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CONTENTS

INFORMATION CONTENT OF CHANGES IN PENSION PLAN FUNDING STATUS AND LONG-TERM DEBT

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ABSTRACT

This study investigates whether investors efficiently incorporate changes in defined benefit pension plan information in stock prices. The sample is comprised of public US companies with available data from 1980 to 2005. Fama and French three factor (1993) and four factor models results reveal that the market inefficiently incorporates changes in defined benefit pension plan information. The results suggest that investors are not paying enough attention to the implications of the changes in funding status for future earnings and cash flows. Investors' reactions to changes in defined benefit pension plan information were compared to reactions to changes in long-term debt account ratios. The results reveal that the market is also inefficient incorporating changes in long-term debt information. Hedge-portfolio tests are performed to verify if there is an opportunity to outperform the market by identifying market inefficiencies. The hedge-portfolio results support the notion that the market overprices firms that have the most negative changes in funding ratio and increases in long-term debt ratio.

JEL: G14, G25, G31, J32

KEYWORDS: long-term debt, defined benefits pension plan, stock prices, four factor model

INTRODUCTION

Accounting information serves different and very critical roles in capital markets. It is vital in providing prospective capital contributors with the necessary means for evaluation of potential investment opportunities and in serving as a monitoring tool for the stakeholders of a company. During the past decade defined benefit pension plan (DBPP) issues have been the center of many debates and research. From markets' efficiency to earnings management, pensions have been of much interest to those who are interested in the reliability of pension disclosures and in maintaining a healthy pension system. Concerns about accounting standards for DBPP have been discussed in different forums during the last decades. Some argue that accounting for pension plans should be easy to prepare and must provide information that is easy for the users to understand. Ironically, it has been regarded as obscure and arcane; too complicated for users to comprehend because of all the estimates and valuation methods involved in the calculations. Through the years, the Financial Accounting Standards Board (FASB) has demonstrated preoccupation with respect to pension plan information disclosures, as confirmed by the changes in disclosure requirements in the last decades.

Efforts to enhance the relevance and understandability of reported pension information also include the enactment of ERISA (Employee Retirement Income System Act of 1974) and the "Pension Protection Act of 2006", the issuance of Statement of Financial Accounting Standards (SFAS) 36, SFAS 87, SFAS 132, and most recently, the SFAS 158. SFAS 158, effective for fiscal years ending after December 15, 2006, provides new pension disclosure requirements intended to address previous shortcomings. Before the issuance of SFAS 158, pension plan information concerning the pension plan status (PPS) was reported in the notes to the financial statements. One of the most important changes of this statement is the presentation of PPS in the balance sheet.

Under the new statement an underfunded (overfunded) pension plan will report a net pension liability (net pension asset) on the balance sheet. A severely underfunded pension plan has future implications in cash flows and earnings. For this reason, it is important for investors to assess the PPS before making investment decisions. By moving this information from the footnotes to the balance sheet the intention of the FASB is to improve and create awareness of the importance of PPS information. The FASB changed the disclosures related to pensions based on the belief that moving the information from the footnotes to the financial statements will gain the attention of investors and other users. Obviously, they assume that footnotes were not good enough to satisfy the objective of creating awareness of the impact of pension plans and decided to move PPS information to the balance sheet. Then, we expect that information users efficiently use the information in the balance sheet and that the recognized amounts are reliable and useful. Studies that examine the efficiency of the markets in using information presented in the balance sheet find interesting and contrasting results (Foster, Jenkins and Vickers, 1986; Sloan, 1996). Particularly, those related to long-term commitments (Harper, Mister and Strawser, 1987; Chen, Kim and Nance, 1992; Hirshleifer, Hou, Teoh and Zhang, 2004; Ahmed, Kilic and Lobo, 2006; Bradshaw, Richardson and Sloan, 2006). Some of these studies find that the type of debt issuance and changes in debt ratings impacts investors' perceptions and decisions.

Have the standard setters considered that just moving the information from the footnotes to the financial statements might not be good enough. What we should be asking is if changes in the presentation solve the problem of information awareness and its incorporation in decision-making. Furthermore, we should consider if it is an issue of presentation of information or reliability of information. And, whatever the reasons are, determine what mechanisms can be used to address this issue.If the main reason of the FASB is to create awareness about the impact of pension status over the financial stability of a firm, then, it is important to verify if the market reacts differently to recognized long-term obligations in the financial statements versus long-term commitments disclosed in the footnotes to the financial statements.

This study examines the incorporation of DBPP disclosures before SFAS 158 and LTD information into stock prices. This assessment is done to verify if the market efficiently incorporates information of long-term commitments as represented by pension obligations presented in the footnotes and LTD as presented in the balance sheet. To measure and verify how efficiently the information is used investment strategies are design. The paper proceeds as follows. The first section discusses the relevant prior literature, followed by hypotheses development and research methodology. Then, the sample selection procedure and data analysis are presented. Finally, the empirical findings and the conclusion are discussed.

LITERATURE REVIEW

Pensions

Previous studies find evidence that suggest that before SFAS 158 investors inefficiently used information related to PPS (Godwin and Key, 1998; Franzoni and Marín, 2006). Other studies consider managers' choice to overfund or underfund their plans (Moody and Phillips, 2003), the association of PPS and capital expenditures (Rauh, 2006), earnings management and pensions (Coronado and Sharpe, 2003; Bergstresser, Desai and Rauh, 2006; Asthana, 2008), the incorporation of pension disclosures in investment decisions (Chen, Yao, Yu and Zhang, 2010), and the association between systematic equity risk and the risk of pension plans (Jin, Merton, Bodie, 2006).

Shaw (2008) argues that SFAS 158 significantly changes the balance sheet reporting for DBPP. Coronado, Mitchell, Sharpe and Nesbitt (2008) state that the increased attention to pension disclosures misuse may have influenced the way investors evaluate pensions since the appearance of SFAS 158 and that it will influence investors' decisions. Recent studies evaluate the impact of SFAS 158. Boylan and Houmes (2010) examine the use of higher discount rates to lower the pension benefit obligations and pension liabilities with the intention of portraying a better financial position. Chen et al. (2010) examine the differences in the use of pension disclosures depending on the level of sophistication of users. And find that the level of sophistication is related to the incorporation of information. Beaudoin, Chandar and

Werner (2010) study whether the recognition of pension asset and liability amounts under SFAS 158 is incrementally value relevant in its first year of adoption versus the same amounts previously disclosed to both equity investor and rating decision makers. Findings suggest that DBPP information is used in the same way before and after the issuance of SFAS 158.

The FASB changed the disclosures related to pensions based on the belief that moving the information from the footnotes to the financial statements will gain the attention of investors and other users. Obviously, they assume that footnotes were not good enough to satisfy the objective of creating awareness of the impact of pension plans and decided to move PPS information to the balance sheet. Then, we expect that information users efficiently use the information in the balance sheet and that the recognized amounts are reliable and useful. Studies that examine the efficiency of the markets in using information presented in the balance sheet find interesting and contrasting results (Foster, Jenkins and Vickers, 1986; Sloan, 1996). Particularly, those related to long-term commitments (Harper, Mister and Strawser, 1987; Chen, Kim and Nance, 1992; Hirshleifer, Hou, Teoh and Zhang, 2004; Ahmed, Kilic and Lobo, 2006; Bradshaw, Richardson and Sloan, 2006). Some of these studies find that the type of debt issuance and changes in debt ratings impacts investors' perceptions and decisions.

Long-Term Debt

Chen, Kim and Nance (1992) study the information content of balance sheet items as conveyed by financial leverage. The evidence suggests that data on financial leverage has some information content. The authors argue that the market reacts to changes in financial leverage. Nevertheless, they observe that the direction of this response seems to depend on the position of a corporation's financial leverage relative to its optimal level. Modigliani and Miller (1958) introduced the proposition that the expected return on equity should increase with the amount of debt in a firm's capital structure. On the other hand, empirical research on the relation between financial leverage and expected stock returns is contradictory. Fama and French (1992) find that leverage based on book values has a negative risk premium. In contrast, Bhandari (1988) identifies leverage measured in market values as a separate risk factor. He finds that firms with higher financial leverage consistently earn lower risk-adjusted returns.

In addition, Kayhan, Lei and Lin (2005) find that this results hold for both market and book leverage. In contrast to Fama and French (1992), they also find that the leverage effect on the risk-adjusted returns persists after controlling for firm size and the book-to-market equity ratio (B/M). Chan, Chan, Jegadeesh, and Lakonoshok (2006) investigate various hypotheses to explain the accruals effect and conclude that the effect is largely due to earnings manipulation. Sloan (1996) finds that the accruals effect reflects that investors overestimate the future earnings of firms with high accruals in current earnings.

Millon-Cornett and Travlos (1989) study the information effect caused by a firm's change in capital structure via debt-for-equity and equity-for debt exchange offers. The evidence suggests that the former transactions lead to abnormal stock price increases, while the latter lead to abnormal stock price decreases. However, Brigham and Gapenski (1985) state that it is usually believed that the average cost of capital curve is shaped more like a shallow bowl than like a sharp V. This may be interpreted that over a wide range, the financial leverage does not have a noticeable effect on the average cost of capital and, therefore, on the value of corporations. They also say that if this pan-shaped curve is valid, stock prices of a corporation will not be affected by the change of financial leverage as long as the corporation remains in this region. This means that, if corporations that had financial leverage (and are at the low side of the optimal leverage range) dominate in portfolios, prior to a new issue of debt, a decrease in financial leverage will cause stock prices to decrease. To the contrary, an increase in financial leverage will not have significant impact on stock prices.

Best (1997) examines the stock price reaction to straight debt announcements by differentiating firms on the basis of any subsequent change in their overall default risk. He finds that firms that will within six months of straight debt announcements, undergo debt rating downgrades experience significant negative abnormal stock returns at the time of new debt announcement. On the other hand, firms with bond ratings that are later upgraded show significant positive abnormal returns.

Finally, Bradley, Jarrell and Kim (1984) use a model that synthesizes the modern balancing theory of optimal capital structure. The model incorporates positive personal taxes on equity and bond income, expected costs of financial distress (bankruptcy and agency costs), and positive non-debt tax shields. The evidence suggests that optimal firm leverage is inversely related to expected costs of financial distress and to the amount of non-debt tax shields. They use simulation analysis to demonstrate that if costs of financial distress are significant, optimal leverage is related inversely to the variability of firm earnings.

DATA AND METHODOLOGY

Samples

In order to examine the data different sets of portfolios are formed. The firm selection criteria are different for each set. The set of portfolios formed based on the change in *FR* is comprised by firms that sponsor DBPP. The sets of portfolios formed based on *LTDR* changes are comprised of all firms with available data for long-term debt. As a result, a separate description of both samples is presented. The *FR* sample is comprised of all the firm years with available data on the Compustat Annual Industrial and Research files for NYSE, AMEX, and NASDAQ firms. The sample period is the end of fiscal year 1980 to the end of fiscal year 2005. 1980 is the starting point because the pension plan data of interest is initially available starting that year. Firms are included if they have at least two years of accounting data in order to correct for the survival bias induced by the way Compustat adds firms to its tapes (Banz and Breen 1986 and Franzoni and Marín 2006). For the formation of pension plan portfolios, only firms that sponsor pension plans are included. There were 52,018 observations (firm-years) before eliminating firms that do not have available information for at least two years. To correct for the effect of outliers, observations for each year in which the *FR* variable is more than five standard deviations away from the annual mean, were dropped from the sample. As a result, there are 51,515 observations (firm-years) that satisfy the criteria mentioned above. Then firms that do not have at least two years of accounting data were eliminated. As a result, 51,441 observations were included in this investigation.

The *LTDR* sample is comprised of all the firm years with available data on the Compustat Annual Industrial and Research files for NYSE, AMEX, and NASDAQ firms. The sample period is the end of fiscal year 1980 to the end of fiscal year 2005. Firms are included if they have at least two years of accounting data in order to correct for the survival bias. There were 187,588 observations (firm-years) before eliminating firms that do not have available information for at least two years. To correct for the effect of outliers, observations for each year in which the *LTDR* variable is more than five standard deviations away from the annual mean, were dropped from the sample. As a result, there are 186,091 observations (firm-years) that satisfy the criteria mentioned above. Then firms that do not have at least two years of accounting data were eliminated. As a result, 185,962 observations were included. Firm returns were obtained from the Center for Research and Security Prices (CRSP), Monthly Stock database.

Variable Measurement

The ratios used by Franzoni and Marín (2006) incorporate the balance of the account as measured at the end of year $t-1$. Some studies, instead of using the account balance presented in the financial statements or in the notes, use the change in the account or accounting element. Xie (2001), Kim, Chen and Nance (1992), Best (1997) use the changes in the accounts of interest for their respective studies. Stober (1986) investigates first occurrences of LIFO liquidations because they are less likely to be anticipated by the market than later occurrences. Stober argues that if these occurrences are unexpected events, and this component of earnings is not disclosed separately from earnings, they should give rise to the type of positive abnormal share price behavior at the earnings release date that is generally associated with positive unanticipated earnings. Consequently, and in order to verify if the changes in *FR* have predictive power the risk-adjusted returns tests are performed for portfolios formed based on the change in *FR* at the end of fiscal year $t-2$ to the end of fiscal year $t-1$.

In order to measure the change in funding status, a similar procedure used by Franzoni and Marín (2006) is used. To solve the problem of the impact that the same dollar amount of underfunding has depending on the size of the firm, the change in funding status needs to be appropriately normalized. The change in funding status is defined as the difference between the fair value of pension assets (*FVPA*) and the pension benefit obligation (*PBO*) in year $t-1$ minus the difference in fair value of pension assets (*FVPA*) and the pension benefit obligation (*PBO*) in year $t-2$. The change in funding status is divided by market capitalization (*Mkt Cap*) at the end of the fiscal year $t-1$. This variable is labeled change in funding ratio (ΔFR). This variable is computed as follows:

$$\Delta FR_{t-1} = \Delta FVPA_{t-1} - \Delta PBO_{t-1} / Mkt\ Cap_{t-1} \tag{1}$$

After calculating the ΔFR, firms-years are sorted into portfolios by ΔFR. Firms sponsoring DBPP are classified as firms with negative changes in *FR* and firms with positive changes in *FR*. Eleven portfolios are formed for these firms. The first ten portfolios include firms with negative changes in *FR* ($\Delta FR < 0$). The eleventh portfolio includes firms with no changes or positive changes in *FR* ($\Delta FR \geq 0$).
As for the change in the long-term debt, ratio it is normalized using market capitalization. The change in long-term debt ratio ($\Delta LTDR_{t-1}$) is computed as:

$$\Delta LTDR_{t-1} = \Delta LTD_{t-1} / Mkt\ Cap_t \tag{2}$$

After calculating the $\Delta LTDR$, firms-years are sorted into portfolios by $\Delta LTDR$. Firms are classified as firms with negative changes in *LTDR* and firms with positive changes in *LTDR*. Eleven portfolios are formed for these firms. The first ten portfolios include firms with positive changes in *LTDR* (increase in debt). The eleventh portfolio includes firms with no changes or positive changes in *LTDR* (decrease in debt).The Fama and French (1993) three-factor model is used to calculate each portfolio's excess return. Portfolios are tested for risk-adjusted returns by running time-series regressions of portfolio returns on the returns on different factors, including the market. Discrepancies in returns among portfolios could be explained by different factor loadings. In formula, the time-series regression (Fama-French three-factor model) for the portfolios is expressed:

$$R_{it} = \alpha_i + b_i EXM_t + h_i HML_t + s_i SMB_t + \varepsilon_{it} \tag{3}$$

where R_{it} is the portfolio excess return. The EXM, HML and SMB factors are constructed as in Fama and French (1993). EXM is the factor that represents the market portfolio minus the risk free rate. The HML factor represents a portfolio long in high book to market (B/M) and short in low B/M firms. The last factor, SMB represents a portfolio long in small and short in large companies. This study, as in Franzoni and Marín (2006), tests for momentum patterns in returns. Jegadeesh and Titman (1993) find evidence that past winners tend to outperform past losers in the following year. This relationship is tested in order to uncover evidence that may suggest that the most underfunded and levered firms tend to be past losers. Chan, Jegadeesh, and Lakonishok (1996), argue that momentum is a short-lived phenomenon. In order to test for the momentum factor, the regressions is estimated as follows

$$R_{it} = \alpha_i + b_i EXM_t + h_i HML_t + s_i SMB_t + m_i UMD_t + \varepsilon_{it} \tag{4}$$

where UMD_t is the momentum factor. It is constructed as a long investment in past twelve month winners and short investment in past twelve month losers. Its inclusion is justified by the evidence in

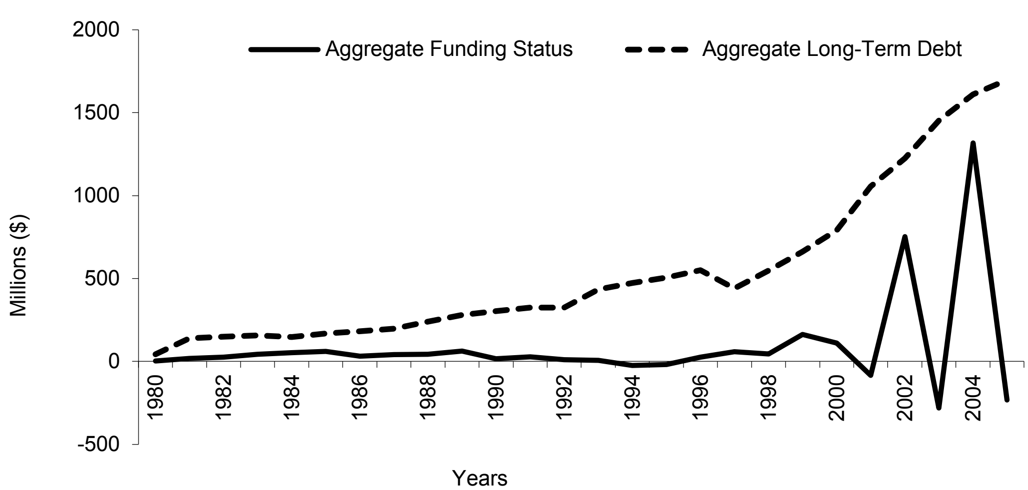
Jegadeesh and Titman (1993). They found that past winners continue to gain extra returns over past losers within a one-year horizon.

Finally, statistical tests are performed to verify if there are statistically significant differences between the risk-adjusted returns of the different portfolios. As in Sloan (1996) and Xie (2001), hedge-portfolio tests are performed to verify if there is an opportunity to outperform the market by creating investment strategies that focus in exploiting the market failure to incorporate the changes in pension plan information. The same tests are performed for the *LTDR* portfolios.

Aggregate Pension Plan Status and Long-Term Debt Historical Trends

The historical evolution of the DBPP status and long-term debt accounts can be helpful in the assessment of any similarities or discrepancies related to the markets' evaluation of stocks. Figure 1 reports the time series of the aggregate funding level for all the companies in Compustat with available pension items. The time series of long-term debt for all firms with available information in Compustat is also presented. The funding level is the difference between the aggregate *FVPA* and *PBO*. As can be observed from Figure 1, an aggregate underfunding appears, for the first time in our sample, in 1994. Starting in 1996 the funding status of DBPP started to improve and in 1997, concurring with the bull market of the second half of the 1990s, pension plan assets grew more than benefits, and peaked in 1999 at about \$163 billion. On March of 2000, the Internet bubble exploded causing stock prices to decrease and as a result, the fair value of pension assets dropped. In 2001, the gap between the *PBO* and the *FVPA* appears reaching almost \$85 million. Major economic events effects arose from September 11, 2001 attacks, with initial impact causing global markets to drop sharply. Then, on 2002, a surplus appears, reaching about \$754 million in aggregate overfunding. However, the volatility in the markets is reflected in years to come. In 2003, another aggregate underfunding appears. This is in contrast to an aggregate overfunding of \$1.3 billion in 2004. This is the highest aggregate overfunding for the whole sample period. For 2005, the last year in the sample, another aggregate underfunding appears. It represents the biggest change in funding status. It reaches almost \$1.5 billion dollars in deficit on a year-to-year basis.

Figure 1: Aggregate Pension Plan Status and Long-Term Debt Levels



The graph reports the difference between aggregate assets (FVPA) and aggregate benefits (*PBO*) for the companies in the sample. In addition, the aggregate level of long-term debt (*LTD*) for the companies in the sample is presented.

As for long-term debt, a tendency to increase over the years is observed. From 1996 to 1997, the increase in the aggregate level of long-term debt represented almost 323%. This is the biggest increase in the level of aggregate debt for the whole sample. It concurred with the bull market associated to the Internet bubble. In 1997, it peaked, reaching an aggregate level of almost $7.5 trillion. Then, in 1998, it started to decrease averaging $6.3 trillion between 1998 and 2005.

Descriptive Statistics: Table 1 reports descriptive statistics of the eleven portfolios created according to ΔFR and $\Delta LTDR$. Panel A shows descriptive statistics for ΔFR portfolios. The characteristics are measured at the end of fiscal year $t-1$ relative to portfolio formation. The change in *FR* is calculated by portfolio. The results show that firms in portfolio one have an average change in *FR* of -210%. As for the other portfolios, the changes range between -6% and 4%. The difference in the level of average *FR* between the portfolio with the firms with the most negative changes and the other portfolios is evident. For portfolio one the average *FR* is about -13.5%. In contrast, for portfolio ten the average level of *FR* is about -0.7%. The average *FR* for portfolio eleven is about 0.5%. The firms with the most negative change (portfolio one) have higher levels of *LTDR*. The rest of the portfolios have considerably less *LTDR* than portfolio one. As for size, the smaller firms are concentrated in portfolio one.

Panel B reports descriptive statistics of the eleven portfolios created according to $\Delta LTDR$. The characteristics are measured at the end of fiscal year $t-1$ relative to portfolio formation. The change in *LTDR* is calculated by portfolio. The results show that, on average, firms in portfolio one have a change (increase) in *LTDR* of 825%. As for portfolios two through ten the changes range between 45% and 0.2%. Portfolio eleven portrays an average reduction of 112% in *LTDR*. For portfolio one the average *LTD* is about $2.5 billion. In contrast, for portfolio ten the average level of *LTD* is about $239 million. The average *LTD* for portfolio eleven is about $395 million. As for size, the smaller firms are concentrated in portfolio one. As for B/M, value firms are concentrated also in this portfolio.

Table 1: Descriptive Statistics for FR and LTDR Portfolios

Panel A: ΔFR Portfolio Characteristics											
	Most (-)									Least (-)	0 or +
	1	2	3	4	5	6	7	8	9	10	11
ΔFR	-2.099	-0.061	-0.033	-0.021	-0.008	-0.009	-0.006	-0.004	-0.002	-0.001	0.039
FR	-0.135	-0.031	-0.018	-0.002	-0.022	-0.02	-0.010	-0.013	-0.008	-0.007	0.005
LTDR	1.168	0.761	0.361	0.434	0.374	0.385	0.398	0.224	0.1778	0.26	0.416
Size	1,406	2,129	3,014	3,070	1,536	4,102	3,633	4,249	3,206	4,431	4,018
B/M	0.268	0.529	0.504	0.453	0.438	0.271	0.462	0.418	0.408	0.404	0.344
Firm-years	1,352	1,664	1,378	1,066	1,092	884	1,118	884	1,040	1,014	8,216
Panel B: ΔLTDR Portfolio Characteristics											
	Most (+)									Least (+)	0 or -
	1	2	3	4	5	6	7	8	9	10	11
ΔLTDR	8.255	0.458	0.259	0.167	0.109	0.07	0.043	0.023	0.009	0.002	-1.12
LTD	2,502	1,587	1,112	1,254	927,1	863,3	759,3	709,2	515,8	238,9	395,2
Size	722.4	1,057	1,213	1,742	1,812	2,253	2,613	3,566	3,535	3,368	1,149
B/M	-1.73	0.24	0.54	0.6	0.43	0.5	0.49	0.52	0.44	0.41	-0.09
Firm-years	6,913	6,927	6,926	6,927	6,928	6,925	6,924	6,930	6,922	6,911	102,262

Two sets of portfolios are examined in this study. In the fourth month after the end of fiscal year t, firms with available data at the end of fiscal year t-1 are assigned to two set of eleven portfolios according to the deciles of the distribution of ΔFR and ΔLTDR. . Panel A presents descriptive statistics for ΔFR portfolios. Portfolios one through ten have most negative change in FR. Firms in portfolio eleven contain firms with positive or zero change in FR. Presented are the average annual change in FR, the annual averages of the FR of the companies in each portfolio; the average of the annual averages of the LTDR of the companies in each portfolio; the average of the annual averages of the market capitalization (in millions of dollars) of the companies in each portfolio at the end of fiscal year t; the average of the annual averages of the book-to-market ratio (B/M) of the companies in each portfolio at the end of fiscal year t – 1; and the average of the annual number of firms in each portfolio. Panel B presents descriptive statistics of ΔLTDR portfolios. Firms in portfolios one through ten have increments in debt from year t-2 to year t-1. Firms in portfolio eleven contain firms with decline or zero change in LTDR. The ΔLTDR is the difference between the balance in the long-term debt account in fiscal year ending in year t -1 and year t-2, divided by the market capitalization at the end of fiscal year t-1. Presented are the average annual change in LTDR, the annual averages of the LTD of the companies in each portfolio; size is measured as the average of the annual averages of the market capitalization (in millions of dollars) of the companies in each portfolio at the end of fiscal year t; the average of the annual averages of the book-to-market ratio (B/M) of the companies in each portfolio at the end of fiscal year t; and the average of the annual number of firm-years in each portfolio. The samples cover formation periods from April 1981 to April 2006.

EMPIRICAL RESULTS

Risk-Adjusted Returns

Table 2 reports the results for the time-series regressions for the returns of the portfolios formed based on the changes in *FR*. Panel A presents the three-factor model results. Portfolio one has significantly negative alpha loadings. Portfolios three and five through eleven have positive and significant alpha loadings. These results indicate that as the negative change in *FR* decreases the undervaluation increases. Portfolio eleven (positive change and improvement in *FR* status portfolio) results indicate that the investors may not be paying attention to the changes in the account and the information related to pension plans at all. Panel B reports alphas, factor loadings, and R^2 for the four-factor model of each set of portfolios. Panel A shows that portfolios five through eleven have positive and significant alpha loadings. The regressions results show slight improvements when the momentum factor is included. Only portfolios one and nine have significant UMD loadings.

Table 3 reports the results for the time-series regressions for the returns of the portfolios formed based on changes in *LTDR*. Panel A reports the alphas of the three-factor model for the eleven portfolios. It can be observed that returns are significantly positive for portfolios four through nine, and portfolio eleven. This is a signal of undervaluation. A negative relation between the change in *LTDR* and the undervaluation can be observed. In other words, as the change in *LTDR* decreases the undervaluation increases. Note that for portfolio one and two the excess return is negative. This may indicate overvaluation for firms that exhibit higher positive changes (largest increments in debt) in *LTDR*.

Apparently, the magnitude of changes in information related to pension plans and long-term debt conveys no additional information to investors. Panel B reports alphas, factor loadings, and R^2 for the four-factor model of *LTDR* portfolios. The results for *LTDR* portfolios are slightly different when the UMD factor is introduced. Panel A shows positive alphas for portfolios five through eleven; this may be a signal of undervaluation. No significant improvements are seen when momentum is introduced. Apparently, momentum has no impact on the portfolios.

Hedge-Portfolio Tests

The risk-adjusted returns estimated using the Fama and French (1993) three-factor and four-factor models indicate that investors may be overpricing firms with negative changes in their funding status and increases in long-term debt levels. In addition, the results indicate that investors may be underpricing stocks with relatively smaller changes in funding status and long-term debt levels. In order to verify if there are statistically significant differences between diverse sets of portfolios, hedge portfolio tests were performed. Table 4 shows time-series means of the average annual returns for each set of portfolios in three years after portfolio formation.

First, hedge portfolio tests were performed between diverse sets of *FR* portfolios. A portfolio hedge that is long in the most negative change in *FR* portfolio (portfolio ten) and short in the least negative change in *FR* portfolio (portfolio one) was formed. The hedge portfolio yields positive returns for each of the three years after portfolio formation: 2 percent (t = 4.39), 1.8 percent (t = 3.74) and 1.6 percent (t = 2.99), respectively.

Table 2: Three-Factor and Four-Factor Model Results for Changes in Funding Ratio

	Most(-) 1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Least (-) 10**	**Positive 11**
Panel A: Three-Factor Model Results											
						Alphas					
Alphas	-0.013*	-0.002	0.003*	0.002	0.005*	0.006*	0.009*	0.008*	0.011*	0.013*	0.006*
	(-6.46)	(-1.48)	(2.25)	(1.89)	(3.80)	(4.22)	(6.22)	(5.90)	(7.76)	(9.65)	(6.14)
						Three-Factor Model Loadings and R^2					
EXM	0.009	0.009	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.009	0.008
	(15.21)	(15.84)	(16.48)	(15.7)	(15.47)	(15.04)	(12.2)	(13.87)	(13.73)	(21.91)	(18.03)
HML	0.008	0.006	0.005	0.005	0.004	0.004	0.003	0.003	0.002	0.002	0.005
	(10.83)	(10.56)	(6.87)	(6.29)	(7.75)	(5.62)	(4.21)	(4.95)	(2.89)	(3.06)	(9.78)
SMB	0.009	0.006	0.005	0.005	0.005	0.004	0.004	0.004	0.004	0.004	0.005
	(11.14)	(9.91)	(7.05)	(7.33)	(6.74)	(6.19)	(4.77)	(5.50)	(5.19)	(6.69)	(14.12)
R^2	0.68	0.76	0.78	0.73	0.76	0.76	0.71	0.76	0.73	0.78	0.89
Firm-years	816	967	1,003	1,024	1,011	1,039	1,024	1,021	1,045	1,027	8,570
Panel B: Four-Factor Model Results											
						Alphas					
Alphas	-0.014*	-0.004*	0.000	0.001	0.003*	0.005*	0.006*	0.007*	0.010*	0.012*	0.005*
	(-5.60)	(-2.33)	(-0.22)	(1.16)	(2.00)	(3.27)	(5.24)	(6.03)	(7.55)	(9.98)	(5.92)
						Four-Factor Model Loadings and R^2					
EXM	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.010	0.009
	(16.78)	(19.53)	(19.02)	(21.37)	(23.12)	(21.75)	(23.62)	(23.56)	(16.66)	(33.42)	(29.94)
HML	0.007	0.006	0.005	0.004	0.004	0.004	0.003	0.004	0.003	0.003	0.005
	(7.25)	(8.65)	(6.52)	(5.78)	(5.74)	(5.59)	(4.10)	(5.58)	(3.54)	(4.03)	(8.20)
SMB	0.012	0.008	0.007	0.007	0.006	0.005	0.005	0.005	0.004	0.005	0.004
	(12.81)	(14.12)	(11.45)	(13.29)	(13.04)	(9.59)	(9.33)	(8.46)	(5.00)	(9.25)	(11.47)
UMD	-0.002	0.003	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(-2.04)	(0.54)	(0.19)	(1.05)	(1.43)	(1.28)	(1.51)	(1.65)	(2.05)	(1.98)	(1.89)
R^2	0.68	0.75	0.77	0.79	0.79	0.72	0.79	0.76	0.74	0.80	0.87
Firm-years	816	967	1,003	1,024	1,011	1,039	1,024	1,021	1,045	1,027	8,570

*In the fourth month after the end of fiscal year t, firms with available data at the end of fiscal year t-1 are divided in deciles according to the change in FR. The stocks in the first portfolio have the most negative changes in FR and the stocks in the tenth portfolio have the least negative changes in FR. Also, in the fourth month of year t, stocks with positive or no change in FR at the end of fiscal year t are assigned to an eleventh portfolio. The change in FR is the difference between the fair value of plan assets (FVPA) and the projected benefit obligation (PBO) in fiscal year ending in year t-1 minus the difference between the fair value of plan assets (FVPA) and the projected benefit obligation (PBO) in fiscal year ending in year t -2, divided by the market capitalization at the end of fiscal year t-1. Panel A reports the constant (alpha) from a time-series regression of portfolio excess returns on the three Fama and French factors for the portfolios. The factors are the market excess return (EXM), the return on HML portfolio, and the return on the SMB portfolio. R^2 from these regressions are also presented. Panel B reports the constant (alpha) from a time-series regression of portfolio excess returns on the four Fama and French factors for the portfolios. The factors are the market excess return (EXM), the return on HML portfolio, the return on the SMB portfolio and the return on a momentum portfolio (UMD). R^2 from these regressions are presented. The sample period is from the fourth month after the end of fiscal year 1987 to 2006. t-statistics are presented in parentheses. * Alphas significant at the 5 percent level.*

These results are consistent with the market overpricing firms with the most negative changes in *FR* in the portfolio formation year (year t). The second comparison is between portfolios one and eleven. This comparison is between the portfolio that contains firms with the most negative changes in *FR* and firms that have positive changes. The hedge portfolio yields positive returns for each of the three years: 1.6 percent (t = 5.90), 1.6 percent (t = 3.81) and 1.4 percent (t = 3.12), respectively. The results are consistent with the market overpricing firms with the most negative changes in *FR* in the portfolio formation year (year t). The last comparison for *FR* portfolios is between portfolios ten (smallest negative changes in *FR*) and eleven (no change or positive change in *FR*). The hedge portfolio yields negative returns for the three years after portfolio formation: -0.4 percent (t = -1.43), -0.3 percent (t = -0.87) and -0.2 percent (t = -0.56), respectively. The results suggest this strategy may not be efficient.

Table 3: Three-Factor and Four-Factor Model Results for Changes in Long-Term Debt Ratio

	Most (+) 1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Least (+) 10**	**Zero or - 11**
Panel A: Three-Factor Model Results											
					Alphas						
Alphas	-0.011*	-0.004*	-0.001	0.002*	0.005*	0.006*	0.008*	0.009*	0.010*	0.017*	0.005*
	(-5.42)	(-3.14)	(-0.51)	(2.11)	(4.97)	(6.32)	(8.33)	(10.12)	(9.70)	(9.48)	(6.38)
					Three-Factor Model Loadings and R^2						
EXM	0.01	0.009	0.008	0.009	0.009	0.009	0.009	0.009	0.01	0.01	0.01
	(17.04)	(19.18)	(22.98)	(21.71)	(23.78)	(27.56)	(26.84)	(34.74)	(36.00)	(23.38)	(39.82)
HML	0.006	0.004	0.003	0.004	0.003	0.003	0.002	0.002	0.009	-0.002	0.002
	(6.28)	(6.53)	(5.63)	(7.04)	(5.13)	(7.43)	(3.89)	(3.98)	(2.09)	(-2.39)	(5.62)
SMB	0.01	0.008	0.008	0.001	0.008	0.007	0.007	0.008	0.009	0.01	0.01
	(10.22)	(14.56)	(16.02)	(13.78)	(16.51)	(16.93)	(15.08)	(15.50)	(15.70)	(14.02)	(16.70)
R^2	0.61	0.80	0.80	0.83	0.83	0.87	0.85	0.85	0.88	0.84	0.89
Firm-years	2,147	2,480	2,599	2,653	2,731	2,730	2,757	2,773	2,794	311	34,495
Panel B: Four-Factor Model Results											
					Alphas						
Alphas	-0.002	0.001	0.0003	0.003	0.006*	0.004*	0.008*	0.009*	0.010*	0.016*	0.007*
	(-0.79)	(0.24)	(0.17)	(1.80)	(3.33)	(2.13)	(5.02)	(6.12)	(5.17)	(5.59)	(3.70)
					Four-Factor Model Loadings and R^2						
EXM	1.06	0.992	0.9	0.978	0.964	0.992	0.921	0.958	1.021	1.051	0.986
	(16.34)	(24.32)	(27.16)	(29.24)	(32.08)	(35.54)	(35.75)	(30.48)	(33.85)	(25.07)	(31.38)
HML	0.581	0.53	0.418	0.467	0.404	0.389	0.256	0.187	-0.006	-0.222	0.174
	(4.71)	(6.67)	(5.43)	(7.55)	(5.78)	(6.93)	(4.52)	(3.07)	(-0.10)	(-2.20)	(2.78)
SMB	0.856	0.713	0.693	0.613	0.676	0.634	0.63	0.703	0.799	0.924	0.866
	(10.55)	(11.93)	(12.34)	(10.42)	(13.76)	(13.16)	(14.80)	(11.76)	(13.99)	(16.88)	(14.34)
UMD	-1.87	-1.23	-0.351	-0.473	-0.423	0.294	-0.163	0.111	0.301	0.289	-0.277
	(-3.40)	(-3.41)	(-0.85)	(-1.36)	(-1.22)	(0.83)	(-0.05)	(0.36)	(0.93)	(0.71)	(-0.77)
R^2	0.58	0.77	0.78	0.82	0.82	0.86	0.85	0.84	0.87	0.84	0.86
Firm-years	2,147	2,480	2,599	2,653	2,731	2,730	2,757	2,773	2,794	311	34,495

*In the fourth month after the end of fiscal year t, firms with available data at the end of fiscal year t-1 are divided in deciles according to the change in LTDR. The firms in the first portfolio have higher positive changes in debt. Firms assigned to the tenth portfolio have lower positive changes in debt. Firms are assigned to portfolio eleven if there is no change or a negative change in LTDR. Panel A reports the constant (alpha) from a time-series regression of portfolio excess returns on the three Fama and French factors. The factors are the market excess return (EXM), the return on HML portfolio, and the return on the SMB portfolio. R2 from these regressions are also presented. Panel B reports the constant (alpha) from a time-series regression of portfolio excess returns on the four Fama and French factors. The factors are the market excess return (EXM), the return on HML portfolio, the return on the SMB portfolio and the return on a momentum portfolio (UMD). R2 from these regressions are presented. The sample period is from the fourth month after the end of fiscal year 1980 to 2006. T-statistics are presented in parentheses. * Alphas significant at the 5 percent level.*

In addition, hedge portfolio tests were performed between diverse sets of *LTDR* portfolios. A portfolio hedge that is long in firms that have the least positive changes in *LTDR* (portfolio ten) and short in firms that have the biggest changes (portfolio one) was formed. The hedge portfolio yields positive returns for each of the three years: 2.4 percent (t = 8.93), 2.2 percent (t = 7.74) and 1.9 percent (t = 6.38), respectively. This strategy yields positive returns for each of the three years after portfolio formation. This type of strategy appears to be efficient. It evidences that the market overprices firms with the greater increments in *LTDR* and undervalues firms with the smaller increments in *LTDR* in the year of portfolio formation. The second comparison is between portfolios one and eleven. This comparison is between the portfolio composed of firms that have the highest positive changes in *LTDR* and the portfolio that contains firms that have no changes or negative changes in *LTDR*. The hedge portfolio yields positive returns for each of the three years: 1.5 percent (t = 7.38), 1.4 percent (t = 6.49) and 1.4 percent (t = 6.08), respectively.

Table 4: Hedge Portfolio Tests for Change in Funding and Long-Term Debt Ratios

	Average Returns Per Portfolio					
Portfolio	**Panel A: ΔFR Portfolios**			**Panel B: ΔLTDR Portfolios**		
Ranking	Year t+1	Year t+2	Year t+3	Year t+1	Year t+2	Year t+3
1	-0.003	-0.004	-0.001	-0.002	-0.002	-0.001
	(0.36)	(-0.06)	(0.39)	(0.03)	(0.02)	(0.46)
2	0.005	0.004	0.006	0.004	0.003	0.004
	(-0.10)	(-0.28)	(0.39)	(-0.01)	(-0.44)	(0.32)
3	0.008	0.007	0.007	0.007	0.006	0.006
	(-0.11)	(-0.22)	(-0.01)	(-0.08)	(-0.36)	(-0.00)
4	0.008	0.007	0.007	0.010	0.009	0.009
	(-0.02)	(-0.52)	(-0.02)	(-0.30)	(-0.47)	(0.02)
5	0.011	0.009	0.01	0.011	0.010	0.01
	(0.05)	(-0.36)	(0.01)	(-0.74)	(-0.50)	(-0.11)
6	0.012	0.011	0.011	0.013	0.012	0.011
	(0.01)	(-0.42)	(0.07)	(-0.36)	(-0.47)	(-0.23)
7	0.014	0.012	0.012	0.014	0.013	0.012
	(-0.02)	(-0.50)	(-0.06)	(-0.61)	(-0.47)	(-0.43)
8	0.013	0.013	0.012	0.016	0.015	0.015
	(-0.30)	(-0.30)	(0.04)	(-0.51)	(-0.47)	(0.04)
9	0.015	0.015	0.013	0.017	0.016	0.015
	(-0.13)	(-0.55)	(-0.13)	(-0.48)	(-0.62)	(-0.35)
10	0.017	0.015	0.014	0.022	0.020	0.018
	(-0.31)	(-0.59)	(-0.04)	(-0.86)	(-0.86)	(-0.52)
11	0.013	0.012	0.013	0.013	0.012	0.013
	(-1.67)	(-0.63)	(0.47)	(-1.18)	(-1.28)	(0.83)
	Panel C: Portfolio Hedge					
Comparison	*FR* portfolios			*LTDR* portfolios		
1 and 10	0.020*	0.018*	0.016*	0.024*	0.022*	0.019*
	(4.39)	(3.74)	(2.99)	(8.93)	(7.74)	(6.38)
1 and 11	0.016*	0.016*	0.014*	0.015*	0.014*	0.014*
	(5.90)	(3.81)	(3.12)	(7.38)	(6.49)	(6.08)
10 and 11	-0.004	-0.003	-0.002	-0.009*	-0.005*	-0.005*
	(-1.43)	(-0.87)	(-0.56)	(-4.78)	(-2.53)	(-2.51)

*Time-series means (t-statistics) of the average annual returns for each FR and LTDR portfolio in three years after portfolio formation are calculated. Panel A and B show the returns for portfolios formed based on the change in FR and LTDR, respectively. In Panel A, the stocks in portfolio one (ten) have the most (least) negative change in funding levels. Firms with positive changes are assigned to portfolio eleven. In Panel B, stocks in portfolio one (ten) have the most (least) positive changes in debt (increase in LTDR). Firms with zero or negative changes (decrease in LTDR) are assigned to portfolio eleven. Panel C presents the hedge between portfolios one and ten, one and eleven, and ten and eleven. * denotes significance at the 0.05 level, based on a two-tailed t-test for the time-series (19 for FR portfolios and 26 years for LTDR portfolios) of annual average returns.*

These results are consistent with the market overpricing firms with the biggest positive changes in *LTDR* in the portfolio formation year (year t). The last comparison for *LTDR* portfolios is between portfolios ten (smaller changes in *LTDR*) and eleven (no change or negative change). The hedge portfolio yields negative returns for the three years after portfolio formation: -0.9 percent (t = -4.78), -0.5 percent (t = -2.53) and -0.5 percent (t = -2.51), respectively. It is important to notice that the overvaluation for firms with no change or negative change in *LTDR* is lower than for firms with the smaller positive changes in *LTDR* at portfolio formation year. These results indicate that this type of strategy may be efficient. To summarize, the hedge portfolio results support the notion that the market overprices firms that have the most negative changes in *FR* and greater increases in *LTDR*.

CONCLUSIONS

This study investigates if the use of information conveyed by changes in funding status of pension plans results in a better assessment of firms' pension commitments as reflected in stock prices. This study contributes to the recent discussion by the Financial Accounting Standards Board (FASB) and the release of SFAS No. 158 about the incorporation and importance of more DBPP information in the financial statements. The results suggest that the market does not incorporate efficiently the information related to the changes in funding status as reflected in stock prices. This may signify that the investors are unable to analyze and interpret the possible implications of increases in the underfunding of pension plans. This may be due to investors having problems in understanding the complex pension accounting calculations and disclosures or the inability to incorporate timely and efficiently the information.

In contrast with previous research, investors' reactions to changes in DBPP information were compared to reactions to changes in long-term debt account ratios. The results reveal that the market is also inefficient incorporating long-term debt information. Further tests were performed to corroborate if investment strategies can be design based on the market inefficiencies suggested by the results of the factor models. Particular to this study is the integration of hedge portfolio tests. Results suggest that strategies to benefit from market inefficiencies may be profitable. These tests also reveal similarities between market valuations of changes in DBPP status and long-term debt information. The results are consistent with Franzoni and Marín (2006) and Godwin and Key (1998). The identified inefficiencies may result from market's inability to integrate information and to identify future consequences related to these long-term commitments. Sloan (1996) argues, investors appear to be "fixating" just on earnings figures. This study uses a sample of US public companies with available DBPP information from 1980 to 2005 but does not include pension data under the new accounting rules (SFAS No. 158). Future studies may focus on periods after the issuance of this new accounting rule.

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DETERMINANTS OF BANK BOARD STRUCTURE IN GHANA

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ABSTRACT

The paper investigates the determinants of bank board structure in Ghana and finds that the Scope of Operations Hypothesis could explain the variation in board size but not board independence. On the other hand, the Board Monitoring Hypothesis could only explain the variation in board independence but not board size. The study also finds that cost-income ratio, foreign majority ownership structure and Ghana Stock Exchange listing status are positively and significantly associated with large bank board size. The paper, therefore, argues that as a bank grows in Ghana the size of its board of directors is likely to increase. However, the increase is likely to result in inefficiency of the bank. Furthermore, the study has evidence to conclude that banks with foreign majority ownership structure are not likely to appoint more independent directors.

JEL: G20, G21, G30, G34

KEYWORDS: Board structure, board size, board independence, Scope of Operations Hypothesis, Board Monitoring Hypothesis

INTRODUCTION

The board structure of firms has received a tremendous attention in the corporate governance and financial economics literature because of the indispensable roles of boards in corporate affairs. Studies on board structure report that optimal board structure is predicated on the costs and benefits of the board monitoring and advising roles coupled with other firm and governance characteristics (Linck et al., 2008). Raheja (2005); Adams & Ferreira (2007); and Linck et al. (2008) identify two most important roles of a board of directors as monitoring and advising. Grounded on the agency theory of the firm (Eisenhardt, 1989, and Jensen & Meckling, 1976), the board of directors serves as monitors of managers of the firm to circumvent pursuit of personal aggrandizement (e.g. shirking and perquisites) that is detrimental to shareholder wealth maximization. The board discharges its advising role by providing strategic direction to the firm through opinions and directions to managers.

Most of the studies on corporate boards have always modeled two specific elements of the boards: board size and board composition (i.e. independent directors) as points of reference (Pathan &Skully, 2010). Thus, the current study is focused on these two dimensions of boards. It builds on the studies such as Pathan & Skully's (2010) study on the determinants of bank board structure. The current study, however, differs from the previous studies and is, therefore, significant for two main reasons. One, unlike the previous key studies that use samples of bank holding companies, the current study uses individual universal banks in Ghana. Two, unlike the previous studies that use samples from the developed economies, the current study uses a sample from Ghana which is a developing economy and, thus, provides board structure perspectives from the developing world. Two main questions constitute the main motivation behind the current study: (1) What are the determinants of bank board size in Ghana? (2) What are the determinants of bank board independence in Ghana?

The remainder of the paper is organized as follows. Section 2 briefly discusses the relevant literature and states the hypotheses to be tested. Data selection, research methodology and empirical model are described in section 3. Section 4 provides analysis and interpretations of the empirical findings and section 5 concludes the paper.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Scope of Operations Hypothesis (SOH) and the Board Monitoring Hypothesis (BMH) are the two main hypotheses that have dominated the discourse on board structure. Consequently, the current study purports to find evidence to either uphold or refute them. The two hypotheses are discussed below.

Scope of Operations Hypothesis

Financial economists have reached few definitive conclusions about the forces that determine board size and composition (Boone et al., 2007). One of the views that have dominated the corporate finance and financial economics literature regarding forces that drive board size and composition is SOH. This view argues that as the operations of a firm grow in size and complexity there is a corresponding increase in its demand for more board members to deal with the concomitant challenges associated with such growth and complexity. This presupposes that a firm's diversification into new product lines or new geographical areas should trigger its quest for new board members to help oversee managers' performance (Fama & Jensen, 1983; and Lehn et al., 2005). Contributing to the SOH debate, Bhagat & Black (1999) and Agrawal & Knoeber (2001) have asserted that a grown and complex firm's motivation for new directors stems from the possibility of new directors possessing specialized knowledge that applies to the new growth areas of the firm. Results reported by Denis & Sarin (1999) and Yermack (1996) lend credence to the SOH as their findings suggest that board size is positively related to firm size. Boone et al. (2007) find that board size and independence increase as firms grow and diversify over time. Consequently, the study proposes the following hypotheses:

$H_{1:}$ *Board size is positively and significantly associated with scope of operations*

$H_{2:}$ *Board independence is positively and significantly associated with scope of operations*

Board Monitoring Requirements Hypothesis

Raheja (2005) and Adams & Ferreira (2007) report that board structure correlates with the net benefits of monitoring managers' private benefits as well as the monitoring costs to directors. BMH states that in terms of 'private benefits' the benefit obtained from board of directors' monitoring of managers of the firm increases if managers have the opportunity to increase their private benefits from the firm (Boone et al., 2007; and Chi &Lee, 2010). Availability of free cash flows as well as managers' immunity to any shareholders' activism (i.e. M&A activities) generally provide opportunities for private benefits to managers (Boone et al., 2007). According to Boone et al. (2007) the tendency for firms to engage the services of more independent directors thereby increasing overall board size is predicated on the presence of the opportunity for greater 'private benefits' to insiders. Regarding 'monitoring costs,' Fama & Jensen (1983) argue that they are greater for firms with high information asymmetry. Empirical studies assert that firms with greater monitoring costs should fall less on outside directors because it is costly to transfer firm-specific information to outsiders since they have relatively less information about the firm's projects (Linck et al., 2008). The theoretical models of Raheja (2005) and Adams &Ferreira (2007) on board structure predict that the number of outsiders decreases with 'monitoring costs. Consequently, the study will explore the following hypotheses:

$H_{3:}$ *Board size is negatively and significantly associated with private benefits*

$H_{4:}$ *Board size is negatively and significantly associated with monitoring costs*

$H_{5:}$ Board independence is negatively and significantly associated with private benefits

$H_{6:}$ Board independence is negatively and significantly associated with monitoring costs

The measures of the two hypotheses and their expected relationships with board size and board independence are presented in Table 1 below.

Table 1: Measures of the Scope of Operations Hypothesis and Monitoring Hypothesis and their Relationships with Board Structure

Variables	Number of Directors	Proportion of Independent Directors
1. **For the Scope of Operations Hypothesis**		
Bank Size	+	+
Bank Age	+	+
2. **For the Monitoring Hypothesis**		
Free Cash Flow (Private Benefit)	+	+
Market-to-Book Ratio (Monitoring Cost)	-	-

This table shows how the two main hypotheses are defined and their relationships with board structure.

RESEARCH METHODOLOGY

This section discusses how the study was undertaken. It describes the econometric model employed, sample size, data source and data collection procedures.

The Model

Two measures are used to measure board structure: board size; and board independence. The board size and board independence are, therefore, dependent variables. In line with the studies of Anderson & Reeb (2003); De Andres et al. (2005); Jackling & Johl, 2009) board size is measured using the natural logarithm of the total number of members of the board of directors. The log transformation of board size is used to make the distribution of the board size dependent variable more symmetric (Eisenberg et al. 1998). Board independence is measured as the proportion of non-executive directors on a bank's board of directors. Independent director has been defined as one that could get a seat in the board without the controlling shareholder's votes (Lefort &Urzúa 2008).

The explanatory variables are size of bank (SIZE); bank age (AGE); free cash flow (CASHFLOW); market to book ratio (MTBRATIO); cost-Income ratio (CIRATIO); Return on equity (ROE); bank ownership structure (BNATURE) and bank GSE listing status (GSELISTING). Size of bank is defined as the natural logarithm of the total assets (Anderson & Reeb, 2003). In keeping with the theory of Klein (2002) that large board promotes efficiency through specialization, Cost-Income ratio is included in the model to measure efficiency of a bank and is defined as operating expenses plus other costs divided by net income. The literature supports a negative correlation between board size and firm performance (Eisenberg et al., 1998; Adusei, 2011). Thus, return on equity has been included in the model and is calculated as profit after tax divided by total equity. The nature of a bank (BNATURE) is a dummy variable. It is set to 1 if a bank is a subsidiary of multinational or international bank and set to zero if not. The listing status of bank (LISTING) is a dummy variable. It is set to 1 if the bank is listed on the Ghana Stock Exchange (GSE) and set to zero if not. Description of the variables is presented in Table 2.

The panel data model for relating the dependent variable to independent variables is compactly stated thus:

$$Y_{it} = \alpha + \beta X_{it} + \delta_1 d_{1\mathrm{it}} + \delta_2 d_{2\mathrm{it}} + \ddot{e}_{it} \quad (1)$$

Where:

Subscript ***i*** represents the cross-sectional dimension of the data

t denotes the time-series dimension of the data

Y represents the dependent variables in the model which are measures of bank board structure

X represents the set of independent variables in the estimation model

δ represents the coefficient of the dummy variable

d represents dummy variables

α and β denote constant and regression coefficient respectively

*ë r*epresents the error term

Following prior studies, including Boone et al. (2007) and Linck et al. (2008), the primary estimation method of regression is pooled ordinary least squares (OLS).

Table 2: Description of Variables

Variable	**Definition**
Board Size(BSIZE): Dependent variable	the natural logarithm of the total number of members of the board of directors
Board Independence (BINDEPEND): Dependent variable	Proportion of outside directors on the board
Bank Size (SIZE)	the natural logarithm of total assets of a bank at the end of a fiscal year
Bank Age (AGE)	the natural logarithm of the number of years of a bank's existence
Private Benefit: Free Cash Flow (CASHFLOW)	Operating Income minus capital Expenditure divided by Total Asset
Monitoring Cost **:**Market-to-Book Ratio (MTBRATIO)	Stated Capital plus capital surplus divided by Total Assets
Cost-Income Ratio (CIRATIO)*	Operating expenses+ other costs divided by Net Income
Return on Equity (ROE)	Profit after tax divided by Total Equity
Dummy for Bank Nature (BNATURE)	= 1:if bank has majority foreign ownership structure; =0: otherwise
Dummy for GSE Listing Status (GSELISTING)	= 1: if bank is listed on GSE; = 0: Otherwise

*This table describes the variables used in the model.. * This is used to proxy the efficiency of a bank. The lower the ratio the better. Thus, a bank that experiences a decline in this ratio becomes more efficient and vice versa.*

Sample and Data Sources

A total sample of 17 out of 26 universal banks in Ghana, representing 65% of the study population was used in the study. Data for the study were gathered from the annual reports of the banks. The website of each of the universal banks in Ghana was visited. On the website, the annual reports for the chosen period of study (2005-2009) were downloaded. Since the study required background data such as age and the structure of board of directors, the websites were surfed to glean such data where they could not be found in the annual reports. Not all banks provided their annual reports for all the years under review. However, any bank that provided at least a two-year financial report was included in the study. The nine (9) banks excluded from the study were excluded because of the non-availability of their annual financial reports covering the study period. In all, 55 observations were obtained after editing the financial reports of the 17 banks.

ESTIMATION RESULTS

The descriptive statistics of the data used are given in Table 3. As can be seen, 55 observations were used for the analysis.

Table 3: Descriptive Statistics

	Panel A: Board Size		**Panel B: Board Independence**	
	Mean	Std. Deviation	Mean	Std. Deviation
BSIZE	0.9513	0.08126	0.9513	0.08126
AGE	1.2593	0.48074	1.2593	0.48074
SIZE	8.5796	0.60224	8.5796	0.60224
CASH FLOW	9.5565	5.47984	9.5565	5.47984
MTB RATIO	91.0664	18.18965	91.0664	18.18965
CIRATIO	71.6578	20.67025	71.6578	20.67025
ROE	22.7815	14.48020	22.7815	14.48020
BNATURE*	0.42	0.498	0.42	0.498
GSELISTING*	0.38	0.490	0.38	0.490
INDEPEND	75.8727	15.26349	75.8727	15.26349
N	55	55	55	55

*This table provides descriptive statistics of the data used in the study. Variables with * notation against them are dummy variables.*

The Pearson Correlation Matrices reported in Tables 4 and 5 indicate that multicollinearity problem is not present in the models (Bryman and Cramer, 1997). The absence of multicollinearity problem in the data is corroborated by the collinearity diagnostics results-Variance Inflation Factor (VIF) and Tolerance (TOL) - reported in Tables 6 and 7.

Table 4: Board Size as Dependent Variable

Correlations										
Panel A: Pearson Correlation										
	BSIZE	AGE	SIZE	CASHFLOW	MTBRATIO	CIRATIO	ROE	BNATURE	GSELITI	INDEPEND
BSIZE	1.000	.527	.152	-.075	-.342	.107	-.142	.211	.364	.106
AGE	.527	1.000	.401	.054	-.407	-.280	.182	.206	.392	-.013
SIZE	.152	.401	1.000	.054	-.115	-.136	.211	.267	.391	-.354
CASHFLOW	-.075	.054	.054	1.000	.311	.146	-.121	-.209	-.178	.076
MTBRATIO	-.342	-.407	-.115	.311	1.000	.293	-.253	-.243	-.310	-.180
CIRATIO	.107	-.280	-.136	.146	.293	1.000	-.456	-.130	-.435	.259
ROE	-.142	.182	.211	-.121	-.253	-.456	1.000	.264	.176	-.141
BNATURE	.211	.206	.267	-.209	-.243	-.130	.264	1.000	.017	-.280
GSELISTI	.364	.392	.391	-.178	-.310	-.435	.176	.017	1.000	-.268
INDEPEND	.106	-.013	-.354	.076	-.180	.259	-.141	-.280	-.268	1.000
Panel B: Sig (1-tailed)										
BSIZE		.000	.134	.294	.005	.219	.150	.061	.003	.220
AGE	.000		.001	.348	.001	.019	.091	.066	.002	.464
SIZE	.134	.001		.348	.201	.161	0.61	.024	.002	.004
CASHFLOW	.294	.348	.348		.011	.143	.189	0.62	.097	.289
MTBRATIO	.005	.001	.201	.011		.015	0.31	.037	.011	.095
CIRATIO	.219	.019	.161	.143	.015		.000	.172	.000	.028
ROE	.150	.091	.061	.189	.031	.000		.026	.099	.153
BNATURE	.061	.066	.024	.062	.037	.172	.026		.452	.019
GSELISTI	.003	.002	.002	.097	.011	.000	.099	.452		.024
INDEPEND	.220	.464	.004	.289	.095	.028	.153	.019	0.24	

This is the Pearson Correlation Matrix of Panel A with Board Size as Dependent Variable

The collinearity diagnostics results satisfy the acceptable standards of Myers (1990) and Menard (1995) respectively and reinforce the robustness of the models. Myers (1990) suggests that if the largest VIF value is greater than 10, then multicollinearity problem may exist. Menard (1995) suggests that TOL below 0.2 indicates a potential multicollinearity problem.

The evidence presented in Table 6 suggests that the SOH could explain bank board size, implying that as a universal bank in Ghana expands its operations the probability of increasing its board size to ensure effective supervision is high. Thus, hypothesis H_1 is supported. This finding is in tandem with the extant literature (Bhagat & Black, 1999; Agrawal &Knoeber, 2001; Denis & Sarin, 1999; and Yermack, 1996; and Boone et al., 2007).

Table 5: Board Independence as Dependent Variable

Correlations										
Panel A: Pearson Correlation										
	INDEPEND	AGE	SIZE	CASHFLOW	MTBRATIO	CIRATIO	ROE	BNATURE	GSELITI	BSIZE
INDEPEND	1.000	-.013	-.354	.076	-.180	.259	-.141	-.280	-.268	.106
AGE	-.013	1.000	.401	.054	-.407	-.280	.182	.206	.392	.527
SIZE	-.354	.401	1.000	.054	-.115	-.136	.211	.267	.391	.152
CASHFLOW	.076	.054	.054	1.000	.311	.146	-.121	-.209	-.178	-.075
MTBRATIO	-.180	-.407	-.115	.311	1.000	.293	-.253	-.243	-.310	-.342
CIRATIO	.259	-.280	-.136	.146	.293	1.000	-.456	-.130	-.435	.107
ROE	-.141	.182	.211	-.121	-.253	-.456	1.000	.264	.176	-.142
BNATURE	-.280	.206	.267	.209	-.243	-.130	.264	1.000	.017	.211
GSELISTI	-.268	.392	.391	-.178	-.310	-.435	.176	.017	1.000	.364
BSIZE	.106	.527	.152	-.075	-.342	.107	-.142	.211	.364	1.000
Panel B: Sig (1-tailed)										
INDEPEND		.464	.004	.289	.095	.028	.153	.019	.024	.220
AGE	.464		.001	.348	.001	.019	0.91	.066	.002	.000
SIZE	.004	.001		.348	.201	.161	0.61	.024	.002	.134
CASHFLOW	.289	.348	.348		.011	.143	.189	.062	.097	.294
MTBRATIO	.095	.001	.201	.011		.015	.031	.037	.011	.005
CIRATIO	.028	.019	.161	.143	.015		.000	.172	.000	.219
ROE	.153	.091	.061	.189	0.31	.000		.026	.099	.150
BNATURE	.019	.066	.024	.062	.037	.172	0.26		.452	.061
GSELISTI	.024	.002	.002	.097	.011	.000	.099	.452		.003
BSIZE	.220	.000	.134	.294	.005	.219	.150	.061	.003	

This is the Pearson Correlation Matrix of Panel A with Board Size as Dependent Variable

Table 6 shows that increasing bank cost-income ratio is associated with increasing size of the bank's board of directors. In other words, an increase in bank board size is likely to be accompanied by an increase in bank inefficiency. This corroborates the position of Fama &Jensen (1983) and Yermack (1996) and challenges the view of Klein (2002). Banks with foreign majority ownership structure as well as GSE listing are likely to have larger board sizes compared to their counterparts. Table 7 indicates that banks with majority foreign ownership structure are not likely to appoint more independent board of directors and vice versa. As Tables 6 and 7 show, profitability does not determine neither board size nor board independence.

Table 7, however, suggests that the SOH has no empirical support as far as board independence is concerned. Hypothesis H_2 is, thus, rejected. This implies that banks in Ghana are not likely to increase the proportion of independent directors on their boards as they grow in size and complexity. This may be attributed to greater information asymmetry inherent in the industry (Linck et al., 2007). Although predictably, and in line with the extant literature (Boone et al. 2007), there are negative relationships between board structure and board monitoring cost yet the relationships between board size and board monitoring requirements variables are statistically insignificant. Hypotheses H_3 and H_4 are refuted. Thus, it is empirically tenable to argue that the size of a bank's board of directors cannot be determined by board monitoring requirements. On the other hand, as Table 7 demonstrates, there is evidence to support the argument that as the bank monitoring cost increases, this is likely to decrease the probability of the bank engaging more independent directors on its board of directors and vice versa (Raheja,2005; and

Adams &Ferreira, 2007). This implies that hypothesis H_6 has empirical backing. Table 7 shows that there is no empirical basis for accepting hypothesis H_5.

Table 6: Regression Results-Panel A: Board Size as Dependent Variable

Variable	β	t	TOL	VIF
CONSTANT	-	5.349***	-	-
AGE	.465	3.615***	0.623	1.605
SIZE	-.148	-1.161*	0.629	1.589
CASH FLOW	-.016	-.136*	0.791	1.265
MTB RATIO	-.110	-.832*	0.590	1.695
CIRATIO	.349	2.673***	0.603	1.659
ROE	-.188	-1.574*	0.724	1.382
BNATURE	.242	2.011**	0.711	1.406
GSELISTING	.411	3.071***	0.574	1.743
INDEPEND	.102	0.804*	0.636	1.573
R^2=*0.537*				
F =5.792; Prob.(F-Statistic) 000				

*This table shows the regression estimates of the equation: $Y_{it} = \alpha + \beta X_{it}+\delta_1 d_{1it}+ \delta_2 d_{2it} + \ddot{e}_{it}$ with Board Size as the dependent variable and AGE, SIZE; CASH FLOW, MTB RATIO, CIRATIO, ROE, BNATURE, GSELISTING, and INDEPEND as independent variables. The first figure in each cell is the regression coefficient. The second figure in each cell is the t-statistic. ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively. The study has, however, adopted 5 percent level as the maximum significance level.*

Table 7: Regression Results -Panel B: Board Independence as Dependent Variable

Variable	β	t	TOL	VIF
CONSTANT		2.778***		
AGE	.082	0.482*	0.485	2.061
SIZE	-.246	-1.679*	0.649	1.540
CASH FLOW	.069	0.521*	0.795	1.258
MTB RATIO	-.353	-2.425**	0.657	1.522
CIRATIO	.191	1.187*	0.536	1.865
ROE	-.054	-0.378*	0.688	1.453
BNATURE	-.317	-2.294**	0.729	1.372
GSELISTING	.273	-1.638*	0.502	1.990
BSIZE	.138	0.804*	0.470	2.128
R^2=0.373				
F= 2.979 *Prob.(F-statistic)* 0.007				

*This table shows the regression estimates of the equation: $Y_{it} = \alpha + \beta X_{it}+\delta_1 d_{1it}+ \delta_2 d_{2it} + \ddot{e}_{it}$ with Board Independence as the dependent variable and AGE, SIZE; CASH FLOW, MTB RATIO, CIRATIO, ROE, BNATURE, GSELISTING, and BSIZE as independent variables. The first figure in each cell is the regression coefficient. The second figure in each cell is the t-statistic. ***, ** and * indicate significance at the 1, 5 and 10 percent levels respectively. The study has, however, adopted 5 percent level as the maximum significance level.*

CONCLUSION

Two main questions constitute the main motivation behind the current study: What are the determinants of bank board size in Ghana? and What are the determinants of bank board independence in Ghana? A total sample of 17 out of 26 universal banks in Ghana, representing 65% of the study population has been used in the study. Data for the chosen period of study (2005-2009) have been gathered from the annual reports of the banks. The study has found that the SOH could explain the variation in board size but not board independence. On the other hand, the BMH could only explain variation in board independence but not board size. The study also finds that cost-income ratio, foreign majority ownership structure and Ghana Stock Exchange listing status are significantly associated with large bank board size. The paper, therefore, argues that as a bank grows in Ghana the size of its board of directors is likely to increase. However, the increase is likely to result in inefficiency of the bank. Furthermore, the study has evidence to conclude that banks with foreign majority ownership structure are not likely to appoint more independent directors. One obvious weakness of this paper is its inability to establish causality between the dependent variables and the independent variables. Another weakness is that data were gathered from published accounts of the universal banks in Ghana. It has always been argued that financial statements of companies are sometimes bedecked with deliberate factual inaccuracies to impress stakeholders. Not all, the current study depends on data from one country which makes its findings limited. Future researchers can enhance the quality of the current findings as well as expand its frontiers by gathering data from other countries to explore the possibility of performing causality tests between the dependent and the independent variables.

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A COMPARISON OF DELTA HEDGING UNDER TWO PRICE DISTRIBUTION ASSUMPTIONS BY LIKELIHOOD RATIO

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ABSTRACT

This paper compares net profits from delta hedging through the Delta of a European call option, by assuming underlying stock prices follows a geometric Brownian motion (GBM) or a Variance-Gamma (VG) process. We employ the maximum likelihood estimation method to estimate corresponding parameters for each process. A Monte Carlo simulation is conducted to simulate spot prices and option prices and a likelihood ratio (LR) method is used to estimate the Delta of the call option over different sample paths. We then implement a dynamic delta hedging strategy through the simulated spot prices, option prices and Delta at different hedging frequencies. Finally, we compare net profits calculated from hedging corresponding to a GBM or a VG process.

JEL: G13, G15, G17

KEYWORDS: likelihood ratio, Variance-Gamma, geometric Brownian motion, delta hedging

INTRODUCTION

Delta hedging is a particular type of hedging strategy. The fundamental of delta hedging is to adjust the shares of stocks longed or shorted according to changes of option prices. Delta is defined as the rate of changes of option prices to spot prices. Therefore, Delta plays an important role in hedging strategy, since it measures the sensitivity of option prices to spot prices and determines how many shares of stocks to purchase or sell to offset risks from changes of option prices. The gradient estimation technique has been widely applied to estimate Delta. Two widely-used gradient estimation methods are (i) the likelihood ratio (LR) method, and (ii) the infinitesimal perturbation analysis (IPA) method.

The main purpose of this paper is to compare net profits from delta hedging by assuming underlying stock prices follow a geometric Brownian motion (GBM) or Variance-Gamma (VG) process. Following Jarrow and Turnbull (1999), we employ the dynamic hedging strategy to hedge periodically before a European call option matures. Since Delta changes frequently before maturity, we estimate the Delta each time we intend to delta hedge, in order to improve the accuracy of stock shares required to offset the risk.

The remainder of this paper is organized as follows. We first provide a literature review of delta hedging, gradient estimation technique, as well as a geometric Brownian motion process and a Variance Gamma process. Then, we introduce the delta hedging strategy, as well as the background of GBM and VG processes. We also provide details of how to estimate Delta for the two processes by the LR method. Finally, a numerical experiment of dynamic delta hedging is conducted to compare net profits from GBM and VG processes.

LITERATURE REVIEW

Delta hedging has been widely applied by investors who are long or short options to hedge risks from changes of option prices. Due to its broad application in financial engineering, there is a vast literature on delta hedging. Hull (2003) provides a general introduction of hedging strategies including delta hedging. Jarrow and Turnbull (1999) provide a detailed explanation of how to implement dynamic delta hedging and replicate portfolios to achieve a delta-neutral position.

The gradient technique is one area in the class of Monte Carlo simulation, which has been broadly applied in financial engineering and has been studied and summarized in Glasserman (2004). Fu (2006) reviews kinds of methods of gradient estimation and their applications in the finance community. Fu and Hu (1995) first bring the gradient estimation technique IPA method into option pricing and sensitivity analysis of options. Broadie and Glasserman (1996) then employ IPA and LR methods to price European and Asian options and analyze sensitivities of these two options. Fu (2008) reviews techniques and applications to derivatives securities. Cao and Guo (2011-1) assume stock prices follow a Variance-Gamma process, and employ the forward difference, IPA and LR method to estimate Greeks for a European call option. Cao and Guo (2011-2) compare the gradient estimates from the Variance Gamma model assumption and geometric Brownian motion model assumption. Cao and Guo (2011-3) analyze the statistic properties of net profits from delta hedging via deltas estimated from LR and IPA methods under a geometric Brownian motion model. Cao and Guo (2011-4) compares results of delta hedging through deltas calculated from two price distributions (a GBM and a VG) by IPA method. In this paper we employ the LR method to estimate Deltas which play an important role in delta hedging, due to its popularity in empirical research.

Before implementing the LR method, we need to make certain assumptions on the underlying processes. The popularly used geometric Brownian motion model is also called the Black-Scholes model, which was first proposed by Black and Scholes (1973) and Merton (1973) assumes stock prices follow a geometric Brownian motion process. However, empirical evidence suggests that the GBM has some imperfections and does not describe the statistical properties of financial time series well. The Variance Gamma (VG) process, as one of the most popular Levy process, was first introduced to the literature in Madan and Seneta (1990) then applied to option pricing in Madan and Milne (1991). Madan, Carr and Chang (1998) developed the VG process by adding one more parameter to describe the negative skewness of stock prices in the market. This VG process has shown more accuracy in pricing stocks. Fu (2007) reviews how to apply this model by Monte Carlo simulation to price options and other derivatives. Cao and Fu (2010) estimate the Greeks of a basket of options called Mountain Range options in the assumption that each asset is defined by this model.

DELTA HEDGING STRATEGY

Delta is the rate of changes of option prices with respect to price changes of underlying assets. In other words, Delta measures the sensitivity of a derivative f say options or the portfolios of options, with respect to stock prices S. We could define Delta Δ as :

$$\Delta = \frac{\partial \mathrm{f}}{\partial \mathrm{S}} \tag{1}$$

Equation (1) implies that when stock prices change by a small amount ΔS, option prices would change correspondingly by an amount of $\Delta \times \Delta S$. An investor could hedge the risk by adjusting (purchase or sell) shares of stocks to make the portfolio's delta be zero, also called the delta-neutral portfolio. Delta hedging is a trading strategy which attempts to maintain a delta-neutral portfolio dynamically by offsetting the change of option positions through the change of stock positions. As Delta changes, an investor's risk-neutral position (delta-hedged position) would exist for only a short time. Thus, we need to adjust hedging positions periodically, which is called rebalancing. If we could rebalance immediately when stock prices change, perfect hedge is achieved; however, perfect hedge is always difficult to achieve in the real world. What we can do is to employ a dynamic hedging strategy and make hedging periods as short as possible. Next, we explain the procedure of delta hedging by setting the portfolio's delta zero.

Suppose an investor writes N_0 number of European call options which will mature after a period of $\tilde{T}$, and each option covers 100 shares of stocks. The investor can buy $100 \times N_0$ shares of stocks to hedge his position, since the gain or loss on his option position can be offset by the loss or gain on his stock position. However, as time changes, Delta changes; the risk-neutral position is destroyed. Thus, he has to adjust the portfolio by delta hedging every Δt period, i.e., at $t = 0, t_1 = \Delta t, \cdots, t_{k-1} = (k-1)\Delta t$, where k is the largest integer satisfying $t_{k-1} < \tilde{T}$ and $t_k > \tilde{T}$. The purpose of delta hedging is to make the value of a portfolio insensitive to small changes of option prices to maintain a delta-neutral portfolio position. In addition, the portfolio is self-financing. The options an investor writes would cover a total of $N = 100 \times N_0$ shares of stocks. Assume he will long m_0 shares of the stock and borrow B_0 dollars at t_0 to offset the risk. Denote the option price by f_0, the stock price by S_0 and the Delta Δ_0 at t_0. The value of the portfolio P at t_0 is set to be 0, that is:

$$P = -N \times f_0 + m_0 \times S_0 + B_0 = 0\,. \tag{2}$$

Taking the derivative of the value of the portfolio P with respect to the stock price at t_0, we have:

$$\frac{dP}{dS_0} = -N \times \Delta_0 + m_0,$$

which could be considered as the delta of the portfolio Δ_p, i.e., $\Delta_p = \frac{dP}{dS_0}$. In order to maintain the $\Delta_p = \frac{dP}{dS_0}$ portfolio delta-neutral, we have $\Delta_p = 0$, i.e.,

$$\Delta_p = -N \times \Delta_0 + m_0 = 0. \tag{3}$$

From Equation (2) and Equation (3), we could calculate shares of stocks to purchase (m_0) and the amount of dollars to borrow (B_0) at t_0. As is mentioned earlier, we have to rebalance the portfolio periodically. At the second hedging period t_1, we have delta Δ_1 at t_1 and follow the same procedure above by setting both the net value and delta of the portfolio to zero, to get the shares of stocks to purchase (m_1) and the amount of money to borrow (B_1) at t_1. We need to rebalance k times from $t = 0$ to $t = t_{k-1}$ before the option matures at $\tilde{T}$.

Following the procedures of rebalancing described above, we have a total of $M_s = \sum_{i=0}^{k} m_i$ shares of stocks at $\tilde{T}$. In order to calculate the replication cost at $\tilde{T}$ in each sample path, we need to consider (i) the payoff V_1 from selling M_s shares of stocks considering having written N_0 number of European call options, and (ii) the cumulative cost V_2 which is accumulated with interest form borrowing cash during the whole hedging procedure. V_1 can be calculated as:

$$V_1 = M_s \times \max(S_{T,} K), \tag{4}$$

where K is the strike price of an option. It is noteworthy that generally $M_s < N$. Let C_i be the cumulative cost of cash borrowed till t_i and B_i be the amount of cash borrowed at t_i we have

$$C_0 = B_0,$$
$$C_1 = B_1 + C_0 \times \exp(r \times \frac{\Delta t}{365})$$
$$\cdots$$

$$C_{k-1} = B_{k-1} + C_{k-2} \times \exp(r \times \frac{\Delta t}{365})$$

V_2 can be calculated as:

$$V_2 = C_{k-1} \times \exp(r \times \frac{\tilde{T} - t_{k-1}}{365}). \quad (5)$$

Therefore, the replication cost V_3 is

$$V_3 = V_2 - V_1.$$

To calculate the net gain of delta hedging in different sample paths, we need to calculate the payoff V_4 from selling all the call options the investor writes at $t = 0$. Thus, V_4 is

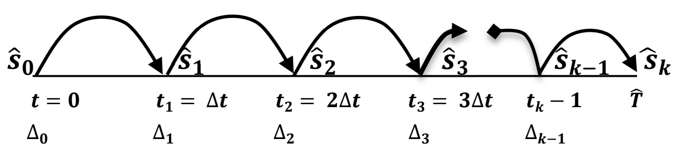
$$V_4 = f_0 \times N_0$$
$$V_2 = f_0 \times N_0 \times \exp\left(r \times \frac{\tilde{T}}{365}\right).$$

The net gain of delta hedging periodically in one sample path is

$$V_{net} = V_4 - V_3.$$

We shall explain how to delta hedge in one sample path in Figure 1.

Figure 1: A Sample Path of Delta Hedging



Notes: This figure shows one sample path of estimating deltas and when to delta hedge.

ALGORITHMS OF DYNAMIC DELTA HEDGING

Algorithm 1 for Spot Prices:

First, we need to simulate all spot prices $\hat{S}_i$ at different periods t_i. The algorithm to simulate spot prices in one sample path is as follows:

At $t_0 = 0$, the spot price is $\hat{S}_0 = \tilde{S}_0$.

At $t_1 = \Delta t$, the spot price $\hat{S}_1$ can be calculated through (10) or (15) by setting$t = \Delta t$, $S_0 = \hat{S}_0$ and $S_t = \hat{S}_1$.

……

At $t_{k-1} = (k-1)\Delta t$, the spot price $\hat{S}_{k-1}$ can be calculated through (10) or (15) by setting $t = \Delta t$, $S_0 = \hat{S}_{k-2}$ and $S_t = \hat{S}_{k-1}$.

At $t_k = \tilde{T}$, the spot price $\hat{S}_k$ can be calculated through (10) or (15) by setting $t = \tilde{T} - (k-1)\Delta t$, $S_0 = \hat{S}_{k-1}$ and $S_t = \hat{S}_k$.

Next we show Algorithm 2 for the calculation of Delta. We need to simulate the Delta at hedging periods t_1. The algorithm to estimate the Delta in one sample path is as follows:

At $t_0 = 0$ the estimators for Delta can be calculated through (12) or (17) by setting $S_0 = \hat{S}_0$, and $T = \tilde{T} - t_0 = \tilde{T}$.

At $t_1 = \Delta t$, the estimators for Delta can be calculated through (12) or (17) by setting $S_0 = \hat{S}_1$, and $T = \tilde{T} - t_1 = \tilde{T} - \Delta t$.
……

At $t_{k-1} = (k-1)\Delta t$ the estimators for Delta can be calculated through (12) or (17) by setting $S_0 = \hat{S}_{k-1}$, and $T = \tilde{T} - t_{k-1} = \tilde{T} - (k-1)\Delta t$.

At $t_k = \tilde{T}$, we cannot hedge on the maturity day and thus do not need to estimate the Delta.

To employ the hedging strategy shown above, we need to estimate the Delta first. In this paper, we estimate the Delta from a GBM or a VG by LR, respectively. In the following sections, we provide an introduction of the LR method in the gradient estimation technique as well as the GBM and the VG processes. In addition, estimators of the Delta by LR are also provided.

GRADIENT ESTIMATION TECHNIQUE: LIKELIHOOD RATIO METHOD

Simulation and gradient estimation are very useful in financial engineering applications. To employ delta hedging, we first estimate the Delta. Delta can be calculated by taking the derivative of the option prices with respect to spot prices. Let's set up the problem first. Assuming the objective function $V(\xi)$ depends on the parameter ξ, we focus on calculating:

$$\frac{d\,V(\xi)}{d\xi}.$$

Suppose the objective function is an expectation of the sample performance measure, that is:

$$V(\xi) = E[L(\xi)] = E[L(X_{1,}X_2, \cdots, X_n; \xi)] \tag{6}$$

where $X = X_{1,}X_2, \cdots, X_n$ are dependent on ξ, and n is a fixed number of random variables. Using the law of unconscious statistician, the expectation can be written as:

$$E[L(X)] = \int y dF_L(y), \tag{7}$$

where F_L is the distribution of L; and

$$E[L(X)] = \int L(x) dF_x(x), \tag{8}$$

where F_x is the distribution of an input random variable X. According to different ways of writing $V(\xi)$ above, we have several methods to estimate the gradient of $V(\xi)$, i.e., finite difference, IPA and LR, of which the last two belong to indirect methods.
To make sense of the right hand side of Equation (11), we write the expectation of $L(X)$ as:

$$E[L(X)] = \int L(x) f_X(x, \xi) dx, \tag{9}$$

where f_X is the probability density function of X. The dependence of parameter ξ can be path-wise from the input random variable X as shown in Equation (8), and LR method originally comes from taking the derivative of Equation (9). Assume the probability density function f_X of X is differentiable. The LR estimate is:

$$\frac{dE[L(X)]}{d\xi} = \int_{-\infty}^{+\infty} L(x) \frac{df_X(x,\xi)}{d\xi} dx = \int_{-\infty}^{+\infty} L(x) \frac{dln f_X(x,\xi)}{d\xi} f_X(x)\, dx,$$

and the estimator is

$$L(x) \frac{dln f_X(x,\xi)}{d\xi},$$

where $\frac{dln f_X(x,\xi)}{d\xi}$ is the score function.

A European call option gives the buyer the right, not the obligation to buy a certain amount of financial instrument from the seller at maturity for a certain strike price. Let S_t be a stock price, T be the maturity time, K be the strike price, and r be the risk-free interest rate. The price (value) of the European call option at t is

$$V_T = e^{-rT}(S_T - K)^+,$$

where S_T can follow a GBM process or a VG (GVG or DVG) process.

ESTIMATING UNDER GEOMETRIC BROWNIAN MOTION PROCESS

A stochastic process price S_t follows a geometric Brownian motion if price $\log(S_t)$ is a Brownian motion with initial value price $\log(S_0)$. In the Black-Scholes model, the price of an underlying stock S_t following a geometric Brownian motion process satisfies

$$\frac{dS_t}{S_t} = \mu dt + \tilde{\sigma} dW_{\mathrm{t}},$$

where W_{t} is a standard Brownian motion. With dividend yield q, spot S_0, volatility $\tilde{\sigma}$ and drift $\mu = r - q$, we can obtain the stock price:

$$S_t = S_0 \exp\big((r - q - \tilde{\sigma}^2)t + \tilde{\sigma} W_{\mathrm{t}}\big).$$

The stock price S_t can be simulated through

$$S_t = S_0 \exp\Big((r - q - \tilde{\sigma}^2)t + \tilde{\sigma}\sqrt{t}\,\tilde{Z}\Big) \tag{10}$$

where $\tilde{Z}$ represents a standard normal random variable. The density of stock price S_t is

$$f(x) = \frac{1}{x\tilde{\sigma}\sqrt{2\pi t}} exp\left\{-\frac{1}{2}\left[\frac{1}{\tilde{\sigma}\sqrt{t}}\left(ln\frac{x}{S_0} - \left(r - \tilde{\sigma} - \frac{\tilde{\sigma}^2}{2}\right)t\right)\right]^2\right\} \tag{11}$$

Applying the density function in Equation (11), we have

$$\frac{dE[V_T]}{d\,S_0} = \int_0^\infty e^{-rT}\,(x-K)^+ \times \frac{df(x)}{d\,S_0}dx = \int_0^\infty e^{-rT}\,(x-K)^+ \times \frac{d(ln f(x))}{d\,S_0} f(x)dx$$

Therefore, the estimator of Delta for a European call option through LR is

$$e^{-rT}\,(x-K)^+ \times \frac{d(ln f(x))}{d\,S_0}. \quad (12)$$

ESTIMATING UNDER VARIANCE GAMMA PROCESS

The Variance Gamma Process is a Levy process of independent and stationary increments. The characteristic function of $VG(\sigma,\nu,\theta,t)$ is given by

$$\Phi_{VG}(\mu,\sigma,\nu,\theta,t) = (1 - iu\theta\nu + \tfrac{1}{2}\sigma^2\nu u^2)^{-t/\nu}.$$

There are two ways to define the VG process. The VG process can be defined as a Gamma-time-changed Brownian motion subordinated by a gamma process. Let W_t be a standard Brownian motion, $B_t^{(\mu,\sigma)} = \mu t + \sigma W_t$ be a Brownian motion with a constant drift rate μ and volatility σ, $\gamma_t^{(\nu)}$ be a gamma process with drift $\mu = 1$ and variance parameter ν. The representation of VG process (say GVG) is:

$$X_t = B_{\gamma_t^{(\nu)}}^{(\theta,\sigma)} = \theta\gamma_t^{(\nu)} + \sigma W_{\gamma_t^{(\nu)}} \quad (13)$$

Second, the VG process is the difference of two gamma processes. Let $\gamma_t^{(\mu,\nu)}$ be the gamma process with drift parameter μ and variance parameter ν, the representation of the VG process as the difference of gamma process is:

$$X_t = \gamma_t^{(\mu_+,\nu_+)} - \gamma_t^{(\mu_-,\nu_-)}, \quad (14)$$

where $\mu_\pm = (\sqrt{\theta^2 + 2\frac{\sigma^2}{\nu}} \pm \theta)/2$, and $\nu_\pm = (\mu_\pm)^2\nu$.

Under the risk-neutral measure, with no dividends and a constant risk-free interest rate r, a stock price is given by

$$S_t = S_0 \exp\big((r+\omega)t + X_t\big), \quad (15)$$

Where $\omega = \ln\left(1 - \theta\nu - \frac{\sigma^2\nu}{2}\right)/\nu$ is the parameter that makes the discounted asset price a martingale.

Madan, Carr and Chang (1998) propose that the density function of the log-price $Z = \ln(S_t/S_0)$ is

$$h(z) = \frac{2\exp\left(\frac{\theta x}{\sigma^2}\right)}{\nu^{\frac{t}{\nu}}\sqrt{2\pi}\sigma\,\Gamma\left(\frac{t}{\nu}\right)}\left(\frac{x^2}{\frac{2\sigma^2}{\nu}+\theta^2}\right)^{\frac{t}{2\nu}-\frac{1}{4}} \widehat{K}\left(\frac{1}{\sigma^2}\sqrt{x^2\left(\frac{2\sigma^2}{\nu}+\theta^2\right)}\right), \quad (16)$$

where $\widehat{K}$ is the modified Bessel function of the 2nd kind, and is $x = z - rt - \frac{t}{\nu}\ln\left(1 - \theta\nu - \frac{\sigma^2\nu}{2}\right)$. Since $h(z)$ doesn't contain S_0, we have to use the Jacobian transform to get the density function of S_T to calculate the derivative with respect to S_0:

$f_{S_T}(s) \times \left|\frac{\partial S_T}{\partial Z}\right| = h(z).$

Therefore, we can get the density function of S_T:

$f_{S_T}(s) = h(lns - ln\, S_0) \times \frac{1}{s}.$

To calculate the Delta, we use $f_{S_T}(s)$ to apply the LR. Since

$\frac{dE[\,V_T]}{d\,S_0} = \int_0^{\infty} e^{-rT}\,(s-K)^+ \times \frac{d(lnf_{S_T}(s))}{d\,S_0} f_{S_T}(s)ds.$

the estimator of the Delta from LR under VG is:

$$e^{-rT}\,(s-K)^+ \times \frac{d(lnf_{S_T}(s))}{d\,S_0}. \tag{17}$$

When the stock price follows a GVG or a DVG process, the estimator in (17) would be the estimators for GVG or DVG accordingly.

NUMERICAL EXPERIMENT

In this paper, we analyze historical data in WRDS of the stock prices of Google Ltd. from March 10th, 2008 to September 10th, 2008. Assuming a stock price follows a geometric Brownian motion or a Variance Gamma process, we apply the MLE method to estimate the corresponding parameters. Assuming the maturity time for the option is 30 days, i.e., $\tilde{T} = 30/365$, the risk free interest rate minus the dividend rate is $r - q = 0.0245174$, we get the variance parameter $\tilde{\sigma} = 0.28983965441613$ for the GBM process; and $\sigma = 0.21370332702956, \nu = 0.01879357471038$, and $\theta = -0.19286112983688$ for the VG process. The spot price is $\tilde{S}_0 = 433.75$ at $t = t_0$ and the strike price is $K = 440$.

We apply a Monte Carlo simulation to follow the algorithm for spot prices and algorithm for the Delta described above to simulate for 10000 sample paths. Moreover, after having the corresponding spot prices and the Delta on each sample path, we employ delta hedging technique to calculate the net gains on each sample path. The summary statistics for the net profits from delta hedging only once initially, i.e., $\Delta t = \tilde{T} = 30/365$ by the methods above is shown in Table (1).

CONCLUSION

Assuming stock prices follow two price distributions, a geometric Brownian motion process and a Variance Gamma process, we employ the dynamic delta hedging strategy to identify net profits and analyze the statistical properties under these two assumptions. Deltas play an important role in the hedging strategy. For different hedging times, we download the historical data of the stock prices of Google Ltd. and calculate the corresponding deltas through one of the gradient estimation techniques called likelihood ratio method. A comparison is made on the numerical results obtained above.

Our main findings can be summarized as follows: 1) The mean values of net gain from higher hedging frequency are always bigger than the ones from lower hedging frequency. But in our experiment, the mean values of hedging just once initially are higher than ones from higher frequency. This exception happens is because the standard error is very large, and the results are probably biased. 2) The standard errors of the net profit from higher frequency are always lower than the ones from the net profit from lower frequency. 3) The mean value of net gain following the Variance Gamma process is bigger than the mean following the geometric Brownian motion process. 4) The mean value of net gain from GVG and DVG are close. Further work is needed to reduce the big standard errors of net profits from hedging at low frequency, making the all results unbiased.

Table 1: Summary Statistics of Net Profit by Delta Hedging

Hedge once initially	**GBM LR**	**GVG LR**	**DVG LR**
Mean	4484.4	4492.4	4439.3
StdErr	100.26	99.85	101.47
Hedge every 14 days			
Mean	3895	3981	3904
StdErr	65.14	60.33	59.73
Hedge every 7 days			
Mean	4059	4051	4077
StdErr	53.52	50.73	69.04
Hedge every 3 days			
Mean	4583	4607	4554
StdErr	26.41	20.98	20.58

Notes: This table shows the summary statistics of net profit by delta hedging at different hedging frequencies. Mean denotes the mean value of net profit, while StdErr is the standard error of net profit. GBM LR is the results from delta hedging with respect to a GBM process by LR method. GVG LR is the results from delta hedging with respect to a GVG process by LR method. DVG LR is the results from delta hedging with respect to the GBM process by LR method. Panel A shows the results of summary statistics of net profits by delta hedging once initially, i.e. $\Delta t = \tilde{T} = \frac{30}{365}$*. Panel B shows the results of summary statistics of net profits by delta hedging every 14 days , i.e.,* $\Delta t = \tilde{T} = 14/365$*. Panel C shows the results of summary statistics of net profits by delta hedging every 7 days, i.e. ,*$\Delta t = \tilde{T} = 7/365$*. Panel D shows the results of summary statistics of net profits by delta hedging every 3 days, i.e.,* $\Delta t = \tilde{T} = 3/365$*.*

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EVIDENCE ON US SAVINGS AND LOAN PROFITABILITY IN TIMES OF CRISIS

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ABSTRACT

In 2008, market disturbances and unexpected price volatility besieged the US financial system. Since then weak balance sheets have heightened risk, thus resulting in an unprecedented rise in non-performing loans and credit-related write-offs in mortgage lending related sectors. This paper examines the determinants of US Savings and Loan (S&L) profitability in the time period 1978 and 2009. We use the recently developed unit root econometrics for time-series data analysis. Using ADF as a statistical test by estimation of least squares trend fitting, the study highlights that high leverage and large non-performing loan to total loan ratio leads to a lower rate of return on capital. In addition, the loan ratio has a significant negative coefficient on return on asset and equity capital. While macroeconomic factors such as low interest rates have a negative effect on bank earnings, the effects of interest rates can vary depending on the profit indicator used. By and large, there is evidence that the quality of loan portfolio rather than size (economies of scale) affects profitability negatively. Our results are confirmed by earlier studies that over-leveraging and under-performing loans have the potential to render S&Ls vulnerable to financial shocks, thus contributing to financial instability.

JEL: G21; B15; C50; E50; P16

KEY WORDS: S&L crisis, bank profitability, economic development, subprime mortgage crisis, mortgage-backed security (MSB), IndyMac

INTRODUCTION

This paper presents evidence on US savings and loan profitability in the period 1978-2009. The S&L industry has changed extensively over the last several decades. Firms are generally fewer and bigger today and offer wide-ranging services and operate in increasingly global markets. While home mortgages and savings deposits have always remained a staple of thrifts since the passage of the Federal Home Loan Bank Act in 1932, S&Ls assumed new roles beyond facilitating home ownership. During the late 1970s and early 1980s, they began marketing a new array of financial products and services like those offered by larger banks. As their new roles reflected a changing financial environment and deregulatory interventions, unique measures were taken to improve performance. Following the S&L debacle in 1989, the OTS was established as the primary regulator of S&Ls. Yet over the period 1986-1995 "1043 thrifts with total assets of over $500 billion failed" (Curry and Shibut, 2000:26). Prior to the subprime mortgage meltdown in mid-2007, more borrowers looked toward mortgage lenders, even if they lacked qualifications for obtaining loans. In 2010, the Wall Street Reform and Consumer Protection Act decided to restructure OTS by distributing some of its functions among the existing regulators—OCC, FDIC, and the Federal Reserve. Under the new rules, all S&Ls are regulated by the OCC, which also regulates federal banks and the US branches and agencies of foreign banks.

This paper examines the determinants of US Savings and Loan profitability in times of crisis. We use yearly aggregated industry data covering a 31-year period from 1978 to 2009, observing 11 variables (financial ratios) before the start of the crisis as well as those that followed. The aim of this analysis is to establish which of these potential determinants of profitability prevail in the US S&L industry. For this purpose, an ADF unit root test is conducted for least squares trend fitting by first-order differences of variables.. The results of the study indicate that high leverage and large non-performing loan to total loan ratio lead to a lower rate of return on capital. This means that higher the probability of consumers to default on their loans, the lower the return on assets and hence less bank profits. While macroeconomic indicators such as a decline in interest rates have a negative effect on profitability, the effects of interest rates are inconclusive depending on the profit indicator used. Everything remaining equal, there is evidence that loan quality problems rather than size (economies of scale) affect profitability negatively. Overall, our analysis is confirmed by earlier studies that over-leveraging and under-performing loans have the potential to render banks vulnerable to financial shocks, thus contributing to financial instability.

The rest of the article is organized as follows. Section 2 briefly discusses the relevant literature and background. Data selection, research methodology and empirical models are described in Section 3. Section 4 provides analysis and interpretation of the empirical findings. Section 5 concludes the paper and draws strategic lessons for future researchers and practitioners in the field of risk management.

LITERATURE REVIEW AND BACKGROUND

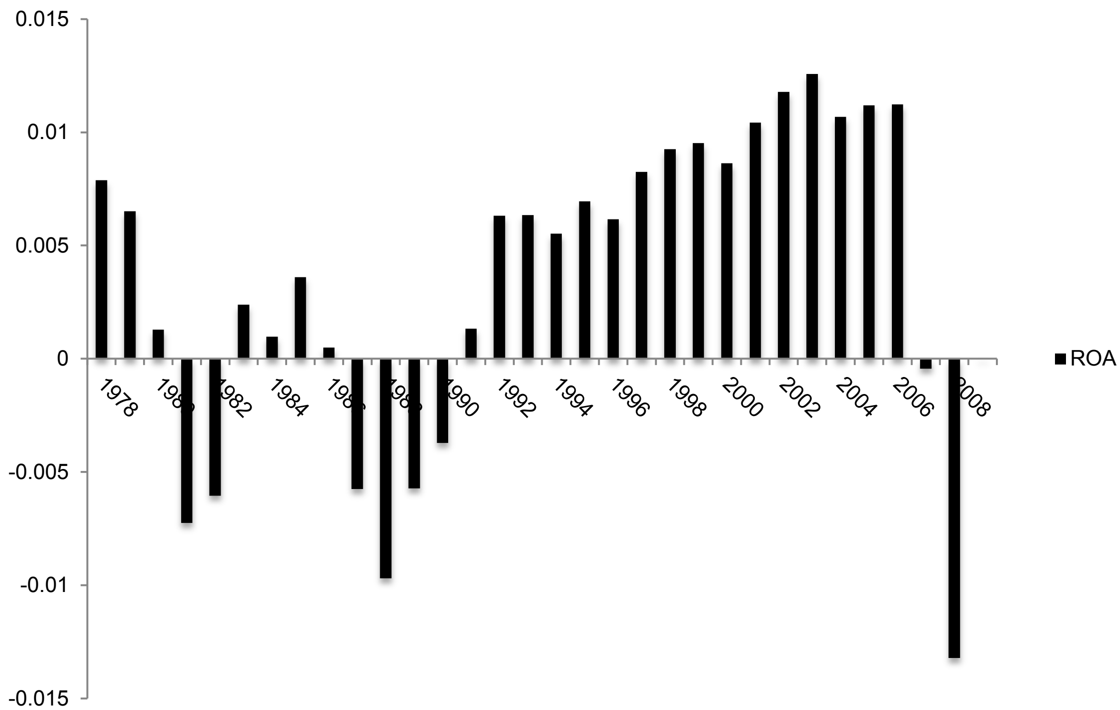
In this section we present a brief overview of studies that examine the bank profitability-microeconomic/macroeconomic nexus. We begin by discussing the most recent and sophisticated studies, employing panel country studies, to older, less complex, historical studies. In extending the research on savings and loan profitability, the starting point has been the pioneering literature as well as previous studies on bank performance (Brigham, 1964; Benston, 1972; Berger, 1995).

S&Ls have always played an important role as facilitators of home mortgages and savings deposits. Unlike commercial banks, however, they mainly provided low-cost funding for long-term mortgage loans, consumer loans, small business, and regional development lending. In acknowledgment of the need to diversify the asset structure and improve earnings, Congress passed the Garn-St. Germain Depository Institutions Act in 1982 phasing out Regulation Q and allowing the use of adjustable interest rates. Federal deregulation was designed to wean thrifts from borrowing-short and lending-long. They would now be put on a competitive footing with new financial institutions (Sherman, 2008:809-810). In 1989, Congress removed barriers between commercial banks and S&Ls.

As a result, much of the thrift industry was deregulated through "outright mergers as well as bank holding company acquisitions of S&Ls" (Ely, 2008). Since then, research has shifted towards the broader financial industry, generating discussions on the causes and consequences of the S&L crisis (Strunk and Case, 1988; Kane, 1989; Barth 1991; White, 1991; Curry and Shibut, 2000). Although S&Ls have become defunct institutions since the original crisis, the collapse of Indy Mac in July 2008 (the largest S&L in California specializing in Alt-A loans) have once again raised discussions about the viability of thrifts in their present form.

The demise of Indy Mac was the fourth biggest bank failure in US history and the second largest failure of a regulated thrift (Shalal-Esa, 2008; Veiga, 2008). Studies on savings and loan performance have drawn largely from US banking literature (Brigham, 1964; Benston, 1972; Verbrugge, Shick and Thygerson, 1976; Geehan and Allen, 1978; Berger, 1995; Kaushik and Lopez, 1996). While pioneering research was conducted in the US, researchers from other countries compiled data based on previous studies and extended the existing literature several ways. With better access to sectoral data and the use of more sophisticated models, panel country studies have highlighted the importance of bank-specific (internal), industry-specific (external) and macro-economic variables. It is impossible to review each study here but would refer readers to the research of Short (1979), Bourke (1986) and Molynex and Thorthon (1992) that developed more sophisticated models for analyzing the relationship between concentration, market structures, and bank profitability. As Berger (1998) notes, this line of research has progressed almost separately from a "microeconomic theory of banking" and has given banking studies a new direction. Under the purview of structural-conduct-performance (SCP) hypothesis, for example, a group of researchers investigated the effects of market structures on productivity change and performance in European and US banking (Gilbert, 1984; Goldberg and Rai, 1996; Casu, Girardone and Molynuex, 2004). Further studies in banking have been critical in orienting methodology towards "single country studies" and "panel country studies" (Naceur, 2003).

Figure 1: US Savings and Loan Profitability



This figure shows the changes in S&L return on assets (ROA) as the ratio of net income to total assets, indicating the vulnerability of bank profits to financial shocks and housing cycles in 1988 and 2008 respectively. Ratios are calculated from OTS (2009) database.

Rasiah (2010) divides the literature into three parts that deal with external determinants, internal determinants, and the relationship between bank profitability and market structures. In an extensive review of empirical work in this area, Bourke (1986) indicates that internal factors are company specific variables, which may not be available in international surveys. They are capital and liquidity ratios, the loan/deposit ratio (equivalent of the liquidity ratio), loan loss expenses and operating expenses on the income statement. External determinants are outside of managerial control, such as financial regulations, competitive conditions, market growth, ownership type, inflation, concentration level, and interest rates (Bourke, 1986:66). In Rasiah's (2010) extensive review, which draws on Bourke's classification, bank-specific variables are internal to the operation of a bank such as "financial statement" and "non-financial statement" variables. Holding external factors constant, internal variables are responsible for explaining institutional variations in profitability and reflect on the quality of managerial decisions. Specifically, financial statement variables relate to the items on "balance sheet" and "profit & loss account". They include asset and liability management (ie., managing margin; loan loss provisions; net charge-offs), cost or expense management (ie., interest paid on deposits, capital ratios, wage and salary payments), bank management policies, loan composition (ie., the ratio of commercial, real estate, consumer loans to total loans) and non-performing loans. Non-financial statement variables, on the other hand, indirectly affect the balance-sheet performance. The examples of items in this category are number of bank branches, bank size (total assets as a proxy for size) and economies of scale, bank location and status of the branch (unit or multiple branches) (Rasiah, 2010:23-49).

Using cost efficiency as a proxy for profits, earlier studies investigated the effects of bank specific variables—especially firm size and scale economies. These studies compare economies of scale among different ownership forms, charter types and in different geographic areas. Although the overall measure of profitability is not estimated in these studies, a positive relationship is expected between size and profits. Size is used to capture the fact that banks with large size (total assets as a proxy for bank size/output) enjoy scale economies because they are able to produce services more cheaply and therefore obtain a higher level of profits than smaller banks. Against this background, Brigham (1964) examines the relationship between operating cost (dependent variable), bank size and rate of growth (independent variables) for two cross-sectional samples of California S&Ls in the period 1956-1962. Bank size is measured as log of assets; rate of growth is measured as growth in new loans, set up costs, new facilities and personnel, and operating characteristics include ratio of offices and equipment to total assets and average deposit size (ie., the cost of servicing savings accounts). Regressing output levels with unit costs, the study concludes that none of the "size-generated" variables is significantly related to economies of scale (Brigham, 1964:20).

In a study of the operating costs of 83 commercial banks and 3159 S&Ls, however, Benston (1972) finds significant economies of scale for both types of institutions, especially in demand deposit and real estate loans. He uses deposit structure (demand and time deposits) and loans as size variables and regresses them against the operating cost as dependent variable. Although it is found that larger size is associated with greater costs, operating cost increases at a decreasing rate in branch banking. Unlike unit banking, branch banks enjoy the "economies of larger scale operation" that reduces marginal cost of branching. This relationship, however, does not seem to hold true for S&Ls because size is not always associated with greater number of branches (Benston, 1972:313).

Verbrugge, Shick and Thygerson (1976) are among the early researchers to develop a comprehensive model for analyzing S&L performance for a sample of 478 associations over the period 1971 and 1972. Using return on net worth (RONW) as a proxy for profit, their study identifies different components of performance across different categories of variables— asset management (liquidity (LIQ), loan yield (YLD), fee income (FEEI); non-operating activity (NOPI)), liability management (certificates (CERT); borrowing (BOR); risk (NWS)) and operating expense management (OPEXP) and other variables (form of organization and size). The study highlights that S&L performance is associated with FEEI (fee income/total income), YLD (interest on mortgage loans/mortgage loans), OPEXP (operating expenses/average assets), CERT (certificates/total savings) and risk (new worth/savings). Their results reveal the importance of bank-specific and regulation variables in profitability performance; for example, fee income tends to be less in S&Ls operating in states with usury laws; such associations purchase rather than service loans although they have marginally less operating costs. In addition, loan composition ("multi-family and other higher-risk non-single family") is a primary influence on profits but positively correlates with operating costs (Verbrugge, Shick, Thygerson, 1976:1440).

Benston (1972) and earlier researchers did not clearly link firm size to profit rates. Instead they correlated output levels to unit costs. Gallick (1976) emphasized the degree to which bank size was linked to profitability as a rate of return on capital—ratio of net income before taxes to total capital. His results appear to confirm earlier studies for a sample of all insured commercial banks (1954-1974) classified by deposit size. On the other hand, Heggestad (1977) regressed bank size (deposit composition) and external/industry-specific factors (three bank concentration ratio) with profitability for a sample of 238 independent banks in 60 medium-size metropolitan areas, but found no clear association. The study indicates rather that rate of return on assets (profitability) tends to decrease as ratio of time and savings deposits to total deposits increases. This supports his argument that banks with high deposit ratio generate

considerably lower returns. There is also evidence that risk and market structure has a significant relationship with profitability; monopolistic banks are more risk averse in their lending decisions and tend to choose safer portfolios than banks in more competitive markets (Heggestad, 1977:1213).
In another study, Benston and Hanweck and Humphrey (1982) do not find major evidence for scale economies across a broad range of variables among US domestic banks. Tschogel (1983) reaches similar conclusions about the relationship between size and transnational growth for a sample of the world's 100 largest banks in 1969-1977. Drawing upon the US experience for European banking, Berger and Humphrey (2003) also show that larger banks do not necessarily experience lower average costs than middle-size banks.

Goldstein, McNulty and Verbrugge (1987), however, discovered that there were significant variations in cost elasticity among S&Ls of different sizes prior to deregulation. The use of a large sample data (all insured S&Ls between 1978-1981) and flexible econometric model ("translog cost function") allow "U shaped cost curves" to be estimated. Translog's flexibility facilitates the observation of scale economies throughout all ranges of bank output. Their findings are different from those estimated by earlier studies that observed the absence of scale economies for large US banks. Since S&Ls are more specialized than commercial banks, asset size can explain variations in cost elasticity (Goldstein, McNully and Verbrugge, 1987:205). For example, large concentration of assets in mortgage loans and savings deposits makes S&Ls more receptive to scale economies than those of commercial banks.

In research into the effect of capital requirements using Granger causality test, Berger (1995) shows that a higher capital-to-asset ratio is not correlated with lower rate of return on equity. Capital requirement determines how much capital banks should aside as a percentage of risk-weighted assets. Capital requirement for long-term viability has become a critical issue following the financial crisis in 2008. Berger's panel analysis of US banks for the 1983-1992 period reveals that there is a "positive Granger causality from earnings to capital". The relationship between higher capital and higher earnings is especially true for banks with low interest rate offerings on uninsured funds; these banks have better management of risk portfolio. Risk management explains a significant variation in higher earnings for banks that also pay "lower uninsured debt rates" (Berger 1995:433).

Aside from some internationally significant panel studies, the most comprehensive evidence on bank performance can be found in the recent work of Demirguc-Kunt and Huizingha (2000) and Athasanoglou, Delis and Staikouras (2006). Based on the panel data for seven Southern European countries for the period 1998-2002, Athasanoglou, Delis and Staikouras (2006) investigate the effects of bank-specific, industry-related (microeconomic) and macroeconomic determinants of bank profitability. Industry-related variables include concentration ratio of 3 largest banks, HHI index and EBRD index of banking system reform whereas macroeconomic indicators include inflation, financial crisis dummy and real GDP per capita. Overall, the study concludes that structure-conduct-performance (SCP) paradigm explains the performance of Southern European banking sector. Concentration measured by HHI and inflation positively affects performance while GDP is unrelated.

Using a multi-country panel of banks for the period 1990-1997, Demirguc-Kunt and Huizinhga also present evidence on the effect of financial structure and economic development on bank performance. Specifically, banks with less developed financial systems are shown to have higher profits and net interest margins. Greater bank development (or transition to a more developed financial system) is correlated with lower profits (through tougher competition and high efficiency). The study also finds that stock market activity leads to higher bank profits in less developed financial systems through the availability of equity financing to firms. Yet such "complementarities" are insignificant in advanced financial systems or at higher levels of economic development (Demirguc-Kunt and Huizingha, 2000:15).

One major difficulty with most of the studies above is the complexity of measuring bank profitability. This is due to the diversity of bank output and the heterogeneous services being offered. Therefore significant relationships may appear because of the researchers' use of aggregate data, which downplays sectoral differences. Another problem is the difficulty of measuring policy interventions. Post-crisis deregulation has encouraged S&Ls to offer a broad spectrum of services ranging from mortgage loans on residential property to consumer loans, credit cards, and checking accounts. Yet, as Benston noted, S&Ls asset structure is more specialized than commercial banks, largely concentrated in real estate loans and savings accounts (Benston, 1972:331). The current study corrects for sectoral differences by analyzing uniform asset structure (mortgage loans) and using yearly aggregated data covering a 31-year period from 1978 to 2009. The financial ratios are in accord with previously published studies in the field. The methodology used in this analysis incorporates many of the recent developments in the literature, namely time-series unit root tests, which may uncover the nature and depth of industry performance.

DATA AND METHODOLOGY

Data Sources and Variables

The current study uses yearly aggregated, time-series data covering a 31-year period from 1978 to 2009. The data is extracted from the Office of Thrift Supervision (OTS) database as well as World Bank, Board of Governors of the Federal Reserve System and Pen World Table of the University of Pennsylvania. The data set consists of variables for S&Ls for which a variety of financial ratios are calculated for each year (see below). S&Ls refer to private savings associations, state or federal charter, supervised by the Office of Thrift Supervision (OTS). Although there are sizable indicators of industry performance going far back to 1964, this paper only analyzes the period for which data on profitability was found—from 1978 to 2009—thus covering both the years before the start of the crisis as well as those that followed. The source for the financial ratios is Office of Thrift Supervision (OTS), *2009 Fact Book: A Statistical Profile of the Thrift Industry*. Time-series for macroeconomic indicators are obtained from the Pen World Table of the University of Pennsylvania (1978-207) and World Development Indicators & Global Development Finance (2008-2009) of the World Bank database.

Model Specification

The objective of this study is to assess the potential determinants of S&L profitability during the period 1978-2009. In the structure-conduct-performance (SCP) paradigm, bank profitability tends to be related to a wide number of factors whose relationship has been well established in the literature (Berger, 1995; Demirguc-Kunt and Huizinga, 2000). This relationship is recognized in research that associates bank profitability with a variety of internal and external factors. Drawing on the existing empirical literature in this area, we specify a standard profitability function that may take the following two forms:

$$Y_{ROA} = \alpha + \beta X_{it} + \gamma Z_{it} + \varepsilon_t$$
$$Y_{ROE} = \alpha + \beta X_{it} + \gamma Z_{it} + \varepsilon_t$$

Since there are no missing values, our data is a balanced time-series with 11 variables observed over a 31-year period. It has a temporal reference, *t,* in this case for a year, and *i* for parameter estimates with autoregressive model of order. The random error captures the time dimension, where *e* is *white noise* and *Y, X, Z* are the observed values of time-series at time *t*. The equation seeks to empirically ground the determinants of industry profitability separately measured in terms of return on assets (ROA) and return on equity (ROE). Bank risk ratio (BRISK), liquidity risk ratio (LIQ), leverage ratios (LEV & LEV1), and ratios of non-performing loans to total loans (NPL_MLO) and total assets (NPL_TA) are proxies for industry performance, represented by a matrix of *X.* Meanwhile, the fixed rate conventional home mortgages (IR), Real GDP capita income (RGDPL), growth rate of Real GDP (GROWTH_RATE_GDP) are macroeconomic indicators, represented by a matrix of *Z*. Macroeconomic ratios are obtained from the work of Demirguc-Kunt and Huizinga (2000). Industry endogenous ratios are calculated from the works of financial industry experts (Verbrugge, Shick, and Thygerson, 1976; Gallick, 1976; Berger, 1995; Pervan, Pervan and Guadagnino, 2009; Papanikolaou and Wolff, 2010).

Our regression equations estimate industry profitability in terms of return on assets Y_{ROA} and return on equity Y_{ROE} respectively. Defined as return on assets, the ROA ratio is computed by dividing the net income over total assets; ROE ratio is computed by dividing the net income over equity capital. These equations show profitability performance as a matrix of six industry characteristics such as total bank risk (BRISK) as the ratio of equity capital to total assets; liquidity risk (LIQ) as the ratio of mortgage loans outstanding and mortgage backed securities to total assets; leverage ratios as the ratio of debt to equity (LEV) and ratio of total assets to equity (LEV1). Due to lack of debt figures, debt is calculated as the ratio of total liabilities minus equity to equity. Loan ratios are the ratio of non-performing loans to total mortgage loans (NPL_MLO) and to total assets (NPL_TA). Mortgage loans outstanding (MLO) are mortgage originations in the year, including "mortgage refinancing and net mortgage loan purchases, minus any principal repayments." (OTS, 2009:78). Non-performing loans are defined as delinquent mortgage loans for which the borrower has failed to make payments as specified in the loan agreement. If the borrower can't pay the mortgage within a certain time period, the lender can start foreclosure proceedings later on. Foreclosure starts only after the borrower has completely defaulted on his or her payments. As a result of this lag factor, home foreclosures are omitted from the analysis. Macroeconomic variables of real GDP per capita income (RGDPL), interest on mortgage loans (IR), and the annual growth rate of Real GDP (GROWTH_RATE_GDP) are external factors that might affect industry profitability.

Time-Series Unit Root Tests

In a time-series analysis, least squares trend fitting is necessary to capture the significance of variables under consideration. In its simplest form, a time-series analysis is a method of studying data observed over a defined time frame in order to reach meaningful conclusions and temporal characteristics about the variables. Profitability performance and firm specific components are important considerations for theorizing finance. Quantification of these components, however, faces challenges. Time-series of a particular industry is complicated by sectoral differences, caused by changes in types of products, production techniques, service quality, adjustment of cost to changes in output, type of ownership and exposure to different economic and regional cycles.

For example, while one bank may display a positive relationship with performance, another may display an opposite but equal effect so that they balance each other. Panel studies, on the other hand, may exhibit typical problems in cross-sectional data, such as "inconsistent definition of output among firms, differences among firms in accounting costs that reflect the time of purchase of equipment and plant and errors in the establishment of firms or plants of suboptimal size" (Benston, 1972:316). From a statistical point of view, any data with temporal dimension suffers from autocorrelation when the preceding and successive values of time-series are highly correlated. Before proceeding to regression analysis, it is essential to verify that all of the variables are integrated to the same order. For this purpose, we have used the ADF (Augmented Dickey-Fuller) unit root test developed by Dickey and Fuller (1979). This is a well-known co-integration procedure that tests the existence of a unit root in a time-series data. Variables with unit roots can exhibit non-stationary or trending behavior in the mean or variance that cause "serial correlations" over time (Cromwell, Hannan, Labys, Terraza, 1994:23). Since much of time-series theory is concerned with stationary time-series, an ADF test is conducted to filter non-stationary behavior by means of first or second differencing equations.

According to Campbell and Perron (1991), unit root test, as applied in macroeconomics, is a valuable tool that "can be used to impose reasonable restrictions on the data" and "gives the best approximation to the finite-sample distribution of coefficient estimates and test statistics". Given the insights of unit root econometrics, it is well known that certain macroeconomic variables such as Real GDP and interest rates have unit roots in levels. As a result, they exhibit trending behavior that results in high R-Square and t-statistics with little real meaning. To achieve our goal of transforming a non-stationary time-series into a stationary one, an ADF test is applied to the regression residuals of autoregressive model. This is done by inclusion of lagged values of Y where ΔY is the first difference operator*,* indicating Y minus its one period prior value: $\Delta Y_t = Y_t - Y_{t-1}$. Transforming the series by differencing eliminates the unit root. As displayed in equations 1 and 2 above, an autoregressive model is estimated relating the profitability measures (dependent variables) to a matrix of internal and external factors (independent variables). For this purpose, we have used the least squares regression where ΔY rather than Y is estimated. The next section summarizes the results of re-estimated least squares using ROA and ROE as dependent variables.

EMPIRICAL RESULTS

This section presents evidence on US Savings and Loan profitability over the period 1978-2009. Our sample shows some variations in terms of basic statistics of variables. Trends in earnings and profitability reflect the continuing US business cycle and housing market weakness. The number of S&Ls supervised by OTS was 765 with assets of $941.7 billion at the end of 2009, decreasing from 4048 in 1978 with total assets of $497.3 billion. From 1978 to 2009, however, total industry assets increased by 89.36% against an 81.02% decrease in the number of enterprises. During the same period, the average number of loans and MBSs constituted 43% of total assets while average mortgage loans outstanding accounted for 38%. Given the increase in total assets, one would expect a higher leverage ratio over time, especially prior to the subprime mortgage crisis. The highest leverage ratios, however, were in 1984, 34.29 and 36.29 respectively, during the height of the S&L crisis. For example, LEV1 ratio (total assets/equity capital) has started to decrease since 1984, at a rate of 74.292%, standing at 9.33 in 2009. The industry reached maximum ROA in 2003, indicating the highest profitability but low leverage. Consequently, basic statistics might give the impression that there is no risk associated with leverage. As explained above, sectoral differences and financial regulations play an important role in the degree to which the industry has become leveraged. Although leverage has been one of top causes of bank failures since 2008, OTS *Fact Book* (2009) notes that regulatory capital requirements for the S&L industry continue to be robust and stable, in excess of minimum requirements.

Table 1: Augmented Dickey-Fuller (ADF) Unit Root Test Results

Variables	ADF T-Statistic (Level)	Variables	ADF T-Statistic (First Differences)
roa	-1.74 (0.39)	Δ roa	-5.11 (0.0003)
roe	-3.41 (0.018)	Δ roe	-4.53 (0.0012)
brisk	-0.03 (0.94)	Δ brisk	-4.16 (0.0031)
liq	-2.13 (0.23)	Δ liq	-4.87 (0.0005)
lev	-2.00 (0.28)	Δ lev	-5.50 (0.0001)
lev1	-2.00 (0.28)	Δ lev1	-5.51 (0.0001)
npl_mlo	-1.84 (0.35)	Δ npl_mlo	-5.42 (0.0001)
npl_ta	-2.12 (0.23)	Δ npl_ta	-5.3 (0.0001)
rgdpl	-1.34 (0.59)	Δ rgdpl	-3.37 (0.02)
growth_rate_gdp	-3.37 (0.019)	Δ growth_rate_gdp	-6.73 (0.000)
ir	-1.59 (0.46)	Δ ir	-3.97 (0.0047)

ADF indicates the Dickey and Fuller (1979) t-test for time-series unit root tests. This test examines the null hypothesis of unit root(non-stationary). The figures in parenthesis are the p-values.

The starting point of our inferential statistics is to check whether the 11 variables included in equations contain unit roots. While there are several unit root tests available for time-series analysis, this study uses the test developed by Dickey and Fuller (1979). Unit roots test gives the researcher an opportunity to re-estimate the slope coefficients of variables in the presence of a unit root in levels. The procedure of applying the ADF test requires the null hypothesis of unit root $\gamma = 0$ tested against the alternative hypothesis of no unit root $\gamma < 0$. If the computed t-value value/statistic is less than the critical value, then the null hypothesis of unit root is rejected and no unit root is present. If a unit root is present, however, we need to apply the first or second difference operator to the auto-correlated variables. If one of these operators shows the differenced time-series to be stationary, then one can apply ordinary least squares to these variables to re-estimate the slope coefficients. In a series of unit root tests below, the coefficients did not show the expected sign in the level.

Based on MacKinnon one-sided p values, they required de-trending. The results of the ADF test indicate that first level is the appropriate difference operator in this particular case (Table 1). First difference operator removes the trend in the mean and transforms the series into stationary. Overall, the unit root test indicates all the variables in both the ROA and ROE models are integrated of order one. A regression equation is then re-estimated taking first difference of 11 variables that had unit roots in levels. Table 2 shows the results of the autoregressive model where ROA is measure of profitability. Two other variables, annual growth rate of GDP and LEV1, also appear in the parameter estimates of Table 3 where ROE is measure of profitability.

Both specifications are significant at 1% level based on Prob. (F Statistic). Overall, these measure the joint relationship between the explanatory variables and dependent variable in each model. Based on R Square values, the right hand side variables explain the dependent variable by almost 63% and 53% and the F statistic supports the regression. Prob. (F-Statistic) suggests that both regression models are significant at a 1% level, so we can be reasonably confident that the good fit of the equation is not due to chance.

Table 2: Parameter Estimates of Model Using ROA as Dependent Variable

Method: Least Square Regression; first difference operator Number of Observations: 31 (1978-2009)	
Variable	**Coefficient**
Constant Term	-0.001 (1.820)
Δ BRISK	-0.026 (0.300)
Δ LIQ	-0.027* (1.718)
Δ LEV	-0.000* (1.976)
Δ IR	-0.001*** (2.862)
Δ NPL_MLO	-0.209** (2.796)
Δ RGDPL	0.000** (2.092)
R-squared	0.634815
Adjusted R-squared	0.539549
Durbin-Watson stat	1.924476
F-statistic	6.663618
Prob. (F-statistic)	0.000347

****Significant at 1% level or 0.01; ** Significant at 5% level or 0.05; *Significant at 10% level or 0.1 The figures in parenthesis are absolute values of t-statistics. Based on the critical value of 2, Durbin-Watson statistic of 1.92 indicates a very insignificant or no positive autocorrelation.*

In Table 2, regression analysis indicates that all variables except bank risk (BRISK) are significant in explaining ROA at 1%, 5%, and 10% levels. In addition to net interest margin, ROA is the most commonly used ratio in bank performance studies (Naceur, 2003). It measures the return a firm is generating on its assets and determines how well a company is using investment funds to produce earnings growth. In the second equation REO is used as a proxy for performance instead of ROA. As Table 2 indicates, industry specific and macroeconomic variables are insignificant except for ratio of non-performing loans to total assets (NPL_TA) and debt to asset ratio (LEV1), which are negatively correlated with ROE. This seems to be consistent with the first model where both loan and leverage ratios reveal how much profit a company generates on its assets (ROA) or with the money shareholders have invested (ROE).As seen in Table 2, liquidity ratio (LIQ), leverage ratio (LEV), fixed mortgage interest rates (IR), and ratio of non-performing loans to mortgage loans outstanding (NPL_MLO) are negatively related with ROA. While Real GDP per capita income (RGDPL) is somewhat significant, its significance is almost trivial when considering how close its p value (0.0477) is to 5% level. Liquidity ratio (LIQ) is hardly significant in the first regression with p value of 0.0991. Similarly, in the second equation, the growth rate of real GDP is found to be insignificant, confirming previous studies that economic growth does not have a major impact on bank profits.

The impact of GDP on bank performance has received attention in Demirguc-Kunt and Huizinga (2000). Their research provides extensive evidence on the significance of economic growth for financial market development in a panel study of developed and developing countries. Banks in well-developed markets face tougher competition and therefore lower profitability. Yet, greater financial market development is correlated with increased bank profits and net interest margins in less developed financial systems. Applying this interpretation to our analysis, the missing link between real GDP growth and S&L performance may indicate that developed countries like the US no longer observe those "complementarities" that are meaningful in less developed countries. In addition, since our data is aggregated rather than on a firm level, sector-related variables were omitted from the analysis, such as explicit and implicit bank taxes, regulatory capital requirements, deposit insurance, general financial structure, stock market capitalization, and several underlying legal and institutional factors.

Table 3: Parameter Estimates of Model Using ROE as Dependent Variable

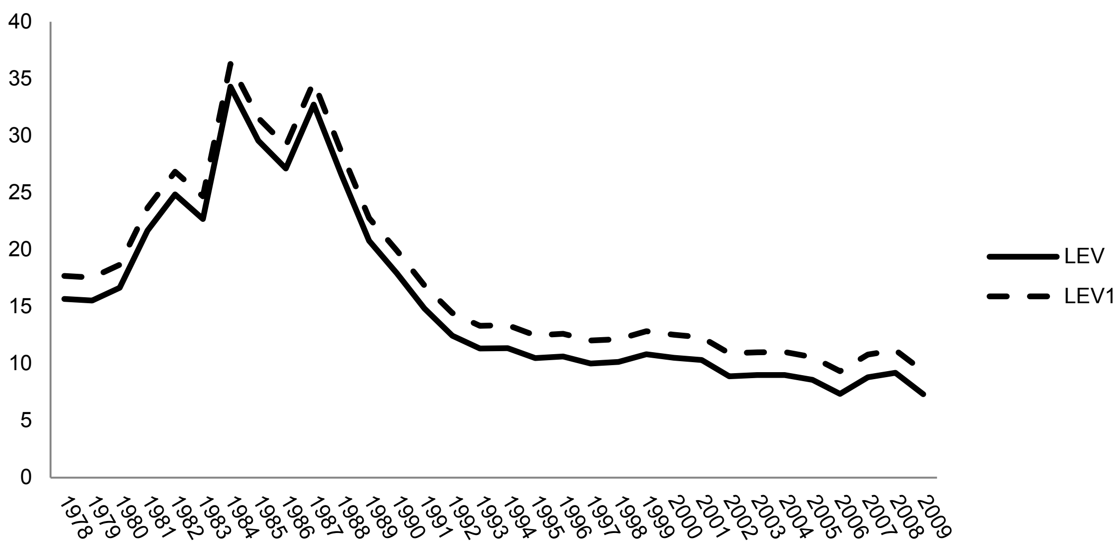
Method: Least Squares Regression; First Difference Operator Number of Observations: 31 (1978-2009)	
Variable	**Coefficient**
Constant Term	-0.010 (0.786)
Δ BRISK	-0.984 (0.534)
Δ NPL_TA	-5.820** (2.116)
Δ LIQ	-0.565 (1.647)
Δ GROWTH_RATE_GDP	0.005 (0.934)
Δ LEV1	-0.010** (2.492)
Δ IR	-0.025*(2.066)
R-squared	0.532731
Adjusted R-squared	0.410835
Durbin-Watson stat	1.705047
F-statistic	4.370364
Prob. (F-statistic)	0.004363

****Significant at 1% level or 0.01; ** Significant5% level or 0.05; *Significant at 10% level or 0.1 The figures in parenthesis are absolute values of t-statistics. Based on the critical value of 2, Durbin-Watson statistic of 1.70 indicates a low positive autocorrelation.*

The statistically significant variables are LIQ, IR, LEV, LEV1, and NPL_MLO and NPL_TA. Although IR, with a negative coefficient value and p value of 0.0088, is significant at a 1% level in the first regression ($p<0.01$), it is also significant at 10% level with a p value of 0.0502 ($p<0.1$). This might suggest that while macroeconomic factors such as low interest rates have a negative effect on bank earnings, the impact of interest rates varies depending on the profit indicator used.

The most statistically significant variables are NPL_MLO and leverage ratios. This indicates that high leverage and large non-performing loan to total loan ratio leads to a lower rate of return on capital. Lower profitability is associated with NPL_MLO, which is statistically significant at almost 1%--significantly lower than 5% at p value of 0.0102. Pair-wise correlation matrix also confirms that ratio of non-performing loans is negatively correlated with bank profitability, with correlation coefficients of -0.62154 and -0.700294 respectively. Leverage ratios vary in significance depending on the leverage indicator used but in both regressions are negatively correlated with return on assets (approximately -0.55). Everything else remaining equal, there is evidence that loan quality problems and impaired assets rather than size of loans affect profitability negatively. Papanikolaou and Wolff (2010) showed that excessive leverage obtained through "explicit and hidden off-the balance sheet" items were the main determinants of liquidity shortages in the banking industry during the financial crisis of 2007. Our analysis is consistent with the view that over-leveraging and under-performing loans have the potential to render banks vulnerable to financial shocks, thus contributing to financial instability.

Figure 2: S&L Industry Leverage Ratios



This figure shows the trend in industry leverage ratio during the period 1978-2009. Leverage has remained more stable prior to the subprime mortgage crisis than at the height of the S&L debacle. Overall, leverage has decreased during this period. Ratios are calculated from OTS (2009) database.

Leverage indicates the extent to which banks are using debt (borrowings) in financing investments such as securitizing loans; it is thus a good map to the riskiness of assets. However, the decrease in leverage ratio might be misleading because securitized assets are not reported in bank balance sheets. With access to securitization and the development of more sophisticated financial instruments, banks are able to appear less leveraged. Lower leverage makes it difficult to establish whether the growth rate of leverage has to do with hidden, off-balance sheet items or with the strength of capital ratios in the S&L industry. Mortgage-backed securities were certainly profitable for banks when the housing market was booming. As mortgage loans were bought from banks, they were packaged into pools as securitized assets and sold to investors multiple times to increase value. By selling mortgage obligations to investors, banks could therefore remove mortgages from their balance sheets and thus give the impression of being moderately leveraged.

This has allowed them to lower their loan requirements and offer mortgages to borrowers who would not otherwise be able to qualify. The lower the loan requirements the more opportunity to profit by increasing the number of lenders. So long as the housing market was booming and mortgages were paid off on time, the mortgage-backed securities had value and could generate higher profits. Since the collapse of the housing market, however, they have not been as profitable. Profits started to slowdown after 2005, making a sharp downturn in 2008 when the housing market crashed. While profits have somewhat leveled since then, they have not reached pre-crisis levels.

CONCLUDING COMMENTS

This paper examined US Savings and Loan performance in the period 1978-2009. In particular, it examined the impact of macroeconomic and industry-related variables on industry profitability. Additionally, the paper discussed the recent trends and policy issues facing the industry performance since the start of the S&L debacle in the 1980s until the subprime mortgage crisis in 2008. This was a period of restructuring during which S&Ls were deregulated with the view of diversifying their activities and increasing profits**.** Financial liberalization, however, has made it difficult for S&Ls, with their specialized products and fixed asset structure, to compete effectively with other providers in the financial services industry. Critics claimed that the S&L resolution served as a model to lenders making high-risk loans during the sub-prime financial crisis (Weiner, 2007).

The objective of this paper was to establish which of these likely determinants of profitability prevailed in the US S&L industry. We used yearly aggregated bank data covering a 31-year period from 1978 to 2009, observing 11 variables before the start of the crisis as well as those that followed. Using ADF as a statistical test for filtering unit root effects by estimation of least squares, we were able to establish meaningful trends in the performance of the S&L industry. To apply the test, we accepted the existence of a unit root assuming that variables were non-stationary. After having found consistent evidence of unit root in variables, the model was re-estimated applying the first difference operator to the series and stationary de-trending. The ADF test indicated that all the variables in both models were integrated of order one.The results of our analysis indicated that industry characteristics explain a substantial part of the variation in profitability measured by return on assets and return on equity.

The most statistically significant variables are NPL_MLO and leverage ratios. Low profitability tends to be associated with industry holding high leverage and large non-performing loan to total loan ratio. This indicates that high leverage and large non-performing loans lead to a lower rate of return on capital. The loan ratio has negative and significant coefficients on ROA and ROE. Our results further demonstrated that macroeconomic indicators such as growth rate of GDP have no impact on industry's profitability, confirming earlier studies in this area. While fixed mortgage interest rate, with a negative coefficient value, is significant at a 1% level in the first regression, it is also significant at 10% level in the second regression. This suggests that while macroeconomic factors such as low interest rates have a negative effect on bank earnings, the effects of interest rate changes vary depending on the profit indicator used.
While it is clearly the case that industry leverage (LEV) has been decreasing by 53.273% since 1978, it has been decreasing at a slower rate (41.086 %) since 1992.

The slow growth rate of leverage might give the impression that there is no systemic risk associated with leverage. Leverage ratios vary in significance depending on the leverage indicator used but in both regressions are negatively correlated with return on assets (approximately -0.55). The work of Papanikolaou and Wolff (2010) examined the impact of that excessive leverage obtained through "explicit and hidden off-the balance sheet" items on bank liquidity shortages during the financial crisis of 2007. Our analysis also confirms that over-leveraging and under-performing loans have the potential to render banks vulnerable to financial shocks, thus contributing to financial instability.

In terms of policy implications, we can draw some recommendations at the industry and country level. Loan quality is one of the most important determinants of financial performance, as it was found to be complementary with profitability. The quality of loan portfolio reflects the extent of credit risk in investment portfolios and maps to the overall riskiness of an institution. Therefore, the improvement of the performance of S&Ls needs to be based on a reinforcement of the supervisory standards and loan examination through national regulation programs. This should be aimed at adequately regulating the proportion of impaired loans and monitoring the size of leverage. It is necessary to frequently monitor the adequacy of Loan Loss Provisions and asset valuation reserves concomitantly with risk management processes and internal regulations at these institutions. One of the limitations of the study is the use of time-series/aggregated data rather than sectoral data. While sectoral data is largely available for US commercial banks, it is not complete for savings and loan associations. Although this has made it difficult to examine the variations in profitability across institutions and posed some autocorrelation problems, the co-integration statistical procedure (ADF test) was able to filter some of the trending behavior in a time-series data. Future research can benefit from the inclusion of exogenous variables in regression analysis, such as policy interventions and regulatory capital requirements that can affect the long-run profitability of the S&L industry at the national level. Structure-conduct-performance (SCP) paradigm highlights the contribution of market structures and financial system variables to banking industry performance. In order to give our findings a stronger basis for prediction, further research is needed on the relationship between bank-specific, industry-related and macroeconomic variables since the start of the S&L crisis.

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TOURISM DEVELOPMENT AND ECONOMIC GROWTH IN DEVELOPING COUNTRIES

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ABSTRACT

The objective of this study is to investigate the relationships between tourism development and economic growth in developing countries using the newly developed heterogeneous panel cointegration technique. This study examines the causal relationship between tourism development and economic growth using Granger causality tests in a multivariate model and using the annual data for the 1995–2009 period. The study finds no evidence to support the tourism-led growth hypothesis. The results of the FMOLS show that, though the elasticity of tourism revenue with respect to real GDP is not statistically significant for all regions, its positive sign indicates that tourism revenue makes a positive contribution to economic growth in developing countries. The results of the study suggest that governments of developing countries should focus on economic policies to promote tourism as a potential source of economic growth.

JEL: F43, L83, O40

KEYWORDS: Tourism, economic growth, panel cointegration, causality

INTRODUCTION

Tourism industry has emerged as one of the leading service industries in the global economy in recent decades. Economic flows generated by international tourism have become vital factors in economic growth and international economic relations in many developing countries. For example, according to the World Tourism Organization (2010), as a result of an ever increasing number of destinations opening up and investing in tourism development, modern tourism has become a key driver for socio-economic progress through the creation of jobs and enterprises, infrastructure development, and the export revenues earned. In addition, the contribution of tourism to worldwide economic activity is estimated at some 5% while its contribution to employment is estimated in the order of 6-7% of the overall number of direct and indirect jobs worldwide. According to the World Tourism Organization, between 1970 and 2009, there was a 48-fold increase in international tourism receipts rising from US$17.9 billion in 1970 to US$852 billion in 2009.

The importance of the tourism sector can further be understood based on recent statistics available from the World Travel & Tourism Council. According to the World Travel & Tourism Council's latest economic impact report (The World Travel & Tourism Council, 2011), the industry's direct contribution to global GDP increased by 3.3% in 2010 to US$1,770 billion and is expected to rise further by 4.5% to US$1,850 billion in 2011, creating an additional 3 million direct industry jobs. In addition, taking into account its wider economic impacts, travel and tourism's total economic contribution in 2011 is expected to account for US$5,987 billion or 9.1% of global GDP, and for 258 million jobs. The report also predicts that the direct contribution of travel and tourism to GDP is expected rise by 4.2% annually to US$2,860.5 billion (in constant 2011 prices) in 2021. In addition, the total contribution of travel and tourism to employment, including jobs indirectly supported by the industry, is forecast to be 258.6 million jobs (8.8% of total employment), visitor exports are expected to generate US$1,162.7 billion (5.8% of total exports), and total industry investment is estimated at US$652.4 billion or 4.5% of total investment in 2011.

Thus the tourism sector has become increasingly important industry to many developing countries as a source of revenue as well as a source of employment. Tourism generates a vital amount of foreign exchange earnings that contributes to the sustainable economic growth and development of developing countries. Given its increasing importance in the global economy, tourism sector has gained much attention in recent academic literature. According to Balaguer and Cantavella-Jorda (2002), international tourism would contribute to an income increase at least in two different ways as the export-led growth hypothesis postulates. First, enhancing efficiency through competition between local firms and the ones corresponding to other international tourist destinations, and second, facilitating the exploitation of economies of scale in local firms. The objective of this study is to investigate the relationships between tourism development and economic growth in developing countries. This study examines the causal relationship between tourism development and economic growth in developing countries in a multivariate model using the annual data for the 1995–2009 period.

The remainder of the paper is organized as follows: Section 2 provides a brief literature review. In Section 3, the empirical framework of the current study is set out by specifying model as well as the econometric methodology. Section 4 discusses the variable definitions and outlines the data sources. Empirical results of panel unit root tests, panel cointegration tests, and error-correction model estimates are presented in Section 5. The last section, Section 6 presents a summary and a brief conclusion as to the results obtained in this study.

REVIEW OF LITERATURE

There are a large number of studies done on tourism and economic growth. These studies can be grouped into two broad categories, namely, single-country studies and country-group studies. Due to the limitation of resources, this review is limited to some of the most recent studies. The empirical results from previous studies on the causal relationship between tourism expansion and economic growth are mostly mixed. For example, Kreishan (2010), Lee and Chang (2008), Kim, et al. (2006), Dritsakis (2004), Durbarry (2004), and Balaguer and Cantavella-Jorda (2002) find evidence supporting the tourism-led economic growth hypothesis. The economic-driven tourism growth hypothesis is supported in studies by Katircioglu (2009), Oh (2005), Narayan (2004), and Lanza et al. (2003). Although relatively few, the reciprocal hypothesis is still supported by, for example, Arslanturk, et al. (2011), Kim, et al. (2006) and Shan and Wilson (2001). The Granger causality test has been widely used in the literature in analyzing the relationship between tourism and economic growth. For a comprehensive survey of current literature on tourism demand and is impact on the economy, please see Song and Li (2008) and Li, Song, and Witt (2005).

A recent study by Schubert, Brida, and Risso (2011) examines the impacts on economic growth of a small tourism-driven economy caused by an increase in the growth rate of international tourism demand. The study uses annual data of Antigua and Barbuda from 1970 to 2008. The model shows that an increase in the growth of tourism demand leads to transitional dynamics with gradually increasing economic growth and increasing terms of trade. The authors perform a cointegration analysis to look for the existence of a long-run relationship among variables of economic growth, international tourism earnings and the real exchange rate. The exercise confirms the theoretical findings.

Arslanturk, Balcilar, and Ozdemir (2011) investigates the causal link between tourism receipts and GDP in Turkey for the period 1963-2006. The study uses the rolling window and time-varying coefficients estimation methods to analyze the Granger causality based on Vector Error Correction Model (VECM). The findings of the paper indicate that there is no Granger causality between the series, while the findings from the time-varying coefficients model based on the state-space model and rolling window technique show that GDP has no predictive power for tourism receipts. However, tourism receipts have a positive–predictive content for GDP following early 1980s.

A study by Kreishan (2010) examines the causality relations between tourism earnings and economic growth for Jordan, using annual data covering the period 1970-2009. The findings of the study showed that there is a positive relationship between tourism development and economic development in the long-run. Moreover, the Granger causality test results revealed the presence of unidirectional causality from tourism earnings to economic growth. In a similar study, Zortuk (2009) focuses on investigating the contribution of tourism sector to economic growth in Turkey. The data pertaining to 1990Q1 and 2008Q3 periods were used in the study and the relationship between the expansion in tourism and economic growth was investigated using granger causality test based on vector error-correction model and finds evidence for unidirectional causality from tourism development to economic development exists between the two variables.

Katircioglu (2009) employs the bounds test for cointegration and Granger causality tests to investigate a long-run equilibrium relationship between tourism, trade and real income growth, and the direction of causality among themselves for Cyprus. Data used in the study are annual figures covering the period 1960–2005. The results of the study reveal that tourism, trade and real income growth are cointegrated; thus, a long-run equilibrium relationship can be inferred between these three variables. In addition, Granger causality test results suggest that real income growth stimulates growth in international trade (both exports and imports) and international tourist arrivals to the island.

A study by Lee and Chang (2008) applies the new heterogeneous panel cointegration technique to re-investigate the long-run comovements and causal relationships between tourism development and economic growth for OECD and non-OECD countries (including those in Asia, Latin America and Sub-Sahara Africa) for the 1990–2002 period. The study finds that tourism development has a greater impact on GDP in non-OECD countries than in OECD countries, and when the variable is tourism receipts, the greatest impact is in Sub-Sahara African countries. Additionally, in the long run, the panel causality test shows unidirectional causality relationships from tourism development to economic growth in OECD countries, bidirectional relationships in non-OECD countries, but only weak relationships in Asia.

Sequeira and Nunes (2008) use panel data methods to study the relationship between tourism and economic growth. The study uses annual data for a group of countries covering the period 1980-2002 and shows that tourism is a positive determinant of economic growth both in a broad sample of countries and in a sample of poor countries. However, contrary to previous contributions, tourism is not more relevant in small countries than in a general sample.

Employing the Engle and Granger two-stage approach and a bivariate VAR model of real aggregate tourism receipts and real GDP, Oh (2005) investigates the causal relations between tourism growth and economic expansion for the Korean economy. Using quarterly data from 1975Q1 to 2001Q1, the results of cointegration test indicate that there is no long-run equilibrium relationship between these two series. In addition, the results of Granger causality test imply the existence of a one-way causal relationship in terms of economic-driven tourism growth. The hypothesis of tourism-led economic growth, therefore, is not held in the Korean economy.

Balaguer and Cantavella-Jorda (2002) use a trivariate model of real GDP, real international tourism earnings, and the real effective exchange rate to examine the role of tourism in the Spanish long-run economic development and confirms the tourism-led growth hypothesis through cointegration and causality testing. The study uses quarterly data for the period 1975Q1-1997Q4 and finds that economic growth in Spain has been sensible to persistent expansion of international tourism. Their results for the Granger causality test indicate that tourism affects Spain's economic growth unidirectionally and thus supports the tourism-led growth hypothesis.

As pointed out by Po and Huang (2008), since the relationship between tourism and economic growth is inherently a long-term one, a biased estimate may be the result of an insufficiently large sample size in the time series, the existence of structural changes, or short-term economic fluctuations. To tackle the insufficient sample size problem, researchers have started to use panel data. In this article we employ recently developed panel data techniques and closely follow empirical growth literature to test the influence of tourism development on economic growth in a broad panel data. Our panel data set includes 140 developing countries and 15 years covering the period from 1995 to 2009.

METHODOLOGY

Model Specification

This section discusses the model specifications to examine the relationship between tourism development and economic growth. The model is derived, in conventional manner, from a production function in which tourism receipts is introduced as an input in addition to labor and domestic capital.

In the usual notation the production function can be written as follows:

$$Y = f(L, K, TR) \tag{1}$$

where Y is the real gross domestic product (GDP) in constant 2000 dollars, L is the labor force in millions, K is the real gross fixed capital formation (K) in constant 2000 U.S. dollars, and TR is the real tourism receipts in constant 2000 dollars.

The data is compiled within a panel data framework in light of the relatively short time span of the data. Assuming (1) to be linear in logs, the estimated model can be written as:

$$\ln Y_{it} = \alpha_i + \delta_i t + \beta_{1i} \ln L_{it} + \beta_{2i} \ln K_{it} + \beta_{3i} \ln TR_{it} + \varepsilon_{it} \tag{2}$$

where i = 1, 2, 3, ..., N for each country in the panel and t = 1, 2, 3, ..., T refers to the time period. Our panel data set includes 140 countries and covers 15 years from 1995 to 2009. According to economic theory, the expected signs of the coefficients β_1 and β_2 are positive. If tourism is expected to contribute to economic growth, the expected sign of β_3 is positive. The parameters α_i and δ_i allow for country-specific fixed effects and deterministic trends, respectively while ε_{it} denote the estimated residuals which represent deviations from the long-run relationship.

Panel Unit Root Tests

Before proceeding to cointegration techniques, we need to verify that all of the variables are integrated to the same order. In doing so, we have used panel unit roots tests due to Im, Pesaran, and Shin (2003) (hereafter, IPS). These tests are less restrictive and more powerful than the tests developed by Levin and Lin (1993) and Levin, Lin, and Chu (2002), which do not allow for heterogeneity in the autoregressive coefficient. The tests proposed by IPS permit to solve Levin and Lin's serial correlation problem by assuming heterogeneity between units in a dynamic panel framework. The IPS test will be considered more important because it is appropriate for a heterogeneous regressive root under an alternative hypothesis. The basic equation for the panel unit root tests for IPS is as follows:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p} \rho_{ij} \Delta y_{i,t-j} + \varepsilon_{i,t} \qquad i = 1,2,3,....,\mathrm{N} \qquad t = 1,2,3,....,\mathrm{T} \tag{3}$$

where $y_{i,t}$ stands for each variable under consideration in our model, α_i is the individual fixed effect, and p is selected to make the residuals uncorrelated over time. The null hypothesis is that $\beta_i = 0$ for all i versus the alternative hypothesis that $\beta_i < 0$ for some i. The IPS statistic is based on averaging individual Augmented Dickey-Fuller (ADF) statistics and can be written as follows:

$$\bar{\mathrm{t}} = \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \mathrm{t}_{iT} \tag{4}$$

where t_{iT} is the ADF t-statistic for country i based on the country specific ADF regression, as in Eq. (3). IPS show that under the null hypothesis of non-stationary in panel data framework, the t statistic follows the standard normal distribution asymptotically. The standardized statistic t_{IPS} is expressed as:

$$\mathrm{t}_{IPS} = \frac{\sqrt{\mathrm{n}} \left(\bar{\mathrm{t}} - \frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \mathrm{E}[\mathrm{t}_{iT} | \rho_i = 0] \right)}{\sqrt{\frac{1}{\mathrm{N}} \sum_{i=1}^{\mathrm{N}} \mathrm{Var}[\mathrm{t}_{iT} | \rho_i = 0]}} \tag{5}$$

Panel Cointegration Tests

We investigate the existence of cointegrating relationship using the standard panel tests for no cointegration proposed by Pedroni (1999, 2004). These tests allow for heterogeneity in the intercepts and slopes of the cointegrating equation. Pedroni's tests provide seven test statistics: Within dimension (panel tests): (1) Panel ν -statistic; (2) Panel Phillips–Perron type ρ-statistics; (3) Panel Phillips–Perron type t-statistic; and (4) Panel augmented Dickey–Fuller (ADF) type t-statistic. Between dimension (group tests): (5) Group Phillips–Perron type ρ-statistics; (6) Group Phillips–Perron type t-statistic; and (7) Group ADF type t-statistic. These statistics are based on averages of the individual autoregressive coefficients associated with the unit root tests of the residuals for each country in the panel. All seven tests are distributed asymptotically as standard normal. Following Pedroni (1999, 2004), the heterogeneous panel and heterogeneous group mean panel of rho (ρ), parametric (ADF), and nonparametric (PP) statistics are calculated as follows:

Panel ν - statistic:

$$\mathrm{Z}_{\nu} = \left(\sum_{i=1}^{\mathrm{N}} \sum_{t=1}^{\mathrm{T}} \hat{\mathrm{L}}_{11i}^{-2} \, \hat{\mathrm{e}}_{it-1}^{2} \right)^{-1} \tag{6a}$$

Panel ρ - statistic:

$$\mathrm{Z}_{\rho} = \left(\sum_{i=1}^{\mathrm{N}} \sum_{t=1}^{\mathrm{T}} \hat{\mathrm{L}}_{11i}^{-2} \, \hat{\mathrm{e}}_{it-1}^{2} \right)^{-1} \sum_{i=1}^{\mathrm{N}} \sum_{t=1}^{\mathrm{T}} \hat{\mathrm{L}}_{11i}^{-2} \, (\hat{\mathrm{e}}_{it-1} \, \Delta \hat{\mathrm{e}}_{it} - \hat{\lambda}_i) \tag{6b}$$

Panel *ADF* - statistic:

$$Z_t = \left(\tilde{s}_{NT}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \ \hat{e}*_{it-1}^{2} \right)^{-\frac{1}{2}} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \ \hat{e}_{it-1}^{*} \ \Delta\hat{e}_{it}^{*} \tag{6c}$$

Panel *PP* - statistic:

$$Z_{pp} = \left(\tilde{\sigma}_{NT}^{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \ \hat{e}_{it-1}^{2} \right)^{-\frac{1}{2}} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \ (\hat{e}_{it-1} \ \Delta\hat{e}_{it} - \hat{\lambda}_i) \tag{6d}$$

Group ρ - statistic:

$$\tilde{Z}_{\rho} = \sum_{i=1}^{N} \left(\sum_{i=1}^{T} \hat{e}_{it-1}^{2} \right)^{-1} \sum_{i=1}^{T} (\hat{e}_{it-1} \ \Delta\hat{e}_{it} - \hat{\lambda}_i) \tag{6e}$$

Group *ADF* - statistic:

$$\tilde{Z}_t = \sum_{i=1}^{N} \left(\sum_{i=1}^{T} \bar{s}_i^{*2} \ \hat{e}_{it-1}^{*2} \right)^{-\frac{1}{2}} \sum_{i=1}^{T} \hat{e}_{it-1}^{*} \ \Delta\hat{e}_{it}^{*} \tag{6f}$$

Panel *PP* - statistic:

$$\tilde{Z}_{pp} = \sum_{i=1}^{N} \left(\sum_{i=1}^{T} \hat{\sigma}_i^{2} \ \hat{e}_{it-1}^{2} \right)^{-\frac{1}{2}} \sum_{i=1}^{T} (\hat{e}_{it-1} \ \Delta\hat{e}_{it-1} - \hat{\lambda}_i) \tag{6g}$$

where

$$\hat{\lambda}_i = \frac{1}{T} \sum_{j=1}^{k_i} \left(1 - \frac{j}{k_i + 1} \right) \sum_{t=j+1}^{T} \hat{\mu}_{it} \hat{\mu}_{i,t-j} \ ; \ \hat{s}_i^2 = \frac{1}{T} \sum_{t=1}^{T} \mu_{it}^2 \ ; \ \hat{\sigma}_i^2 = \hat{s}_i^2 + 2\hat{\lambda}_i \ ; \ \tilde{\sigma}_{NT}^2 = \frac{1}{N} \sum_{i=1}^{N} \hat{L}_{11i}^{-2} \hat{\sigma}_i^2 \ ; \ \hat{s}_i^{*2} = \frac{1}{T} \sum_{t=1}^{T} \hat{\mu}_{it}^{*2} \ ;$$

$$\tilde{s}_{NT}^{*2} = \frac{1}{T} \sum_{i=1}^{N} \hat{s}_i^{*2} \ ; \text{and } \hat{L}_{11i}^{2} = \frac{1}{T} \sum_{t=1}^{T} \hat{\eta}_{it}^2 + \frac{2}{T} \sum_{j=1}^{k_i} \left(1 - \frac{j}{k_i + 1} \right) \sum_{t=j+1}^{T} \hat{\eta}_{it} \hat{\eta}_{i,t-j} \ .$$

The error terms $\hat{\mu}_{i,t}$, $\hat{\mu}_{i,t}^{*}$, and $\hat{\eta}_{i,t}$ are respectively derived from the following auxiliary regressions: $\hat{\varepsilon}_{it} = \hat{\rho}_i \hat{\varepsilon}_{i,t-1} + \hat{\mu}_{it}$; $\hat{\varepsilon}_{it} = \hat{\rho}_i \hat{\varepsilon}_{i,t-1} + \sum_{j=1}^{k_i} \hat{\rho}_{ik} \Delta\hat{\varepsilon}_{i,t-j} + \hat{\mu}_{it}$; and $\Delta y_{it} = \sum_{m=1}^{M} \hat{\gamma}_{mi} \Delta x_{mit} + \hat{\eta}_{it}$.

Of the seven test statistics, except for the panel ν - statistic, the other six Pedroni test statistics are left-tailed tests. In order to find evidence for long-run relationship between the variables, the null hypothesis of no cointegration for these tests should be rejected. If the null hypothesis cannot be rejected, there is no long-run relationship between the variables.

DATA SOURCES AND VARIABLES

Annual data from 1995 to 2009 were obtained from the *World Bank Development Indicators* database for 140 developing countries. Additional information is collected from the United Nations Conference on Trade and Development (UNCTAD) database at http://unctadstat.unctad.org. The list of the countries is presented in the Appendix. The data is compiled within a panel data framework in light of the relatively short time span of the data. The multivariate framework includes the real GDP in constant 2000 U.S. dollars, the real gross fixed capital formation in constant 2000 U.S. dollars, the labor force in millions, and the real international tourism receipts in constant 2000 U.S. dollars. The real gross fixed capital formation in constant 2000 U.S. dollars series was calculated in two steps: First, since the information on gross fixed capital formation was given as a share of GDP, nominal gross fixed capital formation was calculated by multiplying the gross fixed capital formation to GDP share by nominal GDP. Second, the nominal gross fixed capital formation series was deflated by the GDP deflator (2000 = 100) to derive the real gross fixed capital formation in constant 2000 U.S. dollars. The real international tourism receipts in constant 2000 U.S. dollars was derived by deflating the nominal international tourism receipts by the GDP deflator.

EMPIRICAL RESULTS

Panel Unit Root Tests

The starting point of our econometric analysis is to check whether the variables included in Equation (1) contain panel unit roots. In other words, in Equation (1), we need to check whether [Y, L, K, TR] contains a unit root. While there are several panel unit root tests are available, this study uses the IPS unit root tests. In order to compare the results for different regions, the total sample was sub-divided into six regions, namely, East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, South Asia, and Sub-Saharan Africa. The regions were defined using the classifications used by the World Bank. Table 1 shows the summary statistics of the main variables for each of the six regions. Table 2 reports the results of these panel unit root tests which include individual effects. The panel unit root tests indicate all the variables are integrated of order one.

Panel Cointegration Tests

With the respective variables integrated of order one, the heterogeneous panel cointegration test advanced by Pedroni (1999, 2004), which allows for cross-section interdependence with different individual effects, is performed and the results are presented in Table 3. Though the panel cointegrations tests were performed for all six regions and for all countries, only the results for the full sample are presented in Table 3. The results for both within and between dimension panel cointegration test statistics are given in the table. All seven test statistics reject the null hypothesis of no cointegration at the 1% significance level, indicating that the four variable are cointegrated.

After having found consistent evidence of cointegration, the fully modified OLS (FMOLS) technique for heterogeneous cointegrated panels is estimated, following Pedroni (2000). The results of the FMOLS are presented in Table 3. All the coefficients are positive and statistically significant either at the 1% or at 5% significance level. Given that the variables are expressed in natural logarithms, the coefficients can be interpreted as elasticity estimates. The results indicate that, for the full sample, a 1% increase in real tourism revenue increases real GDP by 0.04%; a 1% increase in real gross fixed capital formation increases real GDP by 0.87%; and a 1% increase in the labor force increases real GDP by 0.09%. When we compare the six regions selected, the elasticity of tourism revenue with respect to real GDP ranges from high of 0.1383 for Latin America and the Caribbean to 0.0048 for Middle East and North Africa.

Table 1: Basic Summary Statistics

	East Asia and Pacific				Europe and Central Asia			
	Ln(L)	**Ln(K)**	**Ln(Y)**	**Ln(TR)**	**Ln(L)**	**Ln(K)**	**Ln(Y)**	**Ln(TR)**
Mean	1.8356	6.6320	8.3817	5.8425	0.4116	6.4170	7.8295	4.2990
Median	1.8500	6.6412	8.3491	6.0719	0.4066	6.2420	7.7713	4.3925
Maximum	2.0515	7.3420	8.9116	6.8484	0.4805	7.5584	8.4546	5.2242
Minimum	1.5952	5.8763	7.8619	4.0201	0.3605	5.6144	7.3059	2.7851
Std. Deviation	0.1434	0.4943	0.3577	0.9390	0.0422	0.6629	0.3894	0.8096
Skewness	-0.1805	-0.0925	0.0901	-0.6698	0.2552	0.4052	0.2240	-0.5023
Kurtosis	1.7480	1.7120	1.6310	2.0101	1.5338	1.6300	1.5637	1.9962
Jarque-Bera	24.4043	24.3398	27.4065	39.8792	34.6470	36.4200	32.5405	28.9939
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	633.2838	2288.0350	2891.6940	2015.6510	142.0058	2213.8560	2701.1820	1483.1610
Sum Sq. Dev.	7.0710	84.0666	44.0124	303.3082	0.6119	151.1468	52.1686	225.5002
Observations	345	345	345	345	345	345	345	345
	Latin America and the Caribbean				**Middle East and North America**			
	Ln(L)	**Ln(K)**	**Ln(Y)**	**Ln(TR)**	**Ln(L)**	**Ln(K)**	**Ln(Y)**	**Ln(TR)**
Mean	-3.3630	5.9529	6.6062	5.6585	2.4689	9.7950	11.0054	4.5209
Median	-3.3688	5.8790	6.5454	5.6651	2.4838	9.8177	10.9829	4.6406
Maximum	-3.2475	6.7168	6.9505	5.7835	2.7096	10.3599	11.2471	5.1851
Minimum	-3.4699	5.2080	6.2874	5.5805	2.1931	9.3143	10.7572	3.3578
Std. Deviation	0.0712	0.4673	0.2060	0.0510	0.1574	0.2874	0.1627	0.5100
Skewness	0.1441	0.2159	0.3143	0.4848	-0.1826	0.1883	0.0384	-1.1019
Kurtosis	1.7158	1.9149	1.8749	3.3347	1.8511	2.0854	1.5655	3.1051
Jarque-Bera	40.0617	31.5418	38.4080	24.3312	14.5332	9.7834	20.6375	48.6787
Probability	0.0000	0.0000	0.0000	0.0000	0.0007	0.0075	0.0000	0.0000
Sum	866.4771	3303.8841	3666.4652	3140.4772	592.5454	2350.7912	2641.2893	1085.0181
Sum Sq. Dev.	2.8115	120.9587	23.4993	1.4407	5.9200	19.7444	6.3301	62.1558
Observations	555	555	555	555	240	240	240	240
	South Asia				Sub-Saharan Africa			
	Ln(L)	Ln(K)	Ln(Y)	Ln(TR)	Ln(L)	Ln(K)	Ln(Y)	Ln(TR)
Mean	4.1963	9.3556	10.8352	4.0492	1.8972	7.6105	9.3934	4.1371
Median	4.1968	9.3561	10.8194	4.0951	1.8944	7.6875	9.2863	3.9183
Maximum	4.3647	9.8172	11.2289	4.4308	2.1102	8.2716	10.1052	5.4883
Minimum	4.0293	8.8164	10.4709	3.1480	1.6906	7.0293	8.8222	3.2939
Std. Deviation	0.1065	0.3082	0.2363	0.3629	0.1318	0.4096	0.4072	0.6456
Skewness	0.0063	-0.1688	0.1107	-1.0963	0.0338	0.0556	0.5826	0.9606
Kurtosis	1.7026	1.8635	1.8109	3.5082	1.7296	1.5878	1.9800	2.7250
Jarque-Bera	6.3132	5.2711	5.4862	18.9960	34.3931	42.6408	50.9538	80.0462
Probability	0.0426	0.0717	0.0644	0.0001	0.0000	0.0000	0.0000	0.0000
Sum	377.6627	842.0002	975.1680	364.4290	967.5477	3881.3500	4790.6410	2109.9460
Sum Sq. Dev.	1.0090	8.4563	4.9690	11.7210	8.8434	85.3865	84.3957	212.1824
Observations	90	90	90	90	510	510	510	510

Note: This table shows the summary statistics of the main variables for each of the six regions.

Though the elasticity of tourism revenue with respect to real GDP is not statistically significant for all regions, its positive sign indicates that tourism revenue makes a positive contribution to economic growth in developing countries.

Table 2: Panel Unit Root Tests Results

Variable	Level	First Difference
All Countries		
Real GDP (Y)	-0.354	-2.646***
Labor Force (L)	-0.352	-2.581***
Real Capital Stock (K)	-2.015	-4.001***
Real Tourism Receipts (TR)	-2.127	-2.727***
East Asia and the Pacific		
Real GDP (Y)	-0.936	-3.214***
Labor Force (L)	-1.124	-2.475***
Real Capital Stock (K)	-0.559	-4.839***
Real Tourism Receipts (TR)	-1.564	-2.809***
Europe and Central Asia		
Real GDP (Y)	-0.645	-2.648***
Labor Force (L)	-0.055	-8.371***
Real Capital Stock (K)	-0.969	-3.127***
Real Tourism Receipts (TR)	-0.215	-4.485***
Latin America and the Caribbean		
Real GDP (Y)	-0.043	-2.499***
Labor Force (L)	-0.895	-9.062***
Real Capital Stock (K)	-0.211	-3.719***
Real Tourism Receipts (TR)	-0.321	-7.787***
Middle East and North Africa		
Real GDP (Y)	-0.191	-2.276***
Labor Force (L)	-0.119	-2.715***
Real Capital Stock (K)	-0.245	-8.627***
Real Tourism Receipts (TR)	-0.790	-5.851***
South Asia		
Real GDP (Y)	-0.784	-5.981***
Labor Force (L)	-1.308	-2.854***
Real Capital Stock (K)	-0.203	-2.651***
Real Tourism Receipts (TR)	-1.114	-3.222***
Sub-Saharan Africa		
Real GDP (Y)	-1.378	-2.604***
Labor Force (L)	-0.839	-2.617***
Real Capital Stock (K)	-0.203	-2.462***
Real Tourism Receipts (TR)	-0.113	-6.850***

*Notes: This table presents the results of the IPS panel unit root and stationary tests as proposed by Im, Pesaran and Shin (2003). Panel unit root test includes intercept and trend. The null hypothesis of unit root (non-stationary) is used. *** indicates the statistical significance at the 1 percent level of significance.*

Table 3: Heterogeneous Panel Cointegration Test Results (Full Sample)

Panel cointegration statistics (within-dimension)	Test Statistic
Panel ν-statistic	10.071 (0.000)***
Panel ρ-statistic	-7.621 (0.000)***
Panel *t*-statistic	-10.132 (0.000)***
Panel *t*-statistic	-5.110 (0.000)***
Panel cointegration statistics (within-dimension)	
Group PP type ρ-statistic	-3.789 (0.000)***
Group PP type *t*-statistic	-10.452 (0.000)***
Group ADF type *t*-statistic	-3.143 (0.000)***

*Notes: Of the seven tests, the panel ν-statistic is a one-sided test where large positive values reject the null hypothesis of no cointegration whereas large negative values for the remaining test statistics reject the null hypothesis of no cointegration. The number of lag length was selected automatically based on SIC with a maximum lag of 15. The figures in the parentheses are p-values. *** indicates the statistical significance at the 1 percent level of significance.*

Granger Causality Tests

The procedures described above are only able to indicate whether or not the variables are cointegrated and a long-run relationship exists between them. To test for panel causality, a panel vector error correction model (VECM) proposed by Pesaran et al. (1999) is estimated to perform Granger-causality tests.

Table 4: Panel FMOLS Long-Run Estimates

Region	Constant	ln (L)	ln (K)	ln (TR)	Adjusted R^2
All Countries	2.1741***	0.0918***	0.8756***	0.0361**	0.9722
	(8.995)	(6.410)	(9.505)	(2.367)	
East Asia and the Pacific	2.2716***	0.0436	0.8865***	0.0107	0.9828
	(9.611)	(1.269)	(8.730)	(1.293)	
Europe and Central Asia	2.4246***	0.1388***	0.7847***	0.0998***	0.9717
	(7.573)	(4.999)	(9.928)	(3.906)	
Latin America and the Caribbean	2.3124***	0.2009***	0.7761***	0.1383**	0.9842
	(9.815)	(6.306)	(8.047)	(4.177)	
Middle East and North Africa	1.8425***	0.0744**	0.9725***	0.0048	0.9221
	(5.517)	(2.169)	(9.901)	(1.021)	
South Asia	2.5577***	0.2409***	0.7301***	0.0857***	0.9919
	(5.538)	(4.283)	(9.208)	(2.629)	
Sub-Saharan Africa	2.6329***	0.1400***	0.8136***	0.0229	0.9334
	(8.264)	(4.979)	(8.695)	(1.345)	

*Notes: The figures in parentheses are absolute values of t-statistics. *** and ** indicate the statistical significance at the 1 percent and 5 percent level, respectively.*

The Engle and Granger (1987) two-step procedure is undertaken by first estimating the long-run model specified in Eq. (2) in order to obtain the estimated residuals. Next, defining the lagged residuals from Eq. (2) as the error correction term, the following dynamic error correction model is estimated:

$$\Delta Y_{it} = \alpha_{1i} + \sum_{j=1}^{p}\theta_{11ij}\Delta Y_{it-j} + \sum_{j=1}^{p}\theta_{12ij}\Delta L_{it-j} + \sum_{j=1}^{p}\theta_{13ij}\Delta K_{it-j} + \sum_{j=1}^{p}\theta_{14ij}\Delta TR_{it-j} + \lambda_{1i}\varepsilon_{it-1} + u_{1it} \tag{7a}$$

$$\Delta L_{it} = \alpha_{2i} + \sum_{j=1}^{p}\theta_{21ij}\Delta Y_{it-j} + \sum_{j=1}^{p}\theta_{22ij}\Delta L_{it-j} + \sum_{j=1}^{p}\theta_{23ij}\Delta K_{it-j} + \sum_{j=1}^{p}\theta_{24ij}\Delta TR_{it-j} + \lambda_{2i}\varepsilon_{it-1} + u_{2it} \tag{7b}$$

$$\Delta K_{it} = \alpha_{3i} + \sum_{j=1}^{p}\theta_{31ij}\Delta Y_{it-j} + \sum_{j=1}^{p}\theta_{32ij}\Delta L_{it-j} + \sum_{j=1}^{p}\theta_{33ij}\Delta K_{it-j} + \sum_{j=1}^{p}\theta_{34ij}\Delta TR_{it-j} + \lambda_{3i}\varepsilon_{it-1} + u_{3it} \tag{7c}$$

$$\Delta TR_{it} = \alpha_{4i} + \sum_{j=1}^{p}\theta_{41ij}\Delta Y_{it-j} + \sum_{j=1}^{p}\theta_{42ij}\Delta L_{it-j} + \sum_{j=1}^{p}\theta_{43ij}\Delta K_{it-j} + \sum_{j=1}^{p}\theta_{44ij}\Delta TR_{it-j} + \lambda_{4i}\varepsilon_{it-1} + u_{4it} \tag{7d}$$

where Δ is the first-difference operator, p is the lag length set at two based on likelihood ratio tests, ε_{it} are the residuals of the individual FMOLS long-run relations in Table 4, and u is the serially uncorrelated error term. Based on the above four equations, short-run causality is determined by the statistical significance of the partial F-statistics associated with the corresponding right hand side variables. Long-run causality is revealed by the statistical significance of the respective error correction terms using a t-test.

The empirical results of the panel Granger causality tests are presented in Table 5. In the long run, we observe there is no Granger causality relationship between Y and L, K and TR, as the coefficient of the error correction term (ECT) in the equation with Y as dependent variable is not statistically significant. Similar to the long-run, in the short run, there is no significant causal relationship between Y and L, K, and R, based on the Chi-square statistics of the coefficients of the three variables. In regard to relationship between TR and the three variables, Y, L, and K, we find a similar absence of long run causality running from the latter three to TR. However, we note in the short run the causality runs only from Y to TR and K to TR, where there is no such short-run causality linkage running from L to TR. The results for the individual regions show no evidence of causality either in the long-run or in the short-run.

SUMMARY AND CONCLUSIONS

The objective of this study is to investigate the relationships between tourism development and economic growth in developing countries using the newly developed heterogeneous panel cointegration technique. This study examines the causal relationship between tourism development and economic growth using Granger causality tests in a multivariate model and using the annual data for the 1995–2009 period. The study uses a sample of 140 developing countries. The sample of countries were grouped into six major regions following the classification used by the World Bank, in order to compare any differences of findings between regions. The multivariate framework includes the real GDP in constant 2000 U.S. dollars, the real gross fixed capital formation in constant 2000 U.S. dollars, the labor force in millions, and the real international tourism receipts in constant 2000 U.S. dollars.

The panel unit root tests indicate all the variables are integrated of order one. The panel cointegrations tests show that all seven test statistics reject the null hypothesis of no cointegration at the 1% significance level, indicating that the four variable are cointegrated. The results of the FMOLS show that, though the elasticity of tourism revenue with respect to real GDP is not statistically significant for all regions, its positive sign indicates that tourism revenue makes a positive contribution to economic growth in developing countries. The results of the study suggest that governments of developing countries should focus on economic policies to promote tourism as a potential source of economic growth. The study finds no evidence to support the tourism-led growth hypothesis.

Table 5: Panel Granger Causality Test Results

	Dep. Var.	Sources of causation (Independent variables) - Short-run ΔY	ΔL	ΔK	ΔTR	Long-run ECT
All Countries	ΔY	-	0.407 (0.815)	4.169 (0.124)	0.427 (0.807)	-0.0816 (0.134)
	ΔTR	7.428 (0.024)	0.896 (0.638)	11.863 (0.002)	-	-0.0675 (0.263)
East Asia and Pacific	ΔY	-	0.125 (0.939)	4.074 (0.130)	0.303 (0.859)	-0.2718 (0.200)
	ΔTR	1.341 (0.511)	0.091 (0.955)	2.835 (0.242)	-	-0.2662 (0.202)
Europe and C. Asia	ΔY	-	0.200 (0.904)	0.105 (0.948)	0.252 (0.881)	-0.2108 (0.164)
	ΔTR	0.509 (0.775)	1.546 (0.461)	4.757 (0.092)	-	-0.0856 (0.699)
Latin Amer. & Caribbean	ΔY	-	0.241 (0.886)	0.606 (0.738)	0.780 (0.677)	-0.1476 (0.358)
	ΔTR	4.090 (0.129)	2.077 (0.354)	1.560 (0.458)	-	-0.0536 (0.583)
Middle East & N. Africa	ΔY	-	0.038 (0.982)	0.794 (0.672)	0.150 (0.928)	-0.1650 (0.195)
	ΔTR	0.191 (0.909)	0.077 (0.961)	0.070 (0.965)	-	-0.0564 (0.795)
South Asia	ΔY	-	0.071 (0.965)	2.273 (0.320)	0.665 (0.717)	-0.1302 (0.835)
	ΔTR	0.730 (0.694)	0.051 (0.975)	1.053 (0.590)	-	-0.1090 (0.768)
Sub-Saharan Africa	ΔY	-	0.229 (0.891)	1.409 (0.494)	0.912 (0.822)	-0.0098 (0.898)
	ΔTR	0.964 (0.810)	0.161 (0.922)	2.063 (0.356)	-	-0.0389 (0.727)

Notes: The figures in the parentheses are the probability of rejection of Granger non-causality. Estimates are based on the panel data for the period 1995-2009.

Tough the results of the study finds no evidence to support the tourism-led growth hypothesis, it is worth noting that establishing the relationship between tourism and economic growth is essential concerning the importance that policy makers are attributing to this sector and the rates at which it is growing. The findings of the study could have been different if we had used a longer time period. Future research could concentrate in expanding the time period as well as the coverage of countries or focusing on few selected countries which has relevant data for a longer time period. This would help us uncover the real impact on economic growth in developing countries.

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ARE DOWNSIDE HIGHER ORDER CO-MOMENTS PRICED? : EVIDENCE FROM THE FRENCH MARKET

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ABSTRACT

This study examines the role of downside higher order co-moments in asset pricing models when stock returns are not normal. We test the effect of higher order downside co-moments using a data set of daily returns of Société des Bourses Françaises 250 Index stocks during the period 1987-2009. The results suggest that the downside Beta and higher order co-moments in the downside framework should be considered together when returns are non normal and that they out-perform the traditional beta.

JEL: G12, G15, C21

KEYWORDS: downside Beta, downside higher order co-moments, CAPM, French stock market.

INTRODUCTION

The capital asset pricing model (CAPM) developed by Sharpe (1964) and Lintner (1965) is still the most widely used approach for relative asset pricing, sharing a common idea of the mean-variance efficient portfolio as initiated by Markowitz (1952). The theory predicts that variance is the only measure of risk and the investor chooses his optimal portfolio according to the mean-variance approach implying that the returns are normal or investors have a quadratic utility function.

However several researches report the inadequacy of the variance for two main reasons: first the CAPM may be limited when the assumption of normality of returns distribution is not met. In fact there have been many empirical studies (Mandelbrot, 1963; Fama, 1965; and Levy, 1969) that present evidence of non- normality of return distributions and particularly showed that return distributions are asymmetric and fat tailed. Also it was established that investors have non-quadratic utility functions. This implies that the variance is not sufficient to capture the empirical shape characteristics (asymmetry and fat tail) of the distribution and all moments of the returns distribution should be considered. so there is no reason to stop at the two first moments the mean and the variance (Rubinstein, 1973 and Scott &Horvath, 1980).

Another limitation of the CAPM is the variance is not consistent with investors' perception of risk as long as it considers upside and downside variations both as undesirable events. Rational investors are only sensitive to losses or downside variations. This is a powerful argument for rejecting variance and replacing it by measures of downside risk.

A growing literature argue that, when returns are not normal, higher-order co-moments matter to risk-averse investors and that they are relevant in explaining stock returns. Kraus and Litzenberger (1976), Harvey and Siddique (2000) among others introduce co-skewness into asset pricing models to take into account the asymmetry. Others have looked at co-kurtosis (Fang and Lai, 1997; Dittmar, 2002; Chung, Johnson and Schill, 2006…) to account for the leptokurticity of the returns distribution. However, we suggest that the standard higher order moments present the same limitation as the variance and, therefore, they do not accurately reflect investors' preferences for minimizing only possible losses. For example, the kurtosis identifies extreme gains as well as extreme losses as undesirable events whereas individuals are concerned only about the left tail of returns and hence only about the extreme losses. For this reason, we introduce downside higher order co-moments in pricing models instead of standard higher order co-moments. Downside higher order co-moments enable us to account, both, for the investors' perception of risk and for the non normality of returns distribution.

In this paper, we investigate the risk return relation in a downside framework using higher order co-moments. The aim is to show whether they significantly explain the cross section of daily stock returns on the French stock market and to investigate the extent that they out-perform traditional measures of market risk. For the cross sectional analyses conducted over the period 01/1987-12/2009, we use two methodologies; the first is the methodology used previously by Estrada (2002) which regresses mean returns on estimated measures of risk and the second is the Fama-MacBeth methodology. We find that the downside higher order co-moments, considered together, have additional explanatory power in explaining the cross section of returns. We also find that this result depends on market conditions.

The contribution of this paper is twofold; first it introduces new measures of risk that take into account both the investors' risk perception and the non normality of returns. Using the new measures of risk, the paper provides an explanation of the poor performance of the CAPM and downside CAPM especially when returns are non normal. Second, it is an innovating empirical investigation which contributes to the debate on whether systematic higher order co-moments are able to explain cross sectional stock returns in a downside framework in the French stock market. Therefore studying downside co-skewness and co-kurtosis may provide insight regarding additional factors that could improve the explanatory power of the CAPM and downside CAPM.

The reminder of this paper is organized as follows. Section 2 presents a literature review on downside risk measures. The data and the methodology will be briefly presented in section 3 and the empirical results are discussed in section 4. In Section 5 and 6 some sensitivity analysis to the regression methodology used and to downturns periods of the market are conducted. Finally, section 7 concludes the paper.

LITERATURE REVIEW

The theoretical and empirical attack on the traditional mean-variance model motivated researchers to investigate alternatives to the variance measure of risk. Roy (1952) first suggested the idea of "Safety First". According to this concept individuals consider only outcomes below a certain value defined as a "disaster" and seek to minimize the probability of falling below this level without paying attention to the utility function.

Recognizing the importance of Roy's approach (1952) to describe in an adequate way to perceive risk, Markowitz (1959) realized that investors are interested in minimizing downside risk for two reasons: (1) only downside risk or safety first is relevant to an investor and (2) security returns distribution may not be normally distributed. Therefore a downside risk measure would help investors make proper decisions when faced with a non normal security returns distribution. He proposed an alternative measure of risk called semivariance that weights downside losses differently from upside gains. Statistically, the semivariance is defined as the squared deviation of returns below a target return.

Research on downside risk measures has continued with the development of lower partial moment (LPM) risk measures by Bawa (1975) and Fishburn (1977). The LPM liberates the investor from a constraint of having only one utility function, which is fine if investor utility is best represented by a quadratic equation (variance or semivariance). Lower partial moments represent a significant number of the known Von Neumann-Morgenstern utility functions. Furthermore, the LPM represents the whole range of human behavior from risk seeking to risk aversion. Therefore LPM describes below target risk in terms of risk tolerance. Given an investor's risk tolerance value, the general measure, the lower partial moment, is defined as: $LPM(a,t) = \frac{1}{K}\sum_{T=1}^{K} Min[0,(R_T - t)]^a$, where K is the number of observations, R_T is the security return during time period T, t is the threshold or target return and *a* is the degree of the lower partial moment.

Hogan and Warren (1974) and Bawa and Lindenberg (1977) developed the mean-semivariance CAPM (MS CAPM). Their model preserves all key characteristics of the Mean-variance CAPM, including the two-fund separation principle, efficiency of the market portfolio and the linear risk return relationship. The only difference is the use of the relevant risk measures (semivariance and downside Beta instead of variance and regular beta). The importance of this difference depends on the shape of the returns distribution. For a normal returns distribution, regular beta and downside beta are identical. However, for skewed distributions such as the lognormal, the two models diverge.

Jahankhani (1976) was the first to perform empirical tests comparing the expected return-variance CAPM and the expected return-standard semivariance CAPM developed by Hogan and Warren (1974) using the Fama and Macbeth (1973) methodology. His sample contained all securities in the CRSP database for the period July 1947 to June 1969. The author fails to find any improvement over the traditional CAPM by using downside Beta. The study reveals the following results: (a) The linearity hypothesis between expected returns and downside beta cannot be rejected; (b) The residual hypothesis cannot be rejected; (c) There is a positive relationship between expected returns and downside beta. Price, Price and Nantell (1982) show that the regular beta systematically underestimates the downside beta for low-beta stocks and overestimates the downside beta for high-beta stocks. This finding may help explain why empirical tests of the CAPM find that low-beta stocks are systematically underpriced and high-beta stocks are overpriced (See for example Reinganum, 1981 and Fama and French, 1992). Harlow and Rao (1989) derive a LPM model for any arbitrary benchmark return, thus making the Hogan-Warren and the Bawa-Lindenberg models special cases of their general model. Their empirical tests reject the CAPM as a pricing model but cannot reject their version of the MLPM model.

Post and Van Vliet (2006) used monthly US security data for a long sample period (1926-2002). They used unconditional mean-variance (MV) and mean-semi-variance (MS) tests as well as conditional tests that account for the economic state-of-the-world. They concluded that the MS CAPM seems to capture better the cross section stock returns than the MV CAPM in explaining cross-sectional mean returns. Furthermore they inferred that the explanatory power of the conditional downside beta persists after controlling for size and momentum effects.

Taking into account the limitation of downside risk measures proposed by earlier studies, Estrada (2002) defined a systematic downside risk measure based on a different definition of cosemivariance. The main difference between the two definitions is that the Estrada cosemivariance between assets i and j and the one between assets j and i, are equal whereas it is not true for the cosemivariance used to estimate the downside beta of previous studies. Estrada (2001, 2002, 2004) reveal that downside risk measures excel over the standard risk measures in explaining variability in the cross-section of returns in emerging markets, industries in emerging markets and internet stocks. More recently, Estrada (2005) extended his database and added the entire MSCI of developed markets. The empirical evidence clearly supports the downside Beta and the pricing model based on it over the standard beta and CAPM for joint and separate samples of developed markets and Emerging markets.

Pederson and Hwang (2003) in an investigation of UK equity data show that even though the downside beta explains a proportion of equities over the CAPM beta the proportion of equities benefiting from using the downside beta is not large enough to improve asset pricing models significantly. Ang, Chen, and Xing (2005) find a similar result in the US market. They measured downside risk by correlations, conditional on downside moves of the market. The authors observed that the portfolio with the greatest downside stock correlations outperforms the portfolio with the lowest downside stock correlations and they suggested that this effect cannot be explained by the Fama and French (1993) factors.

Galagedera and Brooks (2007) investigate the issue of co-skewness as a measure of risk in a downside framework. They argue that downside co-variance and downside co-skewness between security returns and market portfolio returns may be alternative measures of downside risk. In other words, in a downside framework, it may be sufficient to include a measure that accounts for the co-semi-skewness in the pricing model rather than a measure of the co-semi-variance. They find that in the cross sectional analysis, downside co-skewness is a better explanatory variable of emerging market monthly returns than downside beta. The motivation behind this study is that securities returns distributions are not normal but they, are typically asymmetric and have fat tails. They also argued that the downside beta and the traditional co-skewness even though they both capture the asymmetry of the distribution they are distinct measures of risk. They explained that downside beta is explicitly conditional on market downside movements whereas the traditional co-skewness measure does not explicitly accentuate asymmetries across up and down markets and may be thought of as a symmetric measure of risk.

Although the downside beta and the downside co-skewness tell us something about the asymmetry of the returns distribution, they fall far short of specifying precisely the peekness encountered in empirical distributions. For this reason we consider the downside co-kurtosis besides the downside co-skewness proposed by Galagedera and Brooks (2007) in the pricing models. This enables us to detect with more precision the departure from normality. In the remainder of the paper, we will empirically analyze the role of downside higher order co-moments in explaining the cross sectional daily returns on the French market.

DATA AND MODELING FRAMEWORK

Sample and Data

This study explores daily security returns for the sample period 1987 to 2009. The sample period is selected to include the bear markets of 1987, 2000-2001 and 2009. We use all stocks of the SBF250 index. Only stocks that entered the index before the 1st of January 2000 and remained in the index until 31/12/2009 and with available market data are maintained in our sample. The composition of the SBF250 is available from 2000. Therefore, our sample is composed of 38 stocks. We investigate the French market for several reasons: (i) the traditional CAPM has failed to explain the variation in equity prices (Molay, 2002), (ii) returns distributions are found to be skewed and (most notably) fat tailed (Aparacio and Estrada, 2001), (iii) the introduction of higher order moments in asset pricing models have improved the explanatory power of the models on the French market (Lajili, 2005) and finally (iv) to our knowledge no other study has previously investigate the issue of higher order co-moments in a downside framework on this market. Daily data on closing prices and dividends are collected from the Datastream database. The yield on the 3-months Treasury bill is chosen to proxy for the risk free rate and the average return of the selected stocks is chosen to proxy for the market return. In order to check the performance of our results, we further use the CAC40 index to proxy the market returns. The results are similar but not reported here.

To investigate the normality assumption, we provide statistics for two standard tests of normality: the third and fourth sample moments against those of a normal distribution and the Jarque-Bera test. Table 1 presents summary statistics of daily returns of the 38 selected stocks and the results of the normality test.

The summary statistics show that daily returns have modest negative asymmetry in the sense of skewness. The values of excess kurtosis indicate clearly that all stocks have leptokurtic behavior which is described by fat tails in the literature. The results of Jarque Bera joint test of normality are consistent with the results of skewness and kurtosis, it strongly rejects normality for all selected stocks at the 1% level. Thus the main features of data are that returns are slightly asymmetric and have fat tails. This first empirical result supports the objective of our study and provides a strong argument to use higher order moments in asset pricing models.

Table 1: Summary Statistics of Securities Daily Returns

stock	rm*10^3	Standard Deviation*10^3	Skewness	Kurtosis	j-b statistic
accor	0.345	19.589	-0.05	3.997	4.492
air france klm	0.138	45.773	-4.222	469.09	61,853,100
air liquide	0.411	16.201	0.043	3.425	3,299
axa	0.392	23.574	0.249	7.804	17,183
bic	0.39	19.523	0.164	5.197	7,619
bongrain	0.154	19.324	-0.165	4.913	6,812
bouygues	0.46	22.66	0.36	6.338	11,434
carrefour	0.55	18.11	-0.113	4.451	5,581
casino guichard	0.384	19.51	0.158	4.234	5,066
cie gl de gphyq	-0.041	28.903	-0.189	5.628	8,940
ciments francai	0.392	23.929	-1.045	22.798	147,273
club mediterran	-0.159	22.661	-0.057	7.811	17,147
danone	0.402	15.445	0.015	3.961	4,409
eiffage	0.702	23.267	-0.777	25.455	182,761
essilor intl	0.454	18.77	0.121	5.753	9,318
esso	0.361	18.858	-0.124	11.358	36,268
faurecia	0.149	23.028	0.684	10.206	29,796
havas	0.097	25.013	0.039	4.422	5,496
imerys	0.531	21.846	0.115	5.432	8,305
l oreal	0.545	18.663	0.017	4.223	5,011
lafarge	0.412	20.602	-0.044	5.062	7,203
locindus	0.165	14.509	0.454	12.168	41,838
lvmh	0.536	20.058	0.12	8.457	20,112
michelin	0.327	22.174	-0.031	3.989	4,473
pernod ricard	0.512	18.885	-0.024	4.611	5,974
peugeot	0.412	21.032	0.001	5.238	7,710
ppr	0.542	22.154	0.225	5.492	8,532
seb	0.406	21.489	-0.102	7.149	14,373
safran	0.441	22.595	-0.81	21.566	131,430
sanofi aventis	0.446	19.021	0.049	3.618	3,681
schneider elect	0.651	22.29	-0.101	6.511	11,926
sodexo	0.417	19.04	-0.869	21.412	129,686
thales	0.34	22.13	-0.002	4.113	4,755
total	0.635	18.115	-0.012	3.816	4,092
unibail rodamco	0.532	15.708	0.004	4.568	5,863
valeo	0.236	22.773	-0.057	4.584	5,908
vallourec	0.694	27.427	-0.262	7.708	16,773
vivendi	0.275	21.484	-0.936	22.63	144,886
max	**0.702**	**45.773**	**0.684**	**469.09**	**61,853,100**
min	**-0.159**	**14.509**	**-4.222**	**3.425**	**3,299**
mean	**0.385**	**21.477**	**-0.189**	**20.242**	**1,656,277**
median	**0.408**	**21.258**	**-0.018**	**5.462**	**8,418**

The table report summary statistics of daily returns of the 38 selected stocks.over the full sample period going from January 1987 to December 2009

METHODOLOGY

Considering that downside measures more appropriately reflect the way investors perceive risk, we suggest that downside co-skewness and downside co-kurtosis should be included in pricing models to account for asymmetry and fat tails observed in stock returns data. To estimate the downside risk co-moments, we consider three well known measures proposed by Hogan and Warren (1974), Harlow and Rao (1989) and Estrada (2002). To provide measure of downside beta and substitute the standard beta, these studies assume perfect markets; a risk-free asset, homogeneous expectations and investors are downside risk averse.

Hogan and Warren (1974) defined the downside beta as:

$$\beta_{im}^{(HW)} = \frac{E\left[\left(R_i - R_f\right).min\left(R_m - R_f, 0\right)\right]}{E\left[min\left(R_m - R_f, 0\right)\right]^2} \tag{1}$$

R_i , R_m are the stock and the market return respectively and R_f the risk free rate.

Hogan and Warren (1974) used the risk-free rate as the benchmark return and consider it as the reasonable threshold that investors should at least guarantee, whereas Harlow and Rao (1989) argue that the relevant benchmark return implied by the data is related to equity mean returns rather than to the risk-free rate. However Estrada proposes a systematic downside risk measure defined by the ratio between an asset's semi-deviation of returns and the market's semi-deviation of returns.

To construct downside co-skewness and co-kurtosis, we follow Galagedera and Brooks (2007). We adopt the methodology of Rubinstein (1973) for building the standard higher order co-moments and adapt it to each of the considered downside risk measures. We propose the following measures. We define the downside co-skewness or the downside gamma corresponding to Hogan and Warren risk measure as:

$$\gamma_{im}^{(HW)} = \frac{E\left[\left(R_i - R_f\right).min\left(R_m - R_f, 0\right)^2\right]}{E\left[min\left(R_m - R_f, 0\right)\right]^3} \tag{2}$$

Similarly the downside co-kurtosis or the downside delta corresponding to Hogan and Warren measure is defined as:

$$\delta_{im}^{(HW)} = \frac{E\left[\left(R_i - R_f\right).min\left(R_m - R_f, 0\right)^3\right]}{E\left[min\left(R_m - R_f, 0\right)\right]^4} \tag{3}$$

For clarity, we present here only the downside risk measures of Hogan and Warren. The other measures are presented in the appendix 2.

For testing the pricing of downside co-skewness and downside co-kurtosis in the cross-section, we adopt the procedure employed previously by Estrada (2002). For each stock, we compute the average return and estimate the risk measures considered in this study: beta, downside beta, downside gamma and downside delta using the full set of the sample data. Returns are regressed on each of the estimated risk measures. First, we estimate models with a single measure of risk in order to analyze the separately explanatory power of each of the considered measures of risk. Next we estimate models including jointly two or three measures of risk. This enables us to examine the incremental explanatory power of downside higher order co-moments in explaining the cross sectional of average returns. The present work employs the following regressions:

Model 1: $R_i = \lambda_0 + \lambda_1 \hat{\beta}_{im} + \varepsilon_i$

Model 2: $R_i = \lambda_0 + \lambda_2 \hat{\beta}_{im}^D + \varepsilon_i$

Model 3: $R_i = \lambda_0 + \lambda_3 \hat{\gamma}_{im}^D + \varepsilon_i$

Model 4: $R_i = \lambda_0 + \lambda_4 \hat{\delta}_{im}^D + \varepsilon_i$

Model 5: $R_{i,} = \lambda_0 + \lambda_2 \hat{\beta}_{\mathrm{im}}^{\mathrm{D}} + \lambda_3 \hat{\gamma}_{im}^D + \varepsilon_i$

Model 6: $R_i = \lambda_0 + \lambda_2 \hat{\beta}_{\mathrm{im}}^{\mathrm{D}} + \lambda_4 \hat{\delta}_{im}^D + \varepsilon_i$

Model 7: $R_i = \lambda_0 + \lambda_3 \hat{\gamma}_{im}^D + \lambda_4 \hat{\delta}_{im}^D + \varepsilon_i$

Model 8: $R_i = \lambda_0 + \lambda_2 \hat{\beta}^{\mathrm{D}}_{\mathrm{im}} + \lambda_3 \hat{\gamma}^{D}_{im} + \lambda_4 \hat{\delta}^{D}_{im} + \varepsilon_i$

Where R_i is the average stock return, β_{im} is the estimated standard beta, $\hat{\beta}^{D}_{im}, \hat{\gamma}^{D}_{im}$ and $\hat{\delta}^{D}_{im}$ are the estimated downside Beta, downside gamma and downside delta respectively. Here the index ***D*** indicates ***D***ownside and in what follows it will be replaced by HW, HR or E to refer to Hogan and Warren, Harlow and Rao or Estrada measures respectively.

$\lambda_0, \lambda_1, \lambda_2, \lambda_3$ And λ_4 are the parameters of the models estimated using the White's weighted least square method.

RESULTS AND DISCUSSION

Pair wise correlations between estimated measures of risk and the mean stocks return are not presented here but are available from authors upon request. They indicate clearly that the mean return has higher correlation with downside risk measures than with the standard beta. The results indicate also that for each of the three measures of risk, the downside co-moments (downside beta, gamma and delta) are highly correlated. We also find that the correlations between downside beta and downside gamma are higher than correlations between downside beta and downside delta or between downside gamma and downside delta for each of the considered measures of downside risk. This result is not surprising since downside beta and downside gamma, both have the potential to capture the same thing, the asymmetry of the returns distribution. For this reason Galagedera and Brooks (2007) state that "in pricing models in a downside framework it may be sufficient to include a risk measure that accounts for co-semi-variance or co-semi-skewness and not both".

In Table 2, we report estimates of the parameters of models 1 to 8. Panel A, B and C of Table 4 provides respectively the HW, HR and E parameters estimates. The three panels provide merely similar results.
Table 2 shows that the standard beta fails to explain mean security returns in a cross section of data. Results reveal also that the downside beta and downside gamma (except the Estrada downside gamma) are potential explanatory variables of the variability of mean returns in the French stock market when they are considered separately in the pricing model.

In order to estimate the incremental explanatory power of downside gamma in explaining mean returns, we test the model introducing jointly the downside beta and downside gamma (Model 5). The results reveal that two variables remain significant at least at the 10% level and the explanatory power in terms of adjusted R^2 reaches more than 20% while it does not exceed 9% in case of single regression models (Models 2-3). This result means that the downside gamma have a significant additional explanatory power in explaining the variability of cross sectional security mean returns. We note as well that downside gamma has slightly more explanatory power than downside beta. Consistent with the results obtained by Galagedera and Brooks (2007) for emerging markets, our results reveal that the risk premium associated to downside beta is positive and the risk premium associated to downside gamma is negative when the two variables are considered together in the same pricing model.

Now considering only downside co-kurtosis (Model 4), the findings indicate that downside co-kurtosis has no significant explanatory power regardless of the model used. However, the later becomes significant when it is considered jointly with the downside beta or the downside gamma (Models 6- 7) and the two variables explain at least 30% of the variability of mean returns.

Finally, when all downside co-moments are jointly considered (Model 8), all the variables come out statistically insignificant for the HW and HR measures, however they are highly significant in the case of

Estrada measures and the total explanatory power of the model exceeds 50%. These ambiguous findings are likely due to high correlation between these three explanatory variables.

Table 2: Cross-sectional Analysis

Panel A: Cross Sectional Regressions Results for the HW-Measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.451***	-0.162				2.10%	1.78
	(3.64)	(-1.335)					
Model 2	0.593***		-0.296**			9.00%	4.65**
	(4.146)		(-2.157)				
Model 3	0.495***			-0.226**		9.30%	4.81**
	(4.223)			(-2.192)			
Model 4	0.419***				-0.14	2.80%	2.07
	(4.478)				(-1.442)		
Model 5	0.599***		0.79*	-1.079*		22.20%	6.27***
	(5.749)		(1.683)	(-1.956)			
Model 6	0.569***		0.358		-0.61**	31.30%	9.42***
	(6.201)		(1.2)		(-2.38)		
Model 7	0.575***			0.741	-0.998*	35.20%	11.03***
	(6.156)			(1.232)	(-1.817)		
Model 8	0.631***		0.023	0.333	-0.681	16.20%	3.39**
	(5.305)		(0.021)	(0.158)	(-0.612)		
Panel B: Cross Sectional Regression Results for the HR-measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.451	-0.162				2.10%	1.78
	(3.64***)	(-1.335)					
Model 2	0.548***		-0.253			5.80%	3.27*
	(3.765)		(-1.808*)				
Model 3	0.547***			-0.262**		8.60%	4.47**
	(4.155)			(-2.114)			
Model 4	0.359***				-0.095	3.50%	1.29
	(4.394)				(-1.138)		
Model 5	0.569***		1.237**	-1.507**		21.70%	6.13**
	(5.105)		(2.065)	(-2.546)			
Model 6	0.487***		0.624**		-0.796***	31.80%	9.64***
	(5.975)		(2.2)		(-3.2)		
Model 7	0.529***			1.007*	-1.217**	40.50%	13.6***
	(6.1)			(1.707)	(-2.275)		
Model 8	0.673***		1.043	-1.717	0.297	17.20%	3.56**
	(5.261)		(0.915)	(-0.811)	(0.27)		
Panel C : Cross Sectional Regressions Results for the E-measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.451***	-0.162				2.90%	2.09
	(3.64)	(-1.335)					
Model 2	0.680***		-0.333**			5.80%	3.27*
	(3.856)		(-2.146)				
Model 3	0.47***			-0.173		8.90%	4.6**
	(3.874)			(-1.448)			
Model 4	0.436***				-0.154	42.15%	2.35
	(4.396)				(-1.534)		
Model 5	0.538***		1.137*	-1.432**		21.70%	14.48***
	(3.252)		(1.721)	(-2.437)			
Model 6	0.565***		0.375		-0.653**	38.60%	12.63***
	(3.788)		(0.976)		(-2.113)		
Model 7	0.553***			0.809	-1.061*	31.80%	9.65***
	(4.511)			(1.19)	(-1.727)		
Model 8	0.495***		3.034***	-5.633***	2.25**	50.30%	13.5***
	(3.016)		(2.819)	(-2.833)	(2.171)		

*The table reports the estimates coefficients associated to each of the considered measures of risk expressed in percentages, their t-Statistics in parenthesis, the adjusted R^2 and the Fisher-statistics issued from the cross-sectional regressions of mean return on the estimated measures of risk over the models 1 to 8. The parameters are White heteroscedasticity–consistent. Pane1 A, B and C report results relative to HW, HR and E measures respectively. ***, ** and * denote significance at 1%, 5% and 10% level respectively.*

To mitigate this problem we perform the analysis by using orthogonalized components. This technique allows measuring the marginal effect of downside higher order co-moments. The explanatory variables considered here are downside beta, orthogonalized downside gamma ($o\gamma_{im}^{D}$) and orthogonalized downside delta($o\delta_{im}^{D}$). The downside gamma is defined as the component independent from the corresponding downside beta and downside delta. Explicitly, the orthogonalized gamma is equal to the intercept plus the individual residual from the cross-sectional regression $\gamma_{im}^{D} = a_0 + a_1\beta_{im}^{D} + a_2\delta_{im}^{D} + \epsilon_i$. Similarly the orthogonalized downside delta is defined as the component independent from the corresponding downside beta and downside gamma and it is equal to the intercept and residual from the cross-sectional regression $\delta_{im}^{D} = a_0 + a_1\beta_{im}^{D} + a_2\gamma_{im}^{D} + \epsilon_i$

Table 3 reports the results from regressions of Models 3 to 8 with the orthogonalized components. Several important findings can be drawn from the analysis; first we observe that downside beta remains statistically significant even when we consider with it the orthogonalized components of downside gamma or downside delta in pricing models considering HW and HR measures. This result is less obvious if we consider the Estrada measures. The downside beta is significant when considered alone becomes insignificant when we include the downside gamma or the downside delta.

The orthogonalized components of downside higher order co-moments are not priced when considered alone or jointly with the downside beta but they do when they are considered together in the same pricing model (Models 7 and 8). This implies they are complementary measures of risk and the isolated component of each do not contain information which is not included in the downside beta.

Overall we find evidence that Model 8 has the highest adjusted R^2 (50% for Estrada measures and 15.5% for HW and HR measures) indicating that the introduction of downside gamma and downside delta improve the explanatory power of the downside CAPM suggested by earliest studies. This finding suggests that the three downside co-moments should be considered in explaining cross sectional variation of selected security returns. Further when downside risk measures are priced, the premiums associated with them have the opposite sign (negative) of that expected. This result is counter intuitive but it is somewhat in line with the results of previous studies. Most interestingly, Artavanis and al. (2010) find that the slope coefficient of the downside Beta is negative in the French market (and also in the UK Market). This result could be explained by the fact that the market is not sufficiently mature to reveal the anticipated direction of the risk-return relationship.

Sensitivity Analysis to the Estimation Methodology

This section examines sensitivity of the results reported in the previous section to alternative regression estimation methodologies. Here we run the regression using the Fama and MacBeth (1973) two pass regression methodology often adopted by cross-sectional studies. For each stock the CAPM beta, the downside beta, gamma and delta are estimated using time series data over the previous 3-years period. Then, for each day inside the period 02/01/1987-31/12/2009, security returns in the subsequent testing period are cross sectionally regressed on the risk measure estimated over the previous estimation period. We repeat this process for all days in the sample period producing T sets of coefficient estimates. We then average the T estimates to produce a sample of Fama-MacBeth coefficient estimates.

Table 3: Results From Cross-Sectional Analysis Using Orthogonalized Components of the Downside Gamma and Downside Delta

Panel A : Cross Sectional Regressions Results for the HW- measures

Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 3	0.305***			0.684		0.10%	0.06
	(8.878)			(0.242)			
Model 4	0.312***				-0.922	1.00%	0.38
	(8.892)				(-0.621)		
Model 5	0.6***		-0.298**	0.676		7.40%	2.48
	(4.053)		(-2.216)	(0.249)			
Model 6	0.621***		-0.311**		-0.98	11.20%	3.34**
	(4.658)		(-2.548)		(-0.679)		
Model 7	0.424***			-14.228**	-8.347**	8.40%	2.69***
	(7.803)			(-2.264)	(-2.302)		
Model 8	0.586***		-0.165	-13.828*	-8.193**	15.25%	3.21**
	(5.234)		(-1.483)	(-1.865)	(-2.114)		

Panel B: Cross Sectional Regressions Results for the HR-measures

Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 3	0.305***			-0.168		0.10%	0.003
	(7.853)			(-0.061)			
Model 4	0.306***				-0.315	0.10%	0.05
	(8.073)				(-0.214)		
Model 5	0.563***		-0.259*	0.226		4.50%	1.87
	(3.571)		(-1.91)	(0.081)			
Model 6	0.588***		-0.283**		-0.593	7.00%	1.87
	(4.056)		(-2.174)		(-0.408)		
Model 7	0.306***			-16.198**	-8.897*	5.00%	1.98
	(9.494)			(-1.995)	(-1.919)		
Model 8	0.599***		-0.278**	-18.546**	-10.623**	15.50%	3.25**
	(4.979)		(-2.329)	(-2.067)	(-2.273)		

Panel C : Cross Sectional Regressions Results for the E- measures

Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 3	0.649***			-0.683**		9.30%	4.8**
	(3.983)			(-2.193)			
Model 4	0.376***				-0.044	1.00%	0.71
	(3.816)				(-0.847)		
Model 5	0.669***		-0.118	-0.447		7.40%	2.48*
	(3.465)		(-0.092)	(-0.168)			
Model 6	0.558***		0.617		-0.451**	40.00%	13.31*
	(3.585)		(1.265)		(-2.185)		
Model 7	0.582***			1.075	-0.396**	35.70%	11.26*
	(4.618)			(1.157)	(-2.105)		
Model 8	0.505***		2.806**	-4.702**	-0.46**	45.60%	11.34*
	(3.236)		(2.453)	(-2.235)	(-2.472)		

*This table reports the estimates coefficients, their t-Statistics in parenthesis, the adjusted R^2 and the Fisher-statistics issued from the cross-sectional regressions of mean return on beta ,downside beta and the orthogonalized components of downside gamma and downside delta over the models 3 to 8. The parameters are White heteroscedasticity–consistent. Panel A, B and C report results relative to HW, HR and E measures respectively.***, ** and * denote significance at 1%, 5% and 10% level respectively*

Panels A, B and C of Table 4 report the resulting average coefficients, statistic of Student –MacBeth, the average adjusted R^2 and the average Fisher statistics for HW, HR and E measures respectively. Although the regressions with the Fama-MacBeth methodology have slightly better explanatory power as measured by the adjusted coefficient of determination, the variables do not appear to be priced in any model except Model 7 which includes jointly the downside gamma and downside delta for whatever the approach used to measure risk. The downside gamma and delta are significant at 10 % (5%) level for HW and HR (E) measures. The results based on the Fama-MacBeth methodology support our earlier finding indicating that downside gamma and downside delta have significant explanatory power over cross-sectional variation in the Paris Bourse when they are jointly considered. However, there is a difference on the subject of the signs of the associated premium; in this case, as expected, we find a positive relation between returns and downside co-kurtosis as it is a risk enhancing and a negative relation between returns and downside coskewness.

Are Downside Co-Moments Due to Recession Market Periods?

In this study we investigate to what extent the results in previous section depend on market conditions. To test this we isolate the period of recession market times as the stock market crash of October 1987 in the last quarter of 1987, the downturns due to the deflation of dot-com bubble and the events of 11^{th} of September, 2001 covering 01/01/2001 to 31/01/2002 and finally the global financial crisis in middle 2007 to 2009.

The results are reported in Table 5 and reveal that none of the downside risk HW and HR measures is significant and the adjusted coefficient of determination is very low (expect for the E-downside gamma and downside delta when they are jointly considered). This result is expected and is in line with the findings of Post and Vliet (2006) which indicates that there is a near perfect relation between return and risk (measured by downside beta) during bad–states of the world advocating that downside risk measures are appropriate in pricing models only when the market is in decline. This result may be also due to the fact that the departure from normality becomes less pronounced when downturn periods are excluded. This is confirmed by the test of normality of returns according to the modified sample data that indicates that the skewness of the returns distribution is nearer to zero and overall kurtosis is weaker than it was for the full sample period showing that the returns distribution is less asymmetric and more peaked and thus weakens the motivation for using downside measures or higher order co-moments in pricing models.

CONCLUSION

In this study, we introduce in the CAPM downside beta, downside co-skewness and downside co-kurtosis to explain stock returns on the French market. We used the three well known measures of risk in a downside framework. In a first analysis we regressed average stock returns on the risk measures over several models. Consistent with previous studies, we find that the CAPM fails to explain the cross sectional variation in the observed returns. The empirical results also provide strong evidence in favor of using three downside co-moments to explain cross-sectional stock returns in the French market and reveal that they are complementary risk measures. Another ambiguous result is that the premium associated with downside co-moments have signs opposite expected. We argue that this result could be explained by the fact that the market is not sufficiently mature to reveal the anticipated direction of the risk-return relationship.

To investigate the sensitivity of our results to the methodology used, we repeated the study using the two pass methodology of Fama-MacBeth. The results provide further evidence to consider jointly the downside co-skewness and downside co-kurtosis in pricing models. Nevertheless we cannot really say that their role is sufficient in explaining economically and statistically cross sectional mean returns in the French market.

Finally we examined the effect of recession market periods on the results. We find that none of the considered measures of risk is priced when we exclude downturn periods that affected the French stock market. This result confirms the findings of Post and Vliet (2004) indicating that there is a near-perfect relation between returns and downside risk measure (downside beta) during bad-states of the world. We find also that the results seem to depend to some extent on the degree of the departure from normality.

Although a theoretical base and an economic and financial interpretation are in somewhat lacking, this study provides further evidence to the debate on whether systematic higher order co-moments are able to explain cross sectional security returns particularly in a downside framework for the French market. Our study is limited as it considers only a small sample of securities. Stronger evidence may be found with a larger sample.

Table 4: Fama and MacBeth Regressions Results

Panel A: Cross Sectional Regressions for the HW- measures							
Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 1	0.052*	-0.024				5.20%	4.0***
	(3.63)	(-1.21)					
Model 2	0.044*		-0.016			5.00%	3.9***
	(3.088)		(-0.789)				
Model 3	0.049*			-0.019		4.20%	4.33**
	(3.462)			(-1.006)			
Model 4	0.039*				-0.008	4.10%	4.20**
	(2.848)				(-0.481)		
Model 5	0.043*		-0.055	0.039		10.00%	5.46**
	(2.904)		(-0.932)	(0.733)			
Model 6	0.043*		-0.042		0.027	10.00%	5.51*
	(2.885)		(-1.347)		(0.898)		
Model 7	0.048*			-0.12***	0.101***	10.00%	6.25*
	(3.313)			(-1.693)	(1.708)		
Model 8	0.031*		-0.109	0.13	-0.025	17.00%	8.44*
	(15.545)		(-1.103)	(0.628)	(-0.087)		
Panel B: Cross Sectional Regressions for the HR- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.052***	-0.024				5.20%	3.9*
	(3.63)	(-1.21)					
Model 2	0.048***		-0.024			5.00%	3.9*
	(3.37)		(-1.157)				
Model 3	0.052***			-0.021		4.70%	3.9*
	(3.66)			(-1.124)			
Model 4	0.041***				-0.01	4.10%	4.20**
	(2.982)				(-0.604)		
Model 5	0.045***		-0.057	0.038		10.00%	5.25**
	(3.073)		(-0.936)	(0.694)			
Model 6	0.05***		-0.038		0.016	10.00%	5.63*
	(3.384)		(-0.996)		(0.528)		
Model 7	0.049***			-0.112*	0.091*	10.00%	6.21*
	(3.355)			(-1.881)	(1.662)		
Model 8	0.037**		-0.11	0.117	-0.019	17.00%	8.56*
	(2.412)		(-0.721)	(0.366)	(-0.106)		
Panel C : Cross Sectional Regressions for the E- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.052	-0.024				5.20%	4*
	(3.63***)	(-1.21)					
Model 2	0.059***		-0.024			4.70%	3.81*
	(3.384)		(-1.157)				
Model 3	0.052***			-0.02		4.50%	3.9*
	(3.326)			(-1.014)			
Model 4	0.044***				-0.014	4.10%	4.20**
	(3.1)				(-0.77)		
Model 5	0.060***		-0.056	0.03		9.70%	5.10**
	(3.192)		(-0.893)	(0.529)			
Model 6	0.063***		-0.054		0.026	9.80%	5.75***
	(3.411)		(-1. 363)		(0.825)		
Model 7	0.060***			-0.125	0.099	10.00%	6.34***
	(3.49)			(-1.967**)	(1.716***)		
Model 8	0.06		-0.06	-0.018	0.052	17.00%	10.6**
	(2.982***)		(-0.381)	(-0.052)	(0.28)		

*This table reports the mean estimates of coefficients, the Student–Fama and MacBeth statistics in parenthesis, the mean adjusted R^2 and the mean Fisher-statistics issued from the cross-sectional Fama and MacBeth regressions of mean return on estimated measures of risk over the models 1 to 8. The estimated parameters estimated are White heteroscedasticity–consistent. Pane1 A, B and C report results relative to HW, HR and E measures respectively. ***, ** and * denote significance at 1%, 5% and 10% level respectively*

Table 5: Cross-Sectional Analysis Excluding Recession Periods

Panel A : Cross Sectional Regressions for the HW- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.531***	0.182				3.60%	1.33
	(3.548)	(1.157)					
Model 2	0.568***		0.145			2.30%	0.86
	(3.79)		(0.928)				
Model 3	0.574***			0.134		1.90%	0.7
	(3.676)			(0.837)			
Model 4	0.621***				0.079	0.00%	0.23
	(3.868)				(0.486)		
Model 5	0.536***		0.211	-0.04		0.00%	0.72
	(3.506)		(0.4593)	(-0.082)			
Model 6	0.549***		0.218		-0.065	4.00%	0.76
	(3.444)		(1.014)		(-0.28)		
Model 7	0.555***			0.409	-0.271	0.00%	0.84
	(3.466)			(1.055)	(-0.669)		
Model 8	0.664***		-1.348	2.974	-1.597		
	(3.807)		(-1.102)	(1.386)	(-1.529)	2.80%	1.35
Panel B: Cross Sectional Regressions for the HR- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.531***	0.182				3.60%	1.33
	(3.548)	(1.157)					
Model 2	0.532***		0.18			3.50%	1.29
	(3.52)		(1.136)				
Model 3	0.549***					2.60%	0.94
	(3.471)			0.159 (0.974)			
Model 4	0.605***				0.096	0.90%	0.33
	(3.697)				(0.579)		
Model 5	0.557***		0.51	-0.361		4.80%	0.89
	(3.547)		(1.043)	(-0.717)			
Model 6	0.544***		0.31		-0.153	0.70%	1.14
	(3.303)		(1.406)		(-0.639)		
Model 7	0.524***			0.54	-0.368	2.00%	1.38
	(3.329)			(1.401)	(-0.926)		
Model 8	0.579***		-0.439	1.309	-0.754	0.10%	0.77
	(3.192)		(-0.382)	(0.671)	(-0.808)		
Panel C: Cross Sectional Regressions for the E- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.531***	0.182				3.60%	1.33
	(3.548)	(1.157)					
Model 2	0.568***		0.145				
	(3.79)		(0.928)			2.30%	0.86
Model 3	0.631***		-0.996			0.30%	0.12
	(3.283)		(-0.358)				
Model 4	0.697***				0.013	0.00%	0
	(4.375)				(0.01)		
Model 5	0.49**		0.241	1.018		1.40%	1.26
	(2.023)		(1.537)	(0.4265)			
Model 6	0.538**		0.226		-0.746	2.30%	1.43
	(2.247)		(1.423)		(-0.714)		
Model 7	0.233			-29.249***	-12.469***	21.20%	5.97
	(1.121)			(-3.196)	(-3.393)		
Model 8	0.268		0.065	-19.904*	-8.125*	10.20%	2.4*
	(1.118)		(0.356)	(-1.761)	(-1.814)		

*This table reports the estimates coefficients, their t-Statistics in parenthesis, the adjusted R^2 and the Fisher-statistics issued from the cross-sectional regressions of mean return on beta ,downside beta and the orthogonalized components of downside gamma and downside delta over the models 1 to 8. The average returns and the estimates of risk measures considered are calculated over the sample period excluding recession periods (the crash of October 1987 on last quarter of 1987, the downturns due to the deflation of dot-com bubble and the attempt of the 11th of September spending from 01/01/2001 to 31/01/2002 and the global financial crisis in middle 2007 to 2009). The parameters are White heteroscedasticity–consistent. Pane1 A, B and C report results relative to HW, HR and E measures respectively. ***, ** and * denote significance at 1% , 5% and 10% level respectively.*

APPENDIX

The downside risk co-moments corresponding to Harlow and Rao (1989) measure are given by:

$$\beta_{im}^{(HR)} = \frac{E[(R_i - \mu_i).min(R_m - \mu_m, 0)]}{E[min(R_m - \mu_m, 0)]^2} \quad (3)$$

$$\gamma_{im}^{(HR)} = \frac{E[(R_i - \mu_i).min(R_m - \mu_m, 0)^2]}{E[min(R_m - \mu_m, 0)]^3} \quad (5)$$

$$\delta_{im}^{(HR)} = \frac{E[(R_i - \mu_i).min(R_m - \mu_m, 0)^3]}{E[min(R_m - \mu_m, 0)]^4} \quad (6)$$

The downside risk co-moments corresponding to Estrada (2002) measure are given by :

$$\beta_{im}^{(E)} = \frac{E[min(R_i - \mu_i, 0).min(R_m - \mu_m, 0)]}{E[min(R_m - \mu_m, 0)]^2} \quad (7)$$

$$\gamma_{im}^{(E)} = \frac{E[min(R_i - \mu_i, 0).min(R_m - \mu_m, 0)^2]}{E[min(R_m - \mu_m, 0)]^3} \quad (8)$$

$$\delta_{im}^{(E)} = \frac{E[min(R_i - \mu_i, 0).min(R_m - \mu_m, 0)^3]}{E[min(R_m - \mu_m, 0)]^4} \quad (9)$$

Where R_i and R_m are the asset's and the market return respectively, μ_i and μ_m is the asset's and market mean return.

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WHY DO BANKS DEFAULT WHEN ASSET QUALITY IS HIGH?

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ABSTRACT

Short-term financing, e.g., asset-backed commercial paper (ABCP) or repurchase agreements (repo), was prevalent prior to the 2007-2008 financial crises. Banks funded by short-term debts, however, are exposed to rollover risk as the banks are unable to raise sufficient funds to finance their long-term assets. Under such circumstance, banks' equity holders need to absorb the rollover loss. Both deteriorating collateral assets' fundamentals and market illiquidity are important drivers of the rollover risk. In this paper, we develop a structural default model based on Leland (1994), in which default is an endogenously determined decision made by equity holders, to analyze the joint effect of market liquidity and interest rate sensitive fundamentals of collateral assets' on the survival times of banks relying on day-to-day short-term finance. The proposed model provides an explanation of the empirical observed phenomenon that banks default even when the quality of their fundamentals is still high.

JEL C41; C36; G17; G21; G33; G32

KEYWORDS: Asset-backed commercial paper (ABCP), Repurchase agreements (repo), Rollover risk, Collateral assets' fundamental, Market illiquidity, Structural default model.

INTRODUCTION

The financial crisis of the years 2007-2008 has been a particular turbulent one for the US banking and financial system. The first bank failure occurred when two Bear Stearns hedge funds invested in sub-prime assets filed for bankruptcy on July 31, 2007. A year later, on September 14th, 2008, the Lehman Brothers declared its bankruptcy which triggered a series of banks and insurance companies announce their failures. Unlike the banking panics of the 19th century in which depositors *en masse* withdrew cash in exchange of demand and savings deposits, the financial crisis of the years 2007-2008 is a systemic banking run driven by the withdrawal of short-term debts, e.g., asset-backed commercial paper (ABCP) or repurchase agreements (repo), with tenors no more than 270 days (Brunnermeier, 2009; Krishnamurth, 2010; Gorton et. al., 2008, 2009).

Such short-term financing was prevalent prior to the 2007-2008 financial crises. Often these short-term debts are collateralized by securities backed by assets like real estate, autos and other commercial assets. One of the determinant economic factors of a debt's capacity is its collateral assets' fundamentals. However, collateral assets with high quality fundamentals do not guarantee a bank's ability to raise new funds when the market liquidity deteriorates (Acharya, Gale, and Yorulmazer, 2009; He and Xiong, 2010b). The failure of Bear Stearns in mid-March 2008 provides such a counter-example. After two Bear Stearns hedge funds filed for bankruptcy on July 31, 2007, the calculation of the net asset values of the other three investment funds was suspended as it is no longer possible to value certain assets fairly regardless of their quality or credit rating (Acharya, Gale, and Yorulmazer, 2009). The same phenomenon is observed in the repo market during the 2007-2008 financial crises (Gorton, 2009).

The implications of the above observations are consistent with the widely held views that both deteriorating fundamentals and market illiquidity are important drivers of bank failures. In this paper, we develop a structural default model based on Leland (1994) to analyze the joint effect of market liquidity and collateral assets' fundamentals that are interest rate sensitive. In the proposed model, default is an endogenously determined decision when the bank does not raise sufficient funds to repay a faction of its maturing debt's principle (Huang and Huang, 2002). Monte Carlo simulations are performed for 24 scenarios of different parameters values on long-term interest rate, the volatility of the collateral assets' fundamental, and the shift and shape parameters that control for the information structure and the likelihood of the occurrence of unusual economic events in the market. The simulation shows that survival curve of banks with the smallest volatility for its collateral asset's fundamental is approximating to that of the highest volatility when the long-term interest rate is lower. The result provides an explanation of the empirical observed phenomenon that banks default even when the quality of their fundamentals is still high.

The paper is organized as follows. Literature reviews are given in Section 2. Section 3 develops a structural default model for banks that rely on short-term debt in a stochastic interest rate environment. In the proposed structural default model, an interest rate sensitive fundamental of collateral assets and a stochastic purely jump debt capacity ratio that accounts for market liquidity are incorporated. A simulation study is performed in Section. Section 5 concludes.

LITERATURE REVIEW

Short Term Debts

According to Diamond and Rajan (2000), banks are best to finance their illiquid long-term investments that are less likely to produce cash flows in the short run with short-term rather than long-term debts. Like banks, asset-backed commercial paper (ABCP) or repo programs issue liquid short term debt that is highly-rated, collateralized to finance illiquid and long-term assets. These short-term debt markets grew dramatically in recent years. The ABCP market nearly doubles in size between 2004 and 2007. At the end of July 2007, just before the widespread turmoil, the total ABCP outstanding is \$1060 billion (Moody's, 2007). In a study of repo markets by Hordahl and King (2008), it was estimated that the top US investment banks funded roughly half of their assets using repo markets before the 2008 financial crisis.

Like traditional banks, ABCP or repo programs are subject to the risk of fundamentals-driven runs, whereby investors quickly flee from potentially insolvent and poorly supported programs (Diamond and Dybvig, 1983). On the other hand, as the demand deposits in the traditional banking create information-insensitive debts (Gorton and Pennacchi, 1990), banks may also be vulnerable to runs not based on fundamentals. Similarly, runs in the ABCP or repo programs maybe linked to non-program specific variables, such as broader financial market strains and market-wide proxies for liquidity risks. With an average haircut zero in 2007 to nearly 50% at the peak of the financial crisis in late 2008, the concerns about the market liquidity of the securitized collateral assets had led to the insolvency of the US banking system (Gorton et. al., 2010a).

However, unlike the traditional banking in which depositors are protected by deposit insurance provided by the Federal Reserve, the ABCPs or repos do not have explicit deposit insurance provided by the government. As a bankruptcy-remote special purpose vehicle (SPV), or conduit, is created in an ABCP or repo program to issue short-term debts to finance assets, for an ABCP program, the committed back-stop liquidity lines are provided by sponsored commercial banks (Fitching Rating, 2001; Covitz et al., 2009). Similar to an ABCP program, the collateral assets, often securitized bonds, are the liabilities of a SPV, and creditors receive these securitized bonds as collateral for protection (Gorton et. al., 2010a, 2010b). This has exposed banks relying on short-term financing such as ABCPs or repos programs to even larger rollover risk that triggers the financial crisis in 2007-2008.

Rollover Risk Associated With Short-Term Debts

When a debt matures, the bank issues a new debt with the same face value and maturity to replace the maturing debt at the new debt's capacity, i.e., the maximum amount of funds that can be obtained based on the debt's collateral assets, which can be higher or lower than the principal of the maturing debt. When insufficient funds can be raised to pay off maturing creditors, banks' equity holders need to absorb the rollover loss. A shorter debt maturity can exacerbate a bank's rollover risk as equity holders are forced to quickly absorb the losses incurred by the bank's debt financing. When the bank defaults, the maturing creditors need to seize and liquidate the collateral assets in an illiquid secondary market at fire sale prices. This in turn has exposed banks to even significant funding liquidity risk and eventually contagious bank failures (Diamond and Rajan, 2000, 2001).

Acharya, Gale, and Yorulmazer (2009) provide a theoretical model with two different information structures, namely, optimistic versus pessimistic, for the market liquidity. The model explains sudden freezes in secured short-term debt markets even when the assets are subject to very limited credit risk. Diamond and Rajan (2005) show that runs by depositors on insolvent banks can have contagious effect on the whole banking system. However, they do not analyze the coordination problem between depositors. In contrast to the static bank-run model, He and Xiong (2010b) derived an equilibrium bank run model, in which the creditors coordinate their asynchronous rollover decisions based on the publicly observable time-varying fundamental of collateral assets. In He and Xiong (2010b), a uniquely determined threshold of the fundamental under which a maturing creditor chooses to run on the short-term debt is derived. In another paper, He and Xiong (2010a) analyze the interaction between debt market liquidity and credit risk due to the intrinsic conflict of interest between debt and equity holders, which causes an earlier default by the equity holders. The model captures the phenomenon of the 2007-2008 financial crisis that even in the absence of any fundamental deterioration, pre-emptive runs by creditors on a solvent bank occur.

Structural Default Models

For modeling credit risk, two classes of models exist: structural and reduced form. Structural models originated with Merton (1974), and reduced form models originated with Jarrow and Turnbull (1992, 1995) and Duffie and Singleton (1999). This paper considers structural models only, which can be classified as exogenously versus endogenously determined default models in literature. The exogenously determined default model assumes that bankruptcy is triggered when the firm's asset value falls to its debt's principle value, where an exogenously determined default barrier is usually assumed in this type of structural model. The pioneer works of Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), and Briys and Varenne (1997) all are cases of the first type structural model. The second type of structural model assumes that bankruptcy is an optimal decision made by equity holders to surrender control to bond holders to maximize the value of equity, and therefore the optimal default barrier is endogenously determined (Leland, 1994; Leland and Toft, 1996).

In either type of the aforementioned structural models, the determinant of a default event is the firm's asset value V: default occurs if the process V falls below to the default barrier for the first time or at maturity. For banks rely heavily on day-to-day short-term debts, as the intrinsic conflict between debt and equity holders arises when equity holders bear the rollover losses while maturing debt holders get paid in full, the equity holders may choose to default earlier (He and Xiong, 2010b). Therefore, we adopt Leland's (1994) endogenously determined default model, in which a short-term debt is continuously rolled over unless terminated because the bank cannot raise sufficient funds to repay a fraction β ($0<\beta<1$) of the maturing debt's principle (Huang and Huang, 2002).

Structure Default Model for Banks

Our model differs from that of Leland's (1994) in two respects. First, an interest rate sensitive fundamental in a stochastic interest rate environment following a mean-reversion diffusion process of Vasicek (1977) is assumed. Second, market liquidity is considered. Instead of a series of Poisson liquidity shocks that drive the debt redemption rate (He and Xiong, 2010b), we use a purely jump VG process to model the dynamics of the debt's capacity ratios, where deterioration of debt market liquidity in terms of jumps of to lower levels.

Stochastic Fundamentals: Diffusion-Based Processes

Suppose the bank holds a collateral asset which matures at time T. Instead of a constant interest rate environment (He and Xiong, 2010a), here we assume a stochastic risk-free interest rate $r(t)$ obeying the mean reverting process by Vasicek(1977) as

$$dr=\theta_r(\pi-r)dt+\sigma_r dZ_r \tag{1}$$

where π is a central tendency parameter, θ_r is the reverting rate, and Z_r is a standard Weiner processes. An interest-rate-sensitive fundamental $R(t)$ obeying a geometric Brownian motion under the risk neutral measure Q

$$dR(t)/R(t)=r(t)dt+\sigma_1 dZ_r+\sigma_2 dZ_R \tag{2}$$

is assumed, where the standard Weiner process Z_R is independent of Z_r. We adopt the standard argument in efficient markets that the collateral asset's market value is the expected present value of cash flows at maturity (Acharya, Gale, and Yorulmazer, 2009). As the interest rate $r(t)$ is stochastic, the time-t asset value $V(t)$ is

$$V(t)=E_t\left[exp\left(-\int_t^T r(s)ds\right)f\left(R(T)\right)\right] \tag{3}$$

where $f(R(T))$ is the collateral asset's cash flow at maturity T. Here we consider an option-like cash flow employed by He and Xiong (2010a), in which the cash flow $f(R(T))$ equals the fundamental $R(T)$ if $R(T)$ is above a threshold R^*, otherwise the cash flow $f(R(T))$ is zero. The closed form solution of the market value $V(t)$ is derived in the following Lemma.

Lemma 1: The time-t price of the collateral asset $V(t)$ is

$$V(t)=P(t, T)F(t)\Phi(w) \tag{4}$$

where $F(t)=R(t)/P(t, T)$, $P(t, T)$is the time-t price of a default-free zero-coupon bond that matures at time T, and the constant

$$w=\frac{\log\left(F(t)/R^*\right)+b^2/2}{b} \tag{5}$$

$$b^2=\int_t^T\left(\sigma_1-S(v,T)\right)^2dv+\sigma_2^2(T-t) \tag{6}$$

Proof. See the Appendix.

To calculate the time-t price of the collateral asset $V(t)$, the time-t price $P(t, T)$ of a default-free zero-coupon bond is required. According to Vasicek (1977), the time-t price $P(t, T)=\exp\{B(t, T)-U(t, T)r(t)\}$, where

$$U(t, T)=\frac{1-e^{-\theta_r(T-t)}}{\theta_r}$$

$$B(t, T)=\{U(t, T)-(T-t)\}\left(\pi-\frac{\sigma_r^2}{2\theta_r^2}\right)-\frac{\sigma_r^2}{4\theta_r}U^2(t,T)$$

<u>Stochastic Haircut: Pure Jump Process</u>

To characterize a bank that rolls over its short-term debt several times before the maturity T of its long-term collateral asset, let a short-term debt be rolled over at discrete times 0, Δt, $2\Delta t$, …, $(K-1)\Delta t$, respectively, where $T=K\Delta t$. At each time point $t=j\Delta t$, $j\geq 0$, the underlying asset's liquidity is measured in terms of the debt capacity ratio α_t, where $0\leq\alpha_t\leq 1$. For simplicity, it is assumed that the debt's capacity ratios $\{\alpha_t: t>0\}$ are independent of the risk-free interest rate $r(t)$ and the asset's fundamental $R(t)$.

In a plot of collateral assets' haircut index, which is one minus the debt capacity ratio α_t, of the repo market from 2007 to 2008, a series of jumps of random magnitudes at random times corresponding to a stream of economic events such as financial crisis, terrorist attacks, … , etc., are exhibited (Gorton *et. al*., 2010a). To describe the dynamics of the jump behavior in the haircut index, or, the debt capacity ratios, a variance-gamma (VG) process is used. Being a purely jump Levy process, the VG process is a popular model in finance for processes with random jump behavior (Madan and Seneta, 1990; Madan and Miline, 1991; Madan, 1998; Geman, 2001). To ensure positivity as in assets' price modeling, we consider the logarithm of a debt's capacity ratio, i.e., $\{\log(\alpha_t): t>0\}$. Specifically, suppose the process $\{\log(\alpha_t): t>0\}$ follows a VG process with drift and volatility θ and σ_g, respectively. It can be shown that the ratio of the logarithms at times $(i-1)\Delta t$ and $i\Delta t$ is

$$\log\left(\frac{\alpha_{i\Delta t}}{\alpha_{(i-1)\Delta t}}\right)=\phi+\theta_g g+\varepsilon_i \tag{7}$$

where the innovation $\varepsilon_i=\sigma_g Z_g(g)$, the random scale g is gamma distributed with shape parameter ν and scale parameter $\gamma=1/\nu$, respectively. Conditional on the random scale g is, the innovation $\varepsilon_i|g\sim N(0, \sigma_g^2 g)$ is normally distributed. The parameter

$$\phi=\nu\Delta t\times\ln\left(1-\frac{\theta_g}{\nu}-\tfrac{1}{2V}\sigma_g^2\right) \tag{8}$$

The derivation of Eqs. (7)-(8) is given in the Appendix.

Since the drift parameter θ_g controls for the skewness of a VG process in that negative θ_g gives rise to negative skewness, while positive θ_g gives rise to positive skewness. Therefore, negative drift parameter θ_g represents a pessimistic information structure, while non-negative drift parameter θ_g represents an optimistic information structure for the liquidity in the market. The shape parameter ν is used to control for the arrival rate of unusual economic events that affect market liquidity due to the fact that smaller shape parameter ν raises the likelihood of larger jumps in the random scale g, and therefore the likelihood of larger jumps of the debt capacity ratios given in (7) .

Defining The Default Event And Survival Probability

To define the default event, we consider a parallel of the specification by Leland (1994) in which a continuously renewable short-term debt will be rolled over if and only if the firm's market asset value is sufficient to repay the debt's principle. Suppose the short-term debt has been successfully rolled over till time $t=j\Delta t$, $j\geq 1$. At time $t'=(j+1)\Delta t$, the maturing debt's principle, or the maturing debt's capacity, $C(t)$ is proportional to the asset's market value $V(t)$ and its debt's capacity ratio α_t in the form

$$C(t)=\alpha_t V(t) \tag{9}$$

Here we adopt the default barrier proposed by Huang and Huang (2002) that a bank defaults if the fund raised at time t' cannot repay a fraction β of the maturing debt's principle $C(t)$. As bank's equity holders need to bear the rollover losses, thus the decision of the level of fraction β is made endogenously by equity holders. Specifically, default occurs at time t' if $C(t')<\beta C(t)$, i.e.,

$$\alpha_{t'} V(t')<\beta\alpha_t V(t) \tag{10}$$

The bank's default time τ can now be formulated as

$$\tau=\inf\{t':\ \alpha_{t'} V(t')<\beta\alpha_t V(t),\ \text{where } t'=(j+1)\Delta t \text{ and } t=j\Delta t, j\geq 1\} \tag{11}$$

Thus the probability that the bank survives after time t is given by $S(t)=\Pr\{\tau>t\}$. In the following, Monte Carlo simulation technique will be employed to explore the three independent determinant factors, namely, the interest-rate sensitive fundamental and the debt's capacity ratio, on the survival probability curve $S(t)$

SIMULATION STUDY

Suppose a long-term collateral asset matures at T=10 years, and short-term debts are rolled over at discrete times 0, Δt, $2\Delta t$, …, $(K-1)\Delta t$, respectively, where Δt=(1/360) year and K=3600. In the following, a simulation study is performed to illustrate the roles the four determinant parameters play in the distributions of a bank's survival times. The four determinant parameters are: (1) The long term equilibrium interest rate (low and high central tendency parameter π=0.05, 0.07); (2) The volatility of the asset's fundamental (low, medium, and high volatility σ_2=0.1, 0.2, and 0.5); (3) The information structure of the market liquidity: Optimistic versus pessimistic (shift parameter θ_g=0.00, -0.05); (4) The occurrence of unusual economic events (low and high shape parameter ν=0.1 and 1). There are a total of 24 various scenarios considered. Throughout the 24 various scenarios, the mean-reverting rate θ_r is set to 0.5, the volatilities of interest rate, asset's fundamental, and debt capacity ratio are set to σ_r=0.01, σ_1=0.1, and σ_g=0.02, respectively. The fraction β of default barrier in (10) is set to 0.9. For each of the 24 scenarios, Monte Carlo simulation of N=10,000 runs are performed.

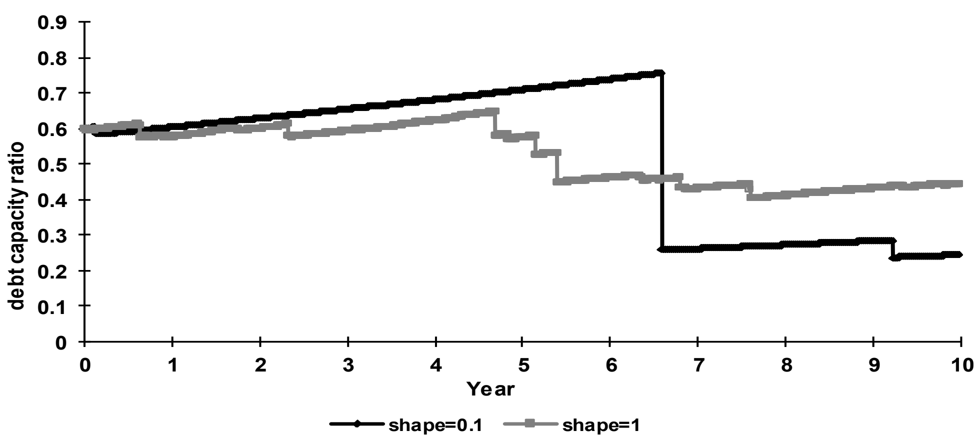
In Table 1, summary means and standard deviations of bank's survival times of 24 various scenarios are given. Figure 1 shows a realization of downward debt capacity ratio corresponding to a pessimistic information structure (θ_g=-0.05), while Figure 2 shows a realization of an upward debt capacity ratio corresponding to an optimistic information structure (θ_g=0.00). In either of the plots, the smaller shape parameter, i.e., ν=0.1, shows larger jump sizes due to unusual economic events.

Table 1: Summary of Survival Times of 24 Scenarios

	π	σ_2	θ_g	ν	Mean	S.t.dev.
1	0.05	0.10	-0.05	0.10	1.1739	1.3861
2	0.05	0.10	-0.05	1.00	1.4048	1.6932
3	0.05	0.10	0.00	0.10	1.5322	1.9348
4	0.05	0.10	0.00	1.00	1.5774	1.9832
5	0.05	0.20	-0.05	0.10	2.2921	1.9850
6	0.05	0.20	-0.05	1.00	2.5515	2.1947
7	0.05	0.20	0.00	0.10	2.9696	2.4473
8	0.05	0.20	0.00	1.00	3.0804	2.5373
9	0.05	0.50	-0.05	0.10	1.0237	1.0970
10	0.05	0.50	-0.05	1.00	1.0749	1.1669
11	0.05	0.50	0.00	0.10	1.1519	1.3082
12	0.05	0.50	0.00	1.00	1.1814	1.2988
13	0.07	0.10	-0.05	0.10	2.6565	2.2843
14	0.07	0.10	-0.05	1.00	3.1196	2.6325
15	0.07	0.10	0.00	0.10	3.6562	2.8269
16	0.07	0.10	0.00	1.00	3.8018	2.9106
17	0.07	0.20	-0.05	0.10	3.0513	2.3569
18	0.07	0.20	-0.05	1.00	3.6450	2.5697
19	0.07	0.20	0.00	0.10	4.2689	2.7721
20	0.07	0.20	0.00	1.00	5.0024	3.0466
21	0.07	0.50	-0.05	0.10	1.1965	1.1893
22	0.07	0.50	-0.05	1.00	1.2919	1.3429
23	0.07	0.50	0.00	0.10	1.3576	1.4670
24	0.07	0.50	0.00	1.00	1.4616	1.5495

Note π is the equilibrium interest rate; σ_2 is the volatility of the collateral asset's fundamental; θ_g and ν are the shift and shape parameters representing the information structure and the likelihood of unusual events, respectively, for the debt capacity ratio process

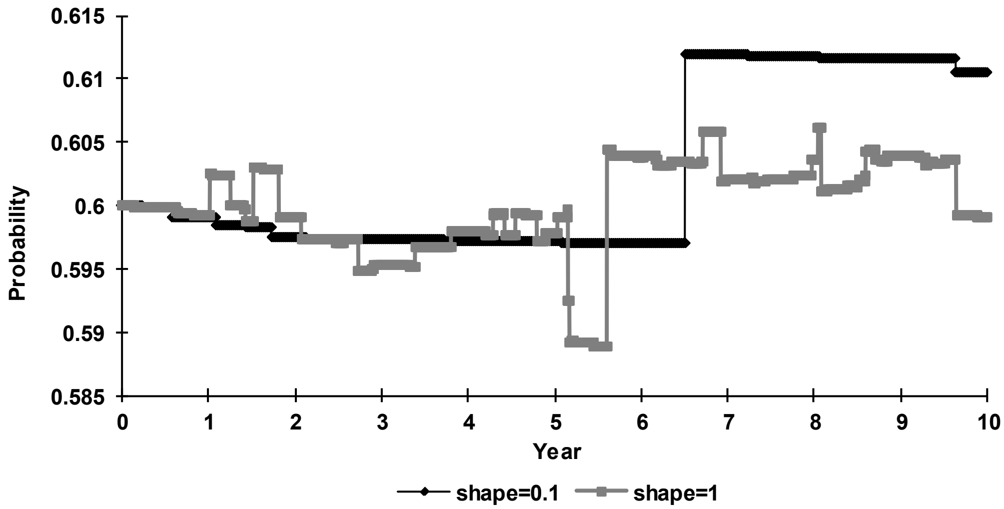
Figure 1: Debt Capacity Ratio in Pessimistic Information



This figure shows the jump behavior of debt capacity ratio when there are unusual events (shape=0.1) versus no unusual events (shape=1) under pessimistic information structure (θ_g=-0.05).

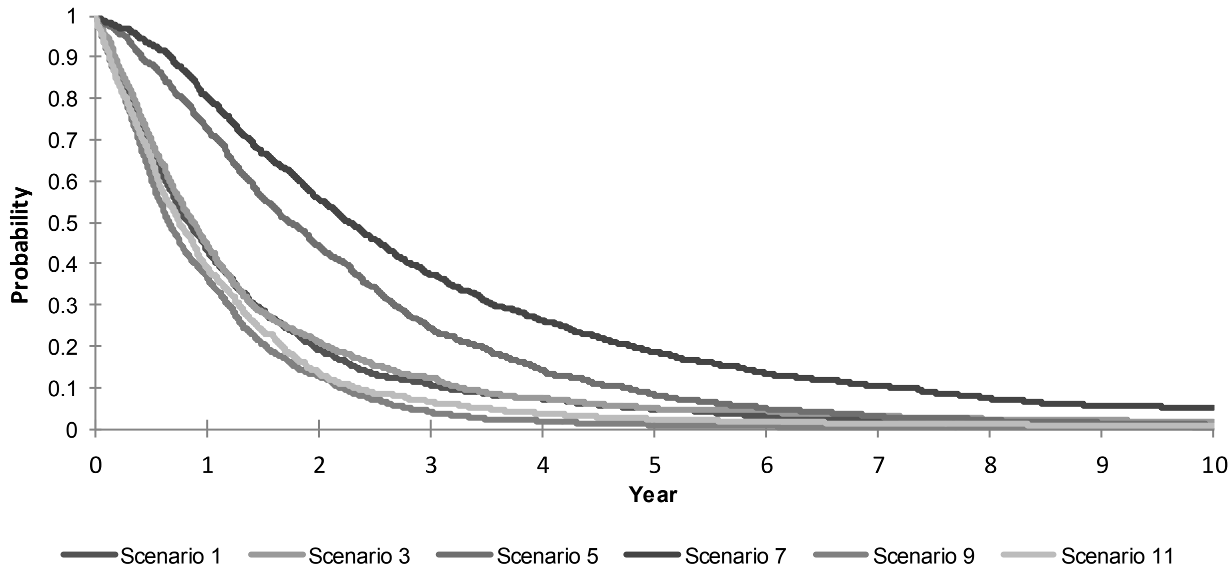
Figures 3-4 (Figures 5-6) plot the bank's survival probability curves $S(t)$ for scenarios 1 to 12 (scenarios 13 to 24) corresponding to low interest rate (high interest rate) environment, respectively. In Figures 3 and 5, the survival curves for scenarios with unusual economic events, i.e., ν=0.1, are given; while survival curves for scenarios without unusual economic events, i.e., ν=1, are given in Figures 4 and 6.

Figure 2: Debt Capacity Ration in Optimistic Information



This figure shows the jump behavior of debt capacity ratio when there are unusual events (shape=0.1) versus no unusual events (shape=1) under pessimistic information structure (θ_g=-0.00).

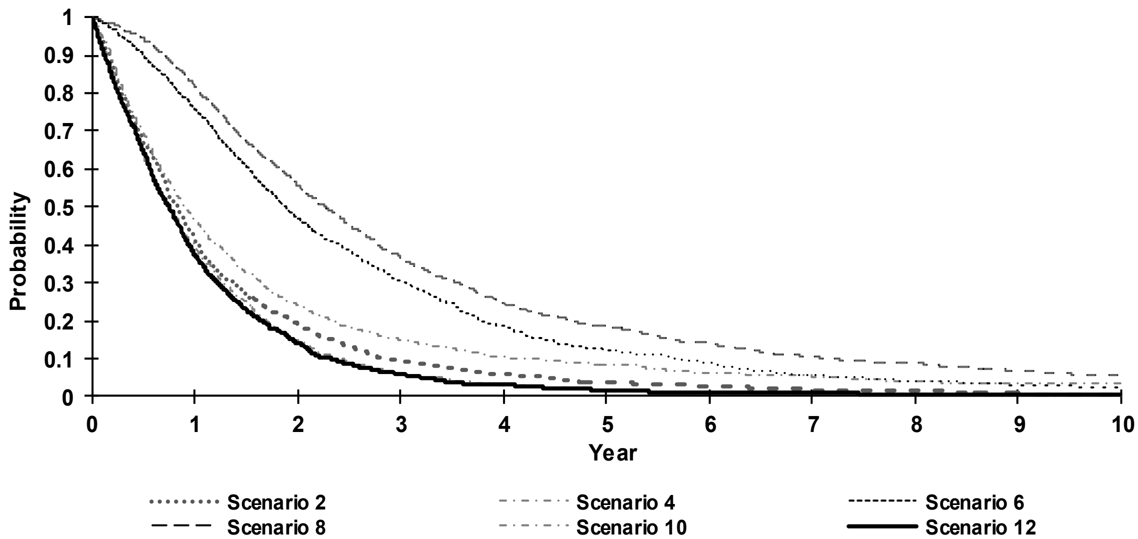
Figure 3: Survival Curves for Equilibrium Interest Rate 0.05



This figure shows the survival curves for scenarios 1,3,5,7,9,11 with unusual events (shape=0.1) in low interest rate environment (π=0.05). Among them, scenarios 1,5,9 are in pessimistic information structure (θ_g=-0.05); whereas scenarios 3,7,11 are in optimistic information structure (θ_g=0.00). The volatility of collateral asset's fundamental of scenarios 1,3 is low (σ_2=0.1), of scearios 5,7 is medium (σ_2=0.2), whereas of scenarios 9,11 is high (σ_2=0.5).

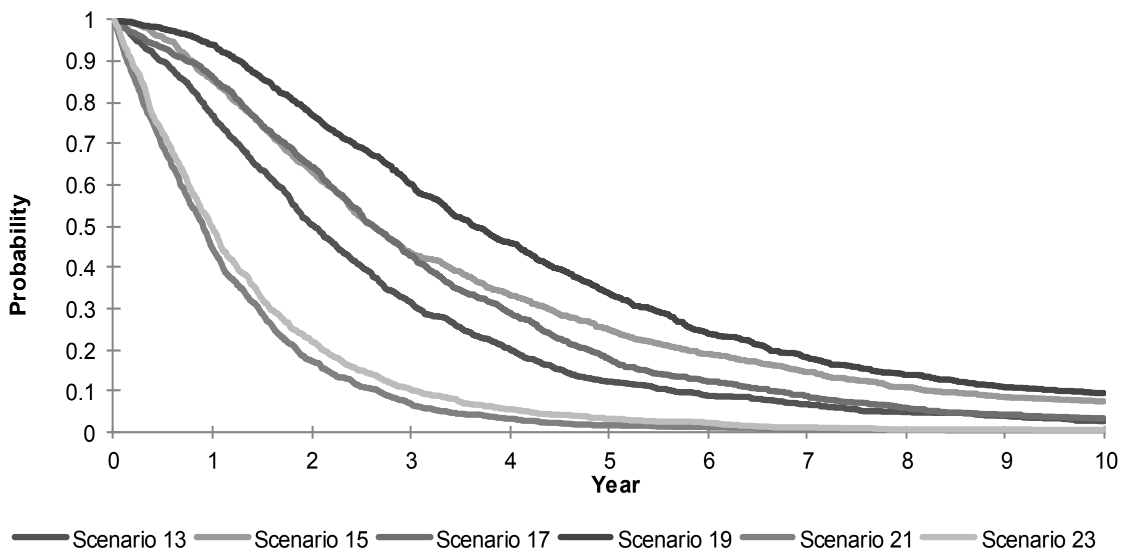
In either of the Figures 3-6, the medium collateral asset's volatility (σ_2=0.2) exhibits the upper most survival curves (in cyan curves), while the high volatility (σ_2=0.5) results in the lowest survival curves (in green curves). Similarly, in Table 1, the medium (σ_2=0.2) and high volatility (σ_2=0.5) give the highest and lowest mean survival times, respectively. magenta This implies that banks relying on short-term debts have longer survival times if medium-risk collateral assets are invested. Nevertheless, high risk collateral assets significant reduce bank's survival times, in both low and high interest rate environment.

Figure 4: Survival Curves for Equilibrium Interest Rate 0.05



This figure shows the survival curves for scenarios 2,4,6,8,10,12 without unusual events (shape=1) in low interest rate environment (π=0.05). Among them, scenarios2,6,10 are in pessimistic information structure (θ_g=-0.05); whereas scenarios 4,8,12 are in optimistic information structure (θ_g=0.00). The volatility of collateral asset's fundamental of scenarios 2,4 is low (σ_2=0.1), of scearios 6,8 is medium (σ_2=0.2), whereas of scenarios 10,12 is high (σ_2=0.5).

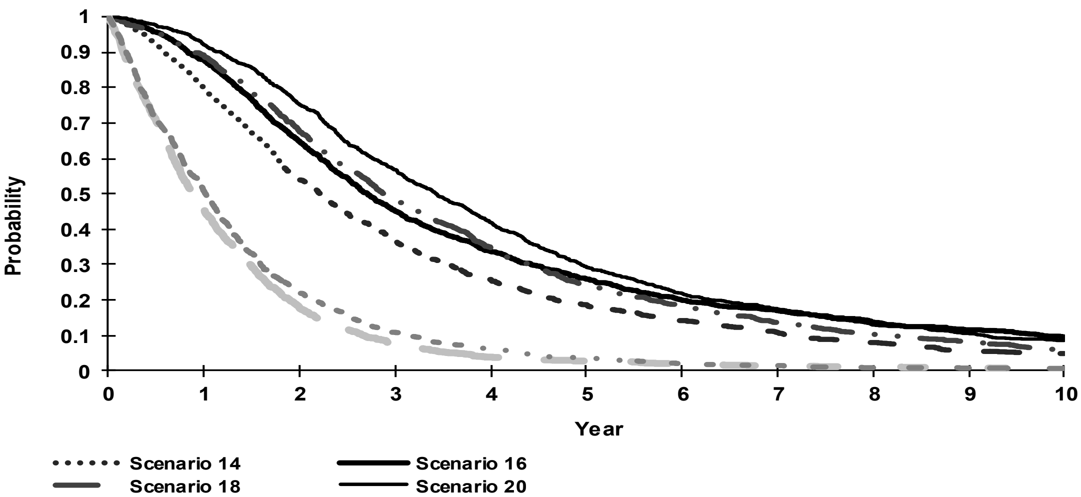
Figure 5: Survival Curves for Equilibrium Interest Rate 0.07



This figure shows the survival curves for scenarios 13,15,17,19,21,23 with unusual events (shape=0.1) in high interest rate environment (π=0.07). Among them, scenarios 13,17,21 are in pessimistic information structure (θ_g=-0.05); whereas scenarios 15,19,23 are in optimistic information structure (θ_g=0.00). The volatility of collateral asset's fundamental of scenarios 13,15 is low (σ_2=0.1), of scearios 17,19 is medium (σ_2=0.2), whereas of scenarios 21,23 is high (σ_2=0.5).

After comparing Figures 3-4 and 5-6, one finds that the larger equilibrium interest rate (π=0.07) increases the survival times of a bank. This is due to the fact that higher long-term interest rate implies higher growth rate of the asset's fundamental and therefore larger collateral asset's market value, which implies larger debt capacity and longer survival time. The impact of the long-term equilibrium interest rate is more prominent when the collateral asset's volatility is small (σ_2=0.1) compared to medium and high volatilities (σ_2=0.2 and 0.5). Figures 3-6 also show that optimistic information structure (θ_g=0.00) increases bank's survival times compared to the pessimistic information structure (θ_g=-0.05). Table 1 shows the consensus result that the mean survival times are larger in the optimistic information scenarios. After comparing Figures 3 with 4 (Figures 5 with 6), one finds the impact of the information structure on survival times is more prominent when the likelihood of unusual economic events is higher (low shape parameter ν=0.1).

Figure 6: Survival Curves for Equilibrium Interest Rate 0.07



This figure shows the survival curves for scenarios 14,16,18,20,22,24 without unusual events (shape=1) in high interest rate environment (π=0.07). Among them, scenarios 14,18,22 are in pessimistic information structure (θ_g=-0.05); whereas scenarios 16,20,24 are in optimistic information structure (θ_g=0.00). The volatility of collateral asset's fundamental of scenarios 14,16 is low (σ_2=0.1), of scearios 18,20 is medium (σ_2=0.2), whereas of scenarios 22,24 is high (σ_2=0.5).

The impacts of long-term equilibrium interest rate and information structure almost disappears as the volatility σ_2 of the collateral asset's fundamental increases to 0.5. This indicates that when the collateral asset's fundamental deteriorates so the volatility σ_2 goes high enough; the collateral asset's fundamental dominates the effects of equilibrium interest rate as well as information structure.

Taken together, the four parameters, i.e., the long-term equilibrium interest rates, the volatility of the collateral asset's fundamental that is independent of the interest rate, the shift parameter that controls for the information structure in the market liquidity, and the likelihood of the occurrence of unusual economic events affect the bank's survival probabilities jointly. Among the four parameters, the impact of the collateral asset's volatility dominates in a way that as the volatility increases to a threshold, the variations for the remaining three parameters make no significant differences for the survival probabilities. In all cases, banks holding collateral assets with medium volatility (σ_2=0.2) have the longest survival times. When the information structure in the market liquidity is pessimistic, maintaining the long-term interest rate at a lower level can offset the differences between optimistic and pessimistic information structures only for the low and medium volatilities of collateral asset (σ_2=0.1 and 0.2). However, the survival curve for banks holding low volatility collateral assets, i.e., σ_2=0.1, is approximating to that of high volatility, i.e., σ_2=0.5, in the low equilibrium interest rate scenarios (π=0.05). This might provide an explanation of the empirically observed phenomenon that banks default even when the qualities of their fundamentals are still high (He and Xiong, 2010a; Acharya, Gale, and Yorulmazer, 2009).

CONCLUSION

In this study, the derivation of the survival/default probabilities for banks holding long-term assets and short-term debts based on a structural model that takes into consideration of collateral asset's fundamentals and market liquidity is given. The attractive feature of the proposed model includes: (1) An interest rate sensitive fundamental of the collateral assets is assumed; (2) A stochastic interest rate environment is assumed; (2) A purely jump stochastic process is used to model the debt capacity ratio.
For simplicity, it is assumed that the interest rate sensitive fundamental and the market liquidity are independent. Nevertheless, as the deterioration of debt market liquidity caused severe financing difficulties for banks, which in turn may exacerbate the fundamental of their assets, therefore the importance of the interaction between the assets' fundamental and the liquidity should not be ignored (Brunnermeier, 2009; Krishnamurthy, 2010). An extension of the proposed structural model by incorporating the correlation between the interest rate sensitive fundamental and the market liquidity will be studied in the future.

APPENDIX

Proof of Lemma 1: Consider the discounted process $F(t)=R(t)/P(t, T)$, where $T>t$, $R(t)$ is the fundamental defined in (2), $P(t, T)$ is the time-t price of a default-free zero-coupon bond that matures at time T. Using (2) and Ito's lemma, one has

$$dF(t)/F(t)=[\sigma_1 - s(t, T)]dZ_1+\sigma_2 dZ \qquad \text{(A1)}$$

where $dZ_1=dZ_r- s(t, T)dt$ and $s(t, T)=\dfrac{\sigma_r\left(1-e^{-\theta(T-t)}\right)}{\theta}$, θ and σ_r are the revert rate and volatility for the interest rate r in (1), respectively. As

$$\exp\left(\int_0^T \frac{\sigma_r^2 e^{-2\theta(T-t)}}{2\theta^2}dt\right) < \infty$$

By Girsanov's theorem, there exists a forward measure Q_1 equivalent to the risk neutral measure Q, such that Z_1 defined above is a Brownian motion under Q_1. Thus, $F(t)$ is a martingale under Q_1. See Musiela and Rutkowski (1997) for details. It follows that the market value in (3) can be rewritten as $V(t)= P(t,T)E_t\left[f\left(R(T)\right)\right]$, where the expectation is taken under the forward measure Q_1. Furthermore, from (A1), given the information set $\mathscr{F}_t$, $F(T)$ is lognormally distributed under $Q_1$with mean

$$m=\log\left(F(t)\right) - \frac{b^2}{2}$$

and variance in (6). Since $F(T)=R(T)$, it can be shown the expectation

$$E_t\left[f\left(R(T)\right)\right]=\int_{\log\left(R^*\right)}^{\infty} e^s \phi\left(\frac{s-m}{b}\right)ds = F(t)\Phi(w)$$

where the constant w is given in (5), ϕ is the standard normal density and the cash flows $f(R(T))=R(T)$ if $R(T)\geq R^*$, else $f(R(T))=0$.

Derivation of Eqs. (7)-(8). A variance-gamma process $X(t)=\theta_g g_t+\sigma_g Z_g(g_t)$ is a Brownian motion with drift and volatility θ and σ_g, respectively, time-changed by a random scale g_t=$g(t)$-$g(0)$, which is the increment of a gamma process $\{g(s: \nu, \gamma): s>0\}$ with shape parameter ν and scale parameter γ, respectively, during time interval (0, t]. According to Jacod and Shiryayev (1987), the process $\exp\{iuX(t)\text{-}\psi_t(u)\}$ is a semi-martingale, where $\psi_t(u)$ is the logarithm of the characteristic function $E[\exp(iuX(t))]$, which can be obtained by first conditioning on the gamma distributed random time-change g_t and applying the characteristic function of a normal distribution, then using the characteristic function of a gamma distribution with shape and scale parameters νt and γ, respectively, to obtain

$$\psi_t(u) = -\nu t \times \ln\left(1 - i\frac{\theta_g}{\nu}u + \tfrac{1}{2\nu}\sigma_g^2 u^2\right) \tag{A2}$$

As in Madan et al. (1991, 1998), let the scale parameter γ=1/ν. To ensure positivity, let the debt's capacity ratio follows the semi-martingale process, i.e., $\exp\{iuX(t)\text{-}\psi_t(u)\}$ with u=1/i. It follows that the time-t debt's capacity ratio is

$$\alpha_t = \alpha_{t_0} \times \exp\left(X(t) + \nu t \times \ln\left(1 - \frac{\theta_g}{\nu} - \tfrac{\sigma_g^2}{2\nu}\right)\right) \tag{A3}$$

Let t_0=(i-1)Δt and t=$i\Delta t$, the logarithm of the ratio of the debt's capacity ratios in (7) can be obtained from (A3) and noting that $X(t)=\theta_g g_t+\sigma_g Z_g(g_t)$, the innovation $\varepsilon_i=\sigma_g Z_g(g)$ and $g=g(i\Delta t)\text{-}g((i\text{-}1)\Delta t)$. As g is the increment of a gamma process with shape parameter ν and scale parameter γ=1/ν, respectively, therefore, g is a gamma-distributed with shape parameter $\nu\Delta t$ and scale parameter γ=1/ν, respectively. As the innovation $\varepsilon_i=\sigma_g Z_g(g)$, therefore given the increment g, the innovation ε_i is Gaussian distributed. Eqs. (7)-(8) are derived.

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ESTIMATION OF PORTFOLIO RETURN AND VALUE AT RISK USING A CLASS OF GAUSSIAN MIXTURE DISTRIBUTIONS

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ABSTRACT

This paper deals with the estimation of portfolio returns and Value at Risk (VaR), by using a class of Gaussian mixture distributions. Asset return distributions are frequently assumed to follow a normal or lognormal distribution. It also can follow Brownian motion or Geometric Brownian motion based upon the Gaussian process. However, many empirical studies have shown that return distributions are usually not normal. They often find evidence of non-normality, such as heavy tails, excess kurtosis, finite moments, etc. We propose a class of Gaussian mixture distributions to approximate the return distributions of assets. This class of Gaussian mixture distributions, having good statistical properties, can accurately capture the above-mentioned statistical characteristics of return distributions. The model is applied easily to estimate the return distribution of a portfolio, and to evaluate the VaR. We demonstrate the model theoretically and provide some applications.

JEL: G10, G11, G32

KEYWORDS: Gaussian mixture distribution, convolution density, portfolio, Value at Risk

INTRODUCTION

In recent times, many works have focused on modeling asset return distributions, by assuming returns follow a Brownian motion or Geometric Brownian motion. It is therefore a Gaussian process with a time factor in its mean and variance or it follows a normal or lognormal distribution. In practice, the normality assumption of returns are usually rejected by statistical tests, such as the Jarque-Bera test (Jarque and Bera 1980), based on the kurtosis and the skewness of observed data. Due to non-normal evidence, such as heavy tails, excess kurtosis (Carol, A., 2004), some researchers simply assume that a financial return follows a distribution with heavy tails, such as the Student *t* distribution, a distribution derived from the Pearson VII family, or a Generalized Error Distribution (GED). However, it is difficult to use a single distribution family to approximate the return distribution with various distributional characteristics (McLachlan and Peel 2000, Tan 2005, Tan and Tokinaga 2006, Tan 2007a). In this paper, we propose a class of Gaussian mixture distributions to approximate the return distribution of an asset or portfolio. In our application, we also show how to evaluate the VaR using our proposed method.

The remainder of the paper is organized as follows. Next the relevant literature is presented. This is followed by a discusses of conventional distribution assumptions. Next the theoretical framework and some applications of our model are presented. The paper closes with some concluding remarks.

LITERATURE REVIEW

Many studies on modeling return distributions of financial assets have been conducted. Among them, the most used three-type distributions are the normal, the lognormal and the non-Gaussian stable distributions. Other types of distributions, such as the Student t, the skewed Student t, the generalized t, the Generalized Error Distribution (GED), the skewed GED, and mixture distribution of Gaussian distributions have been examined and proposed.

The normal distribution is one of the most commonly observed and applied distributions. It was widely used in the 1700's and successfully applied to astronomical data analysis by Karl Gauss in 1800, and became known as the Gaussian distribution. From the late 1960s, the empirical analyses failed to support the normal assumption on estimating the return distribution of real financial data. For example, Mandelbrot (1963) claimed that while financial prices (or its logarithm) following a Brownian motion is mathematically convenient, it is hard to fit the real financial data with this assumption. Meanwhile, Fama (1965) analyzed equilibrium asset pricing and observed that the daily return distribution follows a non-Gaussian distribution. Furthermore, both Mandelbrot (1963) and Fama (1965) have pointed out that excess kurtosis and heavy tails exist in real financial data.

Many empirical studies reject normality of returns. For instance, both Hsu, et al. (1974) and Hagerman (1978) carried out empirical studies and concluded that return distributions are non-normal. Bollerslev (1987) found leptokurtosis in monthly Standard & Poor's 500 Index returns. Kariya, et al. (1995) and Nagahara (1996) find the return distribution of Japanese stocks are fat-tailed and skewed. Kitagawa, Sato and Nagahara (1999) found that daily or weekly return distributions are not normal but fat-tailed and skewed according to observed financial data. Harvey and Siddique (2000), as well as Premaratne and Bera (2000) confirmed the asymmetry of return distribution exists in real business data. Recently, Gerig, Vicente and Fuentes (2009) presented a model that explained the shape and scaling of the distribution of intraday stock price fluctuations and verified the model by using a large database made up of several stocks traded on the London Stock Exchange. Their results showed that the return distributions for these stocks are non-Gaussian, similar in shape and appear to be stable over intraday time scales.

Thus, normality is not acceptable as a rational assumption for returns. In line with the empirical analyses, some researchers found that return distributions have heavy tails and then simply assumed the financial returns follow the Student t distribution. Blattberg and Gonedes (1974) claimed that the Student t distribution is more suitable to estimate return distributions. On the other hand, Seong and Sang (2007) employed a skewed Student t on the estimation of Value-at-Risk, for long memory volatility processes in Japanese financial Markets. Kercheval and Wu (2010) applied the skewed Student t to portfolio optimization, because the skewed Student t can capture the characteristics of the skewness of observed empirical distributions well. Glasserman (2003) also confirmed the basic settings of return distributions are crucial based on numerical approaches. He concluded that a slightly different setting can lead to a completely different risk measurement, since it uses the variances and covariances between all the component asset risks, or the historical data based Monte Carlo simulations.

In order to model the heavy-tailed behavior, Akgiray and Geoffrey (1988) and Nolan (1997) proposed a non-Gaussian stable distribution to describe a return distribution. However, a shortcoming of such a model is that a non-Gaussian stable distribution does not have finite moments. The estimates of variance and kurtosis tend to be increasingly large and not to converge as the sample size increases.

Since the 1980s, the inconsistency between the theoretical models and empirical analysis for the observed skewness and excess kurtosis has been well discussed. To model these statistical properties, Jarrow and Rudd (1982) suggested using an Edgeworth series expansion as well as the Gram-Charlier series to approximate the real distribution of asset returns when the real distribution is unknown. This approach also has been adopted in option pricing by researchers, such as Knight and Satchell (1997), and Corrado and Sue (1997). Although, these expansions can be used to approximate distributions, they are not popularly applied in real data analysis because of the difficulties in mathematical calculation and the existence of non-convergence.

Other proposed distributions to incorporate the observed skewness and excess kurtosis in the financial markets are skewed generalized t distribution, the Generalized Error Distribution (GED), the skewed GED, etc. For example, Theodossiou (1998) suggested using a skewed generalized t distribution which includes the Student t and skewed Student t to model return distributions. Furthermore, Theodossiou (2000) pointed out that a skewed GED fits the financial data well, while the asymmetry and excess kurtosis are observed in the financial data.

It has been shown that it is difficult to simply use a single distribution family to approximate return distributions with various distributional characteristics (McLachlan and Peel, 2000, Carol, 2004). Moreover, Tan (2005), Tan and Tokinaga (2006, 2007a) pointed out that conventional assumptions are inconsistent with the empirical analysis, since either a single distributional family assumption can hardly catch excess kurtosis and heavy tails, and having finite moments simultaneously. It is more complicated in some multimodal cases. Thus, serious estimation bias could be introduced when these assumptions are applied to risk measurement and management risk.

The estimation of Value at Risk (VaR) advocated by Jorion (1996) as a risk assessment tool at financial institutions strongly relies on the shape of a return distribution. For a normal distribution assumption, the VaR such as 1%, or 5% can be easily estimated. While compared to the normal case, a distribution with heavy tails such as a Student t distribution would yield a different estimate at the same percentage level. Also as shown in Zangari (1996), the VaR would be underestimated using a normal assumption under the circumstances of heavy tail phenomena. It might lead to a hefty loss in capital management.

Tan and Tokinaga (2007a) studied the statistical properties of a Gaussian mixture distribution and found that it can provide an accurate approximation for a probability distribution function for data with a complicated empirical distributional shape, by catching heavy tails behavior and excess kurtosis, being finite moments, even for the multimodal cases. This approach has been applied in the RiskMetrics™ (Longerstaey and More, 1995) advocated by Morgan (1996), namely, a Gaussian mixture distribution is utilized to reveal the fat-tailed behavior.

Moreover, a fat-tailed distribution corresponds to a jump process. For example, a return process follows a Geometric Brownian motion with a jump factor. As pointed out in Tan (2005), Tan and Tokinaga (2006, 2007a), in practice, the statistical characteristics, such as, skewed distributional shape, or heavy-tailed behavior, is easily modeled (captured) using a class of Gaussian mixture distributions, as well as a multimodal distributional shape. A mixture distribution has the flexibility to approximate various shapes of distributions, by adjusting its component weights and other component distributional parameters, such as mean and variance.

Furthermore, an effective method to estimate the tail distribution related to the rare events (for example, estimation of the VaR) through a simulation approach, is to use the Importance Sampling (IS) method (Glasserman, 2003, Tan and Tokinaga, 2007b). The IS method can not only reduce the size of simulation samples, but also improve the accuracy of the estimated probabilities. However, for some distributions, it is difficult to identify the optimal parameter in the IS method. But, when the probability density distribution (p.d.f.) of the return distribution is a Gaussian mixture distribution, Tan and Tokinaga (2007b), Tan, et al. (2011) showed that finding the optimal parameter in the IS method is guaranteed. It can increasingly improve the effectiveness of simulation compared to the standard Monte Carlo simulation.

These works have shown that a class of Gaussian mixture distributions can capture the distributional characteristics of various distributions by scaling different component distributions to adjust its statistical properties to meet the observed data, such as the combinational weights, means and standard deviations in this mixture distribution class to fit the real data. Also a Gaussian mixture has advantage in estimating the rare events.

Thus, in this paper, we propose a Gaussian mixture distribution to approximate the return distribution of an asset. We then extend our results and further theoretically show some good statistical properties of this class of Gaussian mixture distributions when used to estimate the return distribution of a portfolio or the VaR (Jorion, 1996). It can provide an accurate distribution approximation and keep the model easily useable in both academic research and business practice.

CONVENTIONAL DISTRIBUTION ASSUMPTIONS

In this section, we review the merits and demerits of conventional distribution assumptions for returns. Hereafter, the normal distribution, the lognormal distribution and the non-Gaussian stable distributions are referred to as conventional distributions. Each of them has its own merits and demerits when applied to estimate an asset return.

The merit the normal distribution is that it makes the return easily tackled. However, the disadvantages are: The simple return has lower bound is -1, but there is no lower bound in the normal distribution. If one-period simple return is normal, then the multi-period simple return is not normal. Empirical results do not support normality since excess kurtosis and heavy tails are well observed in returns.

The Lognormal distribution has the following merits: There is no lower bound in such a setting. It allows the multi-period also to be normally distributed. However, the disadvantage is that it cannot capture the characteristics of excess kurtosis and tail behavior in returns. Therefore, empirical analyses do not support log-normality either.

The merit of the Stable Distribution is it allows the sum of returns still belong to the stable family. It can also fit the tail behavior and catch the excess kurtosis well in some cases. While, the problem is that the non-Gaussian stable distribution has infinite moments. The estimates of variance and kurtosis tend to be increasingly large and not to converge as the sample size increases.

Except the above three conventional distributions, other distributional assumptions of assets returns have been proposed such as the Student t, the skewed Student t, the generalized t, GED, the skewed GED, which turn out to be very complicated distributional forms when applied to estimate the return distribution of a portfolio. Therefore, it is difficult to use merely one of these distribution families to approximate an asset/portfolio return distribution. A Gaussian mixture distribution is assigned to a return distribution of each asset in a portfolio so that a good estimation of the return distribution of a portfolio can be realized. Furthermore, when this class of Gaussian mixture distributions is applied to estimate a portfolio, the convolution of such a class of Gaussian mixture distributions yields the same class of Gaussian mixture distributions with new distributional parameters, namely, the weights, means and variances, which makes the model easily tackled. Our theoretical framework is summarized as follows.

THEORETICAL FRAMEWORK

Suppose we have return distributions $f_1(x)$, $f_2(x)$, … $f_m(x)$ for each investing period *j* (if the total investing periods are *m*). Each $f_j(x)$ is denoted as a Gaussian mixture distribution. Each $f_j(x)$ is a Gaussian mixture distribution of a portfolio return for the *jth* asset (if a portfolio is consisted of *m* component assets). Thus, we have

$$f_j(x) = \sum_{i=1}^{k} \alpha_{ij} f_{ij} \tag{1}$$

where $\alpha_{ij} > 0$, $\sum_{i=1}^{k} a_{ij} = 1$, f_{ij} is a component Gaussian distribution $N(\mu_{ij}, \sigma_{ij}^2)$ in the Gaussian mixture distribution. We now consider the total return distribution during *m* periods. Therefore, generally speaking, the return distribution is a convolution distribution of all *m* periods, an m-fold convolution. For simplicity, and without loss of generality, we just show the case when *m=2*.

Consider the convolution theorem. That is, the convolution of two Gaussian distributions with different means and variances, say, $x_1 \sim N(\mu_1, {\sigma_2}^2)$ and $x_2 \sim N(\mu_2, {\sigma_2}^2)$, results in a new Gaussian distribution with mean and variance equal to the summations of each mean and variance, respectively, namely:

$$g(z) = \int_{-\infty}^{\infty} g_1(z-x) g_2(x) dx = \frac{1}{\sqrt{2\pi}\sqrt{\sigma_1^2 + \sigma_2^2}} e^{-\frac{(z-(\mu_1+\mu_2))^2}{2\sqrt{\sigma_1^2+\sigma_2^2}^2}} \tag{2}$$

where $g_1(x)$ and $g_2(x)$ are the probability density function (p.d.f.) of random variables x_1 and x_2 , respectively.

Now consider the total return distribution within two periods, namely m=2. The p.d.f. of the total return within two periods then can be written as $p(z = x_1 + x_2)$, we then have:

$$p(z) = \int_{-\infty}^{+\infty} f_1(z - x) f_2(x) dx \tag{3}$$

However, the return distributions $f_1(x)$ and $f_2(x)$ are denoted as Gaussian mixture distributions, assuming the number of component Gaussian distributions are two, namely, k=2, we then have

$$x_1 \sim f_1(x) = \alpha_{11} f_{11} + \alpha_{21} f_{21}$$
$$x_2 \sim f_2(x) = \alpha_{12} f_{12} + \alpha_{22} f_{22}$$

It yields,

$$\begin{aligned} f(z) &= \int_{-\infty}^{\infty} f_1(z-x) f_2(x) dx \qquad (4) \\ &= \int_{-\infty}^{\infty} [\alpha_{11} f_{11}(z-x) + \alpha_{21} f_{21}(z-x)][\alpha_{12} f_{12}(x) + \alpha_{22} f_{22}(x)] dx \\ &= \int_{-\infty}^{\infty} \alpha_{11}\alpha_{12} f_{11}(z-x) f_{12}(x) dx + \int_{-\infty}^{\infty} \alpha_{11}\alpha_{22} f_{11}(z-x) f_{22}(x) dx \\ &\quad + \int_{-\infty}^{\infty} \alpha_{21}\alpha_{12} f_{21}(z-x) f_{12}(x) dx + \int_{-\infty}^{\infty} \alpha_{21}\alpha_{22} f_{21}(z-x) f_{22}(x) dx \end{aligned}$$

Equation (4) can be expressed by the summation of the following four terms:

Term 1: $\alpha_{11}\alpha_{12} \int_{-\infty}^{\infty} f_{11}(z-x) f_{12}(x) dx$

which means it follows the following Gaussian distribution with the weight $\alpha_{11}\alpha_{12}$

$$\alpha_{11}\alpha_{12} N(\mu_{11} + \mu_{12}, \sqrt{(\sigma_{11}^2 + \sigma_{12}^2})^2) \tag{5a}$$

Term 2: $\alpha_{11}\alpha_{22} \int_{-\infty}^{\infty} f_{11}(z-x) f_{22}(x) dx$

which means it follows the following Gaussian distribution with the weight $\alpha_{11}\alpha_{22}$

$$\alpha_{11}\alpha_{22}N(\mu_{11}+\mu_{22},\sqrt{(\sigma_{11}^2+\sigma_{22}^2)^2}) \tag{5b}$$

Term 3: $\alpha_{21}\alpha_{12}\int_{-\infty}^{\infty} f_{21}(z-x)f_{12}(x)dx$

which means it follows the following Gaussian distribution with the weight $\alpha_{21}\alpha_{12}$

$$\alpha_{21}\alpha_{12}N(\mu_{21}+\mu_{12},\sqrt{(\sigma_{21}^2+\sigma_{12}^2)^2}) \tag{5c}$$

Term 4: $\alpha_{21}\alpha_{22}\int_{-\infty}^{\infty} f_{21}(z-x)f_{22}(x)dx$

which means it follows the following Gaussian distribution with the weight $\alpha_{21}\alpha_{22}$

$$\alpha_{21}\alpha_{22}N(\mu_{21}+\mu_{22},\sqrt{(\sigma_{21}^2+\sigma_{22}^2)^2}) \tag{5d}$$

Each term above indicates that each part of the convolution operation corresponds to a newly weighted normal distribution. Moreover, for the summation of each weight of each distribution, we have

$$\begin{aligned}\sum w_{ij} &= \alpha_{11}\alpha_{12}+\alpha_{11}\alpha_{22}+\alpha_{21}\alpha_{12}+\alpha_{21}\alpha_{22}\\ &= \alpha_{11}(\alpha_{12}+\alpha_{22})+\alpha_{21}(\alpha_{12}+\alpha_{22})=(\alpha_{11}+\alpha_{21})(\alpha_{12}+\alpha_{22})=1\end{aligned} \tag{6}$$

This means that the convolution of Gaussian mixture distributions yields the same class of Gaussian mixtures as well, though, with some new distributional parameters. This result is also true in an m-fold convolution case. It is easier for one to use the mathematical induction to prove this general result.

Because we have obtained the convolution distribution of the total two periods, we now consider the probability of the return. The probability for the return of the total m periods larger than R can be estimated as

$$P(\sum_{j=1}^{m} x_j > R\ ) = 1-\int_{-\infty}^{R_0} f\ (z)dz \tag{7}$$

where *f(z)* is m-fold convolution density function, the return distribution of total m periods. Thus, the VaR can be also evaluated as

$$P(\sum_{j=1}^{m} x_j \le Q) = \int_{-\infty}^{Q} f(z)dz = \alpha \tag{8}$$

For example, for m=2, we have

$$P(x_1+x_2 \le Q) = 5\%$$

or inversely,

$$Q = F^{-1}(\alpha) = \inf\{x \in R \mid F(x) \geq \alpha) \tag{9}$$

Because the convolution distribution remains the same class of Gaussian mixture distributions, in Monte Carlo simulations one may simply generate the random numbers proportional to each component weight in the convolution distribution, to identify the return characteristics of a portfolio, or evaluate the VaR.

Furthermore, compared to other complicated distributions, in the case when one is applied to the return distribution of an asset, the Student distribution, for example. The convolution distribution of such a portfolio then turns out to be a complicated functional form. Usually a simple and distinct distribution function cannot be obtained under such a setting. Thus, it is difficult not only for one to do further theoretical research, but also in simulation studies, since it is not easy to generate random numbers from such a complicated convolution distribution function.

APPLICATION: RETURN AND THE VaR OF A PORTFOLIO OF M ASSETS

Suppose we have a portfolio of *m* assets and consider the return of the portfolio. We denote the investing weight on the *j*th asset as β_j, where $\sum_j \beta_j = 1$.

Let $z = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m$,

then we have

$$p(z) = p(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_m x_m) \tag{10}$$

By denoting $\beta_j x_j$ as z_j, we have the p.d.f. of z,

$$p(z) = p(z_1 + z_2 + \cdots + z_m) \tag{11}$$

It is an m-fold convolution as well. Since

$$\begin{aligned} x_1 &\sim f_1(x) = \alpha_{11} f_{11} + \alpha_{21} f_{21} + \cdots + \alpha_{k1} f_{k1} \\ x_2 &\sim f_2(x) = \alpha_{12} f_{12} + \alpha_{22} f_{22} + \cdots + \alpha_{k2} f_{k2} \\ &\cdots \\ x_m &\sim f_m(x) = \alpha_{1m} f_{1m} + \alpha_{2m} f_{2m} + \cdots + \alpha_{km} f_{km} \end{aligned} \tag{12}$$

For $z_j = \beta_j x_j$, it corresponds to a Gaussian mixture distribution as follows,

$$z_j \sim \alpha_{1j} N(\beta_j \mu_{1j}, \beta_j \sigma_{1j}^2) + \alpha_{2j} N(\beta_j \mu_{2j}, \beta_j \sigma_{2j}^2) + \cdots + \alpha_{kj} N(\beta_j \mu_{kj}, \beta_j \sigma_{kj}^2) \tag{13}$$

It yields $p(z) = p(z_1 + \cdots z_m)$ as a m-fold convolution with each Gaussian mixture distribution of z_j (j=1, 2,…, m).

Then, again, we get a new Gaussian mixture distribution from this convolution operation in just the manner noted above, and this new Gaussian mixture distribution remains the same Gaussian mixture class. Consequently, the probability for the return of this portfolio larger than R can be calculated as

$$P(\sum_{j=1}^{m} z_j > R\ ) = 1 - \int_{-\infty}^{R_0} f(z)dz \tag{14}$$

where *f(z)* is the m-fold convolution density function.

The VaR can be estimated as

$$P(\sum_{j=1}^{m} x_j \leq Q) = \int_{-\infty}^{Q} f(z)dz = \alpha \tag{15}$$

$$Q = F^{-1}(\alpha) = \inf\{x \in R \mid F(x) \geq \alpha) \tag{16}$$

In our previous studies (Tan, 2005, Tan and Tokinaga, 2006, 2007), we have applied the Genetic Algorithm (GA) to optimize the weights of components Gaussian distributions. GA is known as a tool of Artificial Intelligence (AI), and it has the capability to find out the global optimal solution, not getting stuck in a local optimal solution. Besides, GA has been also applied to many fields from engineering to social issues. Other methods such as the Markov Chain Monte Carlo (MCMC) method can also be applied. One may choose one of the available methods and apply it to one's problem at hand.

CONCLUDING REMARKS

In this paper, we proposed a class of Gaussian mixture distributions to estimate the return distribution of a portfolio and applied it in risk management, estimation of Value at Risk (VaR) for a portfolio. In our previous works, we have shown that a complicated return distribution having non-normal characteristics, such as heavy-tailed behavior, skewed distributional shape etc, can be accurately approximated using a class of Gaussian distributions (Tan and Tokinaga 2007a). Meanwhile various numerical applications, even for multimodal cases, have confirmed the effectiveness and accuracy of our proposed method (Tan and Tokinaga, 2007b, Tan, et al., 2011).

In this work, we extend our previous results and apply our method to the return of a portfolio and VaR. We have theoretically shown that a convolution distribution (return distribution of a portfolio) of several Gaussian mixture distributions (return distributions of component assets) yields a Gaussian mixture distribution as well. Such a good statistical property makes the model easily tackled. For example, in simulation studies, one may generate random numbers easily from such a class of Gaussian mixtures, by simply generating the random numbers proportional to the weight of each component Gaussian distribution, even in the case of estimating some rare events, such as the Value at Risk. Such a class of Gaussian mixtures can represent those non-normal phenomena in the return distribution of a portfolio, such as heavy-tailed behavior, skewness, and excess kurtosis accurately and keep the model simple.

It is no longer necessary to introduce any complicated distribution family, such as, the Student t, Generalized Error Distribution, to capture the statistical characteristics of financial returns, since it is difficult to fit the parameters in a complicated distribution and hard to accurately catch the statistical characteristics of returns using a single distribution family. Meanwhile, the use of a complicated distribution could introduce a convolution distribution for a portfolio with serious complicated function form, and makes it difficult to utilize in both academic research and business practice. However, using our proposed method, once the Gaussian mixture distribution of each individual asset is identified, one can obtain the return distribution of a portfolio. Namely, the combinational weights, and the distributional parameters (mean and variance of each component Gaussian distribution) are obtained automatically by our proposed convolution approach.

We have stated that a Gaussian mixture distribution can be estimated by Genetic Algorithm, or the Markov Chain Monte Carlo simulation. However, with the increased number of components the convergence speed for the parameters estimation could be greatly decreased. Future research will design and develop some parallel computation algorithms to solve this time-consuming problem.

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AN ECONOMETRIC ANALYSIS OF JAMAICA'S IMPORT DEMAND FUNCTION WITH THE US AND UK

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ABSTRACT

This paper investigates Jamaica's aggregate import demand function with the United States and the United Kingdom from January 1996 to September 2010 using cointegration analysis and error correction modeling techniques. Using real gross domestic product, relative price of imports, real foreign reserves and exchange rate volatility as our independent variables, evidence suggests a unique cointegrating relationship between imports and its regressors in both the US and UK models. We also examine the short-run and long run elasticities in both models. In the case of Jamaica-US trade, we find that income has a lower and negative elasticity in the short run compared with the long run. Relative prices are three times as elastic in the short run than in the long run. Volatility is negative in the long run, but positive in the short run. Foreign reserves behave the same irrespective of time. Overall, change takes place much faster in the long run than in the short run. In Jamaica-UK trade, GDP, and volatility are less elastic in the short run than in the long run, but real foreign reserves and relative price adjust much faster. Moreover, in contrast to the long run, real foreign reserves and volatility are both negative in the short run. Tight monetary policy has had a significant impact in the short run only in Jamaica's import demand function with the UK, but not with the US.

JEL: F14, F31, F43, O54

KEYWORDS: import demand, exchange rates, open economy growth, Jamaica

INTRODUCTION

Jamaica, an island economy, is one of the most trade-dependent countries in the world with total trade valuing 116.4 percent of GDP in 2006. Moreover, as a small, open economy with a narrow production base, it is technologically and structurally dependent on imports. In addition, because Jamaica, like most other developing countries, seeks to enhance its trade position in an interdependent globalized world, it is reasonable to study its import demand function. However, it is well understood that most empirical studies of aggregate import behavior have focused almost exclusively on developed countries, Latin America or Asia, while ignoring developing countries and island economies such as Jamaica. As such, the present study seeks to fill this gap in the literature.

The objective of this study is to estimate the import demand function for Jamaica with two of its top ten trading partners, namely, the US and UK for the period 1996 - 2010, for which reliable import data are available. The appropriate import demand function is estimated using the bounds testing approach to cointegration and the unrestricted error-correction model.

In the following sections, we begin with a brief history of Jamaica, after which we review the appropriate literature. Thereafter, we specify an import demand function for Jamaica. Subsequently we provide a description of the variables and data used for our model estimation. We then present and discuss our empirical results, after which the final section concludes the paper with policy recommendations.

LITERATURE REVIEW

Brief History of Jamaica

Jamaica is the third largest island of the Greater Antilles, and is the largest of the West Indian islands of the British Commonwealth Caribbean. It is situated in the middle of the Caribbean Sea on direct trade routes between North and South America and between Europe and Panama. Throughout the island's history, its location at the crossroads of the sea's communication routes has significantly influenced its history, political, economic, social, and professional development (Bakre, May 2008). Gaining independence from British colonialism in 1962, its political, social, and economic affairs reflect many of the post-colonial dilemmas of the third world as a whole (Payne, 1995).

Jamaica is classified by the World Bank as an upper-middle income developing country with real Gross Domestic Product (GDP) per capita of $5,906 in 2010 (The International Monetary Fund, 2011). Despite being a small open economy, Jamaica is highly developed compared to most Caribbean island economies. It has a vital financial sector with many international banks, a large skilled workforce, and a relatively broad-based economy (*All-Jamaica*, 2011). The island's economy, however, is beleaguered by serious long-term problems: a sizable trade deficit, inflation at 11.7%, unemployment rate of 13%, intense corruption, and a debt-to-GDP ratio that is currently estimated at 139.7 percent (IMF, 2011; World Bank, 2011). Jamaica's onerous debt burden, the fourth highest per capita, is the result of government bailouts to ailing sectors of the economy, most notably the financial sector during the 1990s (The Economy: Country Profile Jamaica, 2008). According to *Congressional Research Service* (2007), economic growth averaged 1.5% between 1990-2007, barely above the population growth rate. Major constraints for growth have included the country's vulnerability to external shocks and the large public debt burden (Brown, 2007; Sullivan, 2010).

According to Baker (2003), a significant portion of the economy is dependent on imported consumer goods and raw materials, and the propensity to import is high (Alleyne and Karagiannis, 2003). To finance the process the island is reliant upon foreign credit, foreign direct investments, and aid. Consequently, the last three decades have seen a downward trend in its external trade balance. For example, total imports in 2007 were valued at US$6.9 billion, and increased dramatically to US$8.4 billion in 2008 (Statistical Institute of Jamaica, 2011).

The United States is Jamaica's largest trading partner, accounting for approximately 50% of Jamaica's exports and 37% of its imports (Taylor, et. al, 2007; World Bank, 2010, Statistical Institute of Jamaica, 2011, Punke, 2011). Moreover, almost one million Jamaicans live in the US, and another million visit the US regularly. The UK, which hosts yet another million Jamaicans ranks in the top 10 of all Jamaica's imports, but most of this is in the form of consumer goods. The major commodities imported by Jamaica include food and other consumer goods, manufactured goods, industrial supplies, chemicals, fuel, parts and accessories of capital goods, machinery and transport equipment, and construction materials (Statistical Institute of Jamaica, 2011).

Given the importance of imports to the Jamaican economy's sustainability, it is imperative to understand its import demand function to inform appropriate public policy (Moore, Morris, & Simmons, 2009). However, international economic literature shows that many studies have investigated the import demand functions of developed countries, but not enough for developing island economies such as Jamaica. As such, this study attempts to understand the factors that influence the country's import demand through an empirical estimation of its determinants from the Q1:1996 to Q3:2010. The import demand function is estimated using the bounds testing approach to cointegration and the error correction model.

According to numerous scholars, including Modeste (2011), Thaver and Ekanayake (2010), Narayan and Narayan (2005), Tang (2002), Gafar (1995), Goldstein and Khan (1985), and Murray and Ginman (1976), traditional models estimate import demand as a function of relative prices and income (GDP), omitting changes in foreign reserves. Most of these models assume that macroeconomic variables are stationary, but evidence indicates the contrary, namely, that macroeconomic time series are typically non-stationary, exhibiting high serial correlation between successive observations. This implies that the *t* and F tests are incorrect and lead to false conclusions and spurious regression problems (portrayed by a high R^2 value and a statistically significant Durbin-Watson statistic) (Dolado, Gonzalo, & Marmol, 1999; Dutta and Ahmed, 1999).

As a result, following recent studies to correct for "stationary" assumptions, a cointegration method, which focuses on the econometric implications of non-stationarity, is applied in the present study. This model has been applied by a host of other scholars, among them, Modeste (2011), Hye and Mashkoor (2010), Thaver and Ekanayake (2010), Ghorbani and Motalleb (2009), Rehman (2007), Narayan and Narayan (2005), Chang, Ho and Huang (2005), Dash (2005), Razafimahefa and Hamori (2005), Tang (2002, 2003), and Dutta and Ahmed (1999).

Modeste (2011) provides estimates of income and price elasticities of the disaggregated import demand in Guyana, Jamaica, and Trinidad and Tobago, using a bounds test for cointegration during the period of 1968-2006 for Guyana and Trinidad and Tobago, and 1970 – 2006 for Jamaica. Empirical results indicate the existence of a long-run relationship between the demand for imports and its determinants. The short-run dynamic coefficients reflect theoretically expected signs and are statistically significant at the 10% level. The long-run and short-run results indicate an inelastic but positive impact on import demand of an increase in consumption, investment, and/or exports. However, the import content value is highest for exports. The relative price elasticity of imports is an important determinant of import demand in all three countries. Our current study analyzes the aggregate import demand function of Jamaica, rather than its disaggregated function, thus adding to the literature.

Narayan and Narayan (2005) estimate the disaggregated import demand function for Fiji for the period 1970-2000. Employing the bounds testing procedure developed by Pesaran et al. (2001) within an autoregressive distributed lag framework (ARDL), they find that there exists a unique cointegration relationship among the variables when import demand is the dependent variable. Overall, this study reveals that total consumption, investment, and exports have inelastic and positive impacts on import demand, while an increase in relative price induces fewer imports.

Tang (2002) assesses the long-run aggregate import demand function for Hong Kong using a more robust estimation method for cointegration, based on the estimate of an Error Correction Model. Empirical results strongly revealed that the Hong Kong's aggregate imports demand and its determinants, real income and relative prices are not cointegrated. In the short run, the volume of import demanded is only responsive to real income, with an estimated elasticity of 1.1.

Tang (2003) utilizes the method of cointegration to examine China's aggregate import demand function for the period 1970–1999. In addition to the traditional arrangement for the import demand function, the author includes additional factors believed to have an effect on domestic activity. These include national cash flow, and final expenditure components. Empirical results indicate a long-run equilibrium relationship between these measures of domestic activity and China's import demand. In general, domestic activity and relative prices are inelastic in the long run.

Dutta and Ahmed (1999) express skepticism about the validity of the empirical results of earlier studies on estimating and testing of an aggregate import demand function for Bangladesh. As such, their paper examines the existence of a long-run aggregate merchandise import demand function for Bangladesh from 1974-94, using cointegration techniques developed by Engle and Granger (1987), Johansen (1988, 1991) and Johansen and Jusulius (1990). In addition, the authors seek to estimate an error-correction model (ECM) to integrate the dynamics of short-run changes with long-run level processes. Empirical results confirm other studies of a unique long-run relationship among real quantities of imports, real import prices, real GDP, and real foreign exchange reserves.

Hye and Mashkoor (2010) estimate the aggregate import demand function for the Bangladesh economy using data from 1980-2008, utilizing the autoregressive distributed lag (ARDL) approach to cointegration. The empirical evidence confirms a long run relationship between imports, national income, and relative price. GDP is positive and slightly inelastic while relative price elasticity is negative in the long run.

Chang, Ho and Huang (2005) assess the aggregate import demand function for South Korea from 1980 to 2000. Results show that the volume of imports, income, and relative prices are all cointegrated. The estimated long-run (short-run) elasticities of import demand with respect to income and relative price are 1.86 (0.86) and -0.2 (-0.05), respectively.

Thaver and Ekanayake (2010) empirically analyze South Africa’s aggregate import demand function for the period 1950 to 2008. They include foreign reserves as in independent variable in their model, unlike previous studies, because they argue that foreign reserves positively influence import demand. Their results suggest a long-run cointegrated relationship exists between import demand and its determinants. However, their study reveals that apartheid has had a significant short-run negative impact on import demand, but is insignificant in the long run. Furthermore, international sanctions affected import demand positively in the short-run, but negatively in the long run.

Dash (2005) investigates the behavior of the aggregate demand function for India using yearly time series data, carrying out the Johansen multivariate cointegration technique during the period 1975 - 2003. The results yielded from this study suggest that import demand is largely explained by price of domestically produced goods, GDP, lag of import and foreign exchange reserves.

Razafimahefa and Hamori (2005) determine the specific import demand function of each of two countries namely, Madagascar and Mauritius, by applying the ‘bounds test’ method of Pesaran et al. (2001). The study confirms the existence of a cointegration relationship and finds that the long-run income and price elasticities are, respectively, 0.855 and 20.487 for Madagascar and 0.671 and 20.644 for Mauritius. Both economies’ imports respond similarly to relative prices.

Tang (2002) empirically investigates the long-run relationship between Indonesian aggregate import demand and its determinants, namely real income and relative import prices. In contrast to previous studies (Reinhart, 1995; and Senhadji, 1998), the result of the bounds test (Pesaran et al., 2001) reveals that import volume, real income, and relative import prices are cointegrated. This is an important finding from the viewpoint of the Indonesian economic policy. The estimated long-run elasticity of real income and relative price are 0.98 and –0.4 respectively, indicating that the imports are more responsive to the former than the latter.

Rehman (2007) investigates the aggregate import demand function for Pakistan by employing the Johansen multivariate cointegration technique on annual data for the period 1975-2005. He also utilizes the Augmented-Dickey Fuller (ADF) and Phillips-Parren (PP) tests to determine the order of integration. Results show that there is a long-run equilibrium relationship among variables and the stability tests indicate that import demand function remains stable over the sample period and hence the estimated results are appropriate for policy implications. The elasticities estimated indicate that changes in real income and import prices significantly affect import demand in the long run, but not in the short run. The long-run inelasticity of income implies that imports are considered necessary goods in Pakistan.

Ghorbani and Motalleb (2009) estimates Iran's import demand function for the period of 1960-2005. The determinant variables to determine the respective model include imports, GDP, partial productivity of labor, and the official exchange rate. The Pesaran et al. (2001) method, based on Auto Regressive Distributed Lag (ARDL) reveals that import demand is positive and elastic with respect to GDP.

This study, in line with previous studies, will investigate Jamaica's long-run import demand function and its associated short-run dynamics for the period 1996-2010 with the US and the UK. This import demand function is estimated using the bounds testing approach to cointegration and the unrestricted error-correction model. The dependent variable is real imports, and the regressors are real GDP, relative price of imports, real foreign reserves, and a dummy variable representing the period of tight monetary policy in Jamaica (2000-2010).

MODEL SPECIFICATION AND METHODOLOGY

Because Jamaica is a price taker in international markets (Robinson, 2001), the world supply of imports to Jamaica is perfectly elastic, and therefore we consider using single equation techniques for estimating its aggregate import demand function. As in Thaver and Ekanayake (2010), we assume that only normal goods are imported, and that as a developing country, real imports, GDP, relative price, foreign reserves, and exchange rate volatility are crucial variables in our model because the effectiveness of import trade policy is heavily dependent upon the size of their respective elasticities. Jamaica in 2000 also implemented tight monetary policy that affected import demand, and we capture the impact of this policy on our model in the form of a dummy variable. Consequently, the long-run aggregate import demand function for Jamaica, in natural logs, is identified below:

$$lnM_t = B_0 + B_1 \ln RGDP_t + B_2 lnRP_t + B_3 lnRFR_t + B_4 lnVOL_t + B_5 D_t \ + \varepsilon_t \quad (1)$$

In Equation (1) in period *t*, the dependent variable M_t represents the real import volume, and the independent variables used to predict it include $RGDP_t$, the real GDP; RP_t is the relative price of imports; RFR_t is the real foreign reserves; VOL_t is the exchange rate volatility; D_t and ε_t represent the dummy variable the error term, respectively.

The first variable $RGDP_t$ in the specified model measures the real GDP of Jamaica. Economic theory suggests that income of the importing country is a major determinant of a country's imports and has a positive impact. Thus, we expect that $\beta_1 > 0$. The second explanatory variable RP_t, measures the relative price of imports and is calculated as the ratio of import price to domestic price. Economic theory posits that an increase in the relative price of imports discourages imports so β_2 is expected to be negative. The third explanatory variable, RFR_t measures the availability of foreign reserves, which can be used to Jamaica's ability to import. This variable does not appear in the traditional import demand function. However, it is an important determinant of imports for developing countries. Since higher real foreign reserves tend to encourage imports, we would expect that $\beta_3 > 0$ (Thaver and Ekanayake, 2010). The fourth explanatory variable, VOL_t measures the standard deviation of real exchange rate between Jamaica and its trading partners. The volatility of exchange rates is the source of exchange-rate risk and has certain implications on the volume of international trade. As such, we do not have prior expectation of the sign of β_4. The expected signs of β_1, β_2, and β_3 are borne out in empirical results by numerous scholars, among them, Modeste (2011), Hye and Mashkoor (2010), Thaver and Ekanayake (2010), Ghorbani and Motalleb (2009), Rehman (2007), Narayan and Narayan (2005), Chang, Ho and Huang (2005), Dash (2005), Razafimahefa and Hamori (2005), Tang (2002, 2003), and Dutta and Ahmed (1999). The effects of tight monetary policy on import demand may be assumed to be negative and therefore we expect that $\beta_5 < 0$.

To distinguish the short-run effects from the long-run trend, Equation (1) must be specified in an error correction model (ECM) format following Pesaran, et al. (2001), which has been used in many recent studies, including Thaver & Ekanayake (2010), Chang, Ho, & Huang (2005), Tang (2002), and Dutta & Ahmed (1999). Equation (1) is therefore rewritten in an ECM format in Equation (2) below:

$$\Delta \ln M_t = \alpha_0 + \sum_{i=1}^{n} \beta_i \Delta \ln M_{t-i} + \sum_{i=0}^{n} \gamma_i \Delta \ln RGDP_{t-i} + \sum_{i=0}^{n} \delta_i \Delta \ln RP_{t-i} + \sum_{i=0}^{n} \eta_i \Delta \ln RFR_{t-i} + \sum_{i=0}^{n} \psi_i \Delta \ln VOL_{t-i}$$
$$+ \alpha_1 D_{1t} + \lambda_1 \ln M_{t-1} + \lambda_2 \ln RGDP_{t-1} + \lambda_3 \ln RP_{t-1} + \lambda_4 \ln RFR_{t-1} + \lambda_5 \ln VOL_{t-1} + \omega_t \quad (2)$$

All variables are defined as before, except the first difference operator, which is Δ. The bounds testing approach of Pesaran et al's (2001) is based on two destinctive routine steps. Step one involves using an F-test or Wald test to test for joint significance of no cointegration, $H_0 : \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0$, against an alternative hypothesis of cointegration, $H_1 : \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 = \lambda_5 \neq 0$. This test is performed using Equation (2). Pesaran, et al. (2001) provides two sets of critical values for a given significance level with and without a time trend. As such, it is assumed that variables are I(0) and I(1). And if the calculated F-values surpasses the upper critical bounds value, H_0 is rejected signifying cointegration among the independent variables; if the F-value falls below the critical bounds values, we consequently reject H_0, and lastly, if the F-statistic falls within the bounds, the result is inconclusive. Following evidence of cointegration, the next logical step involves estimating the short-run and long-run coefficients of the cointegrated model (Pesarin et. al., 2001).

DATA SOURCES AND VARIABLES

Quaterly data for the period Q1:1996 to Q3:2010 are used in our model. The data on nominal imports, the import price index, real GDP, foreign exchange reserves series, GDP deflator, and domestic price index are taken from the International Monetary Fund's *International Financial Statistics Yearbook* (2011). Nominal imports measured in Jamaican Dollars (JMD) are deflated by the GDP deflator to derive the real import variable for Jamaica. The real GDP variable is computed in millions of 2005 constant JMD. The relative price of imports series is constructed as the ratio of the CPI of the exporting country (2005=100) to domestic CPI, as measured by the consumer price index (CPI: 2005=100). To obtain the real foreign reserves series, we deflate the nominal foreign reserves series by Jamaica's GDP deflator.

EMPIRICAL RESULTS

Cointegration among Variables

To determine if cointegration exists between the dependent and independent variables, a bounds test is executed. To establish the bounds test for cointegration between variables, the Wald test is carried out to determine the joint significance of the lagged level variables. This is done by comparing the computed *F*-statistics against its critical values set by Pesaran et al. (2001). These authors tabulate an upper bound critical value, assuming all variables to be I (1), and a lower bound critical value, assuming all variables to be I (0). As can be seen in Table 1, the calculated *F*-statistic for Jamaica-US is 6.613, and for Jamaica-UK, it is 16.413. Both these estimates are higher than the upper bound critical value of 5.06 at the 1 per cent level of significance. This result implies that the null hypothesis of no cointegration cannot be accepted for Jamaica in its trade with the US and the UK, and a unique cointegration relationship between imports and its determinants is observable.

Table 1: *F*-test Results for Cointegration: Jamaica-US and Jamaica-UK Trade

Critical value bounds of the F-statistic: intercept and no trend						
	10 percent level		5 percent level		1 percent level	
K	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
4	2.45	3.52	2.86	4.01	3.74	5.06
Calculated F-statistic:						
$F_M(M \mid RGDP, RP, RFR, VOL)$			6.613***(US)	16.413***(UK)		

*Note: This table shows the results of the ARDL bounds testing for cointegration. The Critical values are from Pesaran, Shin, and Smith (2001, Table CI (iii) Case III, p. 300). k is the number of regressors. *** indicates the statistical significance at the 1 percent level.*

Long-Run and Short-Run Elasticities

After establishing the existence of a long-run cointegrated relationship between import demand and its determinants, we estimate the long- and short-run elasticities. These results are presented in Tables 2 & 3. Table 2 shows that aggregate imports are mainly determined by real GDP in the Jamaica-US trade relationship, with a 1% increase in GDP yielding a 5.84% increase in import demand. In the case of Jamaica-UK however, while the relationship is elastic (2.41), it is not significant in the long run.

Table 2: Long-run Elasticities for Jamaica's Import Demand Function with the US and UK

Dependent variable: LnM				
	United States		**United Kingdom**	
Explanatory Variables	**Coefficient**	***t*-statistic**	**Coefficient**	***t*-statistic**
Constant	64.853***	-4.240	-30.174	-1.621433
$lnRGDP_t$	5.836***	4.361	2.407	1.562121
$lnRP_t$	0.683**	3.005	0.931***	3.787455
LnRFRt	0.114	0.567	0.441**	2.211998
$lnVOL_t$	-0.081	-0.972	0.106**	2.158203
D_{1t}	-0.217	-1.412	-0.131	-0.740401
Adjust. R-squared ($\bar{R}^2$)	0.516		0.618	

*Note: This table shows Jamaica's long-run elasticities of the estimated import demand functions with the US and UK. *** and ** indicate statistical significance at the 1% and 5% level, respectively.*

Relative price for both trading partners is highly significant, but has a positive effect on import demand, rather than the expected negative relationship. Import demand from the US, while inversely related to volatility is highly inelastic (-0.08) as expected, but not statistically significant in the long run. In the case of the UK, it is positive, inelastic (.106), and significant. Foreign reserves, while meeting theoretical expectations, also differs for the US (0.11, not significant) and the UK (.44, significant). Reasons for these differences point to the fact that Jamaica is import dependent on capital goods and raw materials (Baker, 2003; World Bank, 2010,2011; Statistical Institute of Jamaica, 2011), and since these come mostly from the US, a change in foreign reserves will not significantly affect imports from the US. This result also reinforces the fact that the US is Jamaica's largest trade partner, whereas the UK lingers around 6^{th} and 7^{th} (Taylor, et. al, 2007; Statistical Institute of Jamaica, 2011). Further, Jamaica is a beneficiary of the Caribbean Basin Initiative (CBI), a U.S. preferential trade agreement (Sullivan, 2010), but there is no such agreement with the UK, revealing that Jamaica is less flexible and therefore, more dependent on trade with the US than the UK.

The coefficient for D_{1t} in Table 2 for both countries is negative (-0.22, US; -0.13,UK) but insignificant, implying that the restrictive monetary policy of 2000 intended to curb the demand for imports has been ineffective in impacting Jamaica's import demand function in the long-run. In the long run model, adjusted $\overline{R}^2$ is sufficiently high for both countries indicating that the independent variables adequately explain the long-run elasticities in Jamaica's import demand with the US and UK.

Short-run elasticities are presented in Table 3. In the case of trade between Jamaica and the US, income has a lower elasticity in the short run and is negative (-4.99) in contrast to the long run (5.58). Relative prices are three times as elastic in the short run (2.07) than the long run (.68). Volatility has a much smaller effect on imports, but it is negative in the long run (-.08) and positive in the short run (.047), which conforms to other empirical studies. Foreign reserves behave the same irrespective of time. In Jamaica-UK trade, volatility is less elastic in the short run (-.088) than in the long run (.11); real foreign reserves and relative price adjust much faster in the short run than in the long run. Moreover, unlike the long run, real foreign reserves, and volatility are both negative in the short run.

Table 3: Error-Correction Model – Jamaica's Short Run Elasticities

Dependent variable: ΔlnM				
	United States		**United Kingdom**	
Explanatory Variables	**Coefficient**	**t-statistic**	**Coefficient**	**t-statistic**
Constant	0.000	0.000	0.000	0.000
ΔlnIMPt-*i*	0.354***(4)	3.365	0.126 (3)	1.421
ΔlnRGDPt-*i*	-4.990***(3)	-3.251	11.63*** (4)	2.809
ΔlnRPt-*i*	2.068**(3)	2.260	3.614 (2)	1.600
ΔlnFRt-*i*	0.161 (1)	1.476	-0.900***(3)	-3.081
ΔlnVOLt-*i*	0.0467(1)	1.158	-0.0875 (3)	-1.526
Dt	-0.133***	-3.509	-0.168**	-2.057
ECMt-1	-0.610***	-6.024	-1.285***	-9.512

*Note: This table shows the results of the short-run elasticities of the error-correction model.***, **, and * indicate statistical significance at the 1% 5%, and 10% level, respectively. Number of lags is indicated in parenthesis.*

D_1 in Table 3, in contrast to Table 2, is significant for Jamaica-UK, but remains insignificant for Jamaica-US. That is, tight monetary policy has had a significant impact on Jamaica's import demand function with the UK, but not with the US in the short run. Our earlier assertion that Jamaica is more dependent upon trade with the US than the UK has been reinforced by these results. The error correction term, ECM_{t-1}, is negative and statistically significant, making certain that the series is non-explosive, and that long-run equilibrium is attainable for both countries. However, once the model in Equation (2) is shocked, convergence to long run equilibrium after the shock is slower in Jamaica-US trade with only 61% of the adjustment occurring in the first year. In Jamaica-UK relations, the adjustment process is very fast at 128%, twice the rate of the US, meaning that it takes less than one period to completely adjust to a previous period's shock.

Table 4 shows the results of diagnostic tests that we ran on our short-run model. These tests include the Durbin Watson (DW) test, the Breusch-Godfrey test (BG), the RESET test for correct model specification, the Jarque Bera (JB) normality test for the error term, and lastly, the Augmented Dickey-Fuller test (ADF). The results are ambiguous. While our model representing Jamaica-US reveals that the model is overall well behaved, the Jamaica-UK model is less clear-cut, with the RESET and ADF tests showing significance at the 5% and 10% levels. Moreover, the adjusted R^2 in both countries is large enough to indicate that the variation in import demand is explained by the variables in the model.

Table 4: Results of the Diagnostic Test for the Selected ARDL Model

	United States		United Kingdom	
Explanatory Variables	Coefficient	p-value	Coefficient	p-value
R^2	0.626		0.708	
$\overline{R}^2$	0.559		0.653	
Durbin Watson Test	2.224	p-value: 0.668	1.827	p-value: 0.216
Breusch-Godfrey Test	3.442	p-value: 0.016	1.793	p-value: 0.150
Reset Test	0.351	p-value: 0.706	3.786	P-value: 0.031
Jarque Bera Test	1.937	p-value: 0.380	3.988	p-value: 0.136
Augmented Dickey-Fuller Test	2.408	P-value: 0.537	-3.191	p-value: 0.098

CONCLUSIONS, LIMITATIONS, AND SUGGESTIONS FOR FUTURE RESEARCH

This study estimates an aggregate import demand function for Jamaica for the US and the UK from January 1996 to September 2010, utilizing the bounds testing approach to cointegration. Evidence suggests that a unique cointegration relationship between imports and its regressors, real GDP, relative price of imports, real foreign reserves, and exchange rate volatility, exists. In addition, the independent variables explain the model well in both countries as indicated by the adjusted R^2 values.

In Jamaica-US trade, GDP affects imports negatively in the short run but positively in the long run. Imports are more responsive to changes in relative prices in the short run than the long run. Volatility has a greater impact on imports in the long run. Foreign reserves behave the same irrespective of time. In Jamaica-UK trade, GDP and volatility are less elastic in the short run than in the long run as expected, but real foreign reserves and relative price adjust much faster. Furthermore, D_1 reveals that tight short-run monetary policy significantly influences Jamaica's import demand function with the UK but not with the US because of its greater dependence upon trade with the US.

From a policy perspective, it is necessary for Jamaica to adopt monetary and fiscal policies to reduce its imports of capital and intermediate goods, especially oil, while simultaneously focusing on diversifying its export base. Strengthening trade relations with other island countries such as Trinidad and Tobago will reduce its dependency on the US. Creating a regional currency with island trading partners could possibly reduce its dependence on imports from the US and UK through higher exchange rates, foreign reserves, and in turn, a better balance of payments.

This study is one of only three studies to focus on the import demand function for Jamaica, a developing island economy. Our results provide fodder for further research that could overcome the limitations of the present model. Since our diagnostic tests were not all according to theoretical expectations we would have to reconsider what independent variables would provide better explanatory value. In the case of Jamaica-US model, we may want to eliminate volatility and D_1 since they are both not significant in the short and long run. In the case of Jamaica-UK, since GDP is not significant in the long run, and since mostly consumer goods are imported, disaggregating GDP into its component parts may yield better results. In addition, since Jamaica has been characterized by an increase in crime, which has affected its trade structure, future studies could include the crime rate as a dummy variable to capture its effect on import demand, allowing for possibly more robust results.

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THE DETERMINANTS OF CASH FOR LATIN AMERICAN FIRMS

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ABSTRACT

We examine the levels and determinants of cash in Latin America. Latin American firms, as opposed to U.S. firms, did not hoard cash during the 1995-2006 period. However, we find remarkable similarities with respect to the determinants of cash between U.S. and Latin American firms. Net working capital, capital expenditures and net leverage all decrease the levels of Latin American firms' cash balances while growth opportunities increase them. Contrary to theoretical expectations, firm size and dividend payments seem to increase Latin American firms' need for cash whereas cash flow volatility does not seem to affect cash levels. We provide a possible explanation for these deviations by disaggregating results by countries and industries.

JEL: G3, G32.

KEYWORDS: Finance, Cash Management, Working Capital, Latin American Firms.

INTRODUCTION

Until recent, corporate finance literature had mainly focused on the study of long term financial decisions. However, with the latest market crashes triggered by lack of financing and liquidity, cash management has gained attention among practitioners and researchers, both in the U.S. and worldwide. Previous research on non-U.S. cash holdings has shown that cash management practices vary around the world as financial markets are segmented and financing and corporate governance realities differ among countries. Our article examines the levels and determinants of corporate demand for cash for Latin American firms. Specifically, we study firms from Argentina, Chile, Mexico, and Peru as the typical academic study on foreign cash holdings does not include all these Latin American countries or, if it does, it includes a relatively small number of firms (Gruninger and Hirschvogt (2007); Lins, Servaes and Tufano (2007)) or periods (Dittmar, Mahrt-Smith and Servaes (2003)). To our knowledge, the use of cash by Latin American firms has not been studied in detail before.

We obtain financial and accounting data for 518 firms from the Economatica database. We describe the levels of cash holdings for the 1995-2007 period and compare them to the dramatic increasing cash holdings of U.S. firms documented by Bates, Kahle and Stulz (2009). Levels of cash and net leverage differ considerably between these two groups. Latin American firms hold significantly less cash and rely more heavily on debt than American firms for the same period. When the results across countries are disaggregated, we find consistent cash holdings patterns across most of our sample of Latin American countries.As for the determinants of cash, we based our empirical model on Opler, Pinkowitz, Stulz and Williamson (1999) and Bates, Kahle and Stulz (2009). We had expected interesting results since Latin American firms operate in a mixed financing environment. Chile (222 firms), Peru (173) and México (127 firms) have more developed capital markets than Argentina (89 firms) as measured by the number of equities (stated in parentheses) listed on each country stock exchange, in accordance to Economatica. All these countries have a common legal origin, the French Civil Law. French Civil Law countries have both weak investor protection and less developed capital markets compared to Common Law countries. Such environment is expected to impact Latin American firms' capital structure and thus their financing (La Porta, Lopez-de-Silanes, Shleifer and Vishny (1997)). However, contrary to our expectations, the results show that the determinants of cash for Latin American firms share a remarkable similarity to the determinants of cash for U.S. firms, which operate in a common law country. Net working capital, capital expenditures, and net leverage all decrease levels of Latin American firms' corporate cash while growth opportunities increase it. In contrast to the case for U.S. companies, firm size and dividend payments increase Latin American firms' need for cash. The influence of idiosyncratic risk as measured by cash flow volatility is inconclusive.We organize the article as follows: In the next section, we provide the literature review and hypotheses development. A description of the sample and methods follows. We then present the empirical results and finally provide concluding remarks.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Corporate managers hold cash for a mixture of reasons. Motivated by legitimate reasons, firms may elect to hold cash to avoid selling non-cash assets under unfavorable conditions (the transaction motive, stated by Keynes (1936) and supported by Baumol (1952)), to deal with adverse shocks when access to capital markets is restricted or too costly (the precautionary motive, in accordance to Keynes (1936) and Myers and Majluf (1984) and supported by Opler, Pinkowitz, Stulz and Williamson (1999), Han and Qiu (2007), Kim, Mauer and Sherman (1998), among others) or to avoid taxes on remitted earnings as it is the case of U.S. multinational corporations (Foley, Hartzell, Titman and Twite (2007)).

But firms may also hold cash to follow entrenched managers' agendas, to the detriment of shareholders (the agency motive, avowed by Jensen (1986)). In the U.S., firms with poor corporate governance mismanage cash by quickly increasing capital expenditures and acquisitions (Harford (1999), Dittmar and Mahrt-Smith (2007), and Harford, Mansi and Maxwell (2008)). Not surprisingly, given the differences in financial systems and corporate governance mechanisms around the world, non-U.S. cash studies have found differences in cash holdings across countries. Firms operating in countries with more developed banking systems tend to hold more cash, as they have more difficulty raising external financing and rely more on bank financing for their short term needs. Likewise, firms in market-based economies tend to obtain financing mainly from capital markets (Pampillón (2000)). Nonetheless, these predictions are not conclusive as empirical results are not consistent across countries. For example, Pinkowitz and Williamson (2001) find that industrial firms in Germany and Japan, both countries characterized as having bank centered systems, differ importantly on their levels of cash holdings.

While German firms' cash holdings are similar to American firms', Japanese firms' cash holdings are significantly higher than American firms'. Thus, Pinkowitz and Williamson's results imply that whether firms are immerse on a bank centered or market centered system is not enough to infer the level of cash holdings in their balances. However, when corporate governance characteristics are incorporated into the analysis, as is the case in Dittmar, Mahrt-Smith and Servaes (2003), firms are found to hold more cash when debt markets are more developed. Researchers have also found that firms in countries with the lowest level of shareholder protection hold more cash than firms in countries with the highest level of shareholder protection and that managerial entrenchment, with its associated agency costs, is linked to higher levels of cash holdings, especially when country's level shareholder protection is weak (Dittmar, Mahrt-Smith and Servaes (2003), Kalcheva and Lins (2007)). In addition, the value of corporate cash holdings is lower in countries with poor investor protection (Pinkowitz, Stulz and Williamson (2006)) and abundant cash bundled with asymmetric information has been found to lead firms to take excessive risks and, in consequence, lower the marginal value of their cash holdings (Gruninger and Hirschvogt (2007)). Thus, overall, the academic literature supports that the differences in corporate governance systems across countries are an important determinant of cash holdings.

In recent studies, as a response to practitioners' concerns, the empirical question of interest has been why firms hold so much cash. Bates, Kahle and Stulz (2009) document that the average cash-to-assets ratio for U.S. industrial firms has more than doubled from 1980 to 2006. They find that cash holdings do not increase for older, established dividend paying firms but they increase dramatically for firms that do not pay dividends. In addition, they document that these high-cash holding firms have reduced their net working capital and experienced an increase in cash volatility, a decline on capital expenditures and an increase on research and development (R&D) expenditures. By and large, their findings are not explained by agency motives but rather by the precautionary motive of holding cash. In this framework, and consistent with Myers and Majluf (1984) and Myers (1997) we expect that firms with better investment opportunities and higher expected agency costs of debt to hold more cash. Small firms are subject to more information asymmetry than large firms are; hence, small firms face more borrowing constraints, higher costs of external financing and should hold more cash. In addition, firms with more volatile cash flows require larger investments in cash (Kim, Mauer and Sherman (1998)). The level of cash is expected to decrease as leverage increases, since the riskier the firm becomes, the costlier is to borrow liquid funds. Therefore, the level of cash borrowed should decrease (Baskin (1987)).

DATA AND METHODOLOGY

We use financial accounting and market data from Economatica, the largest subscription-based database for Latin American publicly traded firms, for the period 1995 to 2007. Economatica includes firms from Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela in a standardized format, which allows comparison across firms, countries, and industries. The industry classification provided by this database is similar to a 3-digit Standard Industrial Classification (SIC). In this study, we use information from four selected countries: Argentina, Chile, Mexico, and Peru. Colombian firms were excluded since the variable depreciation, needed to construct some variables in our models (i.e., cash flow and capital expenditures), was not reported in the database. Similarly, dividends were not available for Venezuela. Firms from Brazil were also excluded as they outnumber the firms listed in any of the other countries. As financial statements of firms in financial industries differ from those of the rest of industries this study covers all but financial industries. In order to explore the determinants of cash for Latin American firms, the following empirical model is estimated on a panel data using both pooled OLS and fixed effects,

$$CASH = \alpha + \beta_1 MB + \beta_2 SIZE + \beta_3 CAPEX + \beta_4 NETLEV + \beta_5 CFVOL + \beta_6\, NWC + \beta_7 DIV + \beta_8 INDUSTRY + \beta_9 COUNTRY + \varepsilon_i\,, \quad (1)$$

where variable *CASH* is the ratio of cash to assets net of cash (i.e., the cash ratio). Cash is defined as the sum of cash and short-term investments. *MB* is market to book value, the proxy for growth opportunities, measured as book value of assets minus book value of equity plus market value of equity all divided by assets. Firm size, *SIZE*, is the natural logarithm of the book value of assets. *CAPEX* is the ratio of capital expenditures (i.e., the change of net fixed assets plus depreciation) to book value of assets. *NETLEV* is net leverage, the ratio of net debt (i.e., net of cash) to assets. *CFVOL* is cash flow volatility, the standard deviation of industry cash flow measured as each firm's cash flow standard deviation for the previous 5 years, and then averaged by industry. Cash flow is earnings after interest, dividends, and taxes but before depreciation, all divided by assets. *NWC*, net working capital, is current assets, net of cash, minus current liabilities net of current debt. *DIV* is the ratio of dividend payments to assets net of cash. *INDUSTRY* and *COUNTRY* are dummy variables to control for industry and country effects respectively (e.g., the fixed effects model). We have three country dummy variables.

ARG is equal to one for Argentina; zero otherwise; CHILE is equal to one for Chile; zero otherwise; and PERU is equal to one for Peru; zero otherwise. The reference level for the country variable is Mexico. Industry dummy variables were set up similarly. Economatica classifies firms into nineteen different industries, although not every country has a representation of every industry. In consequence, there are many observations for some industries but too few for others across countries, which limit the execution of the fixed effects model. To overcome this limitation, we excluded industries with no observations in three or more countries; namely, companies in the electronics, industrial, non-mining, oil, and vehicle sectors. We used the electricity industry as the reference level since it had the lowest mean and median cash holdings across industries.

Financial statements data in U.S. dollars as of the end of each year were used. To estimate the market value of equity we multiplied stock prices as of the end of the year by the number of shares outstanding. Thus, we retrieved data from the financial statements and stock prices modules in Economatica. Files available up to 2008 were retrieved. As some of our variables required the estimation of changes from year *t-1* to year *t*, our sample covers the 1995-2007 period. The final sample includes 4,440 firm-year observations as shown in Panel B of Table 1. Observations by country are shown in Table 2.

RESULTS

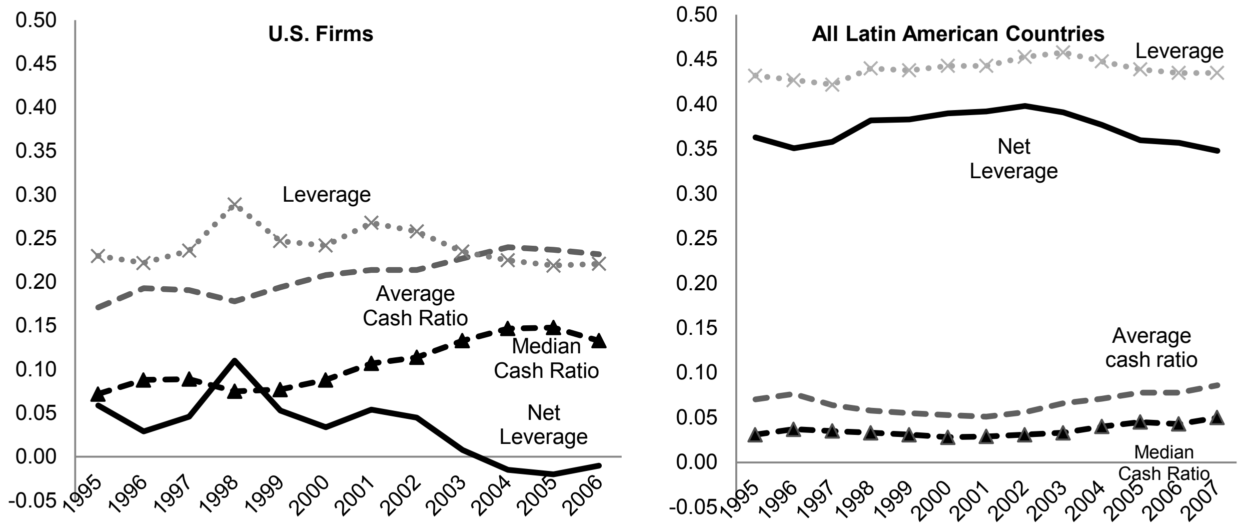
Table 1 provides descriptive statistics comparing the cash ratio, leverage, and net leverage (a measure more commonly used by practitioners than by scholars) for U.S. and Latin American companies. Figure 1 illustrates the trends and differences between U.S. and aggregated Latin American firms. While Bates, Kahle and Stulz (2009) document a secular increase in cash holdings for U.S. firms, cash for Latin American firms has barely increased in the period (i.e., in a regression of the cash ratio on a constant and time, the slope of the estimated parameter is statistically significant at 1% but the coefficient is only 0.001). In addition, while net leverage for U.S. firms has a downward trend, and is negative since 2004, net leverage for Latin American firms has been around 35% to 40% in the last decade.

Table 1: Descriptive Statistics of Cash and Leverage Ratios for U.S. and Latin American Firms

Panel A- U.S. Firms							
	N	Cash ratio		Leverage		Net leverage	
		Mean	Median	Mean	Median	Mean	Median
1995	5,165	0.171	0.072	0.230	0.187	0.059	0.105
1996	5,568	0.193	0.088	0.222	0.170	0.029	0.077
1997	5,605	0.191	0.089	0.236	0.180	0.046	0.085
1998	5,263	0.178	0.075	0.289	0.205	0.110	0.119
1999	4,971	0.194	0.077	0.247	0.198	0.053	0.104
2000	4,947	0.208	0.088	0.242	0.173	0.034	0.075
2001	4,540	0.214	0.107	0.268	0.173	0.054	0.062
2002	4,233	0.214	0.114	0.258	0.172	0.045	0.054
2003	3,992	0.227	0.133	0.235	0.160	0.008	0.016
2004	3,693	0.240	0.147	0.225	0.145	-0.015	-0.003
2005	3,549	0.237	0.148	0.219	0.136	-0.020	-0.005
2006	3,297	0.232	0.133	0.221	0.146	-0.010	0.015
Panel B- Latin American Firms							
1995	283	0.070	0.031	0.432	0.437	0.363	0.378
1996	304	0.076	0.037	0.427	0.420	0.351	0.366
1997	313	0.064	0.035	0.422	0.413	0.358	0.363
1998	325	0.058	0.033	0.440	0.433	0.382	0.398
1999	332	0.055	0.031	0.438	0.427	0.383	0.385
2000	351	0.053	0.028	0.443	0.428	0.390	0.388
2001	371	0.051	0.029	0.443	0.430	0.392	0.387
2002	369	0.056	0.031	0.453	0.440	0.398	0.387
2003	364	0.066	0.033	0.458	0.436	0.391	0.389
2004	363	0.071	0.040	0.448	0.420	0.377	0.365
2005	357	0.078	0.045	0.439	0.409	0.360	0.360
2006	356	0.078	0.043	0.435	0.412	0.357	0.350
2007	352	0.086	0.050	0.435	0.418	0.348	0.356

Panel A shows selected statistics for U.S. firms by Bates, Kahle and Stulz (2009), and Panel B shows estimations for Latin America firms by authors. The Latin America sample was obtained from Economatica, the largest subscription-based database for Latin America publicly traded firms. The sample includes non-financial firms from Argentina, Chile, Mexico, and Peru, with 4,440 firms-years observations. The cash ratio is estimated as cash plus short term investments divided by total assets net of cash; Leverage is long term debt plus debt in current liabilities divided by total assets, and Net leverage is net debt (i.e., net of cash) to assets.

Figure 1: Cash and Leverage Ratios for U.S. and Latin American Firms



Plotted with data from Table 1. The first graph shows selected statistics for U.S. firms by Bates, Kahle and Stulz (2009), and the second graph shows estimations for Latin America firms by authors. The Latin America sample was obtained from Economatica, the largest subscription-based database for Latin America publicly traded firms. The sample includes non-financial firms from Argentina, Chile, Mexico, and Peru, with 4,440 firms-years observations. The cash ratio is estimated as cash plus short term investments divided by total assets net of cash; Leverage is long term debt plus debt in current liabilities divided by total assets, and Net leverage is net debt (i.e., net of cash) to assets.

Table 2 provides statistics disaggregated by Latin American countries and years. The median cash holdings for Argentina, Chile, Mexico, and Peru are 4.28%, 2.38%, 5.07%, and 2.84% respectively. These figures are similar to results in Dittmar, Mahrt-Smith and Servaes (2003) for all the countries, but Argentina. In addition, the statistics indicate that the cash holdings in each country have remained without significant changes in the period of study. In the current financial environment, this difference between U.S. and Latin American firms could be of economic importance as increase in cash could hurt a country's economy. In this regard, a recent article in The Economist states: "For the recovery to proceed smoothly [U.S.] firms must stop hoarding cash…If cautious firms pile up more savings, the prospects for recovery are poor. With interest rates so low, this cash might be put to work more profitably" (Economist (2010)). Pair-wise Pearson correlation coefficients for the determinants of cash are presented in Table 3.

The signs of correlation coefficients in the first row show that with the exception of dividends, all relationships are as expected by theory or according to previous findings (further discussion on these relationships is provided in the regression results section). In addition, all coefficients are small in magnitude (with absolute correlation coefficients of less than 0. 25, with the exception of net leverage, which is viewed as negative cash) suggesting that multicollinearity should not be a problem for the analysis. Table 4 provides the regression results. Model 1a is the pooled regression, model 1b is the panel model with country fixed effects, and model 1c is the complete model as described in the "data and methodology" section. As results of the three models are in general consistent and model 1c explains better the cash holdings than the other models (i.e., the Adjusted R-squared is higher, parameters remain significant, and the significance level increase when the dummy variables are included), we discuss the results of model 1c.

Table 2: Cash and Leverage Ratios for U.S. and Latin American Firms by Countries and Years

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Panel A- Argentina													
Observations	47	50	49	61	61	63	58	60	58	61	60	61	60
Cash ratio mean	0.059	0.070	0.052	0.038	0.041	0.043	0.046	0.064	0.070	0.076	0.075	0.068	0.082
Cash ratio median	0.037	0.027	0.031	0.020	0.025	0.026	0.031	0.052	0.049	0.050	0.055	0.055	0.066
Leverage mean	0.476	0.464	0.492	0.474	0.486	0.507	0.506	0.567	0.602	0.586	0.544	0.532	0.532
Leverage median	0.464	0.438	0.444	0.497	0.496	0.504	0.513	0.534	0.540	0.492	0.521	0.521	0.502
NetLev mean	0.417	0.394	0.440	0.436	0.446	0.464	0.460	0.502	0.532	0.510	0.469	0.464	0.450
NetLev median	0.403	0.380	0.412	0.473	0.464	0.473	0.461	0.465	0.479	0.450	0.465	0.424	0.444
Panel B- Chile													
Observations	102	101	112	115	111	113	109	101	102	101	98	98	96
Cash ratio mean	0.058	0.062	0.057	0.059	0.053	0.052	0.043	0.044	0.067	0.064	0.072	0.074	0.079
Cash ratio median	0.024	0.030	0.025	0.020	0.021	0.019	0.016	0.018	0.023	0.025	0.033	0.026	0.027
Leverage mean	0.383	0.399	0.394	0.405	0.411	0.419	0.423	0.417	0.419	0.404	0.416	0.419	0.410
Leverage median	0.382	0.402	0.387	0.406	0.401	0.414	0.390	0.415	0.405	0.390	0.394	0.402	0.411
NetLev mean	0.325	0.337	0.337	0.346	0.358	0.366	0.380	0.374	0.352	0.340	0.344	0.344	0.332
NetLev median	0.340	0.349	0.330	0.352	0.378	0.365	0.361	0.367	0.362	0.360	0.362	0.366	0.356
Panel C- Mexico													
Observations	118	133	134	137	138	134	133	138	133	130	124	126	117
Cash ratio mean	0.074	0.079	0.076	0.065	0.064	0.060	0.064	0.070	0.073	0.077	0.085	0.080	0.084
Cash ratio median	0.037	0.048	0.048	0.042	0.043	0.045	0.038	0.042	0.047	0.050	0.056	0.057	0.058
Leverage mean	0.459	0.446	0.431	0.457	0.448	0.428	0.433	0.437	0.434	0.433	0.421	0.417	0.424
Leverage median	0.469	0.434	0.416	0.445	0.425	0.416	0.416	0.437	0.445	0.420	0.393	0.395	0.393
NetLev mean	0.385	0.367	0.355	0.392	0.384	0.368	0.368	0.367	0.361	0.357	0.337	0.338	0.340
NetLev median	0.421	0.373	0.365	0.396	0.370	0.357	0.373	0.381	0.381	0.355	0.338	0.339	0.347
Panel D- Peru													
Observations	16	20	18	12	22	41	71	70	71	71	75	71	79
Cash ratio mean	0.145	0.145	0.064	0.075	0.046	0.045	0.041	0.034	0.049	0.065	0.079	0.089	0.103
Cash ratio median	0.044	0.032	0.043	0.044	0.025	0.019	0.026	0.016	0.020	0.019	0.033	0.031	0.047
Leverage mean	0.422	0.355	0.349	0.412	0.377	0.464	0.440	0.441	0.443	0.417	0.415	0.408	0.407
Leverage median	0.431	0.377	0.328	0.354	0.365	0.469	0.418	0.427	0.417	0.399	0.395	0.397	0.409
NetLev mean	0.277	0.211	0.285	0.337	0.331	0.419	0.399	0.401	0.393	0.352	0.335	0.319	0.304
NetLev median	0.382	0.302	0.248	0.314	0.335	0.427	0.390	0.398	0.374	0.347	0.325	0.310	0.326

Table 2 provides selected statistics for Latin America firms by countries and years. The Latin America sample was obtained from Economatica, the largest subscription-based database for Latin America publicly traded firms. The sample includes non-financial firms from Argentina, Chile, Mexico, and Peru, with 4,440 firms-years observations. The ***cash ratio*** *is estimated as cash plus short term investments divided by total assets net of cash;* ***Leverage*** *is long term debt plus debt in current liabilities divided by total assets, and* ***Net leverage*** *is net debt (i.e., net of cash) to assets.*

All parameters but cash flow volatility are statistically significant at the 1% level. With the exception of size and dividends, the sign of the estimated parameters for Latin American firms are as predicted according to theory or previous empirical results. As expected by the precautionary motive (Myers and Majluf (1984) and Myers (1997)), the coefficient of market to book value, the proxy for firm's growth opportunities, is positive (i.e., firms increase their cash holdings to avoid missing growth opportunities). In relation to capital expenditures, the negative coefficient could be explained by the precautionary motive as well. Firms that acquire fixed assets can use them as collaterals for loans, which reduces the need of cash holdings. As expected, net leverage has the highest estimated coefficient. This result is consistent with the view that variables that affect cash holdings are also variables that affect leverage but in the opposite direction. However, this does not imply that firms are indifferent between having one more $ of cash or one more $ of debt (i.e., leverage coefficient is statistically different from negative 1.0). Finally, the estimated parameter for net working capital is negative, consistent with the idea that cash and liquid working capital items, for instance inventories and account receivables, could be used as substitutes.

Table 3: Pair-wise Pearson Correlation Coefficients of the Determinants of Cash for Latin American Firms

	MB	SIZE	CAPEX	NETLEV	CFVOL	NWC	DIV
CASH	0.124***	-0.015	-0.037**	-0.495***	0.023	-0.003	0.130***
MB		-0.050***	-0.005	-0.032	-0.078***	-0.001	0.076***
SIZE			0.103***	0.094***	-0.132***	-0.166***	-0.025
CAPEX				-0.049***	-0.083***	-0.019	-0.246***
NETLEV					0.061***	-0.157***	-0.082***
CFVOL						-0.026*	0.116***
NWC							0.010

*Table 3 presents Pearson correlations for the determinants of cash for Latin American Firms. The Latin America sample was obtained from Economatica, the largest subscription-based database for Latin America publicly traded firms. The sample includes non-financial firms from Argentina, Chile, Mexico, and Peru, with 4,440 firms-years observations. CASH is the ratio of cash to assets net of cash. Cash is defined as the sum of cash and short-term investments. MB is market to book value, measured as book value of assets minus book value of equity plus market value of equity all divided by assets. Firm size, SIZE, is the natural logarithm of the book value of assets. CAPEX is the ratio of capital expenditures to book value of assets. NETLEV is net leverage, the ratio of net debt (i.e., net of cash) to assets. CFVOL is cash flow volatility, the standard deviation of industry cash flow measured as each firm's cash flow standard deviation for the previous 5 years, and then averaged by industry. NWC, net working capital, is current assets, net of cash, minus current liabilities net of current debt. DIV is the ratio of dividend payments to assets net of cash. ***, **, and *, indicate 1%, 5%, and 10% statistical significance respectively.*

Model 1c in Table 4 also provides estimates for the industry and country variables, having Mexico and the electricity industry as benchmarks. The cash holdings for Argentina, Chile, and Peru are statistically different to Mexico's, with Chilean firms holding the lowest cash levels. If it is true that economies of scale for large firms reduce their need for cash (Vogel and Maddala (1967) and Beltz and Frank (1996)), the positive relationship between firm size and cash holdings could be explained by the relative small size of the average Latin American firm compared to the average U.S. firm. The sign of the coefficient for dividends is explained below. To gain additional insights on the determinants of cash holdings, Table 5 provides industry fixed effect regression results per country (to avoid redundancy with Table 4 results, industry parameters are not tabulated). In general, results are consistent with results in Table 4. Coefficient signs for market to book, size, capital expenditures, net leverage, and net working capital are consistent with theory and across Latin American countries. Estimated parameters for dividends across countries are revealing. The coefficient is both positive and statistically significant for Chile only (0.088 at the 10% significance level). The explanation could be that in Chile, unlike in any of the other countries in our sample, firms are required to pay out certain fraction of their income as dividends (Dittmar, Mahrt-

Smith and Servaes (2003)). Thus, by the precautionary motive, it is plausible that Chilean firms hold more cash than they otherwise would hold due to the fact that they have to pay dividends.

Table 4: Pooled and Fixed-Effects Regressions for the Determinants of Cash Holdings for Latin American Firms

Variable	Model 1a		Model 1b		Model 1c	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
intercept	0.047***	3.79	0.062***	4.21	0.045***	3.15
mb	0.008***	7.45	0.009***	7.43	0.009***	7.67
size	0.005***	6.18	0.004***	5.22	0.005***	4.95
capex	-0.043***	-4.20	-0.041***	-4.11	-0.039***	-3.95
netlev	-0.167***	-27.29	-0.166***	-26.65	-0.165***	-26.41
cfvol	0.044	1.18	0.024	0.99	-0.015	-0.33
nwc	-0.000***	-4.24	-0.000***	-3.94	-0.000***	-4.68
div	0.036	1.57	0.053**	2.38	0.066***	2.93
argentina			0.007	1.55	0.010**	2.37
chile			-0.013***	-3.69	-0.010***	-2.75
peru			0.040***	3.57	0.038***	3.37
agriculture					0.004	0.49
basic					0.024***	3.54
chemical					0.019**	2.26
construction					0.057***	7.99
trade					0.018***	3.36
food					-0.003	-0.59
mining					0.034***	3.04
other					0.005	0.96
paper					0.004	0.26
telecom					0.001	0.13
textile					0.007	0.72
transportation					0.065***	6.87
adj r-sq.	0.28		0.29		0.33	

*Regression results for the determinants of cash for Latin American Firms. The Latin America sample was obtained from Economatica, the largest subscription-based database for Latin America publicly traded firms. The sample includes non-financial firms from Argentina, Chile, Mexico, and Peru, with 4,440 firms-years observations. The dependent variable is the ratio of cash to assets net of cash (the cash ratio). MB is market to book value, measured as book value of assets minus book value of equity plus market value of equity all divided by assets. Firm size, SIZE, is the natural logarithm of the book value of assets. CAPEX is the ratio of capital expenditures to book value of assets. NETLEV is net leverage, the ratio of net debt (i.e., net of cash) to assets. CFVOL is cash flow volatility, the standard deviation of industry cash flow measured as each firm's cash flow standard deviation for the previous 5 years, and then averaged by industry. NWC, net working capital, is current assets, net of cash, minus current liabilities net of current debt. DIV is the ratio of dividend payments to assets net of cash. Model 1a is the pooled regression, model 1b is the panel model with country fixed effects, and model 1c is the complete model as described in the "data and methodology" section. ***, **, and *, indicate 1%, 5%, and 10% statistical significance respectively.*

Results for cash flow volatility are difficult to explain. Table 4 shows that cash flow volatility is not statistically significant for the whole Latin America group (but with the expected negative sign, -0.015), and Table 5 shows that cash flow volatility varies across countries (positive and statistically significant for Argentina and Chile, and negative, but not significant for Mexico and Peru). Empirical research has shown that U.S. firms with riskier cash flows are expected to hold more cash (for instance, Campbell, Lettau, Malkiel and Xu (2001) document that idiosyncratic risk has increased in the U.S.; Irvine and Pontiff (2008) show that an increase in risk mirrors and increase in cash flow volatility; and Bates, Kahle and Stulz (2009) model cash flow volatility as a determinant of cash). Given this inconsistency in our results, we investigated more closely the influence of cash flow volatility on cash holdings. We ranked industries by cash flow volatility and compared those volatilities with cash holdings and other selected statistics. Table 6 provides medians of cash flow volatility, the cash ratio, cash flow relative to assets, and market to book by industries (e.g., plotted in Figure 2). The positive relation between cash flow volatility and cash holdings is only clear for the group of industries with the lowest cash flow volatility (i.e., electricity, trade, food, and mining). While this relationship is also observable for other sectors such as telecommunications and construction, the positive relationship is note clear for the rest of Latin American industries. The group of industries with the lowest cash flow volatilities referred to above also reports the highest market to book values, meaning that investors perceive growth opportunities on industries with steady or high cash flows. In general, with the exception of size and dividends, regression results for the determinants of cash for Latin American firms are consistent with previous findings according to the signs of estimated coefficients, the level of statistical significance, and the level of explanatory power (adjusted R-square of 32% in our model compared to 22% in the model by Opler, Pinkowitz, Stulz and Williamson (1999), and 45% by Bates, Kahle and Stulz (2009) for U.S. firms). Cash flow volatility does not seem to affect cash levels.

Table 5: Fixed Effect Regression Results for the Determinants of Cash Holdings Across Latin American Countries

Variable	**Argentina**		**Chile**		**Mexico**		**Peru**	
	estimate	t-statistic	estimate	t-statistic	estimate	t-statistic	estimate	t-statistic
INTERCEPT	0.093***	2.800	-0.038*	-1.67	0.067***	3.40	0.486*	1.88
MB	0.047***	5.400	0.004***	4.14	0.025***	6.89	0.010	1.21
SIZE	-0.006**	-2.290	0.013***	7.52	0.003**	2.46	0.007	0.58
CAPEX	-0.007	-0.530	-0.005	-0.29	-0.033**	-2.22	-0.405**	-2.10
NETLEV	-0.072***	-6.610	-0.224***	-18.84	-0.206***	-22.27	-0.463***	-6.39
CFVOL	0.130*	1.670	-0.235***	-2.66	0.011	0.17	-10.119	-1.70
NWC	-0.000***	-5.770	-0.000***	-3.78	-0.000***	-4.41	0.000	0.61
DIV	0.122	1.080	0.088**	2.01	0.036	1.43	-0.983	-1.69

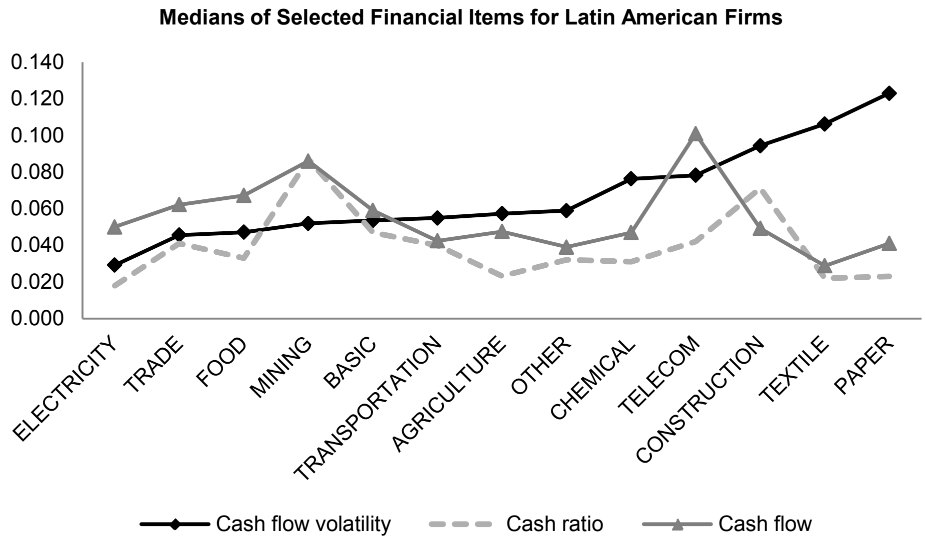
*Industry fixed effect regression results for the determinants of cash across Latin American countries (industry coefficients are not included in the table to avoid redundancy).Model as described in the "data and methodology" section. The Latin America sample was obtained from Economatica, the largest subscription-based database for Latin America publicly traded firms. The sample includes non-financial firms from Argentina, Chile, Mexico, and Peru, with 4,440 firms-years observations. The dependent variable is the ratio of cash to assets net of cash (the cash ratio). MB is market to book value, measured as book value of assets minus book value of equity plus market value of equity all divided by assets. Firm size, SIZE, is the natural logarithm of the book value of assets. CAPEX is the ratio of capital expenditures to book value of assets. NETLEV is net leverage, the ratio of net debt (i.e., net of cash) to assets. CFVOL is cash flow volatility, the standard deviation of industry cash flow measured as each firm's cash flow standard deviation for the previous 5 years, and then averaged by industry. NWC, net working capital, is current assets, net of cash, minus current liabilities net of current debt. DIV is the ratio of dividend payments to assets net of cash.. ***, **, and *, indicate 1%, 5%, and 10% statistical significance respectively.*

Table 6: Cash Flow Volatility and other Selected Items by Industries for Latin American Firms

Industry	**Cash Flow Volatility**	**Cash Ratio**	**Cash Flow**	**Market To Book**
Electricity	0.029	0.018	0.050	1.058
Trade	0.046	0.041	0.062	1.284
Food	0.047	0.033	0.067	1.205
Mining	0.052	0.087	0.086	1.338
Basic	0.053	0.047	0.059	0.906
Transportation	0.055	0.040	0.042	0.976
Agriculture	0.057	0.023	0.047	0.776
Other	0.059	0.032	0.039	0.994
Chemical	0.076	0.031	0.047	1.174
Telecom	0.078	0.042	0.101	1.443
Construction	0.094	0.071	0.049	1.058
Textile	0.106	0.022	0.029	0.813
Paper	0.123	0.023	0.041	0.978

Medians of cash flow volatility, the cash ratio, cash flow relative to assets, and market to book by industries. Cash ratio is cash to assets net of cash. Cash flow volatility is the standard deviation of industry cash flow measured as each firm's cash flow standard deviation for the previous 5 years, and then averaged by industry. Cash flow is earnings after interest, dividends, and taxes but before depreciation, all divided by assets. Market to book is measured as book value of assets minus book value of equity plus market value of equity all divided by assets. Industries are ranked according to cash flow volatility medians.

Figure 2: Cash Flow Volatility and Other Selected Items by Industries for Latin American Firms



Plotted with results in Table 6. Medians of cash flow volatility, the cash ratio, and cash flow relative to assets by industries. Cash ratio is cash to assets net of cash. Cash flow volatility is the standard deviation of industry cash flow measured as each firm's cash flow standard deviation for the previous 5 years, and then averaged by industry. Cash flow is earnings after interest, dividends, and taxes but before depreciation, all divided by assets.

CONCLUDING REMARKS

Given the economic importance of the increase in cash hoardings by U.S. corporations and from other developed economies, we investigate the levels and determinants of corporate demand for cash for Latin American firms. Specifically, we study non-financial firms from Argentina, Chile, Mexico, and Peru during the 1995-2007 period. The typical academic study on foreign cash holdings does not include all these Latin American countries or, if it does, it includes a relatively small number of firms. Following Opler, Pinkowitz, Stulz and Williamson (1999) and Bates, Kahle and Stulz (2009) we modeled the determinants of cash holding by regression analysis with country and industry fixed effects.

Latin American firms, as opposed to U.S. firms, did not hoard cash during the period of study. While Bates, Kahle and Stulz (2009) document a secular increase in cash holdings for U.S. firms, the level of cash for Latin American firms has barely increased in the period (i.e., in a regression of the cash ratio on a constant and time, the slope of the estimated parameter is statistically significant at 1% but the coefficient is only 0.001). In addition, while net leverage for U.S. firms has a downward trend, and is negative since 2004, net leverage for Latin American firms has been around 35% to 40% in the last decade. However, we find remarkable similarities with respect to the determinants of cash between U.S. firms and Latin American firms. Net working capital, capital expenditures and net leverage all decrease the levels of Latin American firms' cash balances while growth opportunities increase them. However, contrary to theoretical expectations and previous findings for U.S. firms, firm size and dividend payments seem to increase Latin American firms' need for cash whereas cash flow volatility does not seem to affect cash levels. If it is true that economies of scale for large firms reduce their need for cash (Vogel and Maddala (1967) and Beltz and Frank (1996)), the positive relationship between firm size and cash holdings could be explained by the relative small size of the average Latin American firm compared to the average U.S. firm. Results disaggregated show consistency across Latin American countries. However, estimated parameters for dividends across countries provide a new insight. The coefficient is positive and statistically significant for Chile only (0.088 at the 10% significance level). Chilean firms (but not in other countries from the sample in this study) are required to pay out certain fraction of their income as dividends (Dittmar, Mahrt-Smith and Servaes (2003)). Thus, it is possible that by the precautionary motive, Chilean firms that have to pay dividends tend to hold higher levels of cash that their otherwise would hold. While empirical research has shown that U.S. firms with riskier cash flows are expected to hold more cash in their balance sheets, cash flow volatility does not seem to affect cash holdings for Latin American firms according to our regression results. However, when we ranked industries by cash flow volatility, we observe a positive relation between cash flow volatility and cash holdings for the group of industries with the lowest cash flow volatility (i.e., electricity, trade, food, and mining). While this trend is also observable for other industries such as telecommunications and construction, this is not a generality for Latin American industries. This group of industries with the lowest cash flow volatilities also reports the highest market to book values, meaning that investors perceive growth opportunities on industries with steady or high cash flows, as is the case of the telecommunications industry

This article provides several avenues for future research. For example, a natural extension of this work would be to analyze the effects of macroeconomic and capital market factors (e.g., interest rate levels, capital market activities such as IPOs, mergers and acquisitions, etc.) on Latin American cash balances. In addition, control variables for differences in corporate governance characteristics could be included.

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