently an increase of bank size leads to an improvement of bank stability. Also, the capital adequacy ratio (CAP) is positively associated with the dependent variable Z-Score. Well capitalized banks are the most stable. Liquidity risk also indicates a surprisingly positive association with bank stability. This means that an increase in this risk implies an increase in the probability of bank stability. Moreover, the crisis variable admits a negative sign and therefore negatively affects banking stability.

<u>Panel Data Analysis</u>

Table 3 below presents descriptive statistics of all variables served in this study. For each variable, we give average value, standard deviation, minimum and maximum values. Descriptive statistics are presented to describe the basic characteristics of the data used in this study concerning ten banks over the period from 1990 to 2015.

Table 3 : Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Z-score	260	7.195	9.393	0.180	47.967
Nim	260	0.028	0.012	-0.030	0.059
Liqr	260	1.198	0.377	0.551	2.597
Rcdr	260	0.718	0.142	0.030	1.501
Liqrrcdr	260	0.871	0.346	0.025	1.969
Size	260	14.779	0.623	13.475	16.169
Cap	260	0.081	0.037	-0.016	0.249
Crise	260	0.308	0.462	0	1
Ihh	260	0.111	0.009	0.088	0.123
Gdpg	260	0.040	0.023	-0.024	0.079
Inf	260	0.042	0.015	0.020	0.082

The average Z-score was 7.195% with a maximum value of 47.967% and a minimum value of 0.180%. The net interest margin recorded a mean value of 2.8% and 5.9% as a maximum value. The average value of liquidity risk is about 119.8% with a minimum of 55.1% and a maximum of 259.7%. This means that total credit is more than double than that of total deposit. For credit risk, the average value is 71.8%, with a minimum value around 30% and a maximum of 150.1%. The average level of the capital adequacy ratio is about 8.1%. On average, we can conclude that Tunisian banks are moderately capitalized. However, we find that the minimum value of CPA is -1.6% indicating that some banks are poorly capitalized. As a macroeconomic variable, the GDPG records an average of 4% with a maximum value of 7.9 % and a minimum of -2.4%. The second variable is the inflation rate. The average of this variable is 4.2% and the maximum level is 8.2%. After giving some statistics about all the variables of our study, the following table gives the level and nature of correlation that exists between the variables used in the econometric model. Table 4 below presents the correlation matrix which gives information on the level and the nature of linkages between variables by determining the coefficients of linear correlations of them taken two by two.

Table 4: Correlation Matrix

	z-score	**Nim**	**Liqr**	**rcdr**	**liqrrcdr**	**Size**	**Cap**	**crise**	**Ihh**	**gdpg**	**inf**
z-score	1.0000										
Nim	-0.0408	1.0000									
Liqr	0.2567	-0.2091	1.0000								
rcdr	0.2003	-0.1042	0.2129	1.0000							
liqrrcdr	0.2832	-0.2120	0.8906	0.6126	1.0000						
size	0.2122	-0.3238	-0.1709	0.1625	-0.0832	1.0000					
Cap	0.3395	0.1385	0.1907	0.3330	0.3075	-0.1103	1.0000				
crise	0.0588	-0.4305	0.1119	0.4762	0.2974	0.4858	0.0758	1.0000			
Ihh	-0.0686	0.2429	0.2482	-0.4506	0.0088	-0.4687	-0.1172	-0.6504	1.0000		
gdpg	-0.0370	0.1793	0.0878	-0.2915	-0.0538	-0.3541	-0.0397	-0.5379	0.4732	1.0000	
Inf	-0.0670	-0.3379	0.1095	-0.0186	0.0894	0.0915	-0.2768	0.1923	0.1240	0.0529	1.0000

From Table 4, it can be seen that the net interest margin, the Hirshmen Hirfendhal index and the two macroeconomic variables decrease bank stability. However, the rest of the variables such as liquidity risk, credit risk, the interaction between liquidity and credit risk, bank size, capital adequacy ratio and crises are positively associated with banking stability. The second observation that can be drawn from this table is that there is no high correlation between the variables. The only exception is the high level of correlation between liquidity risk, credit risk and the interactive variable. This leads to confirm the absence of the multicollinearity problem.

Table 5 below presents the results of the regression of the three models before the selection of indicators that affect bank stability. For the three models, we applied the random effect regression since the Hausman test for the 3 models indicated probabilities of chi-squared which are higher than 5%.

Results of the first three models indicate that the main factors affecting banking (in) stability are capital adequacy ratio, international financial crises, liquidity risk and the interaction between liquidity risk and credit risk. The most surprising is that the effect of credit risk is not significant. For the other bank specific variables (Size and net interest margin), industry specific variables and macroeconomic variables, their effect does not seem to be significant. The capital adequacy ratio (CAP) is positively and highly significantly associated with bank stability. For the three models, this variable has the same effect and level of significance. Banks with sufficient capital can manage their risks well and easily prevent financial crises in the future. A higher ratio of capital adequacy decreases the level of bank risk taking. As for the three Basel Accords, there was an appeal to strengthen the quantity and quality of capital since it was the best way to cover bank risks, as the fundamental hypothesis for bank performance and bank stability. Banks with higher capital ratios tend to face lower costs of funding due to lower prospective bankruptcy costs. This result is in line with Chalermchatvichien et al. (2014), Abreu and Mendes (2002), Goddard et al. (2004), Ben Naceur and Goaied (2008) and García-Herrero et al. (2009)).

Table 5: Results of Regression *Pre*- Indicators Selection

Results of Pre-Indicator Selection						
	Model (1)		**Model (2)**		**Model (3)**	
Z-score	**Coef.**	**Z**	**Coef.**	**Z**	**Coef.**	**Z**
Nim	15.959	0.65	36.151	1.58	26.807	1.13
Size	0.550	1.17	0.748	1.67*	0.562	1.21
Cap	64.339	9.88***	57.338	8.62***	64.656	9.77**
Crise	-1.329	1.74*	-0.374	0.53	-1.188	1.55
Ihh	31.636	0.89	-3.034	-0.10	5.632	0.17
Gdpg	4.132	0.38	1.543	0.15	2.444	0.23
Inf	-1.632	-0.10	1.877	0.12	2.095	0.13
Liqr	-1.969	-2.74***	—	—	—	—
Rcdr	—	—	2.570	1.31	—	—
Liqrrcdr	—	—	—	—	-1.483	-1.89*
_cons	-8.285	-0.96	-11.317	-1.27	-7.020	-0,81
Hausman test	2.115		1.32		1.53	
prob chi 2	0.977		0.995		0.992	
Wald chi 2	124.36		124.64		123.69	
prob chi 2	0.000		0.000		0.000	
R-squared	0.364		0.34		0.348	
N of Obs.	260		260		260	

This table shows the regression estimates of the three equations:
$Z\text{-}SCORE_{i,t} = \beta_0 + \beta_1 SIZE_{i,t} + \beta_2 LIQR_{i,t} + \beta_3 CAP_{i,t} + \beta_4 NIM_{i,t} + \beta_5 IHH_{i,t} + \beta_6 CRISE_{i,t} + \beta_7 GDPG_{i,t} + \beta_8 INF_{i,t} + £_{i,t}$
Model (1) $Z\text{-}SCORE_{i,t} = \beta_0 + \beta_1 SIZE_{i,t} + \beta_2 RCDR_{i,t} + \beta_3 CAP_{i,t} + \beta_4 NIM_{i,t} + \beta_5 IHH_{i,t} + \beta_6 CRISE_{i,t} + \beta_7 GDPG_{i,t} + \beta_8 INF_{i,t} + £_{i,t}$
Model (2) $Z\text{-}SCORE_{i,t} = \beta_0 + \beta_1 SIZE_{i,t} + \beta_2 LIQR*RCDR_{i,t} + \beta_3 CAP_{i,t} + \beta_4 NIM_{i,t} + \beta_5 IHH_{i,t} + \beta_6 CRISE_{i,t} + \beta_7 GDPG_{i,t} + \beta_8 INF_{i,t} + £_{i,}$
Model(3).
****, ** and * denote significance level respectively at 1%, 5% and 10%*

The findings also indicate that bank stability is negatively and significantly associated with liquidity risk. Banking activities are based on liquidity since it is the basic "product". So, banks with sufficient liquidity are less prone to crises, which impose substantial losses in terms of forgone economic output. The recent financial crisis has shown the importance of liquidity. Banks with sufficient liquidity and especially own equity, were more stable during the period of crises. In the cases of unexpected financial shock or unexpected and massive withdrawal of deposit, banks with higher levels of liquidity are more efficient and stable. However, banks with higher liquidity risk are prone to banking fragility and failures (Athanasoglou et al., 2008; Bourke, 1989; Demirguc-Kunt and Huizinga, 1999).

To check the combined effect of the two risks (liquidity and credit risk) we introduced an interactive variable LIQRRCDR. The effect of this variable was tested in the third model. Results show that this variable decreases bank stability. It is worth recalling that the individual effects of credit risk are not significant. On the contrary, liquidity risk significantly decreases bank stability. When, we combined the effect of these two risks, it became negative and significant. This means, that the insignificant effect of credit risk was absorbed by the negative effect of the liquidity risk. Table 6displays the results of the regression of the fourth model that only retained significant variables that threaten or enhance banking stability based on BMA. For this model, we applied also the random effect regression since the Hausman test indicated probabilities of chi-squared which are higher than 5%.

Table 6: Results of Regression Post-Indicators Selection

Results of Post-Indicators Selection		
Model (4) Z-score	**Coef.**	**Z**
Nim	—	—
Size	0.544	1.15
Cap	61.592	9.250***
Crise	-0.325	0.53
Ihh	—	—
Gdpg	—	—
Inf	—	—
Liqr	-3.072	-2.230**
Rcdr	—	—
Liqrrcdr	1.904	1.15
_cons	-3.939	-0.54
Hausman test	2.807	
prob chi 2	0.729	
Wald chi 2	118.14	
prob chi 2	0.000	
R-squared	0.364	
N of Obs.	260	

This table shows the regression estimates of the equation: $Z\text{-}SCORE_{i,t} = \beta_0 + \beta_1 SIZE_{i,t} + \beta_2 CAP_{i,t} + \beta_3 CRISE_{i,t} + \beta_4 LIQR_{i,t} + \beta_5 LIQR{*}RCDR_{i,t} + £_{i,t}$ **** and ** denote significance level respectively at 1% and 5%*

After testing the three models based on the effect of liquidity risk, credit risk and the interaction between these two risks, we discuss findings of the fourth model. It is worth recalling that this model is based on selected indicators by the BMA model. This is to compare findings of the random effect regression of the three models with all indicators (bank specific variables, industry specific variables and macroeconomic specific variables) and the results of the indicators selected by the BMA approach. Results of regression using indicators selected by the BMA approach are only like the findings of the three models in regards to capital adequacy ratio and liquidity risk. Hence, we can conclude that these two indicators are the main determinants of Tunisian banking stability. Sufficient capital and liquidity make banks more sound stable when facing banking risks, fragilities and crises. However, in the fourth model we noticed that the effect of the interaction between liquidity risk and credit risk becomes insignificant. Like the results of models 1, 2 and 3, bank size does not exert any significant effect on bank stability in model 4. To summarize, we can conclude that Tunisian banking stability depends on the level of capital adequacy ratio. The higher the ratio is, the stronger bank stability is. An increase in this ratio leads to more bank stability. However, a decrease in this ratio can threaten bank stability. The second determinant of Tunisian bank stability is liquidity risk. Results confirm that an increase in this risk significantly decreases bank stability. On the contrary, a low level of this risk is associated to a more stable banking system.

CONCLUSION AND POLICY RECOMMENDATIONS

Bank stability is considered as important since it reflects the soundness of the banking system and reinforces the level of trust toward this system. Also, bank stability is a necessary condition for more performance in particular and for bank survival in general. The crucial role of banks in the real economy, on the one hand and the close dependence between finance, banks and growth, on the other hand has spurred both academics and policymakers to seek the main determinants of bank stability. Banking literature focused on financial/banking stability has ranged their determinants in three main groups. Bank specific variables, industry specific variables and macroeconomic conditions are considered as the main relevant indicators. Based on a sample of 10 Tunisian banks over the period 1990-2015, we investigated the main factors that affect bank stability in the Tunisian context. Contrary to previous studies, two econometric approaches were used. The first one is the Bayesian Model Average (BMA) to detect the most important indicators that influence bank stability. The second one is based on the panel data analysis performed to check the results of the first approach. The empirical analysis is based on four steps.

The first step consisted of testing the model after the selection of the principal indicators that affect bank stability. The selection of these indicators was done by the Bayesian Model Average. In the second step, we only checked the effect of liquidity risk on bank stability. In the third step, we only checked the effect of credit risk on bank stability. So, we eliminated the liquidity risk variable and introduced the second risk. We investigated the effect of the two combined risks in the fourth step. For this reason, we introduced an interactive variable (LIQR*RCDR) and we eliminated the credit and liquidity risk. Results of these two approaches indicate that Tunisian bank stability is more sensitive to capital adequacy ratio, liquidity risk and the interaction between credit risk and liquidity risk. The capital adequacy ratio is positively and highly significantly associated with the dependent variable (Z-Score). However, liquidity risk and the interaction variables exert a negative and significant effect on bank stability. As for the other bank specifics (net interest margin and credit risk) their effect is not significant. Similarly, macroeconomic conditions and industry specific variables did not exert any significant effects.

Results of this study have some limitations. First, they are based only on ten banks. This sample appears very limited to generalize these findings. Actually, Tunisian banking sector covers twenty three banks. In this research, we retained the most dynamic and the most involved banks in the financing of the economy. Second, we did not introduce other variables that threaten bank stability such as nonperforming loan (NPL) and loan loss provisions (LLP). Not taking this into consideration is due to the lack of information concerning these variables over the whole period. These results have important policy implications. Governments, banks and policymakers should continue to strengthen the capital adequacy ratio since it greatly contributes to improving bank stability. However, they should pay attention to liquidity risk as the main determinant of bank instability. In this study, liquidity risk was the most disruptive of bank stability. So, banks are invited to manage this risk by reinforcing their own resources since depositors could at any time, for any unexpected reason, withdraw their capital and seek to invest in new activities with higher returns. The Basel Accords recommend the reinforcement of equity to manage risk well, prevent fragility and crises and have a sound banking system. Hence, in future research we will be interested in the effect of strengthening of equity on the credit activity in the Tunisian context. So, what is the optimal level of equity that ensures the reconciliation between the provision of loans and banking stability?

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BIOGRAPHIES

Abdelaziz Hakimi is an Assistant Professor of Finance at the Faculty of Law, Economics and Management of Jendouba, Tunisia. He conducted research related to financial economics and financial intermediation. He is currently working on the bank-enterprise relationships, the consequences of the liberalization process on Tunisian banks and the socio-economic and environmental implications of foreign direct investment and trade liberalization. He published several academic papers in international reviews. E-mail: abdelazizhakimi@yahoo.fr

Khemais Zaghdoudi is an Associate Professor of Economics at the Faculty of Law, Economics and Management of Jendouba, Tunisia. He conducted researches related to Tunisian productive system, Tunisian financial system, financial development, financial structure and growth, Stock exchange, specialization and trade. He is currently working on Insurance and financing of the Tunisian economy, Relationship between banks and insurance, Regional bank and development, and socio-economic and environmental implications of foreign direct investment and trade liberalization. He published several academic papers in national and international reviews. E-mail: k.zaghdoudi@yahoo.fr

Taha Zaghdoudi is a doctor and researcher in economics. He conducted researchers related to financial instability, financial intermediation, economic growth and computational economics. He is currently working on the effect of monetary policy on bank risk-taking, banking crises early warning models, relationship between external debt and poverty, numerical computing and econometric programming with R. He published several academic papers in national reviews. E-mail: zedtaha@gmail.com

Djebali Nesrine is a PhD candidate in Economics at the Faculty of Law, Economics and Management of Jendouba, Tunisia. She conducted research related to credit risk management and Tunisian external debt. She is currently working on the corporate governance mechanisms, credit scoring and default risk estimation on Tunisian commercial banks. She published several academic papers in international reviews. E-mail: djbeli.nesrine@gmail.com

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CAN SKEWED GARCH-TYPE DISTRIBUTIONS IMPROVE VOLATILITY FORECASTS DURING GLOBAL FINANCIAL CRISIS?

Jack J.W. Yang, National Yunlin University of Science and Technology
Chien-Tsung Li, National Yunlin University of Science and Technology

ABSTRACT

This paper is related to the work of Patton (2011), who proposed the required robust loss functions MSE and QLIKE for imperfect fluctuations in the proxy variables, as well as the use of GW and MCS test for statistical analysis. In the same volatility model, the use the GW test pairing for comparing volatility forecasts of skewed and non-skewed error distributions. With the exception of EGARCH, the results produce no clear evidence of better prediction by a non-skewed distribution. In the same volatility model, the comparison of six different error distribution functions for volatility forecast showed no consistent result. In addition to the APARCH model with skewed Student-t distribution, the remaining results favored in non-skewed error distribution function for better prediction. In the comparison of all 30 models for forecasting volatility, better prediction models were all based on APARCH with six different error distribution functions. However, with a 90% confidence level, according to MCS tests, they all were included in the set of better volatility prediction models. A return with skewness, leptokurtic, and thick tail does not necessarily have the best performance in volatility prediction in the skewed error distribution.

JEL: C58, G01

KEYWORDS: Volatility Forecast, Mode Confidence Set (MCS), Global Financial Crisis, Giacomini and White Test (GW Test)

INTRODUCTION

Fluctuation phenomena, such as volatility clustering, kurtosis and leverage effects are important for financial markets. During financial downturns, such as around the 2007-2008 tsunami, accurate volatility forecasts can be risk averse to asset prices, portfolios and risk management. Fluctuations are unobservable and must be estimated from the model. Good volatility models, in addition to being used for estimating, should also be used for prediction.

The financial crises of 2008 caused great disturbance in every country's stock market and such a volatile situation would be worth a closer look. Brownlees et al. (2011) argued the global financial crisis of 2008 raised question about the appropriateness of using financial models, especially the standard tools for estimation and volatility forecasting. Therefore, that they wanted to further investigate the model to verify its accuracy in volatility as the financial crises transmitted across various economic entities through time. The goals is to make valuable prediction of fluctuation. The research result was affirmative. Therefore, our study used the five GARCH categories and six error distribution functions to study volatility forecasts of Taiwan's weighted stock price index during the financial tsunami period and classified them for volatility prediction comparison. The remainder of the paper is organized as follows. The first section introduced the issue. The second section introduces the data and methodology used in the study. The third section illustrates the results and discussions. The final section provides some concluding comments.

LITERATURE REVIEW

In the GARCH model, Engle (1982) first proposed the so-called ARCH model to estimate the return volatility of financial markets, followed by the generalized ARCH model, which was the so-called GARCH model proposed by Bollerslev (1986). Derivatives of GARH models were subsequently proposes. For example: Glosten et al. (1993) developed the GJR-GARCH model, Nelson (1991) developed EGARCH model, Ding et al. (1993) derived the APARCH model, and Engle and Lee (1999) simplified it to propose the CGARCH model. These volatility models were used to complete the study. It is necessary to study the forecasting capabilities of GARCH, and consider the influence of different error distribution functions on the fluctuation forecast. Wilhelmsson (2006) used a single GARCH with nine different error distribution functions to study the volatility prediction of the S & P500 futures index, in which the result showed that Student's t distribution forecast performance was better and a leptokurtic distribution function was better than a normal distribution function. Skewness of the distribution function, with higher dynamic difference, was not good for the fluctuation prediction.

Chuang et al. (2007) investigated a single GARCH model with 13 different error distribution functions. They used seven national stock price indices and six exchange rates as data to study the effect of different error distributions on volatility predictions under the same model. The estimation method was based on rolling estimation. The result showed the volatility prediction of complex residual distribution functions was not necessarily better than the simple one in volatility prediction of the same period. Lin et al. (2010) used the S&P 500 index to study GARCH with four different error distribution functions: Normal, Student-t, heavy-tailed (HT) and skewed generalized-t distribution (SGT), and the GJR-GARCH and EGARCH with normal distribution functions to yield a total of six types, to study the volatility forecasts. It is more important to consider whether the asymmetric distribution function displays leptokurtic, skewness, thick tails or leverage effects when considering the precision of a forecasting volatility model. If asymmetric distributions were not considered, the GARCH model with normal distribution showed better performance in volatility forecast than the other three. Brownlees' study found that, in the case of such severe fluctuations during the financial crisis, although the student-t distribution did take into account the thick tail, the use of Normal distribution and Student-t function was not different or better for volatility forecasts.

Lee and Pai (2010) study the GARCH model, using three different error distribution functions (Normal, Student-t and SGT) on US REIT volatility forecast. By using DM-tests on the loss functions, MSE and MAE, the study found that GARCH-SGED produced better forecast results on volatility than the other two. Therefore, skewness and tail thickness of an error distribution could impact the volatility forecast. Haque et al.(2014) analyzed the forecasting performance of the GARCH model with four error distribution functions, including Normal, Student-t, SGT and HT. They also examined asymmetric models such as GJR-GARCH and EGARCH, to study volatility forecasts for the Karachi Stock Exchange 100 Index (KSE-100) and Value at Risk (Var). Research found that GARCH-HT and GARCH-SGT had better prediction on volatility. However Var, GARCH-T and GARCH-SGT had better prediction results. Acuña et.al.(2015) used IBM stock to study the APARCH model, with five types of error distribution function, including: Normal, Student- t, Generalized Error, skew Student-t and Pearson type-IV distributions. The research used three minimal loss functions of MSE, MAE, and LOG LOSS showing that the skewed error distribution in the APARCH model had better volatility forecasts than the non-skewed distribution. Wilhelmsson (2006) and Haque et.al.(2014) argued that the GARCH-type volatility forecast model, which took into account the influence of different error distributions, were not well studied in the extant literature. Therefore, this article fills this gap in the literature.

DATA AND METHODOLOGY

Data

The research used the Taiwan weighted stock price index. The study was conducted from Jan. 2, 2007 to Dec. 31, 2008, including 496 daily observations. The data employed was retrieved from the database of Taiwan Stock Exchange website. The segmentation method was the same as used by Brownlees et al.(2011) and Ewing et al.(2007) to study volatility during financial tsunami and the Great Depression. The period for in-sample volatility prediction was from Jan. 2, 2007 to Sept. 13, 2008, while the period for out-sample volatility was from Sept. 16, 2008 to Dec. 31, 2008**.** The index return is calculated as r_t=100(lnP_t- lnP_{t-1}), in which P_t represented the index in the t-period. While volatility proxies are commonly shown as squared returns or realized volatility, and according to Poon and Granger (2003) and Patton (2011) realized volatility, when compared with the squared returns, produces a less noisy estimate. Therefore, when forecasting volatility, comparison of loss functions, using the realized volatility as proxy variables would be much better than the squared returns. In this paper, five minutes of squared returns of intraday data were used as volatility proxy variables. The estimation method adopted the rolling window estimation as proposed by Poon and Granger (2003) and Brownlees (2011), which assumed there were T samples in all samples, a number of R = T−P in the sample, and an extra prediction number of P. The method requires disregarding the oldest entry of data to add a new one, to keep the estimated number at R in the samples. It implies that during prediction of the second forecast we use the estimate of 2, 3……R+1 to predict R + 2 until all the data were completed. However, during the financial tsunami, when policies were constantly introduced as measures, the estimation coefficient in the samples might vary, and thus, the method should produce better prediction results.

Volatility Models

The study involved a univariate GARCH-class model and produced one-step-ahead volatility forecasts, in which GARCH-type models included GARCH, EGARCH, GJR-GARCH, APARCH, and CGARCH. The models are described below. The GARCH model was derived by Bollerslev (1986) after Engle (1982) presented the ARCH model. The GARCH (1,1) model was basically described as follows:

$$r_t = u_t + \varepsilon_t \quad (1)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (2)$$

in which, u_t was the conditional mean, and $\varepsilon_t = \sigma_t z_t$ and $z_t \sim$ N(0,1), σ_t^2 were conditional variables. Parameter limits included ω>0, α>0, β>0 and α+β<1. α+β represented the persistence of volatility shock. GARCH estimation could estimate the phenomenon of the volatility cluster. The GJR-GARCH model was developed by Glosten et al. (1993). The original GARCH model was supplemented by an asymmetric condition to capture the effect of negative shocks on fluctuation.

$$r_t = u_t + \varepsilon_t$$
$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 \quad (3)$$

Because the good news $\varepsilon_{t-1} > 0$ and bad news $\varepsilon_{t-1} < 0$ have different effects on the conditional variance of returns, to estimate the effect, it is generally assumed with $\varepsilon_{t-1} < 0$, where I_{t-1}=1, or else I_{t-1}=0. Therefore, the estimation effect on volatility due to good news would be α , while the bad news would have impact of α+γ. When γ > 0, it represents a leverage effect in volatility, and when γ≠ 0, there is sign of asymmetry.

GRJ-GARCH is a nested model of GARCH. The statistical test method is different from the general non-nested model when making accurate comparisons of two models. EGARCH (exponential GARCH) was proposed by Nelson (1991). The linear GARCH model required estimated parameters to be non-negative, but in contrast, there is no such limit for the EGARCH. The EGARCH (1,1) model specification is shown below:

$$r_t = u_t + \varepsilon_t$$
$$\log\sigma_t^2 = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta\log\sigma_{t-1}^2 + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (4)$$

The left-form is the logarithm of the conditional variation. It is estimated that if the leverage effect exists, under the condition of $\gamma<0$, for the magnitude of leverage effect, its γ value should be converted through the index. When the EGARCH is used for volatility prediction, it is necessary to be careful that prediction values cannot be non-negative. When $\gamma\neq$ is 0, there is an asymmetric volatility. APARCH was proposed by Ding et al.(1993) and the configuration of APARCH(1,1) model is shown below:

$$r_t = u_t + \varepsilon_t$$
$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\,\sigma_{t-1}^\delta \quad (5)$$

in which $\delta>0$ and $|\gamma|\leq 1$. γ could reflect the phenomenon of asymmetry. APARCH includes several special examples, derivative from the ARCH model. When $\delta=2$ and $\gamma=0$, the GARCH(1,1) was used, while $\delta=2$, GJR-GARCH would be used. Engle and Lee(1999) considered the short-term and the long-term factors on volatility and proposed the following CGARCH model, as shown below:

$$r_t = u_t + \varepsilon_t$$
$$\sigma_t^2 - m_t = \alpha(\varepsilon_{t-1}^2 - m_{t-1}) + \beta(\sigma_{t-1}^2 - m_{t-1}) \quad (6)$$

$$m_t = \omega + \gamma(m_{t-1} - \omega) + \delta(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (7)$$

In this model m_t, denotes time-varying long-term volatility, derived from $(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$. It depends on γ to converge to a value of ω, where γ was generally between 0.99 and 1. $(\sigma_t^2 - m_t)$ denotes the transitory component, in which β value was commonly converged to 0 and is dependent of the magnitude of $\alpha+\beta$ value. If the estimation produced $0<\alpha+\beta<\gamma<1$, it showed more persistence of influence from long-term factors than from short-term factors.

Error Distribution Functions

The error distribution functions were classified into the skewed and non-skewed error distribution functions. The skewed error distribution functions included: skewed Normal, skewed Student-t, and skewed Generalized error distribution(GED). The non-skewed error distribution functions included: Normal, Student-t, and GED. The functions were described below. The error distribution of time series was generally assumed to be a normal probability density distribution function of the independently and identically distribution (IID) described as follows

$$f(z_t) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left[-\frac{(z_t-u)^2}{2\sigma^2}\right] \quad (8)$$

Information on return rates showed the phenomenon of thick tails. The Student–t distribution would be more appropriate than the normal distribution in describing the feature. If x_v, with degree of freedom as

ν, were the Student t-distribution and if $\nu > 2$, then it was possible to obtain $\mathrm{Var}(x_v) = \frac{\nu}{\nu - 2}$. By the use of $z_t = \frac{x_v}{\sqrt{v/_{v-2}}}$, the probability density function of z_t would be

$$f(z_t \mid \nu) = \frac{\Gamma[(v+1)/2]}{\Gamma(\frac{2}{v})\sqrt{(v-2)\pi}}(1 + \frac{z_t}{v-2}^2)^{-(v+1)/2} \quad , \nu > 2 \tag{9}$$

in which $\Gamma(\cdot)$ was the Gamma function.

The probability density function of the generalized error distribution function is described as follows:

$$f(z_t) = \frac{v \exp(-\frac{1}{2}\left|\frac{z_t}{\theta}\right|^v)}{\theta 2^{(1+\frac{1}{v})}\Gamma(\frac{1}{v})} \tag{10}$$

in which $\Gamma(\cdot)$ was the Gamma function, $\theta = (2^{\frac{-2}{v}}\frac{\Gamma(\frac{1}{v})}{\Gamma(\frac{3}{v})})^{\frac{1}{2}}$. If $\nu=2$, then it would converges to a normal distribution function. When $\nu<2$, there exists evidence of thick tails.

In consideration of the random variable z_t, the probability density function of skewed normal distribution is described as:

$$f(z_t) = 2\phi(z_t)\Phi(\alpha z_t) \tag{11}$$

in which, $\phi(z_t)$ is the probability density function of normal distribution $\Phi(\alpha z_t)$ is the cumulative distribution function of standard normal distribution and α was related with the form factor.

The probability density function of skewed Student- t distribution is illustrated as:

$$f(z_t \mid \nu, \lambda) = \begin{cases} bc(1 + \frac{1}{v-2}\left(\frac{bZ_t+a}{1-\lambda}\right)^2)^{-\frac{v+1}{2}} & if \ z_t < -\frac{a}{b} \\ bc(1 + \frac{1}{v-2}\left(\frac{bZ_t+a}{1+\lambda}\right)^2)^{-\frac{v+1}{2}} & if \ z_t \geq -\frac{a}{b} \end{cases} \tag{12}$$

where $2<\nu$, $-1<\lambda<1$, $a = 4\lambda c\frac{v-2}{v-1}$ 、 $b = 1 + 3\lambda^2 - a^2$ and $c = \frac{\Gamma(\frac{v+1}{2})}{\sqrt{\pi(v-2)\Gamma(\frac{v}{2})}}$.

The probability density function of the standardized skewed generalized error distribution function is specified as:

$$f\left(z_t \mid v, \lambda\right) = v(2\theta\cdot\Gamma\left(\frac{1}{v}\right))^{-1}\cdot\exp(-\frac{|z_t-\delta|^v}{[[1-sign(z_t-\delta)\cdot\lambda]^v\theta^v}) \tag{13}$$

where $\theta = \Gamma(\frac{1}{v})^{\frac{1}{2}}\cdot\Gamma\left(\frac{3}{v}\right)^{-\frac{1}{2}}\cdot S(\lambda)^{-1}$, $\delta=2\cdot\lambda\cdot A\cdot S(\lambda)^{-1}$、 $S(\lambda)=\sqrt{1 + 3\lambda^2 - 4A^2\cdot\lambda^2}$ and $A=\Gamma\left(\frac{2}{v}\right)\cdot\Gamma(\frac{1}{v})^{\frac{1}{2}}\cdot\Gamma\left(\frac{3}{v}\right)^{-\frac{1}{2}}$.

v was related with height and thick tails. λ was the parameter of skewness and $-1<\lambda<1$. $\lambda>0$, indicates negative skewness (right-modal), and vice versa for positive skewness if $\lambda<0$. Sign() is the symbol for function.

Comparison of Prediction Performance

The true volatility σ^2 is unobservable. Choosing a good volatility to represent true volatility is important to assess the volatility prediction model. The volatility proxy variables in this research are the realized volatility σ_t^2 proposed by Andersen and Bollerrslev (1997) and were mainly based on 5-minute intraday data. Realized volatility was an unbiased estimate of the conditional variance, which was the sum of all squared returns in the five-minute intraday data. It would be important to select the appropriate loss function to use the volatility model to obtain the volatility $\hat{\sigma}^2$ and proxy variables to achieve a realized volatility σ_t^2. Patton (2011) demonstrated issues associated with volatility proxies. His research was realted to the use of imperfect volatility proxies, such as squared returns, realized volatility, and intra-day range volatility to assess model prediction performance. He foujnd if the loss function is not robust, it could cause variation in the sequencing of volatility prediction models due to selection of a non-robust loss function. But, if a robust loss function were selected, then it would not be necessary to consider the effect on loss function due to different unit. He concluded that many previous studies with inconsistent results and conclusions may be driven by selection of a non-robust loss function. Further, the necessary and sufficient condition for the selection of the robust loss function should be homogeneous when using imperfectly volatility proxy variables. Brownlees believed that almost all loss functions used in the literatures needed to be excluded, except

$$\text{MSE}=L(\sigma_t^2, \hat{\sigma}^2)=(\sigma_t^2 - \hat{\sigma}^2)^2 \quad (14)$$

$$\text{QLIKE}= L(\sigma_t^2, \hat{\sigma}^2)=\log \hat{\sigma}^2+\frac{\sigma_t^2}{\hat{\sigma}^2} \quad (15)$$

QLIKE was not affected by the extreme value of a tail. Therefore, the main loss function selected in the research was QLIKE with MSE function as the supplement. Diebold (2015) argued that incorrect conclusions occur when comparing the minimum of loss functions, without regard to the significance of statistical precision, to conclude a model as the best or improved. The use of statistical precision comparison models must fulfill the criteria of usage for the model. Common mistakes occur when using the Diebold-Mariano test, including the use rolling estimation in a nested model for comparison and inadequate fulfillment of stationary configuration of loss function. Therefore, in the comparison of loss functions in the research, paired model comparison and multi-model comparison were used. The former employed the Giacomini and White (2006) test (GW test) and the latter employed the model confidence set (MCS test) by Hansen et al.(2011).

Giacomini and White Test (GW Test)

Under the same loss function $L_{t+\tau}(\sigma_{t+\tau}^2,\hat{\sigma}_{t+\tau}^2)$, the comparison of forecasting volatility in the loss function of two models, which was referring to as the prediction value of $\Delta L_{t+\tau} = \left|\sigma_{t+\tau}^2 - \hat{\sigma}_{1,t+\tau}^2\right| - \left|\sigma_{t+\tau}^2 - \hat{\sigma}_{2,t+\tau}^2\right|$, $\hat{\sigma}_{i,t+\tau}^2$ of the model i (i=1,2) in the t+τ period for statistical significance, was a common test for prediction performance of models. The GW test assesses whether the conditional prediction ability of the two models is statistically different, and the prediction estimation method adopts the rolling estimation structure. It can be used in nested model comparison without the prerequisite of considering the problem of model mismatch and stationary state of loss function in the two models. However, it is not applicable when recursive estimation was used as equation. In the study, the GW test was used to compare volatility prediction performance improvement in the same model due to skewness. The null hypothesis was

$$H_0 : E[\Delta L_{t+\tau} \mid \phi_t] =0 \quad (16)$$

The alternative hypothesis was

$$H_1 : E[\Delta L_{t+\tau} \mid \phi_t] \neq 0 \quad (17)$$

in which ϕ_t was an information set. Rejection of H_0 indicates a variation in prediction performance precision in the two models. When $E[\Delta L_{t+\tau} \mid \phi_t]>0$, model 2 had more precise prediction performance than model 1, and vice versa.

Model Confidence Set Test (MCS Test)

The MCS test was used for prediction equivalence comparison of multiple models. The advantage was that the benchmark model was not required thus, it allowed comparison of more than one prediction performance. The MCS test was used for comparison of the robust volatility prediction multiple models. The principle is as follows: M_0 included a finite numbered model with the model number of $1,2,\ldots,m_0$. $L_{i,t}$ indicated the loss function value of the *i* model at t-point. For all $i,j \in M_0$, the difference in prediction loss function of any two models is:

$$d_{ij,t} = L_{i,t} - L_{j,t} \quad (18)$$

$$M^* \equiv \{i \in M_0 \mid E(d_{ij,t}) \leq 0, \forall j \in M_0\} \quad (19)$$

M^* of the selection procedure was based on elimination of the model with statistically poor performance in each and every comparison. The null hypothesis for such elimination was:

$$H_{0,M} : E(d_{ij,t}) = 0, \forall i,j \in M; \ M \subset M_0 \quad (20)$$

The alternative hypothesis was:

$$H_{1,M} : E(d_{ij,t}) \neq 0, \forall i,j \in M; \ M \subset M_0 \quad (21)$$

The MCS test procedure was based on the equivalence test δ_M and the elimination rule e_M. However, δ_M was used for test $H_{0,M}$. And, e_M implied that when $H_{0,M}$ was rejected, the model with poor prediction performance would be eliminated from M. This step is repeated until no other model was eliminated. Until then, $\widehat{M}^*_{1-\alpha}$ was obtained and combined into a set, indicating a collection of models with good prediction performance at 1-α confidence level. For $M \subset M_0$, δ_M and e_M at α significance level, they must fulfill the following three criteria:

$$\lim_{n\to\infty} \sup P(\delta_M = 1 \mid H_{0,M}) \leq \alpha \quad (22)$$

$$\lim_{n\to\infty} P(\delta_M = 1 \mid H_{1,M}) = 1 \quad (23)$$

$$\lim_{n\to\infty} P(e_M \in M^* \mid H_{1,M}) = 0 \quad (24)$$

Lastly, the surviving objects in the model of $\widehat{M}^*_{1-\alpha}$, which were not eliminated, were models with good prediction performance. P-values with higher statistical significance α, indicated better performance of the model. For the statistics of p-value, Hansen et al. (2011) recommended a bootstrap method for constructing t-statistics, including two types. The range statistic T_R and semi-quadratic Statistic T_{SQ} are defined as:

$$\mathrm{T_R} = \max_{i,j \in M} |t_{ij}| \tag{25}$$

$$\mathrm{T_{SQ}} = \max_{i \in M} t_i \tag{26}$$

in which $t_{ij} = \frac{\bar{d}_{ij}}{\sqrt{\widehat{\mathrm{var}}(\bar{d}_{ij})}}$; $t_i = \frac{\bar{d}_i}{\sqrt{\widehat{\mathrm{var}}(\bar{d}_i)}}$; $\bar{d}_{ij} = n^{-1} \sum_{t=1}^{n} d_{ij,t}$; $\bar{d}_i = m^{-1} \sum_{j \in M} \bar{d}_{ij}$.

RESULTS AND DISCUSSIONS

The descriptive statistics, as seen in Table 1, showed that at a 1% statistical significant level, we reject the normal distribution and revealed a unit root. The kurtosis, was leptokurtic. Skewness showed positive shift.

Table 1：Summary Statistics

Obs	Mean	Std. Dev	Kurtosis	Skewness	J-B	Q(20)	ADF
496	-0.11	1.78	4.44	-0.24	47.56***	36.58***	-21.48***

**** Denoted significantly at the 1% level.*

In the paired comparison of the same GARCH performance between the skewed and non-skewed error distribution, the GW test on the loss functions of MSE and QLIKE were shown in Table 2 and 3. From Table 2 and Table 3, we see that at the 10% significance level, the loss functions MSE and QLIKE showed the EGARCH with denied null hypothesis. This finding suggests that the remaining candidates, such as GARCH, GJR-GARCH, APARCH and CGARCH, could not prove that under a fixed GARCH-type, the prediction performance of a skewed residual distribution was definitely better than a non-skewed distribution during the financial tsunami. However, the EGARCH model with non-skewed residual distribution showed a better significance.

Table 2: GW Test of Out-of-Sample Forecasts (MSE)

	SNORM		SSTD		SGED	
	T-Stat	P-Val	T-Stat	P-Val	T-Stat	P-Val
GARCH	4.191	0.123	4.699	0.095	3.811	0.149
EGARCH	5.086	0.079	5.716	0.057	6.069	0.048**
GJR-GARCH	3.271	0.195	3.375	0.185	3.593	0.166
APARCH	0.941	0.625	1.190	0.552	2.522	.0.283
CGARCH	2.192	0.334	0.074	0.964	0.757	0.685

This table presents the statistic and p-values of the GW test performed for pairs of models, with the no-skew distribution as a benchmark. The t-stat indicates the significance of a model's performance relative to the benchmark model.

Table 3: GW Test of Out-of-Sample Forecasts (QLIKE)

	SNORM		SSTD		SGED	
	T-stat	P-val	T-stat	P-val	T-stat	P-val
GARCH	4.738	0.094	4.941	0.085	4.427	0.109
EGARCH	0.744	0.689	6.031	0.049**	6.700	0.035**
GJR-GARCH	0.753	0.686	3.016	0.221	3.462	0.177
APARCH	0.483	0.785	3.125	0.210	1.146	0.564
CGARCH	0.276	0.871	0.478	0.787	0.266	0.876

This table presents the statistic and p-values of the GW test performed for pairs of models, with the no-skewed distribution as a benchmark. The t-stat indicates the significance of a model's performance relative to the benchmark model.

In the financial tsunami, Table 4 and Table 5 report statistics using the MCS statistical test for loss functions MSE and QLIKE and six types of error distribution functions. Results show that under the same GARCH-type model, at a 90% confidence level, the QLIKE loss function, with exception of exclusion of skewed

EGARCH as a better model, the remainders were included. In GARCH, EGARCH, and GJR-GARCH, the non-skewed error distribution for volatility prediction, under the MCS test, was more likely to be included as the better model with a more relaxed confidence level. GARCH, EGARCH and GJR-GARCH showed better volatility prediction in the Student-t distribution. While APARCH had better volatility forecast in the skewed Student-t distribution, the CGARCH had better volatility forecast in normal distribution. Therefore, in the fixed model, because of the model selection, the best prediction of volatility appears in the different error distribution function without a consistent result.

Table 4: MCS Test of Out-of-Sample Forecasts with Different Distributions

	MSE									
	GARCH		EGARCH		GJR-GARCH		APARCH		CGARCH	
	Rank	Pmcs	Rank	Pmcs	Rank	Pmcs	Rank	Pmcs	Rank	Pmcs
Nor	3	0.214	3	0.346	1	1.000	4	0.389	1	1.000
Std	1	1.000	1	1.000	2	0.952	2	0.455	6	0.618
Ged	2	0.762	2	0.346	3	0.952	3	0.389	2	0.831
Snor	6	0.158	5	0.105	4	0.305	6	0.234	3	0.831
Sstd	4	0.214	4	0.105	5	0.305	1	1.000	5	0.618
Sged	5	0.214	6	01.05	6	0.305	5	0.256	4	0.831

Performance based on the different distributions of the GARCH -type and MCS tests (Pmcs) obtained by the same GARCH- type in different distributions. The superscripts ∗, ∗∗, and ∗ ∗ ∗ represent the significance level of 10%, 5%, and 1%.

Table 5: MCS Test of Out-of-Sample Forecasts with Different Distributions

	QLIKE									
	GARCH		EGARCH		GJR-GARCH		APARCH		CGARCH	
	Rank	Pmcs	Rank	Pmcs	Rank	Pmcs	Rank	Pmcs	Rank	Pmcs
Nor	3	0.177	3	0.111	3	0.259	5	0.234	1	1.000
Std	1	1.000	1	1.000	1	1.000	2	0.234	6	0.364
Ged	2	0.586	2	0.111	2	0.259	3	0.234	3	0.876
Snor	6	0.165		0.046**	4	0.240	6	0.149	2	0.876
Sstd	4	0.177		0.046**	3	0.240	1	1.000	5	0.364
Sged	5	0.177		0.046**	6	0.240	4	0.234	4	0.876

Performance based on the different distributions of the GARCH -type and MCS tests(Pmcs) obtained by the same GARCH- type in different distributions. The superscripts ∗, ∗∗, and ∗ ∗ ∗ represent the significance level of 10%, 5%, and 1%.

Table 6 shows that under the MCS statistical tests for all models with loss functions QLIKE and MSE, at 90% confidence level, all models were included in the set with better volatility prediction performance. The best volatility prediction model for the financial tsunami was the skewed Student t-distribution of the APARCH model.

Table 6: MCS Test of All 30 Out-of-Sample Forecasting Models

		QLIKE			MSE2		
		Loss(*10^3)	Rank	Pmcs	Loss(*10^7)	Rank	Pmcs
GARCH	Nor	-6.042	8	0.381	7.725	19	0.560
	Std	-6.048	4	0.381	7.645	16	0.568
	Ged	-6.048	5	0.381	7.652	17	0.568
	Snor	-6.029	16	0.381	7.869	23	0.445
	Sstd	-6.034	11	0.381	7.821	22	0.560
	Sged	-6.030	15	0.381	7.861	24	0.560
EGARCH	Nor	-5.996	28	0.381	7.468	14	0.569
	Std	-6.021	19	0.381	7.385	10	0.569
	Ged	-6.010	24	0.381	7.427	11	0.569
	Snor	-5.987	29	0.167	7.733	20	0.326
	Sstd	-6.000	27	0.191	7.677	18	0.386
	Sged	-5.987	30	0.161	7.737	21	0.329
GJR-GARCH	Nor	-6.033	13	0.381	7.243	7	0.569
	Std	-6.047	6	0.381	7.250	8	0.569
	Ged	-6.040	9	0.381	7.253	9	0.569
	Snor	-6.026	17	0.381	7.463	12	0.560
	Sstd	-6.033	12	0.381	7.467	13	0.568
	Sged	-6.026	18	0.381	7.486	15	0.560
APARCH	Nor	-6.035	10	0.381	7.067	4	0.569
	Std	-6.070	2	0.381	6.826	2	0.569
	Ged	-6.056	3	0.381	6.921	3	0.569
	Snor	-6.031	14	0.355	7.167	6	0.425
	Sstd	-6.122	1	1.000	6.535	1	1.000
	Sged	-6.047	7	0.381	7.142	5	0.514
CGARCH	Nor	-6.017	20	0.381	7.964	25	0.560
	Std	-6.002	26	0.381	8.096	30	0.560
	Ged	-6.014	22	0.381	7.994	26	0.560
	Snor	-6.015	21	0.381	7.997	27	0.560
	Sstd	-6.004	25	0.381	8.083	29	0.560
	Sged	-6.013	23	0.361	8.027	28	0.560

This table presents the Loss functions statistic and p-values of MCS test that is performed for 30 models.

CONCLUSION

Volatility variables play an important role in options and risk management. In this paper, we used the Taiwan's weighted stock price index during the 2007 to 2008 financial tsunami period to study five volatility models and six error distributions. When the extreme condition occurs, could the skewed error distribution function be better than non-skewed function in predicting volatility? The five volatility models included: the standard GARCH, the EGARCH with leverage effect, the GJR-GARCH for explaining the negative impact on volatility, the APARCH for reflecting the asymmetric phenomenon, and the CGARCH for demonstrating variation between short-term and long-term impact on volatility. In a paired study of a volatility model with skewed and non-skewed error distribution, by using GW test to examine the loss function, we found that, an exception to the EGARCH with STD and GED as error distribution and a better volatility forecast by a non-skewed function. No other data produced a better prediction volatility model with skewed error distribution during the time of financial crisis.

In research on a single volatility model with 6 error distribution functions, the MCS-test was used to examine the loss function at a 90% confidence level. We found that skewness was no better than a non-skewed function, and even showed the opposite in the EGARCH model. In the study of all 30 models, using MCS-test at 90% confidence level, to determine if there is any chance that a non-skewed error distribution could result in worse prediction, none of the results support this notion. Therefore, although Taiwan's weighted stock price index showed a high narrow peak and a left skewness in its distribution during a financial crisis period, it could not significantly improve the volatility forecast. The EGARCH predicted a worst case scenario for the financial market. During an extreme event, such as a financial crisis, a volatility model with skewed error distribution function could not significantly improve the prediction result.

Therefore, it was not necessarily true that a return with skewness, leptokurtic, and thick tails would have the best performance in volatility prediction in the skewed error distribution.

We note the following limitations of the work here. In consideration of the impact on MSE loss function during an extreme event, the MSE loss function was listed on the statistical test, but only for reference without further detail description. Future research, might include more volatility models or consider whether different volatility proxy variables could affect the selection choice of the error distribution function. Every market trading mechanism is different and in the future, the impact of a financial crisis on volatility forecast results can be further studied.

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BIOGRAPHY

Jack J.W. Yang is a professor at the Department of Finance, National Yunlin University of Science and Technology, Taiwan, Email: yangjw@yuntech.edu.tw

Chien-Tsung Li is a Doctoral Candidate of Finance and Finance Department lecturer at National Yunlin University of Science and Technology Graduate Institute of Finance. Email: g9724808@yuntech.edu.tw (Corresponding author)

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HOW FUEL PRICE SHOCKS AFFECT AIRLINE STOCK RETURNS: AN EMPIRICAL STUDY OF MAJOR US CARRIERS

Chris, C. Hsu, York College, City University of New York

ABSTRACT

This study investigated how airline stock prices respond to fuel price shocks using the asymmetric Glosten-Jagannathan-Runkle GARCH (GJR-GARCH (1,1)) model. Six airlines were selected, based on their service regions: American Airlines, Delta Air Lines, and United Airlines are larger international carriers that use various types of aircraft in their fleets and provide services in major continents, whereas Southwest Airlines, JetBlue Airways, and US Airways emphasize domestic market services and primarily use single-aisle aircraft. West Texas Intermediate Crude Oil (WTI) prices were adopted as the index of fuel prices. Based on our empirical results, a fuel price shock triggered fluctuations in airline stock returns. Moreover, American Airlines, Delta Air Lines, United, Airlines and US Airways experienced statistically significant negative relationships between their stock returns and fuel price shocks. Also, fuel price shocks significantly impacted airline stock returns during periods in which fuel prices increased but did not correlate with them during those in which such prices fell

JEL: G11, G14

KEYWORDS: Fuel Shocks, GJR-GARCH, Airline Stock Return, Return Volatilities

INTRODUCTION

How changes in fuel price affect a company's stock returns has always been an important topic for company administrators and investors, especially in industries that consume significant amounts of fuel. For most airlines, fuel cost is usually the second highest outlay after labor costs. However, unlike labor costs, which are relatively stable and typically used to reduce a company's expenditures rapidly, fuel costs are inelastic and tend to fluctuate. Therefore, based on the annual fuel consumption of all US airlines of approximately 17-19 billion gallons, an increase in fuel price by 1 penny would incur an additional \$170-\$190 million dollars in fuel costs for the entire US airline industry. Although many studies have focused on the relationships between oil price shocks and stock market returns, few have examined the sensitivity of this industry to fuel costs. This study investigated the impacts of fuel price shocks on airline stock returns. We determined whether fuel shocks increase volatility in airline stock and analyzed the relationship between airline stock returns and fuel price shocks. Specifically, we applied the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH (1,1)) model to evaluate the asymmetrical impacts of fuel price shocks on airline stock returns.

We adopted the daily adjusted closing stock prices of six major airlines in the US and the daily closing prices of West Texas Intermediate Crude Oil (WTI). The six airlines that we selected were American Airlines (AA), Delta Air Lines (DL), United Airlines (UA), Southwest Airlines (SW), JetBlue Airways (JB), and US Airways (US), of which AA, DL, and UA are the largest legacy carriers in the US. AA headquarters are located in Fort Worth, Texas, next to its largest hub, Dallas/Fort Worth International Airport. Currently, AA operates the largest fleet in the world. DL has the broadest services throughout all continents except Antarctica. DL headquarters are in Atlanta, Georgia, which houses Hartsfield-Jackson Atlanta International Airport, the world's busiest airport, based on passenger traffic. UA is headquartered in Chicago, Illinois and operates the second-largest fleet in the world.

Unlike legacy carriers, which operate wide-body, double-aisle aircraft across major continents, SW, JB, and US are classified as low-cost carriers with single-aisle narrow-body aircraft. Although these companies are classified as low-cost carriers in terms of fleet size and passengers served, SW is ranked as one of the top four airlines, along with AA, DL, and UA. JB, founded in February 1999, is the youngest company on the list and is the only airline that is based in the New York metro area, which has the largest volume of passengers in the world. US operates primarily in secondary cities in the US at three major hubs: Charlotte, Philadelphia, and Phoenix.

Table 1 reports the annual fuel consumption of the six airlines and the entire US aviation industry. The total annual fuel consumption of the six airlines was approximately 50% to 60% of that of all US airlines, indicating that our sample was large enough to represent the US market. Among the six airlines, AA had the highest consumption from 2007 to 2009, followed by UA and DL. Due to their operational scopes, the three low-cost carriers had relatively small fuel consumption volumes, especially JB, the annual consumption of which was approximately 20% of that of AA. The annual fuel consumption of DL jumped from 1.9 billion gallons in 2009 to 3 billion gallons in 2010 due to its merger with Northwest Airways. DL inherited the routes of Northwest Airways and thus increased its operational markets. Since 2010, DL has become the largest company in terms of fuel consumption.

Table 1: Annual Fuel Consumption (in Thousand Gallons)

	Entire US	AA	DL	UA	SW	JB	US
2007	19,886,200	2,833,789	1,965,697	2,299,122	1,490,801	443,292	1,191,665
2008	18,872,400	2,694,476	1,965,749	2,182,438	1,514,362	452,968	1,142,235
2009	17,060,500	2,507,855	1,939,316	1,936,981	1,431,253	453,993	1,068,963
2010	17,298,400	2,483,731	3,093,665	1,939,081	1,439,278	486,417	1,072,970
2011	17,558,000	2,445,075	3,133,175	1,889,995	1,508,891	524,784	1,094,586

This table reports the annual oil consumption from 2007 to 2011 of the entire US airlines, and the six sample airlines including: American Airlines (AA), Delta Air Lines (DL), United Airlines (UA), Southwest Airlines (SW), JetBlue Airways (JB), and US Airways (US), Data source: Bureau of Transportation Statistics.

The data period that we selected comprised May 1, 2007 to December 31, 2011, because there were two peaks in fuel price within this period: $145.31 per barrel on July 3, 2008, which was the highest price of WTI in history, and$113.39 per barrel on April 29, 2011. To capture the impacts during price fluctuations, we also separated the data into four sub-periods. Our empirical results revealed that fuel price shocks tended to increase stock return volatilities during the data period. In the sub-data periods, volatility in stock prices increased significantly only during periods in which fuel prices rose, indicating that investors responded to fuel shocks asymmetrically. The remainder of this paper is organized as follows. Section 2 reviews the literature, Section 3 introduces the data and methods, Section 4 discusses the empirical results, and Section 5 makes our conclusions.

LITERATURE REVIEW

A significant amount of studies have focused on the relationships between oil price shocks and stock market returns. Park and Ratti (2008) studied the impacts of oil price on 13 European countries and the US, finding a positive relationship between oil price increases and stock returns. Ciner (2002) evaluated the dynamic links between oil price and the stock market over three decades and suggested that this association was stronger in the 1990s. Zhu, Li, and Yu (2011) applied panel threshold cointegration models to study the relationships between oil price shocks and stock markets in OECD and non-OECD countries from 1995 to 2009. Their findings suggest that a positive relationship exists between oil prices and stock markets, differing from traditional expectations. In contrast, Chang, McAleer, and Tansuchat (2010) studied the conditional corrections and volatility between two major crude oil prices—Brent and West Texas Intermediate—and four major stock indices—Dow Jones, NYSE, S&P 500, and FTSE 100—with a symmetrical DCCGARCH model. Their empirical results indicated that a negative relationship existed between stock markets and oil price changes, especially during the pre-1999 period. Also, Apergis and Miller (2009) concluded that the stock markets did not respond significantly to oil price shocks in developed countries. Several studies have suggested that the relationships between oil price shocks and stock market returns are asymmetric and time-varying. For example, Lyasiani, Mansur, and Odusami (2011) employed the GARCH (1,1) model to investigate how excess stock returns and return volatilities respond to changes in oil returns and oil return volatility in 13 US industries and found robust results, supporting that at the sector level, fuel price volatility is a significant factor of asset price risk. Vo (2011) focused on the volatility of oil futures and stock markets and suggested that the relationships between oil futures and stocks were time-varying and tended to shift when price volatilities changed.

Pinho and Madaleno (2016) used a two-regime multivariate Markov switching vector autoregressive model to examine the nonlinear causalities between oil prices and stock returns with data from 75 countries for November 1992 to October 2012, indicating an asymmetrical relationship between oil prices and stock returns. Bastianin, Conti, and Manera (2016) examined the effects of crude oil price shocks on stock market volatility with monthly data from G7 countries for February 1973 to January 2015, finding that if the shocks originated from the supply side, stock return volatilities were unaffected, whereas if they came from the demand side, volatilities were significantly impacted. Phan, Sharma, and Narayan (2015) analyzed the responses of stock markets to fuel price changes and noted that stock markets responded asymmetrically to them. Specifically, the stock prices of companies in the oil industry moved positively, regardless of whether the direction of fuel prices.

Some studies have applied non-parametric or semi-parametric approaches. Salma (2015) investigated the dependence between oil and stock markets from 2005 to 2012 in Gulf corporate countries with various copula models, indicating that the volatility in the oil market is affected by past innovations in the stock market. Aloui, Hammoudeh, and Nguyen (2013) analyzed the dependence between the stock markets of six Central and Eastern European (CEE) countries and Brent crude oil prices with time-varying copula models, suggesting that the movement of stock markets in these countries and the change in Brent crude oil prices are positively associated. Wu, Chung, and Chang (2012) employed dynamic copula-based GARCH models to examine the dependence between the US dollar index and crude oil prices, showing that the tail dependence structure between them was not significant. Moreover, the dependence between the change in crude oil price and that in the US dollar index was negative and decreased continuously after 2003. Although the relationships between fuel prices and stock returns have been well documented, mixed results have been reported, and few studies have focused on the airline industry. Because fuel cost is one of the most important elements of an airline's cost structure and because the stock prices of airlines are scrutinized by the financial market, this area must be specifically addressed.

DATA AND METHODS

The data in this research were the daily closing stock prices of six airlines—AA, DL, UA, SW, JB, and US—and the daily closing prices of WTI, traded on the Chicago Mercantile Exchange. The data range spanned from May 1, 2007 to December 31, 2011, because fuel prices reached their historical high points during this period. Moreover, this period also covered one of the largest financial crises in the US: the financial crisis of 2008. To better grasp how airlines stock prices respond to fuel shocks during fluctuations in fuel price, we split the entire dataset into four sub-sample periods: May 1, 2007 to July 15, 2008, during which fuel prices rose from the lower \$60s per barrel in May 2007 to over \$140 per barrel in July 2008; July 16, 2008 to December 23, 2008, when fuel prices slumped from \$140 to \$30.28 per barrel; December 24, 2008 to April 29, 2011, during which fuel prices rose to another peak at \$113.39 per barrel;

and May 1, 2011 to December 31, 2011, when fuel prices dropped again. Therefore, the first and third sub-data periods experienced fuel price increases, whereas the second and fourth sub-periods saw declines. The beginning date, ending date, and total observations are also explained in Table 2.

Table 2: Sample Periods

	Beginning Date	Ending Date	Total Observations
Entire Data Period	May 1, 2007	December 31, 2011	1169
Sub Period One	May 1, 2007	July 15, 2008	300
Sub Period Two	July 16, 2008	December 23, 2008	112
Sub Period Three	December 24, 2008	April 29, 2011	588
Sub Period Four	May 1, 2011	December 31, 2011	169

This table summarized the beginning date, the ending date, and the total observation of the entire data period, and the four sub periods.

To evaluate the impacts of fuel shocks on stock returns, we converted the daily stock and WTI prices into continuously compounded changes, as follows:

$$R_{i,t,} = LN(\frac{P_{i,t,}}{P_{i,t-1,}}) \tag{1}$$

where $R_{i,t}$ represents the return/change of the airline or WTI price on day *t*, which is measured as the log-difference between the price on dates t and t-1. The summary statistics of the daily returns of each airline and fuel price are reported in Table 3.

Table 3: Summery Statistics

	Mean (%)	Std	Skewness	Kurtosis	JB Test (P Value Reported in the Parenthesis)
WTI	0.03824	0.0285	-0.1319	8.612	1535 (0.00)***
AA	-0.3711	0.0804	-9.895	233.8	2611,892 (0.00)***
DL	-0.0805	0.0475	0.0008	6.815	708 (0.00)***
UA	-0.0435	0.0617	0.0399	13.94	5,828 (0.00)***
SW	-0.0444	0.0267	-0.4073	8.044	1,270 (0.00)***
JB	-0.0583	0.0399	0.2206	6.606	642 (0.000)***
US	-0.1668	0.0618	0.2254	8.255	1,535 (0.000)***

*This table presents the summery statistics including mean, standard deviations, skewness, kurtosis, and the results of Jarque-Bera (JB) test. The p-value of the JB test is reported in the parenthesis and the asterisks are used to indicate the statistical significance as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

During the sample period, except for WTI returns, the means daily stock returns of the six airlines were all negative. AA had the lowest average return, because it struggled through bankruptcy during that period. The kurtosis of all samples was greater than 3, and the skewness of all samples deviated from 0, which indicated that the daily returns of the six airlines and WTI were not normally distributed. The high values of the Jarque-Bera test results also verified that the data deviated from a Gaussian distribution. Thus, the nature of the data distribution justified the application of the generalized autoregressive conditional heteroskedasticity (GARCH) models. This study used the Glosten-Jagannathan-Runkle GARCH (1,1) model by Glosten, Jagannathan, and Runkle (1993). The advantage of the GJR-GARCH model is that it provides a mechanism for model the asymmetry in the ARCH process, allowing us to examine the asymmetrical impacts of fuel price shocks on airline stock returns. According to Hsu and Huang (2010) and Hsu (2013), the model is defined as:

$$R_{m,t} = \emptyset R_{m,t-1} + \varepsilon_{m,t} \tag{2}$$

$$\varepsilon_{m,t} = Z_t\sqrt{h_t} \tag{3}$$

$$h_{m,t} = \alpha_0 + \alpha_1 \varepsilon_{m,t}^2 + \gamma \varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t \tag{4}$$

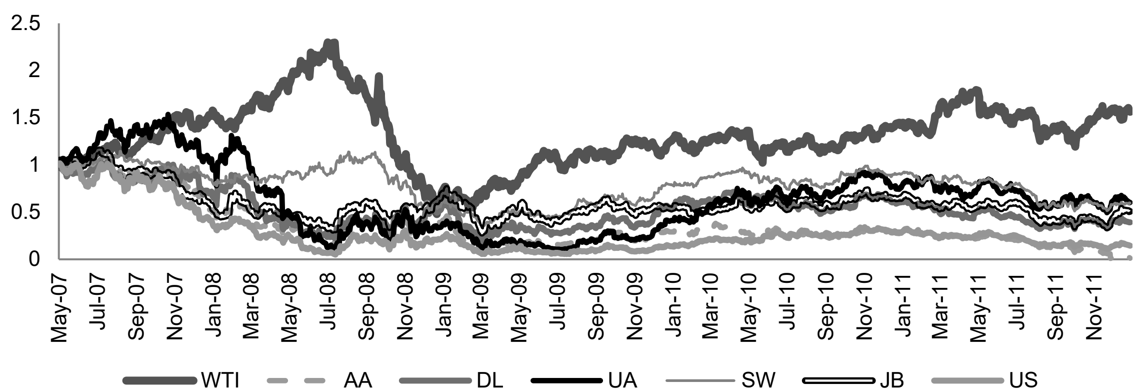
In this model, in equation (2), stock and WTI returns, $R_{m,t}$, follow the AR(1) process with a coefficient ϕ, multiplied by the return on the previous day $R_{m,t-1}$ plus the error term, $\varepsilon_{m,t}$. In equation (2), the error term, $\varepsilon_{m,t}$, contains two elements, h_t and Z_t, where h_t is a scaling factor and Z_t is a sequence that follows a standard normal distribution with mean 0 and variance 1. In equation (4), the residual variance is modeled with a constant α_0, the ARCH and GARCH coefficients α_1 and β_1, η, and dummy variables γ. By setting the dummy valuable $D^p_{t-1}=1$ when $\varepsilon_{m,t-1}<0$ and 0 otherwise, the coefficient γ was used to measure the asymmetrical response of volatility to shock. To investigate the impacts of fuel shocks on airline stock returns, we included a fuel price parameter, *fp,* in the model. Thus, η will be used to examine the relationship between the change in WTI returns and the change in airline stock returns, and γ will be used to evaluate whether fuel price shocks increased the volatilities of airline stock returns.

EMPIRICAL RESULTS

Trends in WTI and Airline Stock Prices

Figure 1 shows the trends in price. The prices were standardized to the base period of May 1, 2007. The WTI prices peaked twice during the data period. The first peak occurred on July 3, 2008, which was the highest price in WTI history, breaking the record of $120 during the energy crisis in 1980. The second peak occurred on April 29, 2011. Stock prices moved in opposite directions from that of WTI during the first peak, which can be explained as follows: when WTI prices were rising from 2007 to 2008, the economy was slowing. High fuel prices increased flight ticket prices, reduced demand for travel, and hurt the revenues of airlines, lowering their stock prices. During the second sub-period, when the financial crisis started in 2008, WTI and airline stock prices slumped. In the third sub-data period, airline and WTI prices climbed back, when the economy began to recover from the 2008 financial crisis. In the fourth sub-data period, when WTI prices began to decline, airline stock prices also fell, possibly because the entire aviation industry experienced a series of consolidations, signaling uncertainty to the market.

Figure 1: The Trends of the WTI and the Airlines Stock Prices



This figure shows the price trends of the WTI and the six airlines. To provide a better view for comparison, the prices were standardized to the base period of May 1, 2007.

Empirical Results of the GJR GARCH Model

The results of the GJR GARCH (1.1) model are reported in Tables 4-8. Table 4 reports the results for the entire sample data range. The negative value of η for all six airlines demonstrated that the changes in WTI and stock returns had negative relationships—a price shock in which WTI increases will lower airline stock returns and *vice versa*. However, only AA, DL, UA, and US reached at least 95% significance for this argument. The positive γ indicated that the change in fuel price increased the fluctuations in stock price returns. During the entire data period, except for AA, the other five airlines met at least 95% significance in supporting the claim that fuel shocks increased the volatility in their stock returns.

Table 4: Empirical Results of the Entire Data Period- 05/01/2007- 12/31/2011

	Parameter	Regression Coefficient	Standard Error	T Statistic
AA	η	-0.0113	0.0042	-2.693***
	γ	0.0226	0.0213	1.069
DL	η	-0.0080	0.0039	-2.029**
	γ	0.0767	0.0274	2.796***
UA	η	-0.0134	0.0048	-2.793***
	γ	0.0456	0.0204	2.237**
SW	η	-0.0023	0.0021	-1.102
	γ	0.0630	0.0258	2.440**
JB	η	-0.0059	0.0030	-1.943*
	γ	0.0906	0.0317	2.854***
US	η	-0.0103	0.0052	-1.966**
	γ	0.0609	0.0220	2.766***

*This table reports regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the entire data period. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with the asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 5 reports the empirical results of the first sub-period. During this period, the price of WTI rose to its historical highest point. As reported in Table 4, the negative value of η for all six airlines indicated that the returns between WTI and airline stocks had negative relationships. However, only AA, UA, and JB met the significance level of at least 95%. Moreover, there was 90% statistical significance with regard to the rise in DL and JB stock return volatility when the price of WTI increased.

Table 5: Empirical Results of the Sub Period One -5/1/2007 to 7/15/2008

	Parameter	Regression Coefficient	Standard Error	T Statistic
AA	η	-0.0165	0.0076	-2.170**
	γ	0.0770	0.0671	1.148
DL	η	-0.0131	0.0070	-1.865**
	γ	0.1596	0.0870	1.835**
UA	η	-0.0342	0.0080	-4.258***
	γ	0.0335	0.0686	0.4888
SW	η	-0.0014	0.0031	-0.4667
	γ	0.0736	0.0773	0.9523
JB	η	-0.0093	0.0043	-2.146**
	γ	0.1781	0.0971	1.833*
US	η	-0.0238	0.0094	-2.537**
	γ	0.0719	0.0587	1.225

*This table presents regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the first sub period from May 1, 2007 to July 15, 2008. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The significance of each regression coefficient is indicated with the asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 6 reports the empirical results during the second sub-sample period. During this period, the price of WTI dropped from its peak at approximately $143 per barrel to $30.28 per barrel within 6 months. However, γ and η did not reach statistical significance.

Table 6: Empirical Results of the Sub Period Two -7/16/2008 to 12/23/2008

	Parameter	Regression Coefficients	Standard Error	T Statistic
AA	η	-0.0101	0.0415	-0.2444
	γ	-0.0036	0.0966	-0.0369
DL	η	0.0003	0.0349	0.0079
	γ	-0.0815	0.3006	-0.2712
UA	η	-0.0090	0.0511	-0.1769
	γ	0.0499	0.1276	0.3906
SW	η	0.0159	0.0195	0.8151
	γ	0.1280	0.1477	0.8667
JB	η	-0.0060	0.0195	-0.3095
	γ	0.6584	0.4249	1.5494
US	η	0.0178	0.0514	0.3452
	γ	0.1241	0.1588	0.7818

*This table shows regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the second sub period from July 16, 2008 to December 23, 2008. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 7 lists the empirical results of the third sub-sample period from December 24, 2008 to April 29, 2011. During this period, the price of WTI rose from the lower $30s per barrel to over $120 per barrel. For AA, DL, UA, SW, and JB, the climb in WTI price increased their stock return volatilities. However, only JB and DL had negative relationships between WTI returns and stock returns.

Table 7: Empirical Results of the Sub Period Three -12/24/2008 to 04/29/2011

	Parameter	Regression Coefficients	Standard Error	T Statistic
AA	η	-0.0031	0.0031	-0.9775
	γ	0.0284	0.0128	2.220**
DL	η	-0.0050	0.0029	-1.731*
	γ	0.0582	0.0235	2.481**
UA	η	-0.0039	0.0033	-1.181
	γ	0.0463	0.0216	2.140**
SW	η	-0.0037	0.0019	-1.946*
	γ	0.0467	0.0273	1.719**
JB	η	-0.0050	0.0025	-2.002**
	γ	0.0576	0.0285	2.021**
US	η	-0.0021	0.0038	-0.564
	γ	0.0351	0.0265	1.327

*This table reveals regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the third sub period from December 24, 2008 to April 29, 2011. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

Table 8 reports the empirical results of the fourth sub-sample period from May 2011 to December 2011. During this period, the price of WTI decreased again. Only UA and US reached 95% statistical significance in claiming a negative relationship between their stock returns and changes in the price of WTI .

Table 8: Empirical Results of the Sub Period Four -05/01/2011 to 12/31/2011

	Parameter	Regression Coefficients	Standard Error	T Statistic
AA	η	0.0075	0.0485	0.1551
	γ	0.5216	0.5435	0.9597
DL	η	-0.0407	0.0421	-0.9673
	γ	0.2952	0.2331	1.2660
UA	η	-0.0905	0.0370	-2.444**
	γ	0.0391	0.1926	0.2029
SW	η	-0.0134	0.0332	-0.4026
	γ	0.1267	0.1366	0.9277
JB	η	-0.0133	0.0449	-0.2970
	γ	0.0721	0.1434	0.5029
US	η	-0.1017	0.0495	-2.0528
	γ	0.2907	0.1811	1.6054

*This table reports regression coefficients of parameters γ and η in the equation $h_{m,t} = \alpha_0 + \alpha_1\varepsilon_{m,t}^2 + \gamma\varepsilon_{m,t-1}^2 D_{t-1}^p + \beta_1 h_{m,t-1} + \eta f p_t$ during the fourth sub period from May 1, 2011 to December 31, 2011. The stand errors and the corresponding T statistics are reported in the third and fourth column respectively. The statistical significance of each regression coefficient is indicated with asterisks as: * 90% statistical significance, **95% statistical significance, ***99% statistical significance.*

CONCLUSION

This paper examined the impacts of fuel price on the stock returns of six US-based airlines: AA, DL, UA, SW, JB, and US. We employed the GJR-GARCH (1,1) model to examine the asymmetrical impacts of fuel price shocks on airline stock returns. The empirical results indicated that during the entire data period, the stock returns for AA, DL, UA, and US had negative relationships with the changes in the price of WTI . Also, with the exception of AA, all airlines experienced greater volatility in their stock returns with fuel shocks.

Due to the nature of the two price peaks in WTI, we split our data into four sub-periods to analyze the stock return responses to fuel shocks during specific fluctuations in the price of WTI . During rises in WTI price, fuel shocks tended to increase airline stock return volatilities, and a negative relationship existed between changes in WTI price and airline stock returns. However, during periods of declines in WTI prices, no significant results were observed.

This analysis should be extended to major airlines worldwide, and the shocks in WTI and Brent should be compared. A greater understanding of the effects of fuel price shocks in WTI and Brent on stock returns for such airlines would help us determine whether the impacts of fuel shocks on airline stocks are global or regional, allowing practitioners and investors to make better investment decisions.

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BIOGRAPHY

Dr. Chris C. Hsu is Director of CUNY Aviation Institute and Associate Professor of Finance at York College, The City University of New York. He can be reached at: Department of Accounting and Finance, School of Business and Information Systems, York College, The City University of New York, 94-20 Guy R. Brewer Blvd., Jamaica, NY 11451. Phone: 718-262-2513. Email: chsu@york.cuny.edu

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THE EFFECT OF ACCOUNTING-BASED DEBT COVENANT DISCLOSURES ON SHAREHOLDER WEALTH

Ping Wang, Pace University

ABSTRACT

This study examines whether disclosures of the terms of accounting-based debt covenants affect shareholder wealth. Specifically, I focus on market reaction at the time of the announcement of technical default. I find that firms that disclosed the terms of the covenants in prior Securities and Exchange Commission (SEC) filings experience less negative price response during the three-day window surrounding the announcements. I also provide evidence that the market reaction to technical default varies systematically with the size of the debt contract over total liabilities, which I use as a proxy for the materiality of the contract. Further analyses show that through such disclosure, first, there is less shareholder wealth loss, in particular, at firms where the contracts are less material, and, second, the relation between market reaction to technical default and the materiality of the contract is significant only when the contracts are material. These findings have financial reporting implications for standard setters.

JEL: M41, M48

KEYWORDS: Shareholder Wealth, Debt Covenants, Technical Default, Voluntary Disclosures, Materiality

INTRODUCTION

The purpose of this study is to investigate whether disclosures of the terms of accounting-based debt covenants affect shareholder wealth. In particular, it examines whether prior disclosures of the terms of accounting-based debt covenants affect market reaction to the announcements of technical default. This research question is important to financial communities and standard setters as it has implications for financial reporting decisions as well as regulation on disclosures.

Prior literature has documented the importance of debt covenants as contributing to efficient debt contracting (Billett et al., 2007; Spiceland et al., 2015; Zhang, 2008), and mitigating agency problems by providing a tool to implement contingent control arrangements for an efficient governance structure (Aghion and Bolton, 1992; Jensen and Meckling, 1976). Another strand of research finds that accounting-based debt covenants affect companies' accounting choices (Betty and Weber, 2003; DeFond and Jiambalvo, 1994; Press and Weintrop, 1990; Sweeney, 1994) and business operations (Chava and Roberts, 2008). However, limited research has been done that examines the relation between accounting-based debt covenants and shareholder wealth. Beneish and Press (1995a) provide empirical evidence that shareholders experienced a 3.52 percent wealth loss during a three-day technical default announcement window. Loosely related to this study is Christensen et al. (2009), who find that market reactions to International Financial Reporting Standards (IFRS) reconciliation announcements are more pronounced among firms that face a greater likelihood of covenant violation, suggesting that covenant violation results in wealth transfer between shareholders and lenders. Griffin et al. (2014) document that insiders are net sellers before covenant disclosures and net purchasers of shares after the disclosures, supporting the hypothesis that insiders time their trades in anticipation of debt covenant violation disclosures.

The negative market reaction to the technical default announcement and the insider trading associated with covenant violation clearly suggest that such information is important to investors. One would think that investors would welcome information that helps them more accurately evaluate the likelihood of technical default in a timely fashion. Information on the terms of debt covenants is one piece of such information, but is not necessarily always available. In fact, practitioners have complained about the underreporting of the terms of debt covenants because lack of information on the actual terms leaves investors blind as to if and when the company might breach a covenant level, as argued in an article in the High Yield Report. An article in The New York Times (2003) also claimed that many companies do not disclose financial covenants or where they stand with regard to the covenants until it is *too late* or they are in danger of violating them. Furthermore, the finding in Griffin et al (2014) suggests that insiders benefit from an information advantage in anticipating debt covenant violation, thus putting other investors at a disadvantage. Nevertheless, to the best of my knowledge, the question whether disclosures of the terms of financial covenants affect shareholder wealth has not been addressed in the literature.

As of today, the Securities and Exchange Commission (SEC) and Financial Accounting Standards Board (FASB) have few regulations and rules governing debt covenant disclosure. The only regulation that explicitly requires disclosure of debt covenants is Regulation S-K item 202 (b), which is applicable exclusively to registered public debt but not to private debt. Press and Weintrop (1991) posit that accounting standards do not expressly require disclosure of debt covenants except in instances where there has been covenant violation. Of course, Generally Accepted Accounting Principles (GAAP) require full and fair disclosures of "relevant" information. Since the SEC and GAAP provide only basic guidelines for debt covenant disclosures, when a firm enters into a debt contract as above, considerable latitude remains as to how much detailed covenant information a firm should provide to the public.

Whether investors wish to take action *before* technical default announcements officially hit the market depends on two conditions. The first is whether the investors are concerned about covenant violations and consider technical default important in their valuations. Beneish and Press (1995a) and Griffin et al. (2014) provide direct evidence that technical default negatively affects share price. The second is whether investors are able to evaluate the probability of covenant violation. To do so, investors need to know the terms of the financial covenants such as the exact amount (e.g., a minimum of $160 million in net worth) and the definitions being used in the computation of the covenants (e.g., the definition of the net worth used in the contract), as well as forthcoming financial performance information. Without the specifics on financial covenants, investors are unable to assess the likelihood of covenant violation.

Core and Schrand (1999) show that investors do price the probability of technical default. Thus, it is reasonable to expect that disclosures of the terms of financial covenants (disclosures of financial covenants, hereafter) can help investors evaluate a firm's covenant positions and firm value *before* the announcement of technical default. Using a similar setting as the one used by Beneish and Press (1995a) that investigates violation of financial covenants, I directly test whether prior disclosures of financial covenants reduces the shareholder wealth loss (i.e., the magnitude of negative market reaction) on the date the company announces technical default.

Drawing on analytical models and empirical results in the literature, I first hypothesize that, *ceteris paribus*, firms disclosing financial covenants in their public filings in prior periods vis-à-vis those not disclosing financial covenants suffer less on the dates they announce technical default. Second, since the disclosure requirement is based on the "relevance" or "materiality" of the information rather than a "bright-line," I examine whether the market reaction to the announcements of technical default varies systematically with the materiality of the lending contracts. I interpret materiality as the importance of the contract to investors and use the size of the debt contract over total liabilities as the proxy for materiality. Heitzman et al. (2010) document that the materiality of information plays a role in disclosure decisions and, consequently, studies that relate to voluntary disclosure should consider information materiality.

I test the above hypotheses using a sample of 66 firms that meet criteria similar to those in Beneish and Press (1995a). To test the first hypothesis, I regress cumulative abnormal returns (*CAR*) on a dummy variable of earlier disclosure decision (*DIS*) and several control variables. Consistent with the first hypothesis, I find that firms disclosing financial covenants in prior SEC filings experience less negative price responses during the three-day window surrounding announcements of technical default. To test the second hypothesis, I use the same model but replace the disclosure decision variable with the materiality variable, proxied by the size of the debt contract over total liabilities, and find that the level of materiality varies systematically with *CAR*. The results show that the market reaction is less negative for a more material contract. One potential explanation is that when a contract is more material, firms tend to disclose the specifics of the covenants earlier and investors are more likely to pay close attention to the firm's financial situation. Another potential explanation is that managers are more likely to discuss the risk of violating the covenants of a more material contract in MD&A, conference calls, etc. Thus, the surprise around technical default is smaller.

Further analysis provides more insights regarding these two hypotheses. By partitioning all samples by the median of the materiality measure, I assume that materiality is likely to be binding for the group above the median and not binding for the other group below the median. The results show that, first, disclosure of financial covenants in prior SEC filings reduces shareholder wealth losses for firms where the materiality condition is not binding. This result suggests that "voluntary" disclosure is especially effective in providing useful information to investors: investors are not caught off guard when the technical default is announced. Second, market responses vary systematically with the relative size of a contract when the materiality condition is binding. Investors in firms with more material contracts are better able to anticipate technical defaults, and therefore, are less surprised when technical default is announced.

This study's contributions are four fold. First, building on Beneish and Press (1995a), this study directly tests the value relevance of accounting-based covenants to shareholders. The covenants are useful as they can signal potential financial trouble on a timely basis. Second, this study expands on prior technical default research by shedding light on how (1) prior disclosure of the terms of covenants, and (2) the materiality of the violated contract, are associated with stock price reactions to technical default. Third, the evidence of this study also contributes to the ongoing debate on firm disclosure decisions discussed by Heitzman et al. (2010). While it is not the purpose of this study to examine disclosure decisions, it does provide evidence that disclosure decisions around financial covenants are positively related to the materiality of the contracts. This evidence supports the argument that the materiality of the information disclosed should be controlled for in the disclosure decision model. Finally, my findings suggest that investors benefit from information on the specifics of debt covenants since they are able to better assess the financial status of the firms on a timely basis. Since not all firms disclose this information, mandating the disclosure of debt covenants could help investors.

The remainder of the paper is organized as follows. Section 2 reviews related literature and regulations. The development of my hypotheses is presented in Section 3. Section 4 introduces research design. Sample selection is provided in section 5. Section 6 presents empirical results and Section 7 concludes.

INSTITUTIONAL BACKGROUND

Related Literature

A few studies have examined the effect of financial covenant violation on shareholder wealth and business operations. Beneish and Press (1995a) document a strong association between technical default and shareholder wealth loss. In examining 87 firms with technical defaults, they find that in the three-day announcement window, the average abnormal return is negative 3.52 percent. Chava and Roberts (2008) find that capital investment declines in response to covenant violations by approximately 1 percent per quarter. These studies document the losses in shareholder wealth and changes in business operations when accounting-based covenants are breached. Griffin et al. (2014) document the association between insider trading and an information advantage around first-time debt covenant violation disclosures, potentially resulting from early access to information about such disclosures.

Moreover, a number of studies show the impact of debt covenants on accounting choices (Beatty and Weber, 2003; Franz, et al, 2014; Jaggi and Lee, 2002; Press and Weintrop, 1990; Sweeney, 1994). For example, Dichev and Skinner (2002) provide large-sample evidence that an unusually large number of firms financially perform at or just above covenant thresholds, suggesting that managers are trying to avoid covenant violations. Franz et al, (2014) find that firms close to violation or in technical default engage in higher levels of earnings management than far-from-violation firms do.

While the findings in the literature indicate the importance of financial covenants, the question as to whether disclosures of financial covenants benefits shareholders has not been empirically examined and is worth exploring.

Current Debt Covenant Disclosure Requirements

I review the disclosure requirements on covenants in general. Disclosure requirements on covenant violation are not specifically reviewed here because the subject of this study is firms that have already disclosed their violation of covenants in SEC filings. The question, however, is whether a firm discloses the specifics of covenants in its filings prior to covenant violation.

The general disclosure requirements related to my study are the following two provisions. Securities Act of 1933 section 3 (77c) requires that any public debt offering that exceeds five million dollars be registered with the SEC. In addition, SEC Regulation S-X item 5-02 states that “the amount and terms of used commitments for long-term financing arrangements shall be disclosed in the notes to the financial statements if significant.” Regulation S-K also has a more detailed filing instruction on the disclosure of registered debt securities, but there is no such guidance for private placed securities. One example of the instruction on the debt covenant disclosure of Regulation S-K is item 202 (b) (4) that requires disclosures of provisions restricting the declaration of dividends or provisions requiring the maintenance of any asset ratio or reserve of debt securities. However, this applies only to registered securities, and private placements are excluded from this requirement. Regulation S-K item 601 (b) (4) requires companies to file exhibits for debt securities being registered and for long-term debt, with the exception of long-term debt not being registered if the total amount does not exceed 10 percent of total assets on a consolidated basis.

In addition, form 8-K filing item 1.01 requires the disclosure of “material definitive agreements.” However, item 1.01 parallels item 601 b (10) of Regulation S-K with regard to the types of agreements that are material to a company. Item 2.03 asks for a brief description of the material terms under which it may be accelerated or increased. Covenant disclosure may also fall into this requirement.

Last but not least, materiality has been the focus of the FASB's recent effort. In September 2015, FASB proposed an Accounting Standards Update with regard to assessing whether disclosures are material. It highlights the importance of considering materiality when examining disclosure decisions.

In sum, I conclude that regulatory disclosure requirements on the terms of covenants are somewhat vague, and thus managers use their discretion in deciding whether to disclose the information.

HYPOTHESES DEVELOPMENT

If financial covenants have been disclosed in previous SEC filings, presumably, investors would include them along with other financial information to assess the status of a company's compliance with financial covenants (status of financial covenants, hereafter). When firms violate accounting-based debt covenants, they may incur costs. Core and Schrand (1999) develop such a model of equity valuation, which predicts that the probability of violating financial covenants affects firm value. Furthermore, they provide evidence that earnings response coefficients on losses and non-permanent earnings are positive and significant only for thrift institutions that are near the minimum regulatory capital requirement. This suggests that investors price information about the status of financial covenants into their valuations, especially for firms close to technical default. Thus, if accounting information (e.g., earnings information) is available, investors can use it to evaluate the covenant status and their evaluation is impounded into the firm's security price.

Demski and Feltham (1994), Holthausen and Verrecchia (1988), and Kim and Verrecchia (1991) predict that price response to earnings announcements is negatively related to price response to information contained in pre-earnings announcements. Empirical research supports this prediction. For example, Shores (1990) documents that market reactions to annual earnings announcements decrease as the amount of interim information increases. In addition, as pointed out in Francis et al. (2002), the financial press has focused on the superiority of analyst forecasts in terms of both timeliness and content. Overall, both analytical and empirical evidence suggest that earnings information and other accounting information are likely to be revealed through different types of pre-announcements such as analyst forecasts and management forecasts. Therefore, the accounting information necessary to compute financial covenant ratios is likely available to investors before current period earnings announcement, 10-Q, or 10-K filing dates.

In sum, the literature has documented that (1) investors evaluate the status of financial covenants even before they are informed about the technical default; and (2) firms disclose information necessary for investors to compute the impact of financial covenants. As a result, I expect that prior disclosures of financial covenants can preempt some portion of the negative stock-price response on the technical default announcement date. Thus, I hypothesize that (the disclosure effect):

> *H1: Ceteris paribus, firms disclosing financial covenants in prior public filings will suffer less on the dates they announce technical default compared to those not previously disclosing financial covenants.*

My second hypothesis relates to the impact of relative debt-contract size on the market reactions to technical default announcements. Although Securities Act of 1933 section 3 (77c) requires that any public debt offering that exceeds five million dollars be registered with the SEC, there is no such requirement for private debt. Since my sample is comprised of private debt, the disclosure requirement that governs this sample is Regulation S-X item 5-02, which requires that the amount and terms of used commitments for long-term financing arrangements be disclosed in the notes to the financial statements, *if significant*. In addition, Regulation S-K requires companies to file exhibits for long-term debt when the total amount exceeds 10 percent of total assets on a consolidated basis. These regulatory requirements mandate disclosures about contracts if they are "significant" or "material" to a company. The recent study by Heitzman et al. (2010) argues that materiality indeed plays an important role in disclosure decisions.

For material contracts, the market reaction to technical default would be twofold. On the one hand, if the contract is material to the company, it is more likely that the covenant violation will be a significant event to the company, and consequently, the market will react more negatively to the violation announcement (hereafter, the materiality effect). On the other hand, although regulations do not have specific provisions regarding the disclosure of accounting-based covenants, the larger the debt contract, the more likely companies are to disclose the covenant terms in their SEC filings. If the first hypothesis holds, then the negative market reaction would be reduced. In addition, firms are more likely to discuss the default risk of material contracts in their SEC filings under MD&A, and in their conference calls. Material contracts are more likely to attract investors' attention, and thus, the negative reaction to the announcement of technical default may be smaller. This effect is similar in spirit to the disclosure effect in Hypothesis 1. Because these two effects move in opposite directions, I state the second hypothesis in null form:

> *H2: The market reaction on the announcement date of the technical default does not vary systematically with the materiality of the lending contract.*

RESEARCH DESIGN

To test *H1* and *H2*, I use models similar to Beneish and Press (1995a):

Model 1 (*H1*):

$$CAR = \alpha_0 + \alpha_1 DIS + \alpha_2 WAIVER + \alpha_3 NEWS + \alpha_4 LEV + \alpha_5 SUR + \alpha_6 LTA + \varepsilon \qquad (1)$$

Model 2 (*H2*):

$$CAR = \beta_0 + \beta_1 DT\_SIZE\_SL + \beta_2 WAIVER + \beta_3 NEWS + \beta_4 LEV + \beta_5 SUR + \beta_6 LTA + \upsilon \qquad (2)$$

where *CAR* is the cumulative abnormal return, namely, the raw stock return minus the CRSP equal-weighted market portfolio return, measured over a three-day window (-1, +1), where 0 is the date of the earliest announcement; *DIS* is a binary variable, which is coded 1 if financial covenants are disclosed in the 10-K, 10-Q, or 8-K filings prior to a firm's announcement of technical default, and 0 otherwise; *DT_SIZE_SL* is the aggregate lending commitment amount under the debt agreement scaled by total liabilities measured at the beginning of the fiscal year of violation. I use this variable as a proxy for the materiality of the debt contract. *WAIVER* is coded 1 if a waiver is granted at the time of the violation announcement, 0 otherwise; *NEWS* is defined as 1 if the violation announcement first appears in the 8-K or on the newswire, 0 if it first appears in the 10-K or 10-Q; *LEV* is leverage defined as total liabilities over book value of total assets measured at the end of the violation year; *SUR* is earnings surprise measured as actual quarterly earnings per share minus the most recent forecast of earnings per share closest to, but still prior to, the quarterly earnings announcement. A random walk model is used to obtain the last period quarterly earnings when a forecast is not available in I/B/E/S; *LTA* is the natural logarithm of total assets measured at the beginning of the fiscal year of covenant violation.

This model does not include the three variables related to the technical default cost in Beneish and Press (1995a). The three variables are: (1) incremental interest costs, (2) the change in the amount of loan credit, and (3) the increased number of constraints following default and renegotiation. Beneish and Press (1995a) document that while (1) and (3) are significant, the change in the amount of loan credit is insignificant in determining the market reaction. Since half of my sample firms have not finished renegotiation with their lenders at the date they announce technical default, it is not possible to determine the three variables. Instead, I include leverage as a control variable since it is significantly correlated with incremental interest costs after technical default (Beneish and Press, 1993).

Leverage ratio is also frequently used as a proxy for closeness to covenant violation and for the cost of covenant violation (Aboody et al. 2000; Duke and Hunt, 1990; Press and Weintrop, 1990; Zhang, 2008). I control for leverage for three reasons. First, as mentioned above, Beneish and Press (1993) show that leverage measured at the end of the violation year is significantly correlated with incremental interest cost (refinancing cost) caused by technical default. Second, Press and Weintrop (1991) find in their randomly selected sample that tangible net worth, working capital, and leverage are the most frequently used covenants. Dichev and Skinner (2002) also show that leverage ratio is among the most frequently used covenant in their large sample. Thus, leverage is a good proxy for future covenant violation. Third, many credit facility agreements contain cross-default provisions for covenants, so violating one covenant could result in a default under another contract. As a result, a firm with higher leverage is more likely to have cross defaults and a hard time rectifying such problems.

I control for whether the firm is granted a waiver when it announces technical default, because a waiver signals to the market that the liquidity problem is, either permanently or temporarily, relieved as documented in Beneish and Press (1993, 1995a). I include *NEWS* as a control variable because Beneish and Press (1995b) document that news media announcements generate more adverse *CARs*. For example, such disclosures of technical default have -5.54 percent *CAR* versus -2.40 percent *CAR* for SEC filings. In addition, it appears that the majority of newswire announcements coincide with 8-K filings, so I code both 8-K and newswire announcements as 1.

I also control for earnings surprise, *SUR,* and total assets, *LTA*. Earnings surprise, *SUR*, is controlled for because among the 66 firms, 27 firms released the technical default information along with their earnings. *LTA* is used to control for firm size. Lobo and Mahmoud (1989) find that market reactions to earnings announcements decline as firm size increases. However, for the other 39 firms, their announcements do not accompany earnings announcements, so the sign of *LTA* is not clear.

Hypothesis 1 predicts a positive coefficient on DIS. A positive coefficient on DIS suggests that firms disclosing their accounting-based covenants before the default experience less negative market reaction when they announce the technical default because their investors are able to already account for the probability of technical default. With regard to Hypothesis 2, a positive β_1 indicates that the disclosure effect dominates the materiality effect. In other words, firms with larger debt contracts experience smaller negative market reaction at the time of the technical default announcement. On the contrary, a negative β_1 indicates that the materiality effect dominates the disclosure effect.

It is best to include both DIS and DT_SIZE_SL in one regression so that any interpretation of DIS is immune to the effect of DT_SIZE_SL, and vice versa. However, as developed above, the relative size of the contract is potentially correlated with the firm's tendency to disclose financial covenants, leading to collinearity. Collinearity is problematic when the purpose of the regression is to interpret the coefficient. Moreover, collinearity makes it more difficult to achieve significance of the collinear parameters. These two variables are in fact correlated at 0.005 level, with Spearman correlation of .34 (untabulated to conserve space). Therefore, to consider materiality while eliminating the collinearity problem in Model 1, I partition the sample into two groups based on level of materiality. Since there is no unambiguous definition of a "significant" or "material" contract, albeit somewhat arbitrary, I choose the median DT_SIZE_SL as a cut-off, and test both hypotheses again on two groups to see whether DIS and DT_SIZE_SL still affect shareholder wealth within each group while eliminating the omitted correlated variable problem. Other possible ways to partition exist: for example, 10 percent of total assets (Regulation S-K). However, I do not use this for two reasons. First, Regulation S-K only requires companies to file exhibits for long-term debt but does not explicitly require disclosure about covenants when the total amount exceeds 10 percent of total assets. Second, this cut-off results in 14 firms in one group where regression can hardly be performed.

SAMPLE SELECTION

I construct my sample similarly to Beneish and Press (1993, 1995a). The major difference is in the fact that I include 10-Q files, whereas Beneish and Press (1995a) limit their study to only 10-K files because of the data limitation at that time. Out of 66 firms in my final sample, 18 chose a 10-Q filing and 7 an 8-K filing as the first report to announce their financial covenant violations.

I use the 10-K filings to identify firms that violated financial covenants. I start with non-financial firms listed on either the New York Stock Exchange or the American Stock Exchange, with a reporting date between January 1, 2003 and December 31, 2007. Using three groups of keywords — "technical default," "violation," and "not in compliance" — I identify firms that disclosed their technical default in their 10-K filings. For each 10-K filing, I also read their 10-Q and 8-K filings one year prior to that filing date to pinpoint the earliest date the violation information was disclosed. I then search Factiva using keyword "covenant" for a one-year period before the 10-K filing dates. Comparing the date from the SEC filings and the date from the Factiva for each firm, I choose the earlier date as my event date.

Consistent with Beneish and Press (1995a), I impose the following restrictions on my sample:

1. To reduce the impact caused by contamination from other events, I exclude firms that announced violations along with debt service default, filing under chapter 11, or with a qualified auditor opinion, etc. I exclude such firms because it is unclear whether these different types of events would have similar effects on the *CAR*.
2. For firms that violated financial covenants multiple times during my sample period, only the first violation is included in the sample. By doing this, I eliminate the problem that the market may react differently to the second violation than it did to the first violation.
3. Along the same line of reasoning as restriction 2, firms in my final list do not have a violation in the prior year.

Finally, for firms that satisfy all of the above restrictions, I search the SEC filings for detailed information on the contracts related to the violated covenants. *DIS* is coded 1 only if the exact terms of the financial covenants are disclosed. For example, ANGELICA CORP disclosed in its 2001 10-K filings that the most restrictive of its loan agreements requires that the company maintain a minimum of $160,000,000 in consolidated net worth. In this case, DIS is coded 1. One example where *DIS* is coded 0 is COMFORT SYSTEMS USA INC. In its second quarter 10-Q filings in 2000, it only says that the credit facility provides for the maintenance of certain levels of EBITA. Besides *DIS*, I also collect the aggregate lending commitment amount under the agreement to capture the size and the materiality of the contract.

Table 1 presents a summary of how the final sample is obtained. I begin by identifying 206 filings that include violation of financial covenants. Of these 206 filings, 69 had previous violations. This is consistent with the findings in Chava and Roberts (2008), Dichev and Skinner (2002), DeAngelo et al. (1994), and Sweeney (1994) that private lenders set debt covenants tightly and use them as "trip wires" for borrowers. As a result, technical violations occur relatively often. There are four announcements accompanied by bankruptcy filings, five with other legal matters, eight with debt service default, seven with qualified auditor opinions, two with initial public offering, five with restatements, and two with non-accounting based covenants. Thirteen firms did not disclose what covenants they violated and the contracts to which the covenants belong. In addition, because I use the CRSP stock price data to compute the abnormal return, 22 firms that do not have enough price information in CRSP are also dropped. I also delete three observations because the necessary control variables are not found in COMPUSTAT. I end up with 66 observations.

Table 1: Sample Selection

Filings with violation announcement[1]			206
Less:	violations which are either not the first-time violation in my sample period or have a violation in the prior year	69	
	violations announced with bankruptcy filing	4	
	violations announced with other legal matters	5	
	violations announced with debt service default	8	
	violations announced with qualified auditor opinion	7	
	violations announced with IPO	2	
	violations announced with restatement	5	
	violations announced with non-accounting based covenant	2	
	violations without detailed information	13	
			91
less:	firms with no CAR results on EVENTUS	22	
			69
less:	firms with missing necessary COMPUSTAT items	3	
Final sample			66

Table 1 presents sample selection process.
[1]filings include 10-K, 10-Q, and 8-K.

EMPIRICAL RESULTS

Market Reactions to the Announcement of Financial Covenant Violation

To compute abnormal returns, I choose the market model and CRSP equally weighted market portfolio return. I use an estimation period of 300 trading days from day +61 to day +360, where day 0 is the technical default announcement date. By using the post-event estimation period, I avoid the effect of potential risk shifts immediately preceding the technical default announcement (Beneish and Press, 1995a; Holthausen and Leftwich, 1986).

The descriptive statistics of cumulative abnormal returns are reported in Table 2. As Table 2 shows, the mean cumulative abnormal return from days -1 to +1 is -1.67 percent, a shareholder wealth loss, which is significant at the 3 percent level. The mean cumulative abnormal return on the exact date of announcement is -1.25 percent, significant at the 2 percent level. The negative market reaction on the date of the technical default announcement contributes most to the wealth loss during the three-day event window. Hereafter, I use three-day cumulative abnormal returns as the measure of shareholder wealth loss on announcement dates of technical default.

Table 2: Descriptive Statistics of Cumulative Abnormal Return

Variable	N	Mean	Median	Std Dev	First Quartile	Third Quartile	P-value
(-30,-2) CAR	66	-0.0287	-0.0240	0.1812	-0.1038	0.0548	0.2031
(-1,0) CAR	66	-0.0123	-0.0098	0.0484	-0.0378	0.0145	0.0424**
(0,0) CAR	66	-0.0125	-0.0085	0.0412	-0.0205	0.0991	0.0164**
(0,+1) CAR	66	-0.0168	-0.0122	0.0614	-0.0374	0.0049	0.0295**
(-1,+1) CAR	66	-0.0167	-0.0193	0.0607	-0.0433	0.0067	0.0292**
(+1,+30) CAR	66	-0.0286	-0.0450	0.1948	-0.1207	0.0447	0.2370

[1]CAR is cumulative abnormal return is the raw stock return minus the CRSP equally-weighted market portfolio return. Market portfolio return is estimated over 300 trading days from day +61 to day +360.
*[2]P-value is for H0: CAR=0 using a two-tailed student-t. * significant at 10%; ** significant at 5%; *** significant at 1%.*

To further examine whether shareholders are more likely to experience a wealth loss on the announcement date of a technical default, I implement a binomial test of equal likelihood of positive and negative *CAR* around violation announcement dates. The result is shown in Table 3. The null hypothesis is rejected at the 0.0016 level, indicating that firms are more likely to experience a negative market reaction when they announce technical default.

Table 3: Binomial Test of Equal Likelihood of Positive and Negative CAR (-1, +1)

CAR(-1,+1)	Frequency	Percent	Cumulative Frequency	Cumulative Percent
CAR<0	45	68.18	45	68.18
CAR>=0	21	31.82	66	100
Test of H0: Proportion = 0.5				
ASE under H0		0.0615		
Z		2.954		
One-sided Pr > Z		0.0016		
Two-sided Pr > |Z|		0.0031		
Exact Test				
One-sided Pr >= P		0.0021		
Two-sided = 2 * One-sided		0.0043		

CAR is cumulative abnormal return is the raw stock return minus the CRSP equally-weighted market portfolio return. Market portfolio return is estimated over 300 trading days from day +61 to day +360. P-value is for H0: firms are equally likely to experience a positive and negative market reaction.

<u>Descriptive Statistics of Other Variables</u>

Other descriptive statistics for the sample are presented in Table 4. In Panel A of Table 4, 62 percent of firms disclosed financial covenants in previous SEC filings before they announced technical default. Seventy-seven percent of the firms obtained waivers by the time they announced technical default to the public. Seventy-four percent of the firms chose to announce the covenant violation in 10-K or 10-Q fillings; for the remaining 26 percent of firms, the violation announcements first appeared on either the newswire or 8-K filings. Mean (median) *LEV* is 0.60 (0.57), similar to the mean (median) leverage of 0.62 (0.62) in Beneish and Press (1993). Both the mean and median of the earnings surprise, *SUR*, are negative, which indicates that most firms experienced unexpected low earnings in the quarter right before they announced technical default. The size of the debt contract, *DT_SIZE*, differs from one million to one billion. However, the mean contract is 46 percent of the total liabilities of an individual firm. The sizes of my sample firms are larger than that of Beneish and Press (1993). Mean and median of total assets in my sample are approximately 1,501 and 329 million; in Beneish and Press (1993, 1995a), the mean and median are 493 and 104 million, respectively. Overall, my sample firms are relatively larger compared to Beneish and Press (1993, 1995a), but the capital structures of firms in both samples are similar in terms of leverage.

Panel B and C of Table 4 take a closer look at the sample from the contract materiality perspective. First, Panel B shows that 49 firms have debt that exceeds 10 percent of their total assets, which is the Regulation S-K threshold, whereas 14 firms have debt below the threshold. To further decompose the sample, I find that among the contracts that exceed the threshold, 78 percent of the firms chose to disclose their covenants, whereas among the contracts under the 10 percent threshold, only 21 percent disclosed covenants. This result is consistent with the intuition that firms tend to disclose their financial covenants when the debt contract is above the materiality threshold. Using the proxy for materiality in this study, I also partition the sample by the median of debt contract size over total liabilities to see whether there is the same trend as discovered above. As expected, the number of firms that disclose their financial covenants is 18 percent higher in the group where contracts exceed the median of *DT_SIZE_SL* than in the other group. These two panels not only provide the evidence that materiality is positively correlated with the tendency to disclose the covenant but also show that the proxy for materiality threshold chosen, median *DT_SIZE_SL*, is valid.

Table 4: Descriptive Statistics and Number of Observations by Materiality Threshold (1)

Panel A: Descriptive Statistics						
Variable	**N**	**Mean**	**Median**	**Std Dev**	**1st Quartile**	**3rd Quartile**
DIS	66	0.6212	1			
WAIVER	66	0.7727	1			
NEWS	66	0.2576	0			
LEV	66	0.5982	0.5676	0.3617	0.3882	0.7161
SUR	66	– 0.1522	– 0.0850	0.5934	– 0.2700	0
TA	66	1,501.1	329.37	6,267.7	100.55	854.63
LTA	66	5.6891	5.797	1.657	4.611	6.751
DT_SIZE	58	88.646	18.200	177.65	3.900	125
DEBT_USED	58	0.4328	0.1228	2.304	0.0140	0.2130

Panel B: Number of Observations by Materiality Threshold (1)			
	Disclose Covenants	**Not Disclose Covenants**	**Total**
contracts that exceed 10% threshold[1]	38 (78%)	11 (22%)	49
contracts that do not exceed 10% threshold	3 (21%)	11 (79%)	14
Panel C: Number of Observations by Materiality Threshold (2)			
	Disclose Covenants	**Not Disclose Covenants**	**Total**
contracts above the median of DT_SIZE_SL[2]	23 (74%)	8 (26%)	31
contracts below or equal to the median of DT_SIZE_SL	18 (56%)	14 (44%)	32

CAR is cumulative abnormal return that is the raw stock return minus the CRSP equally-weighted market portfolio return during three-day window. Market portfolio return is estimated over 300 trading days from day +61 to day +360.
DIS is 1 if the firm disclosed its financial covenants in either a 10-k, 10-Q, or 8-K filing before it announced the violation, 0 otherwise.
WAIVER is 1 if a waiver is granted at the time of violation announcement, 0 otherwise.
NEWS is 1 if the violation announcement first appears on the 8-K or newswire, 0 if it appears first on the 10-K or 10-Q.
LEV is the ratio of total liabilities to book value of total assets measured at the end of the fiscal year of covenant violation.
SUR is actual quarterly earnings per share minus the most recent forecast earnings per share closest to, but prior to, the quarterly earnings announcement. A random walk model is used to obtain the last period quarterly earnings when a forecast is not available in I/B/E/S.
TA total assets at the beginning of the fiscal year of covenant violation in millions.
LTA is natural logarithm of total assets measured at the beginning of the fiscal year of covenant violation.
DT_SIZE is the amount of used commitment under the debt agreement.
DEBT_USED is the amount of used commitment under the debt agreement scaled by the total assets at the beginning of the fiscal year
[1]Regulation S-K requires a company to file an exhibit to form 10-K if the amount of debt exceeds 10% of its total assets.
[2]DT SIZE SL is defined in Panel A.

Regression Results

In Table 5, I present the results of a multivariate analysis using the ordinary least squares estimation. The dependent variable is *CAR* during the (-1, +1) event window. I start with two benchmark models. Column (1) presents the result of the first benchmark model with three independent variables, *LEV*, *SUR,* and *LTA*. By adding two covenant-related variables, *WAIVER* and *NEWS*, the model in column (2) is improved by an increase of 3.58 percent in adjusted R-squared. To test Hypothesis 1, I show in column (3) that the variable of interest, *DIS*, increases the model's explanatory power by 1.9 percent. More to the point, as hypothesized, *DIS* is significantly positively correlated with *CAR* with a coefficient of 0.0217. This suggests that firms disclosing financial covenants experience 2.17 percent less negative returns than those firms not disclosing related covenants.

Table 5: Regression Analysis

Variable	Predicted Sign	Benchmark Models		Main Models	
				MODEL1	MODEL2
		(1)	(2)	(3)	(4)
Intercept	?	0.0193	0.0068	– 0.0076	– 0.0336
		(0.4089)	(0.8180)	(0.8013)	(0.3264)
DIS	+			0.0217	
				(0.0524)*	
DT_SIZE_SL	?				0.0325
					(0.0899)*
WAIVER	+		0.0059	0.0071	0.0033
			(0.3592)	(0.3287)	(0.4219)
NEWS	–		– 0.0318	– 0.0374	– 0.0428
			(0.0220)**	(0.0098)***	(0.0042)***
LEV	–	– 0.0378	– 0.0348	– 0.0392	– 0.0255
		(0.0240)**	(0.0319)**	(0.0184)***	(0.0892)*
SUR	+	0.0486	0.0475	0.0480	0.0489
		(<.0001)***	(<.0001)***	(<.0001)***	(<.0001)***
LTA	?	– 0.0011	0.0014	0.0022	0.0062
		(0.7961)	(0.7270)	(0.5964)	(0.1624)
Sample Size		66	66	66	63[1]
Unadjusted R^2		0.3146	0.3697	0.3975	0.4280
Adjusted R^2		0.2814	0.3172	0.3362	0.3667
Regression P-value		<.0001	<.0001	<.0001	<.0001

CAR is cumulative abnormal return that is the raw stock return minus the CRSP equally-weighted market portfolio return during three-day window. Market portfolio return is estimated over 300 trading days from day +61 to day +360.
DIS is 1 if the firm disclosed its financial covenants in either a 10-k, 10-Q, or 8-K filing before it announced the violation, 0 otherwise.
DT_SIZE_SL is the aggregate lending commitment amount under the agreement scaled by total liabilities at the beginning of the fiscal year of covenant violation.
WAIVER is 1 if a waiver is granted at the time of violation announcement, 0 otherwise.
NEWS is 1 if the violation announcement first appears on the 8-K or newswire, 0 if it appears first on the 10-K or 10-Q.
LEV is the ratio of total liabilities to book value of total assets measured at the end of the fiscal year of covenant violation.
SUR is actual quarterly earnings per share minus the most recent forecast earnings per share closest to, but prior to, the quarterly earnings announcement. A random walk model is used to obtain the last period quarterly earnings when a forecast is not available in I/B/E/S.
LTA is natural logarithm of total assets measured at the beginning of the fiscal year of covenant violation.
[1]Compared to Model 1, Model 2 has 63 firms because lending commitment amounts for three contracts are unavailable. I also run the benchmark models based on these 63 firms, and the R-squares are 0.2888 and 0.3447, respectively.
P-values are provided below the coefficients (one-tailed when sign is predicted) and are in parentheses. significant at 10%; ** significant at 5%; *** significant at 1%.*

The signs for all control variables are as expected. I find that although the sign on *WAIVER* is positive, it is not statistically significant. This insignificance might be due to the fact that waivers are routinely granted. As private lenders try to set tighter covenants in order to obtain more frequently updated financial information (Dichev and Skinner, 2002), firms violate covenants more often but are also granted waivers more often. In addition, Beneish and Press (1993) and Chen and Wei (1993) show that waivers are not costless, since firms that obtain waivers following renegotiation face higher interest rates, have more covenants, and divest more frequently. Hence, even if a firm is able to obtain a waiver, the market does not necessarily consider it a positive signal.

NEWS is negatively related with *CAR*, indicating that the price reaction is 3.74 percent more negative when technical defaults are announced on Newswire or an 8-K than in the 10-Ks or 10-Qs. This price response difference is similar to the 3.14 percent difference found in Beneish and Press (1995b). This is consistent with the argument in Beneish and Press (1995b) that news media selectively report events that affect a relatively larger number of investors or that are relatively more costly covenants.

Consistent with prior research, *LEV* is significantly negatively related to the market reaction, suggesting that the higher the leverage ratio, the higher the cost of technical default, and thus the stronger the negative price reaction. As expected, earnings surprise, *SUR*, has a positive coefficient, indicating that a larger magnitude of positive earnings surprise is more likely to have a positive market reaction, or at least a less negative reaction. *LTA* is positive but insignificant.

To test Hypothesis 2, I run Model 2 by substituting *DT_SIZE_SL* for *DIS* in Model 1. The sign and significance of all the control variables are similar to the results of Model 1. The significant positive coefficient on *DT_SIZE_SL* provides evidence that the disclosure effect dominates the materiality effect. As discussed earlier, the materiality effect predicts that the technical default of material debt contracts would induce a stronger negative market reaction, whereas the disclosure effect predicts a smaller magnitude of negative price response since firms tend to disclose material contract terms, managers are more likely to discuss the default risk of larger contracts, and larger contracts are more closely watched by investors. The result shows that the technical default of material debt contracts leads to a smaller negative market reaction than that of less material contracts: it indicates that the disclosure effect dominates the materiality effect.

To further examine the disclosure effect from the effect of the materiality of the contract, I partition the sample into two groups by the median of relative importance of the contracts, *DT_SIZE_SL*. Group 1 includes firms where *DT_SIZE_SL* is less than or equal to the median, while group 2 consists of firms with *DT_SIZE_SL* greater than the median. Heitzman et al. (2010) report that in general, the firms choose the materiality threshold as a result of negotiation among management, auditors, and regulators. Since the materiality threshold of covenant disclosure is unobservable, I use median *DT_SIZE_SL* to proxy for the materiality threshold for disclosure decisions. This materiality threshold is a cut-off such that for group 2 (above the threshold), the information is material enough to warrant disclosure. While for group 1 (below the threshold), the information is not material enough to require disclosure. Hence, the materiality threshold is assumed likely not to be binding for group 1, but is assumed binding for group 2. Of course, it is possible that some firms in group 1 do disclose. If a firm in group 1 discloses the terms of debt covenants, then I interpret it as a case of "voluntary" disclosure. First, I test whether *DIS* still plays a role in determining *CAR* for each group.

In Table 6, results of Model 1 are presented in columns (1) and (2). First, the coefficient on *DIS* (α_1=0.0275 and p-value=0.0798) of group 1 in column (1) suggests that when a contract is less material, disclosing covenants in previous filings alleviates 2.75 percent of the negative market reaction. Heitzman et al. (2010) posit that even when the materiality threshold is not binding, managers may voluntary disclose the information if they expect the benefits (for example, market reaction in this case) to outweigh the costs. My results provide evidence that supports the argument in Heitzman et al. (2010). For group 2 in column (2), *DIS* (α_1=0.0164 and p-value=0.2283) is insignificant, which indicates that *DIS* does not explain much about the *CAR*. This insignificance might be due to the fact that those firms met the materiality threshold and disclosed their financial covenants anyway. Therefore, there is not much variation in *DIS* itself. As a result, group 1, where materiality is not binding, primarily drives the finding that the disclosure decision affects market reaction to technical default.

Second, to further support the hypothesis that the disclosure of financial covenants reduces shareholder wealth loss mainly for less-material contracts, I re-run Model 2 for the two groups. If the first hypothesis still holds, I expect that *DT_SIZE_SL* will not be significant in group 1 because it is *DIS* and not *DT_SIZE_SL* that explains the variance of *CAR*. Regression results are reported in Columns (3) and (4) on Table 7. As expected, *DT_SIZE_SL* is insignificant in group 1, indicating that the relative size of a contract is not correlated with price responses to technical default when materiality is not binding. However, *DT_SIZE_SL* shows significance (β_1=0.073 and p-value=0.0203) in group 2, and this implies that when materiality is binding, *CARs* are positively, significantly related to the relative size of a contract, consistent with the finding shown on Table 6.

Table 6: Regression Analysis for Partitioned Sample

Variables	Predicted Sign	Model 1 Group 1 (1)	Model 1 Group 2 (2)	Model 2 Group 1 (3)	Model 2 Group 2 (4)
Intercept	?	0.0012	–0.0154	–0.0177	–0.0636
		(0.9805)	(0.7202)	(0.7675)	(0.1578)
DIS	+	0.0275	0.0164		
		(0.0798) *	(0.2283)		
DT_SIZE_SL	?			0.0079	0.0730
				(0.9251)	(0.0203) **
WAIVER	+	0.0064	0.0272	0.0033	0.0114
		(0.3954)	(0.1466)	(0.4519)	(0.3168)
NEWS	–	–0.0137	–0.0552	–0.0214	–0.0516
		(0.3054)	(0.0071) ***	(0.2441)	(0.0052) ***
LEV	–	–0.0446	–0.0628	–0.0361	–0.0145
		(0.0290) **	(0.1024)	(0.0624) *	(0.3760)
SUR	+	0.0547	0.0330	0.0566	0.0360
		(0.0002) ***	(0.0602) *	(0.0003) ***	(0.0320) **
LTA	?	0.0006	0.0033	0.0060	0.0024
		(0.9179)	(0.6014)	(0.4221)	(0.6796)
Sample Size		34	32	31[1]	32
Unadjusted R^2		0.5203	0.3142	0.5302	0.4368
Adjusted R^2		0.4137	0.1496	0.4127	0.3016
Regression P-value		0.0017	0.1189	0.0034	0.0172

Group 1 includes firms with DT_SIZE_SL<=0.4545; group 2 includes firms with DT_SIZE_SL>0.4545 where 0.045 is the median of DT_SIZE_SL of whole sample.
CAR is cumulative abnormal return that is the raw stock return minus the CRSP equally-weighted market portfolio return during three-day window. Market portfolio return is estimated over 300 trading days from day +61 to day +360.
DIS is 1 if the firm disclosed its financial covenants in either a 10-k, 10-Q, or 8-K filing before it announced the violation, 0 otherwise.
DT_SIZE_SL is the aggregate lending commitment amount under the agreement scaled by total liabilities at the beginning of the fiscal year of covenant violation.
WAIVER is 1 if a waiver is granted at the time of violation announcement, 0 otherwise.
NEWS is 1 if the violation announcement first appears on the 8-K or newswire, 0 if it appears first on the 10-K or 10-Q.
LEV is the ratio of total liabilities to book value of total assets measured at the end of the fiscal year of covenant violation.
SUR is actual quarterly earnings per share minus the most recent forecast earnings per share closest to, but prior to, the quarterly earnings announcement. A random walk model is used to obtain the last period quarterly earnings when a forecast is not available in I/B/E/S.
LTA is natural logarithm of total assets measured at the beginning of the fiscal year of covenant violation.
**0.045 is the median of DT_SIZE_SL of whole sample.*
***group 1 under model 2 lost three firms because of no information on lending commitment amounts for the three firms.*
*P-values are provided below the coefficients (one-tailed when sign is predicted) and are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.*

To summarize the results for group 2, this group has contracts that meet the materiality threshold, so firms in this group are more likely to disclose the contracts and attract more attention from the public through the terms of their debt contracts. Last, but not least, the omitted correlated variable problem between *DIS* and *DT_SIZE_SL* no longer exists on Table 7, since only one of them relates to the dependent variable *CAR* within each group.

Collectively, the results from both Table 5 and Table 6 are generally consistent with Hypothesis 1. Disclosure of financial covenants in SEC filings reduces shareholder wealth loss when the technical default is announced, in particular, for firms where materiality condition is not binding. That is, voluntary disclosure of covenant information allows investors to assess the financial condition of firms in a timely fashion so that the impact of a technical default announcement is better anticipated and the negative market reaction is attenuated. Regarding Hypothesis 2, this study provides evidence that market responses vary systematically with the relative size of a contract at times when materiality is binding.

CONCLUSIONS AND LIMITATIONS

This study investigates the benefits of disclosing financial covenants in SEC filings to shareholders. Specifically, it provides empirical evidence that disclosing financial covenants in previous SEC filings reduces the negative price responses on the announcement date of a technical default. Additional tests reveal that this specific type of benefit mainly shows up for firms where materiality is not binding. This result suggests that "voluntary" disclosure is especially effective in providing useful information to investors in a timely manner, so that investors are able to better assess the probability of technical default and take appropriate action, if they wish. Thus, shareholders experience a less negative market reaction on the announcement date of technical default. When materiality is binding, firms are more likely to disclose the covenants of these contracts, and thus, the disclosure variable is no longer the distinguishing factor. The result shows that material contracts tend to have smaller negative market reactions. As discussed earlier, one potential reason is that the risk of violating the covenant of such material contracts is more frequently discussed by management. Another reason could be that material contracts tend to receive more attention from investors. As a result, the surprise on the announcement date of the technical default is smaller. These findings have financial reporting implications for financial communities and standard setters. Specifically, since FASB has been trying to improve the disclosure effectiveness by clarifying materiality, it might consider the evidence that debt covenant disclosure is material to investors, especially for debt contracts that fall short of extant disclosure requirements. At the same time, this finding is also useful for companies that are trying to decide whether to disclose the terms of debt covenants.

One limitation of this study is the small sample due to the hand-collected data collection process, which restricts research design. For example, I could not partition sample firms based on the 10 percent criterion because one of the sub-samples would be too small to run a multivariate analysis. In addition, the collinearity problem between *DIS* and *DT_SIZE_SL* is difficult to remedy in a small sample. Future studies could employ larger samples to conquer these limitations and improve our understanding of how the disclosure of debt covenant terms affects shareholder wealth.

APPENDIX

Appendix A: An Example of how Investors Use Covenant Information to Evaluate the Probability of Technical Default

<u>Part 1: Disclosure of Financial Covenants in the Year the Contract Is Signed</u>

The following information is extracted from 10-Q filings on Nov 15, 1999 of HOOPER HOLMES INC (ticker: HH).

AMENDED AND RESTATED REVOLVING CREDIT AND TERM LOAN AGREEMENT

The borrowers shall not:

8.14 Consolidated net loss: suffer a consolidated net loss in any two fiscal quarters occurring in any period of twelve consecutive months.

8.15. Consolidated fixed charge coverage ratio: permit its consolidated fixed charge coverage ratio to be at any time less than 1.50 to 1.00, measured on a quarterly basis for the relevant test period.

Consolidated net loss shall mean for any fiscal period relevant to the determination thereof, the circumstance that would exist if the results reported on an income statement of the borrower prepared in accordance with GAAP, consistently applied, on a consolidated basis, report a net loss for such fiscal period.

Consolidated fixed charge coverage ratio shall mean the ratio of (A) the borrower's net income (excluding non-cash extraordinary items or non-cash post-tax non-operating earnings adjustments) plus amounts (without duplication) deducted from net income in respect of income tax expense, interest expense, depreciation and amortization expense and lease and rental expense to (B) the sum of (y) the current maturities on long term indebtedness (excluding, however, in all cases any current maturities in respect of borrower's obligations under the revolving credit loans) plus (z) the interest expense and lease and rental expense otherwise added back into the borrower's net income pursuant to clause (A) above, in each case determined for the relevant test period on a consolidated basis in accordance with GAAP, consistently applied.

Part 2: Announcement of Technical Default

The following information is extracted from 10-K filings on May 2, 2006 of HOOPER HOLMES INC (ticker: HH).

For the year ended December 31, 2005, the company was not in compliance with two financial covenants: (i) that the company will not incur a consolidated net loss in any two fiscal quarters in any twelve consecutive months; and (ii) that the company will not permit its consolidated fixed charge coverage ratio to be less than 1.50 to 1.0 for the period ended December 31, 2005. The company recognized a consolidated net loss for the quarters ended September 30, 2005 and December 31, 2005. At December 31, 2005, the company's consolidated fixed charge coverage ratio was 1.10 to 1.00. On April 25, 2006, the company obtained a waiver of the above-described issues of non-compliance from the lenders.

Part 3: How Investors Use Covenant Information to Evaluate the Probability of Technical Default as Evidence in Support of Hypothesis 1 (H1)

The company reported a $2,491,000 net loss for the quarter ended September 30, 2005 on October 30, 2005. In addition, median (mean) analyst forecast made during the third quarter is a $5,500,000 ($5,500,000) net loss for the quarter ended December 31, 2005. As a result, (1) investors are able to see that this company is highly likely to violate the covenant related to consolidated net loss; (2) regarding the consolidated fixed charge coverage ratio, here is the simplified version of the formula to compute the ratio:

$$\frac{\text{net income} + \text{non - cash extraordinary} + \text{income tax expense} + \text{interest expense} + \text{depreciation/amortization}}{\text{current - maturity of long - term debt} + \text{interest expense}} \quad (3)$$

Using the data for the third quarter ended on September 30, 2005, one finds that the net loss is 2.5 million, and the numerator is likely to be negative. Thus, the covenant minimum level of 1.5 cannot be easily met.

Part 4: Conclusion

Before the news of technical default first appeared in the news media (PR. Newswire) on April 25, 2006 and was later announced in 10-K filings on May 2, 2006, investors were able to find that this company was about to violate its financial covenants during the fourth quarter of 2005.

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BIOGRAPHY

Ping Wang is an Assistant Professor at Lubin School of Business, Pace University. She can be reached at pwang@pace.edu

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INVESTOR ATTENTION, PSYCHOLOGICAL ANCHORS, AND THE STEALTH INDEX

Chih-Wen Yang, National Yunlin University of Science and Technology
Chun-An Li, National Yunlin University of Science and Technology
Sam Ting-Hsin Hsu, National Yunlin University of Science and Technology

ABSTRACT

We categorize the stocks in the Taiwan share market by size, value, and growth, then form the portfolio index for each group according to the Taiwan Stock Exchange's weighted index method. Li and Yu's (2012) measurement method for investors' under- and overreactions, as well as Fama and French's (1993) three-factor analysis, are utilized to examine under- and overreactions regarding shares that cannot be observed by investors. The empirical results indicate that aside from the existence of under- and overreactions in the Taiwan Stock Exchange's weighted index, the indices formed according to stock size, value, and growth also contribute to price reactions. Li and Yu (2012) measure investors' reactions based on anchoring and limited attention. This study discovers that aside from a highly exposed market index, various stocks' non-observable weighted indexes also demonstrate the under- and overreaction phenomenon. This indicates that share prices would still be affected by both limited attention to other important information and the investor's anchoring.

JEL: G12, G14

KEYWORDS: Underreaction, Overreaction, Three-Factor Model

INTRODUCTION

The anomaly of share prices displaying both short-term momentum and long-term reversal has recently piqued scholars' research interest. The behavioral finance realm attempts to provide a different explanation for this phenomenon involving the short-term underreaction and long-term overreaction. Barberis, Shleifer, and Vishny (1998) attribute such phenomenon to investors' psychological anchors and representative biases. Daniel, Hirschleifer, and Subrahmanyam (1998) believe that the phenomenon is due to investors' overconfidence and self-attribution biases. Hong and Stein (1999) claim that the phenomenon can be explained by the limited rational and psychological interaction between news watchers and momentum traders.

The subject matter regarding "Attention" in the behavioral finance field primarily addresses describing the variation in investor psychology, which consequently changes investment behavior when no change occurs in the firm's internal and external environments. This produces abnormal fluctuations and transaction volumes. Li and Yu's (2012) proposed empirical evidence, based on anchoring and limited attention, believes that a 52-week high can be a proxy for investors' underreaction to news events, and a historical high may be a proxy for investors' overreaction to news events, hence forecasting the effect for overall market returns. Despite Li and Yu's (2012) utilization of the highly exposed Dow Jones Industrial Index as a basis for measurement, investors under limited fundamentals will still only react to shares that they hold, or are familiar with (Grullon, Kanatas, and Weston, 2004). However, many news events can spur investors' attention, such as revenue announcements, technical innovations, and new order acquisitions, among other major announcements. Investors' subsequent reactions would not be limited by a highly exposed market index. As the connotation of news events directly affects investors' behavior (Joe, Louis, and Robinson, 2009), we assume that Li and Yu's (2012) measurement would still be effective, despite its existence outside of the high exposure market index. We have consulted a market index's compilation rules to utilize the composite index within the asset portfolio as a proxy for the shares that caught specific investors' attention due to their relevant information.

We then utilized this in our hypothesis testing. As Fama and French's (1993) three-factor model cannot fully explain the short-term returns in the momentum anomaly, financial scholars utilize the behavioral perspective in an attempt to explore the causes of book-to-market (overreaction) and momentum (underreaction) effects. Thus, we consider the aforementioned line of reasoning to utilize the asset portfolio index and follow Li and Yu's (2012) proposed measurement method, which notes under- and overreactions for 52-week high and historical high proxies, respectively. We will discuss both under- and overreaction scenarios according to the following grouping characteristics: large or small, and value or growth shares. For example, small sizes display the underreaction phenomena, but this is not the case with large sizes. Thus, we can be certain that such an anomaly is already captured by size effects; if overreaction exists in valued shares, but not in growth shares, then overreaction can be denoted by the book-to-market effect. The use of such a method can more precisely estimate whether other characteristics would affect the asset portfolio's returns in the momentum and reversal effect groups. We will then conduct a three-factor model analysis of the post-grouping for the under- or overreaction phenomenon. This study focuses on the Taiwanese share market, and the analysis indicates that the Taiwan Stock Exchange's weighted index exhibits both under- and overreaction phenomenon. Further, we group the shares as large, small, value, and growth shares according to the Taiwan Stock Exchange's weighted index rules. The discussion also extends to whether different groups' indices display under- or overreaction. The results demonstrate that the value share index does exhibit under- and overreaction phenomenon. Regarding growth shares index, underreaction only exists in one-month short-term holdings (with a less than 5% significance level) and overreaction appears in various other holding periods, with the exception of the three-month holding period. Regarding the size index, small sizes display apparent under- and overreaction phenomenon and, to a certain extent, display an expanding trend over time (12-month holdings decline); the overreaction phenomenon does not demonstrate a significant relationship with future returns in large sizes, regardless of whether the holding period is 1 to 12 months.

This result implies that the book-to-market and size factors can capture the under- and overreaction phenomenon. As the Taiwan share market displays an approximately 10-year cycle, we dissect this into three subsamples of 10 years each to test whether our hypothesis is robust. The results indicate that the α intercept is not significant in two subsamples, between 1995 and 2005; thus, the three-factor model explains the excess returns. This consequently justifies our inference, whereas Li and Yu's (2012) methodology stipulates that value and scale indices display under- and overreaction phenomenon despite the fact that these indicators are not apparent and not easily observable to investors. This finding indicates that investors would still focus on important information relevant to the shares they hold, and is effective on those shares. Such finding is the major contribution of this study. This study is organized as follows: the first section provide introduction; the second section presents a literature review on market under- and overreactions as well as the three-factor pricing model; the third section establishes the framework for limited attention and anchoring of investors, as well as a proxy measurement for investors' under- and overreaction and a three-factor analysis; the fourth section explains the empirical analysis' results; and the fifth section concludes.

LITERATURE REVIEW

Current finance theories assume an efficient market, in which the market price would immediately react to variations in information. However, recent empirical studies have discovered many anomalies that cannot be explained by modern finance theories. Such empirical studies posit that these are caused by the assumption that the investors are completely rational, but it is apparent that this notion does not hold in an actual finance setting, as investors are both irrational and challenged in their knowledge and skills. Behavioral finance scholars have initially used the cognitive psychology perspective to propose a series of discussions regarding investor behavior to generate a more substantial explanation of market anomalies. It seems that the topic of investor attention is especially perceived as the single most important driver for substantial variations in share prices. Kahneman (1973) claims that investor attention is actually a scarce source of cognition, which would cause the overreaction in a stock's fundamentals due to a specific event. Alternatively, limited attention, as proposed by Engelberg, Sasseville, and Williams (2012), is a situation in which the investor cannot completely process and understand a specific event. The effects of investors' under- and overreaction can explain profit forecasts' underreaction, as stated by Doyle, Lundholm, and Soliman (2003); as well as the price reaction of profit disclosure on Fridays, as noted by DellaVigna and Pollet (2009); plus the excess optimism to net operating earnings, as stated by Hirshleifer and Teoh (2003); and finally, abnormal share purchase levels near announcement dates, as posited by Barber and Odean (2008). The measurements in past literature of under- and overreactions primarily adopt a methodology that involves grouping by different investment strategies. Li and Yu (2012) divert from the conventional method and base their study on investor psychology, which includes anchoring and limited attention. These concepts suggest that indices nearing 52-week and historical highs are capable of acting as proxies for under- and overreaction, respectively.

Their research has proven that such a method is robust in forecasting abilities, and is unaffected by macroeconomic variables. A crucial assumption is that the Dow Jones Industrial Average index significantly affects investors' decisions due to its widespread nature; investors' limited attention occurs due to its high exposure. Such relationships result because, as Peng and Xiong (2006) note, the investor would process more market information than specific company information. Further, Griffin and Tversky (1992) state that investors' behavior only overreacts to prominent long-term records. Due to the low likelihood that the firm can maintain long-term growth, non-observable variables would therefore no longer be able to forecast the market index's historic highs. The proxy for overreaction, in other words, must depend on a high-exposure market index to be sustainable. However, much highly exposed information exists, and the market index is only one of these.

Engelberg, Sasseville, and Williams (2012) traced CNBC's "Mad Money" program to discover that after the host has recommended certain stocks, these shares subsequently experience higher price and trade volumes; Grullon, Kanatas, and Weston (2004) believe that, under the assumption that all conditions are equal, a firm's higher spending on advertising can lead to more investor attention toward the firm, hence receiving expanded investments; Cutler, Poterba, and Summers (1989) state that a relevant relationship exists between the media's report on a firm and its share price; DeLong et al. (1990) believe that media reports (on a firm) affect investor emotion, hence affecting the share price; Urrutia and Vu (1999) note that after information regarding a firm's profitability level becomes significant news, share prices' abnormal returns become apparent; Mian and Sankaraguruswamy (2012) prove that investors' emotions impact the sensitivity of share price reactions to company-specific news; and Joe, Louis, and Robinson (2009) find that the information content expressed by the media can directly affect investors' decisions. In summary, after the release of company-related news or information, the firm and its related industry would receive investor attention leading to variations in asset pricing.

The literature review not only explains the market index, but also highlights the fact that investors' decisions are also significantly affected by other information. Alternatively, investors are limited by time and ability, and cannot thoroughly investigate all stocks for investment. This leads to a constraint on the amount of information that must be analyzed, as further noted by Aboody, Lehavy, and Trueman (2010). Moreover, Merton (1987) highlighted the individual investor's tendency to hold a few stocks in a portfolio; the investor only purchases stocks that are familiar, and does not act impulsively in buying unfamiliar stocks. Barber and Odean (2008) also indicate that individual investors tend to be more prone to being affected by media reports, and consequently purchase the shares reported by the media. Grullon, Kanatas, and Weston (2004) state that due to their limited attention, investors often buy into familiar shares that caught their attention. The literature discussed here, other than that pertaining to the market index, allows this study to draw inferences regarding the other important information that stimulates investors' attention, as reflected in the share price in the investor's possession. If the shares held by the investor are perceived as an investment portfolio that follows the market indices' grouping method, we then assume such a portfolio index is equipped with the same effect as those that adopt the Dow Jones Index, as Li and Yu (2012) have posited.

Fama and French's (1993) three-factor pricing model greatly affects modern asset-pricing theories. This pricing model is a descendant of both the asset portfolio theory, as discussed by Markowitz (1959), Sharpe (1964), and Lintner (1965); and Black's (1972) CAPM theory, which explains asset returns from a risk perspective. Fama and French (1993) believe that portfolio returns can possibly relate to factors other than merely size, BM ratio, debt ratio, or PE ratio, among others. The authors posit that this is a result of risk tradeoff, in which the return is determined by the risk. This excludes the market factor, which leads to abnormal returns in the asset portfolio; this can also be explained by such risk factors as the "small minus big" (SMB) and "high minus low" (HML) factors, and as a summation of multiple influential factors. However, no model can completely rectify the existence of return momentum. Concurrently, expressing the Size and BM risk factors only as risk factors are strongly questioned. Daniel, Hirshleifer, and Subrahmanyam (1998) explain this through investor overconfidence and a self-attribution bias. Barberis, Shleifer, and Vishny (1998) believe that investors' limited ability causes an inadequate reaction from the short-term share price, and history will repeat itself, leading to overreaction. Hong and Stein (1999) alternatively perceive that investors' under- and overreaction is due to the velocity of spreading information. Previous studies have widely discussed the causes of BM and momentum effects. For example, Li and Yu (2012) utilized anchoring and limited attention in investor psychology to discover two important variables, namely, under- and overreaction. They also prove during this process that these two variables are not affected by macroeconomic fluctuations. Our study utilizes their method to group the three-factor model's key elements—namely, the Size and BM factors—before illustrating a portfolio index in various groups to explore the variation in momentum and reversal effects. Finally, we use a three-factor cross-sectional regression analysis to confirm whether our hypothesis regarding asset portfolio returns can provide extended explanatory ability.

DATA AND METHODOLOGY

This study's data is sourced from the *Taiwan Economic Journal*. The sample period spans June 1995 to May 2015, and the sample includes publicly traded shares from the Taiwan Stock Exchange, excluding delisted shares; we do not exclude financial shares and full-cash delivery stocks. We adopt weekly data for our empirical study, which differs from the monthly data used in previous research, as the abnormal anomaly of investors' under- and overreaction can end in a short span of time. Therefore, this study increases its data intensity to capture this specific phenomenon, to adhere to the true nature of investor behavior and avoid a result impacted by low data frequency. Li and Yu (2012) discovered two important variables for modern investors' under- and overreaction behavior from the New York Stock Exchange's data, based on the limited attention and anchoring concepts. The Dow Jones index, in nearing its 52-week high proxy for investor underreaction, is expressed as follows:

$$X_{52,t} = \frac{p_t}{p_{52,t}} \tag{1}$$

The Dow Jones index nearing its historic high proxy for investor overreaction is expressed as follows:

$$X_{max,t} = \frac{p_t}{p_{max,t}} \tag{2}$$

The former positively relates to future share market returns, and the latter negatively relates to future share market returns. Li and Yu (2012) also prove that these two proxies' explanatory ability would not be affected by macroeconomic variables. This finding provides a sound method to examine past debates on abnormal market phenomenon. Contrary to the traditional method, which involves a grouping analysis through factor dimensions, we can be more intuitive in comparing the differences in investors' under- and overreactions, as an apparent contrast in various assumptions of factors. A retrospective analysis can be conducted, and a specific cause can then be discovered. Li and Yu's (2012) methodology involves conducting a monthly overlapping regression on the share trading data from the US market, and using international data to prove that such a method has sound explanatory power among G7 member nations. As the data used here is not listed in the G7 nations, we utilize the Taiwan Stock Exchange's weighted index as a proxy for the US market's Dow Jones index; thus, we can confirm its suitability in Taiwan's stock market. Further, the five explanatory variables are used to deduct the risk-free rate from the actual rate of return in the Taiwan Stock Exchange's weighted index, and forms $R_{pass,t}$ to represent past abnormal returns (1, 3, 6, and 12 months). The risk-free rate here is taken from the First Bank of Taiwan's one-year term deposit rate. Further, $X_{52,t}$ represents the extent of the Taiwan Stock Exchange's weighted index nearing its 52-week high, which acts as a proxy for investors' underreaction; $X_{max,t}$ represents the extent of the Taiwan Stock Exchange's weighted index nearing its historic high, which acts as a proxy for investor overreaction; D_t is the dummy variable, which assumes a value of 1 when the Taiwan Stock Exchange's weighted index is at a historic high, and 0 otherwise; I_t is also a dummy variable, which represents the stock price index's reaching a new high to imply investors' underreaction, and assumes a value of 1 when the 52-week high of the Taiwan Stock Exchange's weighted index equals the historic high, and 0 otherwise. The regression to examine under- and overreaction is as follows:

$$R_{future,t} = \alpha_0 + \beta_1 R_{pass,t} + \beta_2 X_{52,t} + \beta_3 X_{max,t} + \beta_4 D_t + \beta_5 I_t + \varepsilon_t \quad (3)$$

The dependent variable $R_{future,t}$ represents the future abnormal returns (1, 3, 6, and 12 months) and corresponds to $R_{pass,t}$. Table 1 presents the summary statistics for the correlated variables. Panel A indicates that the last month's abnormal return in the Taiwan Stock Exchange's weighted index R_t has an average value close to 0, the X_{52} average value nearing the 52-week high is 0.84, and the X_{max} historic high is only 0.57. This demonstrates that the Taiwan Stock Exchange's weighted index does not exhibit abnormal returns in the short-term (1 month), and the time nearness to a 52-week high is significantly longer than those close to the historic high, which parallels our expectations. Panel B illustrates a correlation coefficient between X_{52} and X_{max} of 0.56, which is higher than expected. However, these two variables' market return forecasting operates in contradictory directions; therefore, these two variables will incorporated into the forecast regression.

Table 1: Descriptive Statistics

Panel A： Summary Statistics					
	R_t	X_{52}	X_{max}	D_t	I_t
Mean	0.00	0.84	0.57	0.02	0.13
Std.	0.09	0.16	0.17	0.15	0.34
Skewness	-0.24	-1.30	0.54	6.30	2.18
Kurtosis	7.22	4.52	3.09	40.70	5.75
Panel B：Correlation Matrix					
	R_t	X_{52}	X_{max}	D_t	I_t
R_t	1.00				
X_{52}	0.34	1.00			
X_{max}	0.26	0.56	1.00		
D_t	0.31	0.15	0.41	1.00	
I_t	0.05	-0.22	0.44	0.40	1.00

Panel A presents the forecast variables' mean, standard deviation, skewness, and kurtosis. R_t represents the abnormal return of the past one month; X_{52} represents the extent of the Taiwan Stock Exchange's weighted index approaching a 52-week high; X_{max} represents the extent of the Taiwan Stock Exchange's weighted index approaching a historic high; D_t represents the Taiwan Stock Exchange's weighted index reaching a historic high; I_t represent the Taiwan Stock Exchange's weighted index reaching a new high. Panel B explains the same forecast variables through the correlation matrix. The sample period of the Taiwan Stock Exchange's weighted index occurs between June 1986 to May 2016.

We utilize the past 30 years of data from the Taiwan Stock Exchange's weighted index to test the model's applicability. Table 2 illustrates the results, and indicates that $X_{52,t}$, the proxy variable for investor underreaction, has a strong and positive explanatory ability for future abnormal returns (1, 3, 6, and 12 months) and increases through the period. This begins with 1 month, at 0.06, to 12 months, at 0.72, and positively relates to future returns, which fits the assumption that compensatory growth follows investor underreaction. Table 2 also reveals that the other variable $X_{max,t}$, a proxy for investor overreaction, has a significantly negative explanatory ability over various future periods of abnormal returns, from -0.09 at 1 month, declining to -1.13 at 12 months. The absolute value increases with the return forecast over time, which fits the assumption that compensatory decline follows investor overreaction. Although the correlation index of X_{52} and X_{max} is quite high (0.56), our forecast variance inflation factor is 2.9, or significantly less than the recommended value of 10 proposed by Kutner, Nachtsheim, and Neter (2004). This demonstrates that our empirical result is not affected by multicollinearity.

Further, only the abnormal return from the past 6 months $R_{pass,t}$ can explain the negative relationship of future abnormal returns, as no other group has such explanatory ability. Only the one-month holding from the historic high in the Taiwan Stock Exchange's weighted index exhibits a positive relationship with future abnormal returns, while other groups do not indicate this significance. Finally, the I_t variable, which implies investor underreaction, displays a significant, positive relationship with future abnormal returns in all groups; therefore, in the process of reaching a new high, compensatory growth is apparent due to investors' underreactions. Generally, Table 2 displays the significant under- and overreaction anomaly in the Taiwan Stock Exchange's weighted index. As the examination method mirrors Li and Yu's (2012) offered assumption, not the only G7 nation can be explained by this method when it is applied to the Taiwan share market such would still offer sound explanatory ability.

Table 2: Monthly Overlapping Regression – Taiwan Stock Exchange's Weighted Index

Horizon	R_t	X_{52}	X_{max}	D_t	I_t	R^2
1 Month	0.07	0.06***	-0.09***	0.07*	0.03*	0.03
	(1.61)	(3.91)	(-3.81)	(1.84)	(1.91)	
3 Months	0.06	0.19***	-0.31***	-0.06	0.16***	0.04
	(1.25)	(6.76)	(-6.80)	(-1.07)	(5.00)	
6 Months	-0.07**	0.46***	-0.73***	-0.01	0.32***	0.10
	(-2.53)	(12.85)	(-12.69)	(-0.10)	(7.66)	
12 Months	-0.04	0.72***	-1.13***	0.15	0.45***	0.12
	(-1.35)	(15.70)	(-15.33)	(0.95)	(10.37)	

This table adopts a monthly overlapping regression, expressed as follows: $R_{future,t} = \alpha_0 + \beta_1 R_{pass,t} + \beta_2 X_{52,t} + \beta_3 X_{max,t} + \beta_4 D_t + \beta_5 I_t + \varepsilon_t$ *where* $R_{future,t}$ *represents future (1, 3, 6, and 12-month) abnormal returns;* $R_{pass,t}$ *represents the past (1, 3, 6, and 12-month) abnormal returns and corresponding future abnormal returns;* $X_{52,t}$ *represents the extent of the Taiwan Stock Exchange's weighted index approaching the 52-week high;* $X_{max,t}$ *represents the extent of the Taiwan Stock Exchange's weighted index approaching a historic high;* D_t *represents the Taiwan Stock Exchange's weighted index reaching a historic high; and* I_t *represents the Taiwan Stock Exchange's weighted index reaching a new high. The risk-free rate, used to calculate the abnormal rate of return, is the one-year fixed-term deposit offered by the First Bank of Taiwan. The sample period for the Taiwan Stock Exchange's weighted index data spans June 1986 to May 2016, and sampling occurs on a monthly basis, with the Newey-West control used to contain heteroscedasticity and autocorrelation. The t-values are presented in brackets. *, **, and *** represent 10%, 5%, and 1% levels of significance, respectively*

Section 170 of Taiwan's Corporations Law states that an annual shareholders' meeting is to be held within six months after the end of the financial year, and relevant financial reports should accompany this meeting, which explains why most publicly traded firms publish their financial reports before the end of June every year. Therefore, in compliance with Fama and French's (1993) methodology, which utilizes the annual change-in-weight method to define SMB and HML. Grouping by size is conducted by an observation of the firm's market value one trading day before each first trading day in June from 1995 to 2015. Stocks are categorized as "big" or "small," or B (50%) and S (50%). Similarly, the book-to-market value is calculated using the first trading day in June compared to the net value of the first quarterly report with the market value at the end of May. After excluding firms with negative net value, the sample is reorganized from big to small, and further categorized into "high" (30%), "medium" (40%), and "low" (30%). Two of each are then cross-grouped into six combinations, namely "SL," "SM," "SH," "BL," "BM," and "BH," and the returns for each of the six are then calculated, from June of the current year to May of the following year. The size premium is represented by (SMB = [(SL + SM + SH) – (BL + BM + BH)] / 3), and the book-to-market premium is represented by (HML = [(SH + BH) – (SL + BL)] / 2).

The market risk premium is represented by (RMF = Rm – Rf), where Rm is the return from the Taiwan Stock Exchange's weighted index; and Rf is the risk-free rate for the First Bank of Taiwan's one-year term deposit. The asset portfolio's abnormal return is represented by (RPF = Rp – Rf), where Rp is the weighted return of six combinations, namely SL, SM, SH, BL, BM, and BH; the intercept α (Jensen's alpha) is the indicator for abnormal returns. If α is significant, the asset portfolio bears abnormal returns that cannot be explained by the three-factor model. Taiwan's stock market has a large number of small shares, and great disparity in its larger stocks, as the value of the top 20 largest stocks exceeds 50% of the entire market. Concerning this specific characteristic of Taiwan's share market, value weights cannot be used to capture the effects of small stocks. We use avoid any distortion of our results by adopting the equal-weight method to calculate the weighting, and specifically DeBondt and Thaler's (1985) calculation method for the accumulative abnormal returns for the 1-, 3-, 6-, and 12-month holding periods. The defining three-factor model, based on the above description, is as follows:

$$RPF_t = \alpha + \beta_1 RMF_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t \tag{4}$$

It is noteworthy that Li and Yu's (2012) reference index (Equation 3) would no longer stand after grouping the samples; hence, we must reconstruct the asset portfolio index. Another grouping method is noted below that considers the Taiwan Stock Exchange's rule (Equation 5), and the groups' weighted stock price index is shown in the following expression:

$$INDEX = \sum_{t=1}^{n} P_t Q_t \; / \, BV \times 100 \tag{5}$$

The INDEX is given by the market value of total shares issued (PtQt) divided by the base value (BV), then multiplied by 100. The base value is the market value of the total shares issued from the first transaction day; the adjustment point for the base value occurs at the first transaction in June. The adjustment is conducted by multiplying the previous base value by the compared value of the total market value prior to the change.

EMPIRICAL RESULTS

This research provides an empirical study of the prices of publicly traded firms listed on the Taiwan Stock Exchange, with a data set spanning 1995 to 2015. The first part of the empirical examination involves the behavioral perspective, comparing the under- and overreaction anomalies under a book-to-market ratio grouping, with the differences in reaction between value stocks and growth stocks. The firm size grouping allows us to examine the differences in price reactions between large and small stocks; the study further extends to explore an explanation for the difference in the groupings by book-to-market ratio and firm size. The second part of this examination begins with the traditional perspective, and compares not only value and growth stocks, but also large and small stocks, using Fama and French's (1993) three-factor method to explain the difference in abnormal returns. This is followed by an examination of our results' robustness.

Under- and Overreaction Phenomenon

This section analyzes groupings by the book-to-market ratio and firm size. Table 3 illustrates the overlapping regression result of grouping by the book-to-market ratio. The result of the value stock analysis in Panel A indicates that both variables X_{52} and X_{max} have the capability to forecast future abnormal returns, and such a capability expands with the increase in the holding period. This result demonstrates that Taiwan's stock market exhibits apparent under- and overreaction. The extent of underreaction increases from 0.11 at 1 month to 1.15 at 12 months; the extent of overreaction increases from -0.11 at 1 month to -1.14 at 12 months. The explanatory capability improves with an increase in the holding period, from 0.04 at 1 month to 0.31 at 12 months. The analysis result for normal stocks in Panel B approximates that in Panel A, but the related reaction is reduced for future abnormal returns. Alternatively, the results in Panel C reveal that only the 6-month period is not significant for X_{52}, as the 1-, 3-, and 12-month holdings indicate significant relationships. The 1-, 6-, and 12-month holding periods all demonstrated significant relationships for X_{max}, while the 3-month period did not. The results in Panel C also indicate that all the groups except for the 6-month holding period exhibit underreactions, while all groups except for the 3-month holding period display the overreaction phenomenon.

The short-term share price momentum displayed in Table 3 is the same as Rosenberg, Reid, and Lanstein's (1985), in which firms with high book-to-market ratio have higher average returns. This also corresponds with Fama and French's (1998) notion that value stocks have higher future returns, and further explains that firms with higher book-to-market ratios (value stocks) are more capable of generating abnormal rates of return than those with low book-to-market ratios. A significant relationship is demonstrated between the variable X_{52} and value stocks toward future abnormal returns for the 6-month holding period, whereas growth stocks do not indicate such a phenomenon. The three-factor model's book-to-market effect confirms that the HML factor includes the underreaction phenomenon. Similarly, the variable X_{max} also confirms that the HML factor exhibits an overreaction phenomenon for the 3-month holding period. Overall, Table 3 reveals that value stocks have both under- and overreaction phenomenon. However, growth stocks' under- and overreactions are not as consistent.

Table 3: Monthly Overlapping Regression – Grouping by Book-to-Market Ratio

	Horizon	1 Month	3 Months	6 Months	12 Months
Panel A: Value Stocks					
	X_{52}	0.11***	0.35***	0.63***	1.15***
		(3.44)	(6.26)	(9.49)	(15.30)
	X_{max}	-0.11***	-0.35***	-0.6***	-1.14***
		(-3.16)	(-5.51)	(-7.93)	(-12.93)
	R^2	0.04	0.09	0.21	0.31
Panel B: Normal Stocks					
	X_{52}	0.05***	0.16***	0.36***	0.61***
		(2.61)	(4.38)	(8.98)	(12.54)
	X_{max}	-0.05**	-0.17***	-0.37***	-0.63***
		(-2.31)	(-3.88)	(-7.39)	(-10.11)
	R^2	0.02	0.04	0.12	0.20
Panel C: Growth Stocks					
	X_{52}	0.05***	0.07*	-0.08	-0.09*
		(2.69)	(1.65)	(-1.5)	(-1.65)
	X_{max}	-0.05**	-0.04	0.21***	0.32***
		(-2.18)	(-0.73)	(3.28)	(4.67)
	R^2	0.02	0.05	0.18	0.34

This table displays the result of the monthly overlapping regression, as follows: $R_{future,t} = \alpha_0 + \beta_1 R_{pass,t} + \beta_2 X_{52,t} + \beta_3 X_{max,t} + \beta_4 D_t + \beta_5 I_t + \varepsilon_t$ *where* $R_{future,t}$ *represents the future abnormal returns (at 1, 3, 6, and 12 months);* $R_{pass,t}$ *represents the past abnormal returns (1, 3, 6, and 12 months) and the corresponding future abnormal returns;* $X_{52,t}$ *represents the extent of the Taiwan Stock Exchange's weighted index reaching its 52-week high;* $X_{max,t}$ *represents the extent of the Taiwan Stock Exchange's weighted index reaching its historical high;* D_t *represents the Taiwan Stock Exchange's weighted index reaching its historical high;* I_t *represents the Taiwan Stock Exchange's weighted index reaching a new high. The risk-free rate for the calculation of abnormal returns is that of the First Bank of Taiwan's one-year term deposit rate. The sample period of the Taiwan Stock Exchange's weighted index spans June 1995 to May 2015, and sampling is conducted monthly. A Newey-West t-statistic is adopted to control for heteroskedasticity and autocorrelation, with the t-values noted in brackets. *, **, and *** represent the 10%, 5%, and 1% levels of significance, respectively.*

Table 4 notes the overlapping period regression result for the grouping by firm size. The analysis for small stocks in Panel A reveals that X_{52} and X_{max}, which respectively proxy for under- and overreaction, are extremely capable of forecasting future abnormal returns. The value of X_{52}increases from 0.18 at 1 month, 0.73 at 6 months, and to 0.53 at 12 months, where it approximates the 3-month level. This indicates that small stocks in Taiwan's stock market demonstrate significant under- and overreaction anomalies, and the extent of underreaction increases in the withholding period while demonstrating an expansionary trend. Alternatively, a similar situation appears in the overreaction, with an expansion from -0.2 at 1 month to -0.69 at 6 months, ultimately reaching -0.34 at 12 months. Panel A in Table 4 indicates that the extent of small stocks' under- and overreactions both peak at six months, then decline thereafter. The model's explanatory capability increases with the withholding period, with 0.08 at 1 month to 0.22 at 12 months. An analysis of large stocks, in Table 4, Panel B indicates that the underreaction anomaly is only apparent under the 1- and 12-month holding periods, relative to the future abnormal returns of 0.04 and 0.18. No significant relationship exists in the 3- and 6-month holding periods. Overreaction anomalies show no significant relationship in large stocks, regardless of the holding period. The model's explanatory capability approximates that of small stocks, in which withholding periods are expanded, from 0.04 at 1 month to 0.40 at 12 months.

Table 4 notes that large stocks' under- and overreactions are less significant than those of small stocks. This short-term momentum result is similar to Banz's (1981) finding, in which small firms provide higher returns than large firms. Further, a future abnormal return is positively associated with X_{52}, a proxy for underreaction; and negatively associated with X_{max}, a proxy for overreaction. This finding also parallels the assumptions outlined in Li and Yu's (2012) method. We can compare the performance of X_{52} in small and large stocks to observe that these stocks appear to exhibit both significant and non-significant relative associations for the 3- and 6-month holding periods, and by defining size effects, we can confirm that the SMB factor covers the underreaction anomaly; following the same method, the utilization of X_{max} also confirms the 1- to 12-month holding period groups, with the SMB factor covering the overreaction anomaly. Generally, Table 4 indicates that small stocks exhibit consistent under- and overreactions, whereas such an anomaly is mostly not significant for large stocks.

Table 4: Monthly Overlapping Regression – Grouping by Firm Size

	Horizon	1 Month	3 Months	6 Months	12 Months
Panel A: Small Stocks					
	X_{52}	0.18***	0.54***	0.73***	0.53***
		(5.82)	(8.71)	(7.88)	(5.36)
	X_{max}	-0.20***	-0.58***	-0.69***	-0.34***
		(-5.53)	(-7.83)	(-6.19)	(-2.73)
	R^2	0.08	0.10	0.17	0.22
Panel B: Large Stocks					
	X_{52}	0.04**	0.05	0.04	0.18***
		(2.00)	(1.20)	(0.73)	(3.18)
	X_{max}	-0.04	-0.01	0.08	-0.01
		(-1.44)	(-0.15)	(1.31)	(-0.13)
	R^2	0.04	0.11	0.26	0.40

*Taiwan Stock Exchange's weighted index reaching its historical high; and I_t represents the Taiwan Stock Exchange's weighted index reaching a new high. The risk-free rate for the calculation of abnormal returns is that of the First Bank of Taiwan's one-year term deposit rate. The sample period of the Taiwan Stock Exchange's weighted index spans June 1995 to May 2015, with sampling conducted monthly. A Newey-West t-statistic is adopted to control for heteroskedasticity and autocorrelation, with t-values noted within brackets. *, **, and *** represent 10%, 5%, and 1% levels of significance, respectively.*

We combine the results of Tables 3 and 4 to confirm that various holding period groups capture both under- and overreactions, and especially in Table 3, Panel C, in which growth stocks with 6- and 12-month holding periods indicate the X_{52} variable changes from positive to negative. Further, the X_{max} variable changes from an expected negative value to a positive value. Therefore, we presume that it is likely that an interference factor exists in the holding period groups of 6 months and longer, but the discussion of such a topic shall be left for future research.

The Three-Factor Model's Explanatory Capability

As the explanatory result is obtained after grouping, it is necessary to be prudent with the research by conducting tests prior to the grouping process. An observation of Tables 3 and 4 regarding the reaction of holding periods prior to grouping reveals that value stocks exhibit high levels of significance for the 3-month holding period group in Table 3, when comparisons are made between the coefficients of variables X_{52} and X_{max}. However, growth stocks indicate marginal and no significance for these coefficients, respectively; the 3-month group in Table 4 reveals significant coefficients of variables X_{52} and X_{max} with small stocks, but not with large stocks. Therefore, the 3-month holding period group can, in theory, completely capture the under- and overreaction anomalies through the calculations made on the HML and SMB factors.

The regression analysis of the three-factor model results is quite meaningful. If the intercept α still has the explanatory capability for the asset portfolio's future returns, then this reveals that other characteristics still exist that the model cannot capture, aside from the momentum and reversal factors. If the intercept α does not have the explanatory capability for the asset portfolio's future returns, then the three-factor model does completely explain future returns. We test the 3-month holding period group, meanwhile extending our test to subsamples from various periods. As there appears to be a 10-year cycle in Taiwan's share market, we segment the data into three subsamples, with each sample including a 10-year period. The subsamples cover the 1997 Asian financial crisis, the 2000 technology bubble, the 2007 subprime crisis, and the 2008 global financial crisis. We can use the frequency and length of the subsamples' systemic risk to determine whether our findings are robust; Table 5 illustrates these results.

Table 5: Three-Factor Model Regression Analysis

	RMF	SMB	HML	α	R-squared
Sample A: 06/1995–05/2015					
	1.1004***	0.8963***	0.2059***	0.0020*	0.9395
	(122.2059)	(35.8085)	(19.5420)	(1.6840)	
Sample B: 06/1995–05/2005					
	1.0710***	1.0630***	0.1934***	-0.0028	0.9442
	(88.6076)	(31.5415)	(16.1242)	(-1.6010)	
Sample C: 06/2000–05/2010					
	1.1036***	0.8831***	0.2172***	0.0007	0.8885
	(61.5883)	(16.8372)	(11.9012)	(1.2747)	
Sample D: 06/2005–05/2015					
	1.1408***	0.6206***	0.2104***	0.0084***	0.9460
	(91.5360)	(18.3760)	(8.0475)	(5.6846)	

The three-factor model in this table is expressed as follows: $RPF = \alpha + \beta_1 RMF + \beta_2 SMB + \beta_3 HML + \varepsilon i$ *where* RPF *represents the asset portfolio's abnormal returns;* RMF *represents the market risk premium;* SMB *represents the size premium; and* HML *represents the book-to-market premium. The risk-free rate used to calculate abnormal returns is sourced from the First Bank of Taiwan's one-year term deposit rate. The sample period spans June 1995 to May 2015. The asset portfolio's holding period is 3 months. The grouping standard is determined by whether the firm issues cash dividends. The t-values are noted within brackets. *, **, and *** represent 10%, 5%, and 1% levels of significance, respectively.*

Table 5 indicate that all three factors, RMF, SMB, and HML, are significant; therefore, these factors can properly explain abnormal returns. As we have confirmed that overreaction can be captured by the HML factor, and underreaction can be captured by SMB and HML, the three factors should theoretically be able to completely explain abnormal returns. Therefore, the intercept α is critically significant. We discover that the subsample's intercept α in Table 5, Panel A, is not meaningful. The intercept α of the subsample in Panel D displays high significance, indicating that the intercept α of Panel A exhibits marginal significance due to the effect of the 2005 to 2015 subsample.

An interesting phenomenon is apparent in Taiwan's stock market, in that a major change has occurred in the investment structure in the past 20 years ("Securities Trading Value Percentage by Type of Investors" is presented in the Appendix). There is a decline in the overall composition of individual investors, from 45.84% in 1995 to 26.62% as of 2015. In a period of relatively higher-level individual investors, the three-factor model's explanation as outlined in Table 5, Panel B proves our inference. In a period with a relatively low level of individual investors, other characteristics still cannot be captured by the three-factor model. These results fit our assumption from Section 2, in which important information other than the market index would invite individual investors' attention, consequently contributing to the prices of shares in their possession. Meanwhile, we also proved that the asset portfolio index has the same effect as the Dow Jones index, as noted by Li and Yu (2012).

CONCLUSION

This study discusses the under- and overreaction phenomenon from the behavioral finance perspective. The measures adopted in past literature are primarily based on comparisons of different investment strategies. Li and Yu (2012) contrast traditional methods by proving that the market index, approaching 52-week and historic highs, can respectively proxy for under- and overreaction based on the anchoring mentality and investors' limited attention. Such a method has an adequate forecast capability, and is not affected by macroeconomic variables; however, the proxy variables should be attached to a highly exposed market index for it to endure. As a vast amount of information exists, we believe that investors are still attracted to information other than that of the market index, and ultimately react based on the prices of the stocks that they possess. If various shares are perceived as a category portfolio, with an index formed according to the market index, we anticipate that such an index would also exhibit under- and overreaction phenomenon.

This research utilizes as its subject the publicly traded stocks listed on the Taiwan Stock Exchange, and the empirical result indicates that aside from under- and overreactions, changes in investor composition in this stock market lead to the changes in these phenomena. A measurement (by the portfolio index) of investors' reaction in the representative category portfolio and group, by both the book-to-market and size factors, captures this under- and overreaction phenomenon. An examination using the three-factor model reveals that other characteristics still exist in periods with low levels of personal investors that cannot be captured by the three-factor method. However, the three-factor model has a complete explanatory capability for abnormal returns during periods more highly composed of individual investors. The results fit our inference, in which investors would still focus their attention on other important information aside from a highly exposed market index, and subsequently react. This proves that the category asset portfolio index has the same effect as the Dow Jones index, as adopted by Li and Yu (2012).

This study extends an application of the methodology to measure investor reaction, as posited by Li and Yu (2012). Although this does not include the highly exposed information readily available to investors, one can still utilize the asset portfolio-grouping method to measure and observe investors' under- and overreactions. This stealth index greatly improves the methodology's practicality, further enhancing the breadth of the subject under investigation, and no longer limiting it to market indices. As this study utilizes a three-factor model to test its robustness, an analysis is conducted regarding the asset groups categorized by firm size, value stocks, and growth stocks, but does not further analyze other firm characteristics. Moreover, the growth stocks within the 6-month holding period group display signs in the opposite direction, as anticipated; we logically suspect that the existence of an unknown interfering factor or the holding period's length causes investors' different reactions. Therefore, we recommend that subsequent research also conducts further groupings based on other firm characteristics, aside from the asset portfolio's holding period, as well as a more detailed examination of the sub-grouping, by considering the behavioral perspective to investigate the causes of under- and overreactions. The method adopted by this research has newly illuminated the debate between the rationalist and three-factor momentum effects in the behaviorist perspective, in terms of the use of HML and SMB factors to capture under- and overreaction phenomena. This clarifies the debate by reexamining the arguments proposed in past literature.

The development of the Taiwanese stock market lags behind those in developed nations; hence, the financial dataset's span is restricted to a 20-year period. Therefore, certain observed values are sacrificed due to incomplete firm data. We recommend that future studies adopt data from more advanced markets as the subject of research for a more robust examination. More importantly, the investors in more advanced markets are psychologically more mature. The aforementioned conditions would then be more advantageous for a longer period of study, and international data would allow our research to be more complete. Finally, it is not possible to obtain detailed data on the transaction parties' categories due to data limitations. The depth of this research has exhibited minor inadequacies, as only the transaction parties' primary category can be obtained. If future research allows for the gathering of such detailed data, we recommend that further examination be conducted regarding specific investor types to develop more objective results.

APPENDIX

Appendix A: Securities Trading Value Percentage by Type of Investors

Unit: %

Year	Domestic Individual		Domestic Juridical Person		Foreign Individual		Foreign Juridical Person	
	Purchase	*Sale*	*Purchase*	*Sale*	*Purchase*	*Sale*	*Purchase*	*Sale*
1990	48.36	48.30	1.63	1.68	0.00	0.01	0.00	0.01
1991	48.56	48.35	1.41	1.62	0.00	0.00	0.04	0.01
1992	48.08	48.02	1.80	1.84	0.00	0.01	0.13	0.12
1993	46.95	47.18	2.70	2.67	0.00	0.01	0.36	0.13
1994	46.75	46.75	2.89	2.92	0.00	0.01	0.36	0.32
1995	45.84	46.08	3.37	3.32	0.00	0.01	0.78	0.59
1996	44.60	44.65	4.28	4.34	0.00	0.01	1.12	1.00
1997	45.43	45.29	3.77	3.78	0.00	0.01	0.79	0.92
1998	44.92	44.81	4.27	4.36	0.00	0.01	0.81	0.81
1999	44.05	44.17	4.53	4.83	0.00	0.01	1.41	0.99
2000	42.83	43.27	5.28	4.99	0.00	0.01	1.89	1.73
2001	42.02	42.39	4.72	4.97	0.00	0.01	3.26	2.63
2002	41.20	41.10	4.95	5.10	0.52	0.45	3.34	3.34
2003	38.62	39.22	5.39	6.12	0.74	0.50	5.25	4.16
2004	37.82	38.12	5.63	5.93	0.92	0.71	5.62	5.25
2005	34.02	34.82	6.10	7.19	1.36	1.05	8.52	6.94
2006	34.87	35.69	5.36	5.68	1.21	1.04	8.57	7.58
2007	33.51	33.75	6.57	6.44	1.07	1.04	8.85	8.77
2008	31.10	30.56	7.18	6.79	1.05	1.21	10.67	11.45
2009	35.67	36.38	5.75	5.84	0.02	0.02	8.56	7.76
2010	33.83	34.12	6.69	6.89	0.02	0.02	9.46	8.97
2011	31.48	31.26	7.87	7.58	0.02	0.02	10.63	11.15
2012	30.72	31.32	7.80	7.55	0.01	0.04	11.47	11.10
2013	29.24	29.92	8.12	8.05	0.01	0.02	12.63	12.01
2014	29.02	29.77	8.69	8.72	0.01	0.02	12.27	11.49
2015	26.62	26.65	9.14	9.21	0.01	0.01	14.23	14.13
2016	28.41	27.20	8.26	8.33	0.01	0.01	13.32	14.46

Source: The Taiwan Securities Exchange

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BIOGRAPHY

Mr. Chih-Wen Yang is a Ph.D. student in the Department of Finance at the National Yunlin University of Science and Technology. He can be contacted at g9924801@yuntech.edu.tw.

Dr. Chun-An Li is a Professor of Finance at the National Yunlin University of Science and Technology. He can be contacted at 123 University Road, Section 3, Douliou, Yunlin 64002, Taiwan, R.O.C. E-mail: liica@yuntech.edu.tw. Phone: +886-5-534-2601, ext. 5411.

Dr. Sam Ting-Hsin Hsu is a graduate of the Department of Finance at the National Yunlin University of Science and Technology. He can be contacted at g9924805@yuntech.edu.tw.

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U.S. AND COSTA RICA STOCK MARKET COINTEGRATION

Jed Baker, Alliant International University

ABSTRACT

This paper tests the stationarity and cointegration of the historical daily data on the S&P 500 and the Costa Rican Bolsa Nacional de Valores (BNV). Both the Engle-Granger and Johansen Cointegration Tests are used to estimate this relationship. Results suggest that S&P 500 data and BNV are cointegrated although causal indicators between the two methods are contradictory. Specifically, the Granger Causality test suggests the S&P 500 is causal of BNV movement, while the coefficients in the error corrected model of the Johansen test are insignificant between S&P lags and BNV movement.

JEL: G15

KEYWORDS: International Financial Markets, Financial Market Cointegration

INTRODUCTION

Financial market interdependencies have been studied at length in the literature. Both for purposes of understanding linkages, as well as volatility transmission during periods of elevated market volatility. Much of the work that has been done in this area has focused on interdependence between major world markets. For example, Becker, Finnerty and Gupta (1990) examined the relationship between the Tokyo Stock Exchange (TSE) and the New York Stock Exchange (NYSE), Tabak and Lima (2002) and Aggarwal and Rivoli (1989) examined causality and cointegration in the major Latin American markets and Asian markets, respectively. These papers found significant connections between the markets examined and the U.S. market. A much smaller body of work has focused on the less mature markets around the world and their corollary with the world's major markets (e.g. DAX, FTSE, TSE, etc.). Research on the extremely small emerging or "pioneer" markets (Boehmer, Chava and Tookes, 2012) is much more limited. Data on these markets are also somewhat more inconclusive (Agharyev, 2012).

Within the context of the America's, the countries making up Central America (Costa Rica, El Salvador, Guatemala, Honduras and Nicaragua) have experienced increased political stabilization, growth in foreign direct investment and done so while maintaining low rates of inflation over the last decade. The body of literature examining financial market linkages of the Central American markets with other markets is very limited. This is likely the result of limited levels of financial market liberalization in nearly 70% of the Central American markets (with the exception of Costa Rica and Panama). Costa Rica and Panama have experienced significant increases in high productivity led growth in both high technology industries and knowledge intensive services (Bashir, Gindling and Oviedo, 2012). As Costa Rica's export market has matured so too has its financial market. In fact, between 1995 and 2013 the IMF's Financial Development Index indicated an approximately 80% growth rate for Costa Rica's financial markets (Heng, Ivanova, Mariscal, Ramakrishnan and Wong, 2016). Although Costa Rica still has significant strides to make in financial market development its improvement has been well documented.

As the financial market has liberalized and grown, the need for research focused on Central American financial markets has become more relevant, despite their relatively small size (when compared to the emerging markets of Africa, the Middle East and Asia). This is particularly true for Panama and Costa Rica as the most developed of Central America's financial markets. As a financial market grows sufficiently large, research begins to emerge that examines the cointegration of the emerging market with more developed markets (c.f., Diamandis (2009), Todorov (2012) and Dania and Spillan (2013)). The literature on Costa Rica's financial market cointegration with other countries is non-existent. This is likely due to the fact that the market capitalization is still small when compared to the major world markets. As a result there exists a gap in the literature. This research will contribute to the literature by examining the financial market cointegration between Costa Rica (Bolsa Nacional de Valores) and the U.S. (S&P 500). The next section will review the existing body of literature, followed by a section on the data and methodology, thereafter, results and concluding comments will be discussed.

LITERATURE REVIEW

Since the South American and Asian financial crises, there has been an abundance of work on both contagion and cointegration. For example, Diamandis (2009) found that four major Latin American (Chile, Argentina, Brazil and Mexico) stock exchanges were partially cointegrated and shared common components with U.S. markets. While these markets are still fairly small relative to TSE, NYSE, DAX standards, their importance in the world financial system is growing rapidly. According to a capital markets report by PriceWaterhouseCoopers, there will be nearly 25% growth over the next five years in companies offering IPO's on medium sized emerging market exchanges. The primary markets in Latin America (i.e. Brazil, Mexico and Chile) are still large relative to true "emerging" market standards. In particular, there is very little in the literature as it relates to Central American markets and their co-movement with U.S. and other primary international financial markets. A likely reason for this is due the extremely small size of Central American markets and the limited volumes in which they trade. The combined market volume on Central American exchanges accounts for less than 1% of the volume on the NYSE (CIA Fact book, 2013). The oldest and most well developed market in Central America is the Bolsa Nacional de Valores (BNV) in Costa Rica. The BNV has been opened since 1974 and as of 1993 is wholly owned by private investors (Fiabnet, 2012). Although, the volume of shares traded is still relatively small (and below its 2006 peak), the Costa Rican market will play a significantly important role in the financial development of the region, along with Panama and El Salvador (Ascher and Hubbard, 1989) (Figure 3 below describes the characteristics of the BNV). This is not only evidenced by the large numbers of American and European retirees moving into Costa Rica, but also the result of increasing levels of European and American Foreign Direct Investment into Costa Rica. Currently American FDI accounts for approximately 70% of all FDI into Costa Rica, which is up significantly from only ten years earlier (CIA World Fact book, 2013). These facts not only make Costa Rica an interesting case to examine, but also a very relevant growing market in the Central American financial landscape.

With much of the work on the Latin American market dynamic focused on high impact markets (e.g. Mexico, Brazil, etc.), an opportunity exists in the literature to focus on smaller financial (and in particular Central American financial) market characteristics. It has been suggested that smaller economies are not only impacted by lagged movements of the S&P 500, but also by S&P futures markets (Todorov, 2012). This suggests that while findings in Latin America generally indicate market co-movement with major U.S., European and Asian markets, smaller emerging markets may be less impacted than larger markets by historical trends. For example a 2013 paper by Dania and Spillan found that Middle East and North African (MENA) markets were not fully integrated with more mature markets in Europe, the Americas and Asia. While this may be due to the lack of liquidity in these markets and/or lack of external influence (e.g. FDI), the growth trajectory of these markets will be important to understand in the context of their emerging predecessor markets.

DATA AND METHODOLOGY

Data

The data used are daily closing prices of the S&P 500 index and the BNV. The data for the S&P 500 are taken from Yahoo finance (finance.yahoo.com). The data for the BNV are taken from Banco Central de Costa Rica (BCCR). According to the IMF (2011) Costa Rica has been a managed float exchange rate regime, which has been largely tied to the dollar. The government is currently in the process of liberalizing the exchange management regime, although there have been struggles as a result of fiscal imbalances and political party misalignment. Since approximately 2007 the Costa Rican Colon (CRC) has been loosely pegged to the USD. The period covered is from January 3, 1995 through March 6, 2013**.** Historical log levels can be seen in Figure 1 below.Figure 1 shows the log daily values for the BNV from 1/3/1995 through 3/6/2013. When compared to the log daily values of the S&P 500 over the same time interval, it is clear that the tech bubble that afflicted the U.S. market was far less pronounced in the Costa Rican market. On the other hand, the most recent financial crisis of 2009 was observed in the BNV as can be observed in Figure 2. The trends in Figures 1 and 2 illustrate that there are marginal similarities between the log daily values of the S&P 500 and the BNV. Table 5 (as well as Figures 3 and 4 below), show the summary statistics for each market, as well as the histograms for the distribution of the daily returns over the period being examined.

Figure 1: Log Index Values Over Time: BNV

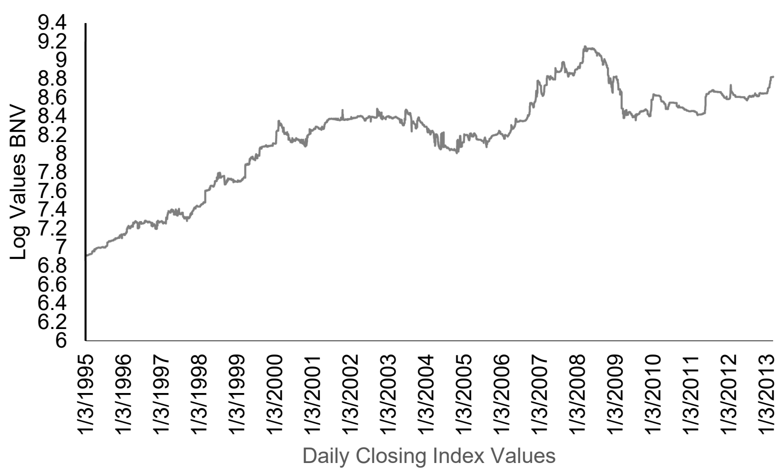

Figure 1 exhibits the log daily values for the BNV from 1/3/1995 through 3/6/2013.

Data in Table 1 characterize the more normally distributed S&P index (skewness=-0.049 and kurtosis=7.82) versus the BNV (Skewness=1.74 and kurtosis=50.38). Mean daily returns in the S&P are lower than the BNV (0.04% versus 0.03%) with nearly equivalent standard deviation 1.25% in the S&P as compared to 1.26% in the BNV.

Figure 2: Log Index Values Over Time: S&P 500

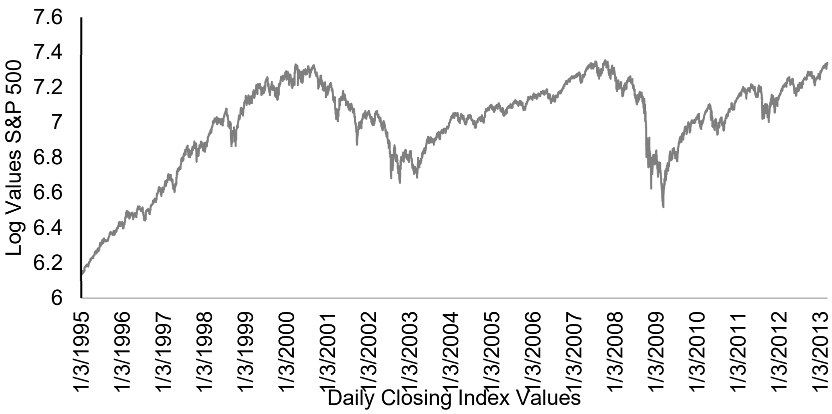

Figure 2 exhibits the log daily values for the S&P 500 from 1/3/1995 through 3/6/2013.

Table 1: Summary Statistics for Daily Returns for BNV and S&P 500

Measure	BNV	S&P 500
Mean	0.04%	0.03%
Median	0.0%	0.07%
Maximum	17.12%	11.58%
Minimum	-15.52%	-9.03%
Standard Deviation	1.25%	1.26%
Skewness	1.74	-0.049
Kurtosis	50.38	7.82

Table 5 shows summary statistics for daily return data for the BNV and the S&P500. Mean average daily returns are similar between both BNV and the S&P 500 (.04% and .03%, respectively). Range of returns is higher for the BNV than for the S&P 500.

Both daily return histograms illustrate different levels of skewness and kurtosis, despite similar mean return and standard deviation values. While clearly not normally distributed, the S&P 500 exhibits skewness and kurtosis statistics closer to Gaussian. This can also be seen in the histograms in Figures 3 and 4 as well.

Figure 3: Histogram of Returns: BNV

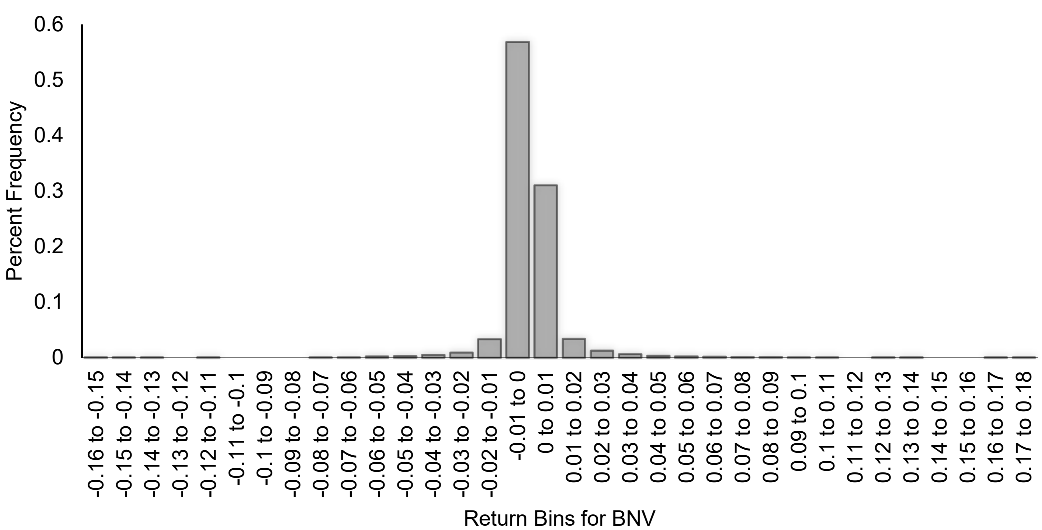

Figure 100 shows the frequency of returns for different return bins, ranging from -.16 to 0.17. Relative to the S&P 500, exhibits less variability, on average

Figure 4: Histogram of Returns-S&P 500

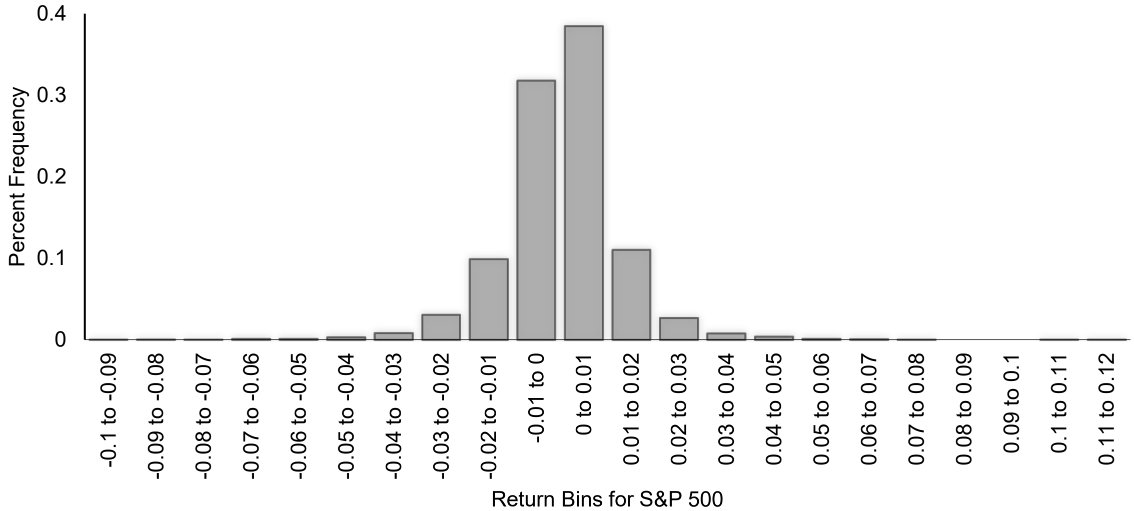

Figure 4 shows the frequency of returns for different return bins, ranging from -0.1 to 0.12.

It is important to note that the volume of trades (in terms of $US) are less than one half of one percent than the S&P indicating a somewhat low liquidity market relative to the S&P 500 index. Figure 5 below from Fiabnet shows some characteristics of the BNV market over time. The current market trading hours are from 9:00AM to 3:00PM. Costa Rica does not participate in daylight savings time (DST). During DST in the U.S., Costa Rica is one hour ahead of Pacific Time. During standard time, Costa Rica is two hours ahead of Pacific Time, hence there is significant overlap with the U.S. in trading time during the trading day.

Table 2: Summary Market Data BNV

Item	2000	2005	2010	2011
Total Market Cap (Millions of US$)*	2,924	2,202	1,445	1,498
Number of Listed Companies	21	19	9	9
BNV Stock Index	3,813.77	3,679.29	4,687.98	5,350.24
Number of Brokerage Companies	21	19	17	17
Total Value of Share Trading (Millions of US$)*	63	203	160	196
Total Value of Bond Trading (Millions of US$)*	n.a.	1,897	5,158	6,397

*Source: Fiabnet, 2012 *In 2012 Dollars The historical data (fiabnet.org, 2012) show high-level characteristics of the BNV market, over time.*

METHODOLOGY

A majority of the tools utilized in previous research to test market interdependencies is based on work done by Engle and Granger (1987), Dickey and Fuller (1979) and Johansen (1991). In order to test cointegration between the S&P 500 and BNV, two approaches will be taken. First of all, the test to determine whether or not the series are stationary will be done using the Augmented Dickey Fuller (ADF) test for unit root. Thereafter, the Engle-Granger two-step method (EGTSM) will be conducted. Finally, the more comprehensive Johansen Cointegration Test (JCT) will be done to ensure cointegration result stability between the two methods.

ADF and the Engle Granger Method

In order to test whether or not the two series (S&P 500 and BNV) are stationary, the ADF test for unit root will be examined. The process for testing the existence of unit root is as follows:

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_{p-1} \Delta Y_{t-p+1} + u_t \tag{1}$$

where, α is an intercept term, β is the coefficient on the time trend (assuming intercepts and time trends are included). The null hypothesis of unit root is γ=0. The ADF statistic is calculated as,

$$\frac{\hat{\gamma}}{SE(\hat{\gamma})} \tag{2}$$

If t*>ADF, then we fail to reject the null hypothesis of unit root (i.e. the series is non-stationary). If t*<ADF, then the null hypothesis is rejected and the series is assumed stationary. In the case above, non-stationarity does not necessarily imply series cointegration. The subsequent step is to determine whether or not the series are integrated of the same order. By definition integration is the number of series differences required in order to observe a stationary series. A time series is integrated of order *t* if, $(1\text{-d})^k Y_t$ is integrated of order k, where d is a lagged value. The first difference (1-d) =$(1\text{-d})Y_t = Y_t - Y_{t-1} = \Delta Y$. Assuming d=1 then the series is integrated of order one (I(1)). Testing that the series of the S&P 500 and the BNV are I(1) can be done in two ways. The first is simply to difference the series and rerun the ADF test. If the series is I(1) then the ADF on the level value of the variables of interest should indicate a failure to reject the null and the differenced ADF should yield a rejection of the null hypothesis. Alternatively, in the EGTSM one could take the model, $Y_t = \beta Xt + u_t$, where Y_t is the value of the BNV and X_t is the value of the S&P 500. Obtaining the residuals, the relationship of the first differenced error can then be tested on the lagged value of the error, $\Delta u_t = \delta u_{t-1} + \varepsilon_t$. From this step, the null hypothesis of δ=0 is tested. If the null hypothesis is rejected this implies that the series are cointegrated. This result will be equivalent to differencing the series and testing the null hypothesis of stationarity on the first difference (results shown in the Results section of the paper).

Johansen Cointegration Test

Confirmation of cointegration is tested using JCT and the Vector Error Correction Model (VECM). The JCT allows tests of multiple I(1) process to be tested. In the previous ADF/EGTSM only one cointegrating relationship is allowed. This makes the JCT much more flexible. Johansen's method uses a vector autoregression (VAR) as a starting point. The VAR takes the following form,

$$y_t = \alpha + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + u_t, \tag{3}$$

where y_t is an nx1 vector of variables assumed to be I(1) (although, according to Hjalmarsson and Österholm (2007), the JCT doesn't require all variables to be integrated of the same order due to the maximum likelihood estimation of the cointegrating equations.
Equation (3) above can be rewritten as,

$$\Delta y_t = \alpha + \Pi y_{t-1} + \sum_{i-1}^{p-1} \Gamma_i \Delta y_{t-1} + u_t \tag{4}$$

Where

$$\Pi = \sum_{i-1}^{p} \alpha_i - \mathrm{I} \tag{5}$$

and,

$$\Gamma_i = -\sum_{j-i+1}^{p} \alpha_j \ . \tag{6}$$

If Π, the coefficient matrix, has reduced rank $r<n$, then there exists nxr matrices. Where r is the number of cointegrating relationships and n is the number of variables. Then A and B are matrices each with a particular rank r, such that Π is stationary (Johansen, 1993). From this, there are two tests that are promoted by Johansen, the max-eigenvalue test and the max-trace test, defined in the following two equations.

$$J_{trace} = -T \sum_{i-r+1}^{n} \ln(1-\lambda_i) \tag{7}$$

and,

$$J_{\max} = -T \ln(1-\lambda_{r+1}) \tag{8}$$

Where (7) is the trace test statistic and (8) is the max eigenvalue. Given that cointegrating equations are identified in the Johansen test (via either significant trace or eigen statistics. This step allows us to test the following null and alternative hypotheses (Brooks, 2008).

H_0: r=0	H_1: 0<r≤n
H_0: r=1	H_1: 1<r≤n
H_0: r=2	H_1: 2<r≤n
H_0: r=n-1	H_1: r=n

Where the first statement tests the null hypothesis of no cointegrating vectors (Π having zero rank). If the null hypothesis is rejected then the hypothesis of r=1 is tested, if r=1 is rejected then r=2 is tested and so on. This cycles until the null fails to be rejected, at which point the number of cointegrating vectors is determined. If it is determined that the cointegrating equations are non-zero, then the VECM (the first differenced VAR), then needs to be run in order to capture the vector error correction model. Once this takes place the VECM can be run in OLS and the results can be interpreted as normal.

HYPOTHESES

Three primary hypotheses will be tested.

Hypothesis 1: The series for the S&P 500 and BNV will be I(1)

Hypothesis 2: S&P 500 and BNV series are cointegrated

Hypothesis 3: Lagged S&P 500 values will "Granger cause" BNV

The hypotheses will be tested via the methods listed above. First, an ADF test will be run on both series to test for unit root. Then (assuming unit root exists) the first differenced series will be tested in order to ensure an I(1) process. If confirmed, a second check will be done using the EGTSM to test for cointegration.

Next, a Granger Causality test will be run to test the hypothesis of causality between the two series. Finally, to test for consistency among the different methods of cointegration testing, the JCT will be run on the series to determine (1) if they are integrated, (2) how many cointegrating equations exist and (3) determine the causality between BNV and the S&P 500.

RESULTS

The ADF test results for the BNV and the S&P 500 in Table 1 indicate that unit root exists in both series, in other words, the series are non-stationary. Table 3 shows that the BNV series are both non-stationary in the log level (ADF>t-critical of 2.15>-2.56) measure and significant (-37.14<-2.56) implying the series first difference is stationary. It can thus be inferred that the series is also integrated of order 1. As a result of the four ADF tests above the series on the S&P 500 and BNV are both non-stationary and I(1). As a result it is possible to test the cointegration of the series using the Engle-Granger two-step method (EGTSM) described in the methodology section.

Table 3: ADF of S&P 500 (Log Level Series) and First Difference of S&P 500 Series

Augmented Dickey Fuller Test-S&P 500		**t-Statistic**	**Prob.**
ADF Test Statistic		1.485	0.9665
Test Critical Values	1% Level	-2.565	
	5% Level	-1.941	
	10% Level	-1,617	
Augmented Dickey Fuller Test-S&P 500 First Difference		**t-Statistic**	**Prob.**
ADF Test Statistic***		-52.039	0.0001
Test Critical Values	1% Level	-2.565	
	5% Level	-1.941	
	10% Level	-1.617	

**** indicates significance at the 5% level. Table 3 reports the ADF results for the S&P 500 and the first difference of the S&P 500. For the S&P 500 (log level series) The ADF statistic is greater than the critical values at all levels of significance, which implies a failure to reject the null hypothesis. This implies that the S&P 500 series (log level values) are non-stationary and exhibit a unit root. The ADF (differenced series) statistic is significant at the 1% and 5% levels (-2.65 and -1.94, respectively). The first difference of the S&P series is stationary indicating that it is an I(1) process. In table's 3 and 4 below are the results for the ADF test on the log level and first differenced series of the BNV.*

Table 4: ADF of BNV (Log Level Series) and First Difference of BNV Series

Augmented Dickey Fuller Test-BNV		**t-Statistic**	**Prob.**
ADF Test Statistic		2.151	.9929
Test Critical Values	1% Level	-2.565	
	5% Level	-1.941	
	10% Level	-1.617	
Augmented Dickey Fuller Test-BNV First Difference		**t-Statistic**	**Prob.**
ADF Test Statistic***		-37.139	0.0000
Test Critical Values	1% Level	-2.565	
	5% Level	-1.941	
	10% Level	-1.617	

**** indicates significance at the 1% level.*

The EGTSM results indicate that the series are cointegrated. The p-value on both S&P 500 and BNV are statistically significant indicating that we reject the null hypothesis of non-cointegration. The results for the EGTSM are listed in table 5 below.

Table 5: Engle-Granger Single Equation Cointegration Test

Dependent	Tau-Statistic	Prob.	Z-Statistic	Prob.
BNV	-37.232***	0.0	-3982.622***	0.0
S&P 500	-52.076***	0.0001	-5426.527***	0.0

**** indicates significance at the 1% level.*

Finally, in order to identify whether a causal relationship exists, table 6 displays the results of the Granger Causality test. Results in table 6 above indicate that we reject the null hypothesis that the S&P 500 does not Granger Cause the BNV. This result implies that BNV does not impact movements in the S&P but the S&P does impact movements in the BNV. Results for the EGTSM were all consistent with expectations both in terms of outcome and magnitude.

Table 6: Granger Causality BNV and S&P 500

Null Hypothesis	Observations	F-Statistic	Prob.
BNV does not Granger Cause S&P 500	4210	0.0823	0.9923
S&P 500 does not Granger Cause BNV***	4210	1.160	0.0249

**** indicates significance at the 5% level.*

A shortcoming of the EGTSM is that it can only test one cointegrating relationship. The JCT is able to overcome this and test multiple cointegrating relationships. Although there are not additional variables of interest within this paper, the test will be run to examine the stability of the results. Table 7 below shows the results of the JCT.

It is clear from table 7 that more than one cointegrating relationship exists. Furthermore, both the trace and max-eigenvalue tests yield similar results, both of which are statistically significant, which supports results from the EGTSM method above.

Table 7: Johansen Test of Cointegration –BNV and S&P 500

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized Number of Cointegrating Equations	Eigenvalue	Trace Statistic	.05 Critical Value	Prob.
None***	0.0048	29.043	15.495	0.0003
At Most 1***	0.0015	6.933	3.841	0.0085
Unrestricted Cointegration Rank Test (Trace)				
Hypothesized Number of Cointegrating Equations	Eigenvalue	Max Eigenvalue	.05 Critical Value	Prob.
None***	0.00483	22.110	14.265	0.0024
At Most 1***	0.00152	6.933	3.841	0.0085

**** indicates significance at the 1% level. Trace and Max Eigenvalue test indicate two cointegrating equations exist*

The VECM was run, although the results are an intermediate step and will not be shown here. The corrected model was specified in equation 7 below.

$$
\begin{aligned}
d\ln BNV = {} & \beta_0 + \beta_1 * (\ln BNV_{t-1} - 1.85 * \ln SP500_{t-1} + 4.77) + \beta_2 * d\ln BNV_{t-1} + \\
& \beta_3 * d\ln BNV_{t-2} + \beta_4 d\ln SP500_{t-1} + \beta_5 d\ln SP500_{t-2}
\end{aligned} \tag{7}
$$

where, dlnBNV is the change in log values of the BNV in the current period (in this case trading day). This is dependent on values of the variables on the right hand side of equation. Variables that include *d* are changes, *ln* refers to the natural logarithm of the index levels and subscripts *t-n* represent values from the prior period. The results from the corrected model are shown in table 8.

Table 8: Error Correction Model –BNV and S&P 500

Variable	Coefficient	Standard Error	t-Statistic	Prob.
β_0**	0.00042	0.0002	2.42	0.0156
β_1 ***	-0.002	0.0005	-5.06	0.000
β_2 ****	-0.103	0.0148	-6.95	0.000
β_3***	0.0383	0.0148	2.59	0.010
β_4	0.0095	0.0145	0.65	0.515
β_5	0.0065	0.0145	0.44	0.659

**** and ** indicate significance at the 1% and 5% levels, respectively. The coefficient on β_1 is significant and negative. This is the error correction variable from the prior steps vector autoregression. Variables that include lag values of the S&P 500 were not significant in the model, which was counter to results from the EGTSM.*

The term beginning at the RHS of the equation is the error correction parameter. The model then includes lags on BNV and S&P (denoted SP500). Interestingly, and inconsistently, the results for the coefficients on the lags of the S&P are not significant (β_4 and β_5). These parameters were jointly tested to be equal to zero and the null hypothesis was not rejected indicating that these variables jointly are not different from zero on their impact on BNV. There are a number of potential reasons for this. First of all, Todorov (2012) found that for small emerging markets S&P futures had more impact on these markets than the S&P index. Moreover, there could be a problem of spuriousness in the regression. There are a number of markets correlated to the S&P 500 that could be more highly related to the value of the BNV than the S&P 500. These are ideas for future research and are not in the scope of this paper.

CONCLUDING COMMENTS

This paper evaluated the market comovement between the S&P 500 and the Costa Rican BNV. Specifically the stationarity of the historical daily data on the S&P 500 and the Costa Rican BNV were evaluated and found both series to be non-stationary. After differencing the cointegration of these markets was examined and found significant in both the EGTSM and the JCT. Results are somewhat conflicting, however, in that the Granger Causality tests suggests that movement in the S&P 500 causes movement in the BNV. The error correction model suggests that the lagged S&P values do not have an impact on the BNV. While the results definitively suggest cointegration exists, potential spuriousness and/or omitted variable bias in the JCT could be causing these conflicting results. Another possible reason for the conflicting the results are the number of periods over which the cointegrating relationship was evaluated (in this paper approximately 18 years of closing prices). Breaking the time periods up into temporal segments (i.e., every five years) may yield different results. In addition, a shortcoming of this paper is that variability in the USD/CRC were not accounted for and this could be another cause of inconsistency in the results. The rationale for not incorporating this was due to the limited trading volume observed for the BNV in the earlier period evaluated (1995-2000).

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^GSPC: Key statistics for the S&P 500 Index. (n.d.). Retrieved February 15, 2013, from http://finance.yahoo.com/

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BIOGRAPHY

Jedediah Baker is affiliated with Alliant International University and California State University San Marcos. Dr. Baker can be reached at jbaker@csusm.edu.

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