The Impact of Loan Growth and Business Model on Bank Risk-taking in the Jamaican Banking System

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Abstract

This paper uses a two-step generalized method of moments to analyse data from a panel of Jamaican DTIs. The paper examines the impact of loan growth and these institutions' business model on their risk-taking over the period 2006-2020. The study explores other factors such as the variability of interest and non-interest income and the risk associated with these DTIs. The results showed that DTIs with high rates of loan growth reflect a higher level of bank risk-taking. The model confirms that there is higher risk and instability in the Jamaican banking sector during a financial crisis. Moreover, the findings showed that the benefits of a larger bank size decrease as banks become more active in non-interest income activities. Overall, the results indicate that differences in the lending activities and business models of banks help to identify systemic risks that could materialize in the event of a change in the business cycle.

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[1] The views expressed in this paper are solely of the author and do not necessarily reflect those of the Bank of Jamaica.

1. Introduction

Jamaica is a developing country with a largely bank-based financial sector. [2] As such, any crisis within the deposit-taking institutions' (DTI) sector may fuel a recession. The global financial crisis in 2008 provided us with clear evidence that it is important to maintain a safe and healthy banking system. Jamaica's economic development is very dependent on the DTI sector, as these institutions are necessary to finance existing and future economic development. DTIs play an important role in economic activity, as these financial institutions serve as intermediaries between parties with excess funds and those without funds. Furthermore, this channelling of funds by DTIs, also known as credit channelling, is influenced by bank liquidity conditions.

Lending activities contribute significantly to bank performance and profits largely through the interest income received by DTIs.[3] Profitability also affects company value, as higher profitability is associated with increased company value.[4]Against this background, DTIs tend to drive credit growth by, where possible, lowering interest rates on loans, loosening the terms of collateral required to obtain credit, as well as loosening other criteria for prospective debtors.

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[2] The financial system is bank-centric and is largely dominated by commercial banks which account for approximately 35.0 per cent of total financial system assets.

[3] Based on data submitted by DTIs to the Bank of Jamaica, credit forms the largest component of DTI assets (see **figure A.1**).

[4] The company's value also known as firm value is the sum of the market value of all outstanding securities which consists of common shares, preferred shares, and debt. Profitability affects the firm value because profit is viewed as a positive achievement that can justify the payment of dividends, which will likely increase the stock price of the firm.

However, excessive credit growth may have an impact on the credit risk faced by banks. High credit growth implies the onboarding of relatively more risky debtors who are more likely to fail to make payments or fulfil their obligations related to their loans.

In addition to accelerated and excessive credit growth, there are several other aspects of banks' business models that can affect the riskiness of banks' portfolios and by extension the banking system. Studies have shown that lower dependence on customer deposits, size and weaker capital led to higher levels of distress in banks during the global financial crisis. Other factors, including the amount of market funding and lack of diversification in income sources, also contributed to bank risk.

Moreover, the study was motivated by notably high credit growth and an increase in non-interest income in the Jamaican DTI sector over the period. The objective of this paper is to assess the effect of credit growth and bank business models on bank risk in Jamaican DTIs. The results of this paper provide a guide and signal for excessive lending patterns that may materialize into credit and market risks.

This study contributes to the banking and finance literature by employing the z-score specific to the Jamaican DTI sector, linking the determinants of bank risk-taking to aggregate credit growth, bank size, interest and non-interest income. The results indicate that an increase in bank lending results in lower stability in banks with high rates of individual loan growth. Moreover, the findings showed that as banks get larger, they shift operations away from core business activities to market-driven activities. Furthermore, the results showed that a higher share of non-interest income decreases banks' risk-adjusted return. The effect differs for leverage risk with a positive coefficient indicating that a higher share of non-interest income is associated with lower leverage risk. Notably. the study makes use of an informative dataset of DTIs covering a time span which includes two financial crisis periods.

The paper is organized as follows: Section 2 presents a brief review of related literature. The data and methodology used in the empirical analysis are presented in Section 3. Section 4 presents the diagnostic and empirical results. Finally, Section 5 presents the conclusions and recommendations of the paper.

2. Literature review

Bank credit is the main source of external funding in most economies. However, there is a downside to excessive credit expansions, which may adversely affect bank riskiness. Salas and Saurina (2002) used data for a large set of Spanish commercial banks for the period 1985-1997 and found that loan growth of banks impacted bank stability. Their results highlighted that higher loan growth is associated with higher loan losses three or four years ahead.

Amador et al. (2013) used a panel data approach to examine the relationship between abnormal loan growth and risk-taking behaviour of financial institutions in Colombia. The results suggested that persistent growth in abnormal loans over prolonged periods leads to a reduction in solvency and a notable increase in the ratio of non-performing loans (NPLs) to total loans. Furthermore, Ruckes (2004), Dell'Ariccia and Marquez (2006) found that, to the extent that lending standards decline more than justified by economic fundamentals, this leads to an increase in bank risk. They noted that bank's reduced lending standards and collateral requirements during booms, but were more restrictive in granting loans to businesses during an economic downturn. This leads to a build-up of systemic risk in the banking sector.

As it relates to high credit growth during booms and financial crises, Borio and Lowe (2002) found that a combination of sharp increases in asset prices and high credit growth constitutes a very good leading indicator of subsequent episodes of financial instability. Accordingly, a decline in performance during the crisis can be used as an indicator of risk-taking, where banks with high loan growth rates incur greater risks than banks with low rates of loan growth. Borio (2009) showed that excessive credit growth is the main leading indicator of a financial crisis in a twelve-month horizon.

According to Kohler (2012), banks' loan growth is an important determinant of risk-taking in the European Union (EU) banking sector. Foos et al., (2010), after using two different indicators to characterize periods of excessive lending growth, found that if banks raise lending by lowering their lending standards, relaxing collateral requirements or a combination of both, this is associated with greater risk. Additionally, banks which exhibit significantly higher loan growth rates than their competitors may attract customers who were not offered a loan by other banks, because they offered loan rates that were too low or required insufficient collateral relative to the borrowers' credit quality.[5]

Changes in capital regulations may also increase bank risk-taking. Owners/shareholders might compensate for the loss of utility from more stringent capital requirements by selecting a riskier portfolio (Koehn and Santomero, 1980, Buser, Chen, and Kane, 1981), intensifying conflicts between owners and managers over bank risk-taking.

As it relates to diversification of income sources and risk-taking, Altunbas et al. (2011) used non-interest income as an indicator of risk-taking and posited that banks with high non-interest

[5] In addition to this, Baradwaj et al. (2014) investigated the impact of lending growth on the riskiness of Chinese banks from the period of 1992–2007. Their findings indicate that growth in lending increases loan loss provisions, interest income, but lower capital ratios.

income are riskier.[6] They found that larger banks and those with more aggressive loan growth are less stable, while banks with less risk-taking are characterized by a strong deposit base.[7] DeYoung and Roland (2001) posited that a large share of non-interest income may destabilize banks since non-interest income is usually more volatile than interest income because it is more difficult for borrowers to switch their lending relationship due to information costs. However, according to Boyd et al. (1980), a higher share of non-interest income to total income makes banks less dependent on interest income and improves risk diversification which should make them more stable.

3. Methodology and Data

This paper examines the relationship between abnormal loan growth, non-interest income and bank risk using information for Jamaican DTIs over the period 2006 and 2020.[8] The method utilized in this study closely follows Kohler (2012), which used a two-step system generalized method of moments (GMM) as proposed by Arellano and Bond (1991).

More specifically, this study examines the impact of a DTI's business model on their level of risk-taking, by analysing the variability of interest and non-interest income, and their correlation with bank risk-taking, covering prior and subsequent to the global financial crisis. Similar to Kohler (2012), this paper used second or higher-order lags for dependent and other endogenous variables as instruments to check for endogeneity bias, with the validity of the

[6] Non-interest income includes activities like income received from investment, advisory fees, fiduciary income and trading.

[7] Similarly, Demirgüc-Kunt and Huizinga (2010) show that banks with a high level of fee and trading income are riskier. Banks that heavily rely on wholesale funding are riskier as well and found no evidence that high rates of asset growth result into greater risk-taking.

[8] See list of variables in table A.1.

instruments showing the reliability of the GMM estimator. The system GMM was utilised to solve issues of endogeneity that arose when bank-specific variables were used and also to eliminate the correlation between the lagged dependent variable and the error term.

The z-score, which computes the probability that a bank will fail or go bankrupt, is used to measure banks' risk.[9] It is defined as the ratio of the return on assets plus the capital ratio divided by the standard deviation of the return on assets and was computed over the period 2006 to 2020 (see **equation 1**).[10] The study uses the z-score as an indicator of the probability of bankruptcy and by extension bank stability. In this context, a higher z-score indicates that a bank incurs fewer risks and is therefore more stable while a lower z-score indicates greater risk and less stability.[11]

$$\boldsymbol{z-score} = \frac{\mathbf{ROA}_{\boldsymbol{it}} + \mathbf{CAR}_{\boldsymbol{it}}}{\boldsymbol{SDROA_i}} \qquad \textbf{(1)}$$

where ROA is the return on assets, CAR is the ratio of total equity to total assets of bank *i* in year *t* and *SDROA* is each bank's standard deviation of the ROA.[12] The model uses the quarterly average return on assets, its standard deviation and the capital-asset ratio over 2006-

[9] This z-score is the number of standard deviations that a bank's return on asset has to fall to become insolvent. The z-score is used as a measure of financial soundness. It captures the likelihood of a bank's earnings in a given year becoming low enough to eliminate the bank's capital base and thus the likelihood of the bank becoming insolvent.

[10] The model does not use loan loss provisions or non-performing loans to measure bank risk, since they are traditionally backward looking and highly procyclical (Laeven and Majnoni, 2003 and Bikker and Metzemakers, 2005).

[11] More specifically, it indicates the number of standard deviations below the expected value of a bank's return on assets at which equity is depleted and the bank is insolvent.

[12] The ratio of equity to total assets is sometimes used to measure capital adequacy.

2020. The z-score is fundamental in determining bank risk as it is the inverse of the probability of insolvency.[13] Since the z-score is highly skewed, the paper used the natural logarithm of the z-score, which is normally distributed.[5] The test statistics indicate no second autocorrelation in the error terms in the model which includes only the first lag of bank risk, as such, the model includes the first lag of the z-score. Thus, confirming that the model assumptions hold and the instruments are appropriately specified.

3.0 Empirical Model

In order to identify the determinants of bank risk-taking, the following dynamic regression model for panel data is estimated[14]:

$$RISK_{it} = \sum_{l=1}^{1} RISK_{it-l}\,\beta_l + V_{it}\,\beta_3 + J_{IT}\,\beta_4 + B_i\,\beta_5 + \varepsilon_{it} \qquad \textbf{(2)}$$

where $RISK_{it}$ is measured using the z-score of banks i in year t. V is a matrix of the bank variables: aggregate loan growth (AGGLOANGR), net interest margin (NIM), non-interest income to total income (NNINC), liquid assets to total assets (LIQUID), logarithm of bank assets (SIZE). J is a matrix of country-specific variables: credit gap (CREDITGAP), short-term interest rates such as treasury bill rate (TBILL) and weighted average lending rate (WALR), GDP growth (GDPGR) and unemployment (UNEMPLOYMENTRATE).

In addition, a CRISIS dummy variable was included in matrix B in order to control for crisis periods such as the global financial crisis, the Jamaica debt exchange and the national debt

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[13] The z-score is an overall measure of bank risk capturing not only credit, but also liquidity and market risk that primarily arises from non-lending activities.

[14] The model includes the first lag due to the test statistics indicating no second autocorrelation in the error terms in the model including only the first lag of bank risk.

exchange. The coefficient vectors are $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$, $\beta 5$ and ε_{it} is the error term. The paper models bank risk-taking as dynamic by including the first lag of the z-score as an independent variable. The variance–covariance matrix of the error terms is specified to account for heteroskedasticity across panels (the variance of each panel differs), and to account for autocorrelation of order one specific to each panel. The loan growth rate of each bank was compared to the other banks in the sample in order to determine the abnormal loan growth rate. Note that loan growth is deemed abnormal when it is greater than the median loan growth rate for all banks. Aggregate loan growth (AGGLOANGR) is defined as the difference between a bank's loan growth rate and the median loan growth rate of all banks.

The control variables include variables that are bank-specific determinants including deposits, the lag of bank risk-taking (l.RISK), the liquid assets to total assets (LIQUID) to measure bank liquidity, the logarithm of bank assets (SIZE) to control for bank size and the net interest margin (NIM) to measure bank profitability. Additionally, the main indicator used to determine banks' strategy include the share of non-interest income to total income.[15] A higher share of non-interest income to total income (NNINC) means that there is higher risk diversification and that banks are less dependent on interest income which should make them more stable.[16]

Bank size is estimated by taking the logarithm of total assets for each deposit-taking institution. Growing banks have a high concentration of market activities, pursue lending diversification, focus on consumer financing and are unconcerned about the asymmetric

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[15] In general, a large share of non-interest income may destabilize banks, since it is usually more volatile than interest income, because it is more difficult for borrowers to switch their lending relationship due to information costs (DeYoung and Roland, 2001).

[16] Boyd et al.,1980

information of borrowers. Thus, the model is constructed on an expectation that relationship between bank assets and past due loans is negative. Moreover, the paper captures other aspects using indicators that capture the macroeconomic landscape. These include the credit-to-GDP gap, short-term interest rates, GDP growth and unemployment. The inclusion of macroeconomic variables account for the country-specific characteristics that could have direct or indirect non-linear relationships with the bank-specific variables utilized. The indicator GDP growth was used to give an indication of the direction of economic progress. It is argued that promising economic growth enhances the income of households and boosts business activity. A booming economy and enhanced market activity encourage lending and borrowers then have sufficient reserves/disposable income to service their debts. The country-specific variables are treated as exogenous.

The model measures excessive and abnormal aggregate credit growth using the credit-to-GDP gap (CREDIT GAP). Specifically, this is the deviation of credit-to-GDP growth from its long-term trend. The credit-to-GDP gap indicator, when it is sufficiently above its long-term trend signals the emergence of financial imbalances that lead to future distress.[17] This analysis of the long-term trend of the credit-to-GDP ratio is obtained using the Hodrick-Prescott (1981) filter.[18] In regard to the country's economic landscape, another macroeconomic variable that is as important as GDP growth is unemployment.[19] A test for the effect of abnormal loan growth on banks' financial health (solvency and profitability) was done, using data on

[17] Appendix Figure 2 shows the credit to GDP gap for Jamaica over the period 2006 to 2020. Moreover, figure 2 compares the average z-score with the credit to GDP gap and highlights a negative relationship.

[18] Although Hamilton (2017) debates against the use of an HP filter given its end-point problems, which could result in spurious dynamics, Drehmann & Yetman (2018) while agreeing, argue that in the absence of clear theoretical foundations, all proposed gaps are but indicators. In this regard, they suggest that the matter is an empirical question and rests on the measure that performs the best.

[19] According to Bai (2015) credit spreads are sensitive to labour market conditions, the economy occasionally runs into economic disasters. Default rates are also countercyclical, typically rising in recessions with low productivity and high unemployment.

Jamaican financial institutions between 2006 and 2020. All bank variables were winsorized at the 1.0 per cent and 99.0 per cent level.[20]

The method employed modified the baseline model to assess the country-specific impacts in Model 2. This was further modified to determine the impact of non-interest income based on bank size in Model 3. Subsequently, model 4 decomposed the z-score to assess the robustness of the findings and determine which component has the greater impact on risk.

In order to test the robustness of the findings, the z-score was decomposed into its two additive components: portfolio and leverage risk. For the portfolio risk component, the formula is the return-on-asset (ROA) of bank i in year t is divided by the standard deviation of the return on asset (SDROA) (see **equation 3**).

$$\text{Portfolio Risk}_{it} = \frac{\text{ROA}_{it}}{\text{SDROA}_{i}} \qquad \textbf{(3)}$$

This is a measure of portfolio risk and represents a bank's risk-adjusted return. A higher value is indicative of greater bank stability. The second component of the z-score represents leverage risk and each bank's ratio of bank's equity to total assets (CAR) over the standard deviation of the return on asset. Similarly, a high value indicates greater bank stability (see **equation 4**).

$$\text{Leverage Risk}_{it} = \frac{\text{CAR}_{it}}{\text{SDROA}_{i}} \qquad \textbf{(4)}$$

The model is estimated using Windmeijer's (2005) finite sample correction. This estimation technique is particularly suitable for small time periods and large panels samples as seen in this paper.[21] Previous Monte Carlo studies have shown that covariance estimators can produce

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[20] Winsorizing is the transformation of statistics by limiting extreme values in the statistical data to reduce the effect of possibly spurious outliers.

[21] The ''system GMM'' estimation technique is more suitable for the panel data models with a large number of individuals and a small number of time periods (Small T and large N).

standard errors that are downward biased in small samples. Windmeijer (2005) observes that part of this downward bias is due to extra variation caused by the initial weight matrix estimation being itself based on consistent estimates of the equation parameters. This technique was used to calculate bias-corrected standard error estimates which consider the variation of the initial parameter estimates.[22]

3.1 Diagnostic test

Instrument validity

Furthermore, the validity of the instruments was tested using Hansen's J test statistic of overidentifying restrictions. In all cases, the test statistic accepted the null hypothesis that the instruments were exogenous. Thereafter, the Arellano-Bond test was utilized to test for serial correlation in the residuals. The null hypothesis was not rejected for the second order correlation, indicating that there is no second correlation in the first difference regression. [23] Thus, finding no evidence of higher order autocorrelation, supporting the model's validity assumptions. However, the null hypothesis was rejected for the first order correlation, indicating that previous risk will influence current risk. This is primarily due to the model utilizing the first lag of the dependent variable.

4. Empirical Results

4.1 Model 1: Bank Characteristics and Risk-Taking (baseline)

[22] Windmeijer provides two forms of bias corrected standard errors; one for GMM models estimated in a one-step (one optimal GMM weighting matrix) procedure, and one for GMM models estimated using an iterate-to-convergence procedure.

[23] The Sargan-Hansen test assumes that model parameters are identified via a priori restrictions on the coefficients, and tests the validity of over-identifying restrictions. The test statistic can be computed from residuals from instrumental variables regression. The Sargan-Hansen test results showed no evidence of over-identifying restrictions indicating that the instruments used in the model were valid.

The baseline model examines the relationship between the z-score and the bank-specific variables. The results from Model 1 were similar to the findings of Altunbas et al. (2011) and Foos et al. (2010), whose findings showed that banks with higher rates of abnormal loan growth are generally riskier. The findings of model 1 suggested that banks with higher rates of abnormal loan growth engage in more risk-taking as captured by the negative coefficient on aggregate loan growth in all three models (See table A.4).

Furthermore, the model showed that there exists persistence in bank risk-taking. This is indicated by the positive coefficient for the first lag of bank risk (l.RISK) in all models, while the second lag of bank risk was insignificant. Thus, current bank stability is primarily influenced by the last period's z-score. The model captures short-term persistence by using only the first lag of z-score. Furthermore, the coefficient for the lagged dependent variable further supports the validity of the model, since the coefficients for the first lag of bank risk are present in the OLS and the Fixed Effects model.[24]

Model 1 also showed that banks with a higher share of non-interest income are riskier and by extension less stable. This is contrary to the a priori expectations for this model as a higher non-interest income share means more diversification results. That is, banks that are less dependent on interest income are generally expected to be more stable. This is evident in the negative coefficient for the NNINC variable in the baseline system GMM model (See table A.4). Larger banks generally engage in activities[25] that allow them to increase their financial leverage. Furthermore, banks' benefiting from larger financial leverage may experience greater earnings volatility. This suggests that banks with a higher share of non-interest income may be riskier and less stable than

[24] This is expected in the presence of endogeneity, because the OLS estimate should be upward and the Fixed Effects estimate be downward biased if the lagged dependent variables are correlated with the error term (Roodman, 2009).

[25] These activities include commitments or guarantees; which are more risky off-balance sheet activities.

banks that mainly supply loans. Thereby, offsetting any positive effects resulting from income diversification.

As it relates to bank stability and other bank characteristics, generally the results showed that banks are more stable with a larger share of liquid assets to total assets (LIQUID). This is evidenced by the significant and positive relationship with the z-score. As it relates to bank size, the results showed evidence that larger banks, as measured by its total assets, are associated with less risk (see **table A.4**). This is evident by the positive significant coefficient for SIZE, indicating that this is a key determinant for risk-taking. In addition, the results demonstrate that an increasing weighted average lending rate (WALR) lowers banking risk. This may be because increasing loans rates increases interest income which in turns improve profitability for banks.

4.2 Model 2: Bank characteristics, country specific characteristics and risk-taking

Model 2 is a modification of the baseline model in order to control for the country-specific characteristics. The additional variables included in this model were the unemployment rate, GDP growth rate, the credit-to-GDP gap and an exogenous dummy variable to capture crisis periods such as: the national debt exchange, Jamaica Debt Exchange Programme (JDX) as well as the global financial crisis (CRISISDUMMY).

The results from the model showed that there are delayed effects of an increase in the GDP growth rate. This increase in the GDP growth rate is associated with higher risk-taking and greater financial instability. The model showed that there exists a negative relationship between the GDP growth rate and z-score (See table 5). The results showed that, although negative, this impact has a one-period lagged effect on risk in the banking system. The results of model 2 suggested that there is an increasing demand for banks' services and products during the cyclical upswings of the economy, which results in higher bank profitability as banks might engage in riskier lending practices, expecting continued economic growth. Therefore, an increase in economic growth results in greater financial stability for banks in past periods but current financial stability is compromised due to increased exposure to insolvency risk.

In addition, the results showed that risks that arise from loan growth may not materialize immediately. This is evidenced by the negative association of the lagged effect of credit-to-GDP gap and risk. While the contemporaneous effect of the credit-to-GDP gap is significant and positive, the lagged term is negative and significant at the 5.0 per cent, in the near-term the large credit gap will increase the z-score as banks initially make higher profits in credit booms. However, in the long-term, bank stability is offset by the heightened risk exposure during that period of credit boom. The results further highlighted that a higher unemployment rate is associated with greater credit risk.[26]

As it relates to short-term rates, the results showed that the rates on the 30-day T-bill 30-day (TBILL) are positively associated with the z-score. This indicates that an increase in the T-bill 30-day rate is associated with lower risk. The positive coefficient suggests that deposit-taking institutions become more stable if the level of short-term interest rates is high. This is in contrast to a priori expectations that increases in short-term interest rates lead to higher risk.

Furthermore, this model confirms that there is higher risk and instability in the Jamaican banking sector in periods of crisis. This higher risk during crisis periods is reflected in the consistent negative coefficient of the parameter 'CRISISDUMMY' across all models.[27] Of importance is that, the coefficient on the parameter labelled 'LIQUID' is statistically significant at the 10 per

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[26] This is consistent with the view that as people lose their jobs they become unable to cover debt obligations.

[27] The JDX involved the extension of maturity and reduction of coupon rates on local currency denominated GOJ bonds.

cent level. The results confirm that within the Jamaican banking system, a larger share of liquid assets to total assets will increase the z-score and lower the probability of insolvency. Therefore, this impacts the system positively by increasing stability and lowering risk-taking across the sector.

Importantly, the model confirms that abnormal loan growth results in a lower z-score and heightened risk in the banking system. This is indicated by the negative coefficient on AGGLOANGR, which is statistically significant at 5.0 per cent. This means that an increase in bank lending results in lower stability in banks with high rates of individual loan growth.[28] These results suggest that it is excessive credit growth that leads to bank instability. When country-specific characteristics are included, SIZE has a negative coefficient which is statistically significant at 10.0 per cent. This confirms the view that larger banks may invest more in risky assets due to the "too-big-to-fail" effect. The results show the strong impact larger banks have on the system.

4.3 Model 3: Relationship between DTI's Business Mix and Size

Model 2 was further modified to include the impact of non-interest income based on bank size. The results were similar to that of DeYoung and Roland (2001) that the increasing reliance of large banks on non-interest income may outweigh the benefits that arise from a larger size.[29] The findings showed that an increasing share of non-interest income is influenced by bank size. This means that as banks get larger, they shift operations away from core business activities to market-driven activities. The interaction term SIZENNIC is largely negative and significant at the 5.0 per cent level (See table A.6). This indicates that the benefits of a larger bank size decrease as

[28] Furthermore, high rates of aggregate credit growth increase systemic risk.

[29] Bank size offers better risk diversification if the shift toward non-interest activities is associated with higher revenue volatility.

banks become more active in non-interest income activities. One potential explanation is that diminishing returns to diversification may set in at the very largest sizes due to increased complexity.[30]

4.4 Model 4: Decomposition of DTIs' Risk taking

Model 4 utilized decomposed z-score components: portfolio risk and leverage risk to assess the robustness of the findings (see **equations 3** and **4**).

$$\text{PORTFOLIO } RISK_{it} = \sum_{l=1}^{2} \text{PORTFOLIO } RISK_{it-1}\,\beta_1 + V_{it}\,\beta_3 + J_{IT}\,\beta_4 + B_i\,\beta_5 + \varepsilon_{it} \quad \textbf{(3)}$$

$$\text{LEVERAGE } RISK_{it} = \sum_{l=1}^{2} \text{LEVERAGE } RISK_{it-1}\,\beta_1 + V_{it}\,\beta_3 + J_{IT}\,\beta_4 + B_i\,\beta_5 + \varepsilon_{it} \quad \textbf{(4)}$$

The results showed that a higher share of non-interest income decreases banks' risk-adjusted return. However, the effect differs for leverage risk with a positive coefficient indicating that a higher share of non-interest income is associated with lower leverage risk (See **table A.7**). This confirms previous findings that larger banks are more likely to engage in riskier off-balance sheet

[30] The findings are consistent with Stiroh (2004) who shows that a greater reliance on non-interest income, in particular trading income, is associated with higher risk across commercial banks. Larger banks may also be more likely to engage in riskier off-balance sheet activities such as securitization relative to smaller banks.

activities that increase leverage. As it relates to portfolio risk, the results showed that higher rates of loan growth are associated with higher returns. This is indicated by the positive, significant coefficient for LOANGR in the regression for portfolio risk. This is in line with the findings of Model 2, which showed that the contemporaneous effect of the credit-to-GDP gap is positive while the lagged impact is negative. This affects both portfolio and leverage risk in the case of Jamaica.

In addition, short-term interest rates remain significant and positive in the leverage risk model. This indicates that a higher level of interest rates is associated with decreased exposure to leverage risk. However, TBILL increases the level of portfolio risk, but not significantly. This is indicative of the inverse relationship between market rate and asset prices. It may be safe to assume that the positive impact found in the previous z-score models of higher 30-day T-Bill rates on bank stability is mainly driven by a lower leverage risk.

Generally, the results suggest that large DTIs are more exposed to credit risks and confirm the robustness of the findings of the z-score model which indicates that increases in loan growth is associated with heightened risk-taking. As a result, systemic risk could become more prominent and could potentially affect all DTIs in the long run.[31]

[31] As DTIs' lending portfolios increase, default and solvency risks also increase.

5. Conclusion & Policy Recommendation

The study provides new evidence on the relationship between abnormal loan growth and DTIs' risk-taking behaviour. The findings support the hypothesis of banks' inter-temporal short-sightedness, where the current decisions to influence profits can impact the future position of the institution. The short-term liquidity of bank credit, driven by high interest income, results in increased risk in banking operations, thereby creating a degree of volatility. The study demonstrates that abnormal loan growth during a sustained period leads to reductions in banks' capital ratios which results in a reduction in the z-score. This is primarily due to a greater volatility in assets (loans) of DTIs. As such, additional regulatory measures should be undertaken in order to maintain financial soundness when abnormal loan growth is observed. This may be undertaken by the imposition of a capital conservation buffer to bolster resilience as well as the implementation of a counter cyclical capital buffer (CCyB) which would build the resilience of DTIs in normal times and maintain credit to the economy if a downturn arises. Furthermore, DTIs' size offers better risk diversification, as larger banks tend to offer a wider range of services. However, when DTIs size is coupled with volatile investments holdings, size may increase solvency risk. Therefore, expanding the macroprudential policy toolkit to include a capital requirement for systemically important financial institutions (SIFIs) may reduce structural imbalances and insolvency risks.

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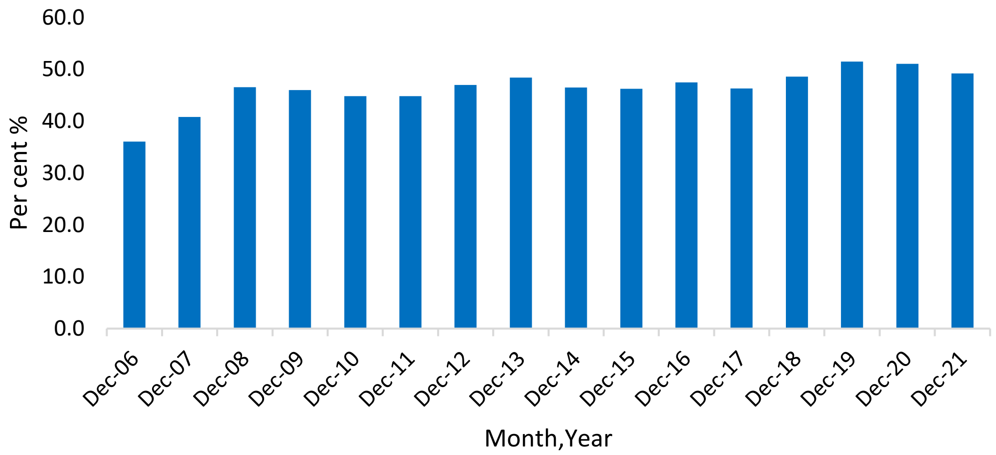
7. Appendix

Figure A.1: DTIs Loans to Assets



Source: Bank of Jamaica

Table A.1: List of variables shows the list of variables used in the regression analysis.

Variable	Description
CAR	Winsorized fraction a bank's equityl divided by its risk-weighted assets. The capital used to calculate the capital adequacy ratio is divided into tier 1 and tier 2 capital.
CREDIT GAP	Annual growth rate of PCRDBGDP minus its long-term trend. The long-term trend is obtained using the Hodrick-Prescott (1981) filter
l.CREDITGAP	First lag of credit-to-GDP gap.
GDPGR	Real GDP Growth. The rate at which Jamaica's Gross Domestic product (GDP) changes from one year to another.
l.GDPGR	First lag of real GDP growth.
l.RISK	First lag of Z-Score.
LIQUID	Winsorized fraction of liquid assets to total bank assets.
LOANGR	Quarterly rate of customer loan growth calculated as ((LOANSt-LOANSt-1)/LOANSt-1)*100 of all DTIs.
NIM	Winsorized fraction of net interest revenue divided by average earning assets.
NNINC	Winsorized fraction of (1-abs(Net interest income)/abs(Total income)).
Risk	This is calculated as the Z-score defined as the ratio of the return on assets (ROA) plus the capital ratio (CAR) divided by the standard deviation of the return on assets (SDROA).
ROA	Winsorized fraction of pre-tax profits divided by total assets.
SDROA	Standard deviation of ROA calculated for the period between March 2006 and December 2020.
SIZE	Winsorized logarithm of total bank assets.
SIZENNIC	Interaction term between the ratio of net non-interest income to total income (NNINC) and bank size (SIZE).
WALR	The interest rate charged on all the outstanding loans of banks: (Weighted average lending rate).
CRISIS	Dummy variable that is one for crisis periods in Jamaica and zero otherwise.
TBILL	The percentage return on investment on the Jamaican government's debt.
UNEMPLOYMENT	This is the percentage of unemployed individuals in the economy among individuals currently in the labour force.

Note: All bank variables are winsorized at the 1%- and 99%-level.

Table A.2: Descriptive statistics

	Obs.	Mean	Median	Std.Dev.	Max.	Min.
ZSCORE	1840	42.602	35.678	38.552	249.168	5.491
NNIC	1840	-5.047	0.560	10.785	0.095	-77.296
AGGLOANGR	1840	6.143	-0.047	44.835	225.759	-66.791
WALR	1840	19.109	20.108	3.639	25.573	11.798
TBILL	1840	8.272	7.710	4.410	22..01	0.770
SIZE	1840	8.374	8.335	0.267	8.855	7.900
CREDITGAP	1840	0.146	-0.498	2.778	8.116	-4.005
UNEMPLOYMENT	1840	11.813	11.821	1.975	16.284	7.185
CAR	1840	0.093	0.106	0.027	0.136	0.044
LIQUID	1840	136.547	210.900	180.751	295.226	96.000
GDPGR	1840	0.213	0.859	3.165	4.240	-18.391

Table A.3: Correlation matrix

	ZSCORE	NNIC	AGGLOANGR	WALR	TBILL	SIZE	CREDITGAP	UNEMPLOYMENT	CAR	LIQUID	GDPGR
ZSCORE	1.000	0.240	-0.055	-0.117	0.110	0.240	-0.157	0.101	0.382	0.440	0.091
NNIC	0.240	1.000	0.041	-0.222	-0.058	0.405	0.140	-0.125	0.444	0.589	0.050
AGGLOANGR	-0.055	0.041	1.000	-0.014	-0.074	0.015	0.021	-0.066	-0.075	-0.054	-0.036
WALR	-0.117	-0.222	-0.014	1.000	0.749	-0.924	0.151	0.134	-0.685	-0.427	0.362
TBILL	0.110	-0.058	-0.074	0.749	1.000	-0.614	0.352	0.041	-0.365	-0.090	0.103
SIZE	0.240	0.405	0.015	-0.924	-0.614	1.000	-0.033	-0.197	0.815	0.665	-0.344
CREDITGAP	-0.157	0.140	0.021	0.151	0.352	-0.033	1.000	-0.455	-0.173	0.163	-0.469
UNEMPLOYMENT	0.101	-0.125	-0.066	0.134	0.041	-0.197	-0.455	1.000	0.204	-0.108	-0.004
CAR	0.382	0.444	-0.075	-0.685	-0.365	0.815	-0.173	0.204	1.000	0.753	-0.314
LIQUID	0.440	0.589	-0.054	-0.427	-0.090	0.665	0.163	-0.108	0.753	1.000	-0.173
GDPGR	0.091	0.050	-0.036	0.362	0.103	-0.344	-0.469	-0.004	-0.314	-0.173	1.000

Figure A.2: credit-to-GDP gap

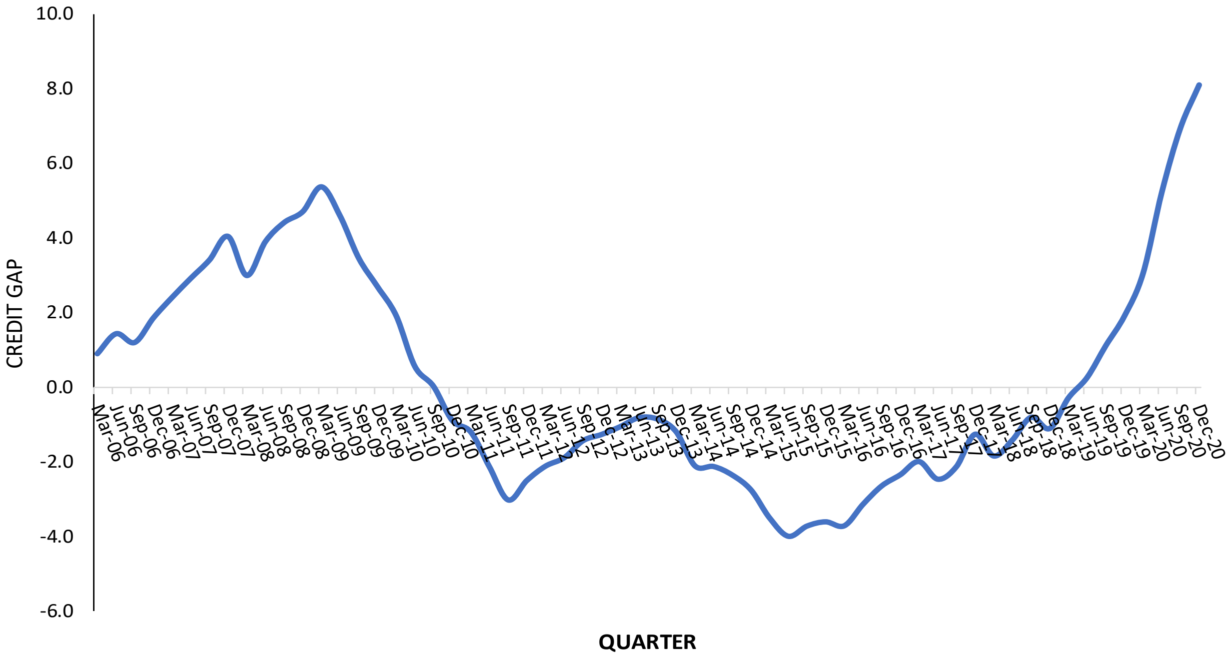


Figure A.3: DTIs' risk and credit-to-GDP gap

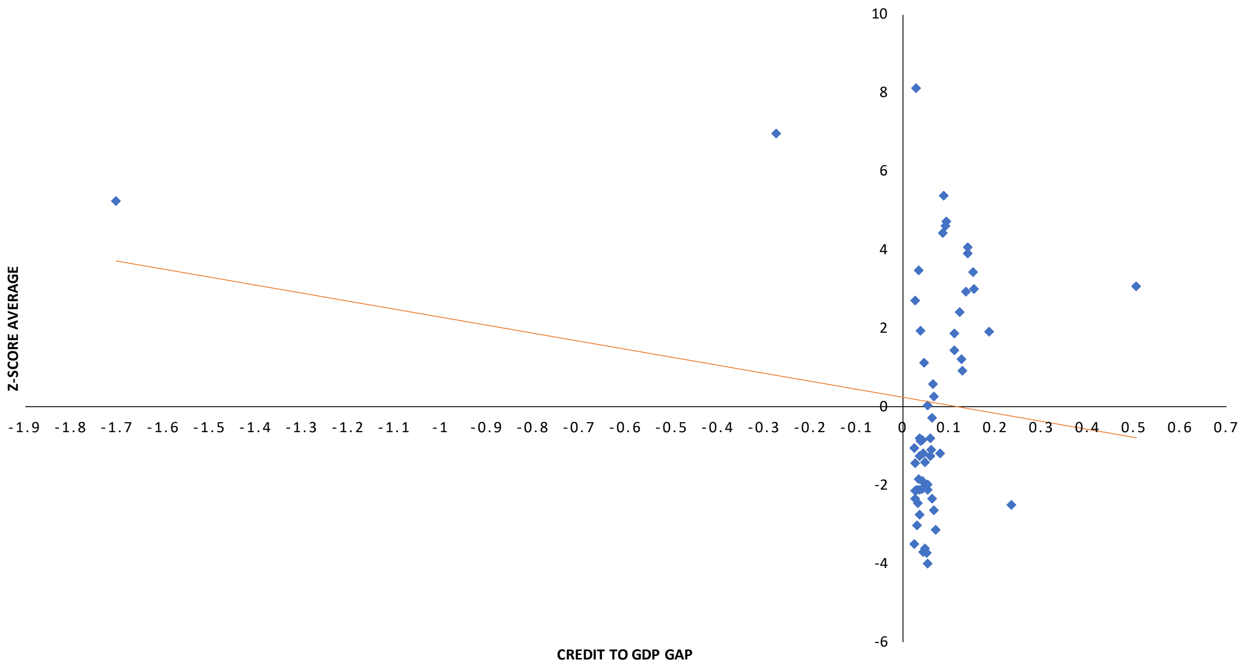


Figure A.4: Development of the average z-score

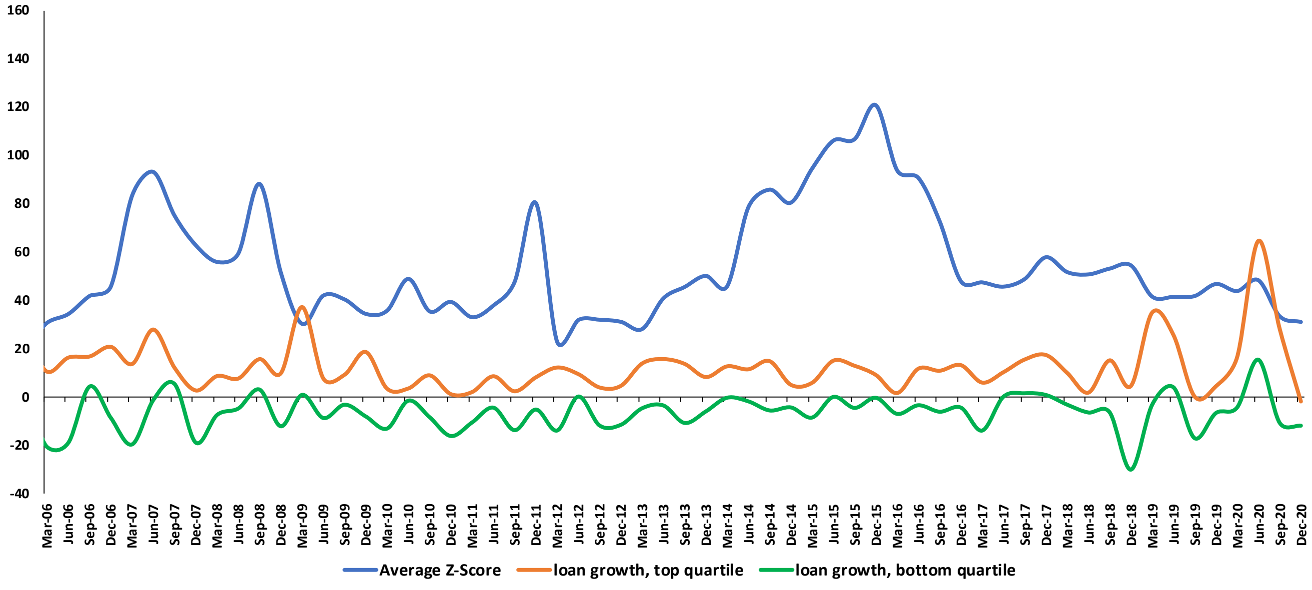


Figure A.5: z- score and CAR

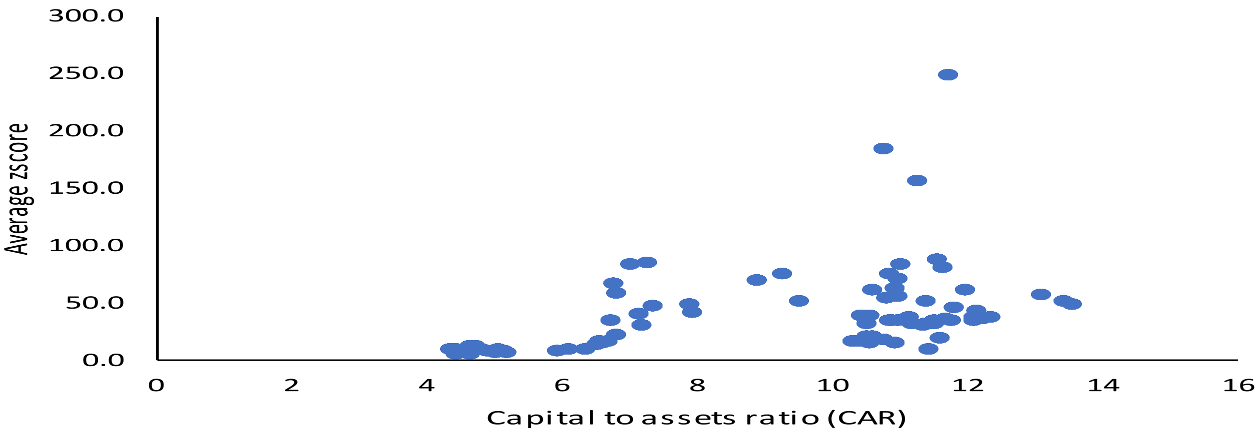


Figure A.6: DTIs' lending and profitability measures

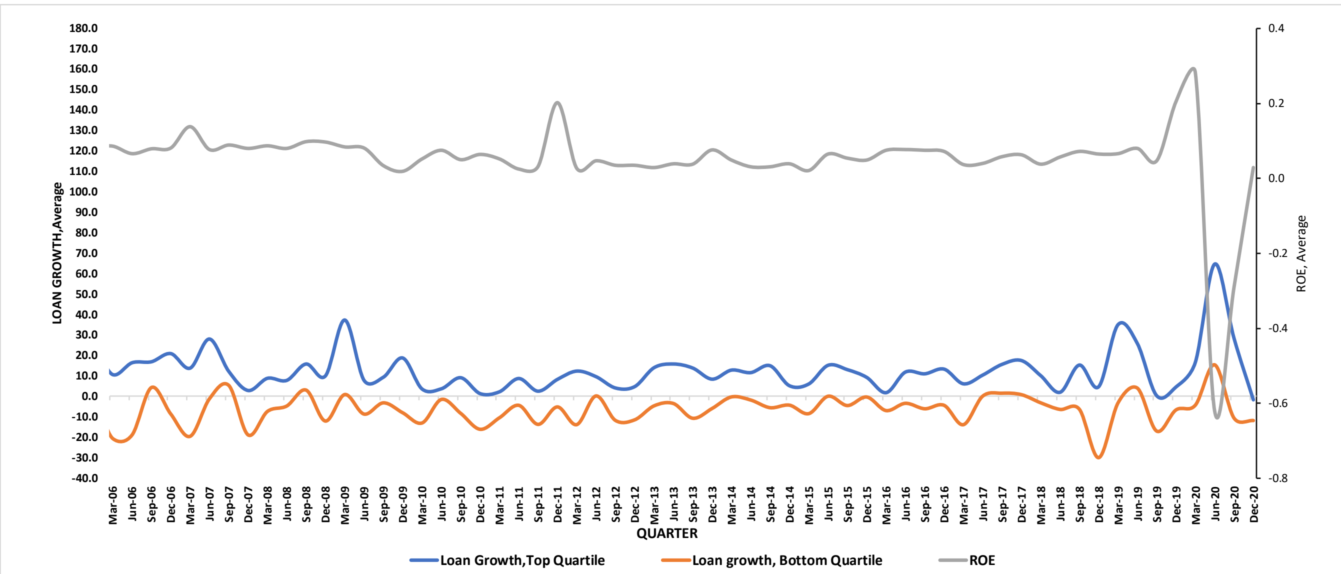


Table A.4: Model 1 Baseline results

	OLS	FIXED EFFECTS	SYSTEM GMM
L.Z-Score	0.13861***	0.13861***	0.77376***
	0.0252	0.0252	(0.133)
L.AGGLOANGR	-0.0599***	-0.0599***	-0.1045
	(0.025)	(0.025)	(0.075)
LIQUID	0.37461***	0.37461***	-0.1938
	(0.036)	(0.036)	(0.229)
SIZE	1.0957***	1.0957***	6.5003***
	(0.355)	(0.355)	(1.789)
NIM	2.97176	2.97176	-4.45874***
	(3.216)	(3.216)	(2.975)
NNINC	3.6592	3.6592	-0.541734
	(2.638)	(2.638)	(3.395)
WALR	7.1601***	7.1601***	8.48094***
	(2.002)	(2.002)	(9.962)
CAR	3.3563***	3.3563***	7.629901***
	(7.778)	(7.778)	(2.263)
Constant	-11.688***	-11.688***	-6.200316***
	(3.323)	(3.339)	(1.687)
No. of Observations	1,380	1,380	1,380
Durbin Watson (p-value)	2.10	2.10	1.85
AR1	0.00	0.06	0.33
AR2	0.41	0.69	0.59
Hansen Test (p-value)	0.71	0.82	0.42

NOTES:
Standard errors are reported in parentheses. ***/**/* indicates significance at the 5%-/1%-/10%- level.

Table A.5: Model 2 country specific controls

	SYSTEM GMM	SYSTEM GMM	SYSTEM GMM
L.Z-Score	0.55649***	0.2489***	0.209***
	(0.144)	(0.092)	(0.127)
CAR	-1.16621***	1.5637***	2.6019***
	(0.524)	(0.231)	(0.541)
LIQUID	-0.917	0.8804***	1.0421***
	(0.310)	(0.226)	(0.225)
L.AGGLOANGR	0.64783***	-0.279***	-0.448***
	(0.165)	(0.056)	(0.073)
NIM	-1.613	-2.486	-4.350637***
	(0.341)	(0.459)	(0.629)
WALR	1.3644*	-2.296***	-6.617576***
	(0.751)	(0.934)	(1.389)
SIZE	2.8173	-2.002	-1.09264***
	(1.432)	(1.597)	(2.521)
NNINC	-1.598	-7.361***	-5.68349
	(0.591)	(0.408)	(0.406)
CRISISDUMMY	0.56219	-0.6865	-2.47015
	(0.887)	(1.517)	(1.530)
L.GDPGR	-7.201796***	1.4908***	-0.76477
	(3.757)	-0.7277	-0.9383
CREDITGAP	0.746017	0.2167***	0.414232***
	(0.067)	(0.081)	(0.078)
L.CREDITGAP	0.300355	-0.042	-0.03682***
	(0.033)	(0.042)	(0.015)
TBILL		7.7717***	8.836441***
		(4.081)	(2.905)
UNEMPLOYMENTRATE			-1.320645***
			(0.529)
Constant	-3.044034***	1.633848	1.000377***
	(1.342)	(1.525)	(2.390)
No. of Observations	1380	1380	1380
Durbin-Watson stat	1.77	1.47	1.82
AR1	0.050	0.01	0.04
AR2	0.320	0.56	0.78
Hansen Test (p-value)	0.710	0.38	0.43

NOTES:
Standard errors are reported in parentheses. ***/**/* indicates significance at the 5%-/1%-/10%- level.

Table A.6: Model 3 Interaction term results

	SYSTEM GMM	SYSTEM GMM	SYSTEM GMM
L.Z-Score	0.093144***	0.2105***	-0.0939
	(0.049)	(0.084)	(0.181)
CAR	1.102973***	1.7277***	1.953589***
	(0.270)	(0.265)	(0.749)
LIQUID	0.616878***	-0.1279	1.4582***
	(0.116)	(0.218)	(0.200)
L.AGGLOANGR	-0.01527	0.0739	-0.448***
	(0.036)	(0.061)	(0.092)
NIM	-9.7559***	-5.423	-5.3943***
	(2.119)	(4.458)	(4.755)
WALR	2.136944***	-2.296	-10.095***
	(0.454)	(0.934)	(4.448)
SIZE	3.80996***	-2.002***	-1.7613***
	(0.910)	(1.597)	(2.605)
NNINC	1.435931	-2.7637***	3.2887***
	(0.821)	(0.960)	(0.877)
CRISISDUMMY	0.07381926	-3.8065***	-0.247015
	(0.087)	(0.168)	(0.153)
L.GDPGR	2.4960***	2.4794***	0.3511
	(0.045)	-0.5119	-1.0879
CREDITGAP	0.19597	0.0868	0.2197***
	(0.050)	(0.099)	(0.055)
L.CREDITGAP	-0.10882***	-0.1329***	-0.1298***
	(0.014)	(0.018)	(0.015)
TBILL		2.779	12.177***
		(2.647)	(2.984)
UNEMPLOYMENTRATE			-20.396***
			(6.291)
SIZENNIC	-1.7308***	3.168***	-3.9565***
	(0.934)	(1.099)	(9.907)
Constant	-3.8585***	1.633848	1.000377
	(0.859)	(1.525)	(2.390)
No. of Observations	1380	1380	1380
Durbin-Watson stat	1.79	1.98	1.71
AR1	0.03	0.01	0.12
AR2	0.42	0.37	0.56
Hansen Test (p-value)	0.72	0.88	0.67

NOTES:
Standard errors are reported in parentheses. ***/**/* indicates significance at the 5%-/1%-/10%- level.

Table A.7: Model 4 Components of DTIs' risk results

	Portfolio Risk	Leverage Risk
L.LEVERAGERISK		0.8233***
		(0.151)
L.PORTFOLIORISK	0.253661***	
	(0.049)	
CAR	1.896704***	2.02098***
	(0.215)	(1.976)
LIQUID	0.084078***	0.83476***
	(0.014)	(0.156)
L.AGGLOANGR	0.028209***	0.46097***
	(0.006)	(0.098)
NIM	-2.255995***	-8.1785***
	(0.223)	(4.400)
WALR	0.546246	-1.834069
	(0.562)	(1.231)
SIZE	1.192599	-4.19844
	(1.206)	(2.234)
NNINC	-5.679373***	0.124503
	(0.826)	(6.507)
CRISISDUMMY	1.071837	-0.4597
	(0.827)	(0.932)
L.GDPGR	0.210699	-0.07142
	(0.052)	(0.990)
CREDITGAP	0.032914	0.00248
	(0.005)	(0.004)
L.CREDITGAP	-0.06446	-0.0006
	(0.010)	(0.000)
TBILL	0.304768	14.1551***
	(0.130)	(2.827)
UNEMPLOYMENTRATE	-0.65529	-6.133289
	(0.198)	(4.792)
SIZENNIC	0.606127	-0.2065
	(0.101)	(0.487)
Constant	-1.394795	2.374895
	(1.157)	(2.121)
No. of Observations	1380	1380
Durbin-Watson stat	2.11	1.89
AR1	0.02	0.03
AR2	0.36	0.51
Hansen Test (p-value)	0.32	0.83

NOTES:
Standard errors are reported in parentheses. ***/**/* indicates significance at the 5%-/1%-/10%- level.