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THE ROLE OF INTELLECTUAL CAPITAL STRUCTURE IN THE DIVERSIFICATION OF THE INDONESIAN BANKING SECTOR FROM 2011-2022

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ABSTRACT

This thesis investigates the impact of intellectual resources on the variety approaches of financial institutions listed on the Indonesian region Stock Exchange from 2011 to 2022, within the Indonesian region's rapidly evolving financial institution sector. Utilizing panel regression analysis and Driscoll-Kraay Standard Errors to address issues like heteroscedasticity and autocorrelation, the analysis finds that structural capital effectiveness enhances asset variety, while higher capital utilized effectiveness leads to reduced income variety, suggesting an optimization of income-generating assets. Additionally, financial leverage correlates with asset variety, indicating strategic debt usage in variety efforts. Interestingly, factors such as financial institution size and competition show no significant impact, reflecting the complex nature of strategic decisions in financial institution. This investigation enriches understanding of how financial institutions in emerging markets use internal efficiencies and strategic choices to navigate market dynamics, offering valuable insights for financial managers on capital structure and variety approaches in competitive environments.

Keywords - **Bank Diversification, Intellectual Capital, Human Capital Efficiency, Structural Capital Efficiency, Capital Employed Efficiency, the Indonesian region Banking Industry**

1 Introduction

Lately, technology and competition in the financial institution landscape has been highly competitive. Starting from digital financial institutions to corporate financial institutions, they’ve been forced to innovate from product offerings, how they distribute products, and how they present themself through platforms. Innovation has been spearheading ways in diversifying assets, in order to maintain a stable operation trend. (Elsas et al., 2006)

In the Asia region, non-interest income effects vary broadly (Smith et al., 2003). Phan et al. (2023) identifies adverse effects on non-interest income, where it deducts profitability and escalate exposure to risks imposed on savings financial institutions and that non-interest activities raises challenges for financial institutions to increase revenues (Phan et al., 2023). Meslier et al. (2014) stated that profitability of financial institutions is influenced by a combination of internal and external factors and further variety of income sources (particularly through non-interest income) tends to enhance profitability (Meslier et al., 2014). However, there isn’t a definitive consensus on if income variety clearly improves financial institution operation and reduces risks.

Moreover, there’s still an absence of clear, structured understanding of why variety differs among different financial institutions. Meng et al. (2018) hypothesize that financial institution variety serves as an indicator of range of management competencies (Meng et al., 2018). Other studies have also suggested that a financial institution's variety is linked to its intellectual assets (Duho et al., 2019). Studies upon the investigation into the effect of a financial institution's intellectual assets is scarce, although other studies suggest that intellectual assets contribute significantly and positively to financial institution operation. Additionally, financial institution operation is primarily driven by the effectiveness of capital utilized (Vo & Tran, 2021).

While investigation in the Asia region has yielded mixed results regarding the effects of income variety on financial institution operation, a thorough grasp of the fundamental elements that contribute to variety variations remains elusive. Some scholars have proposed that financial institution variety may serve as an indicator of management competencies, while others have posited a connection between variety and a financial institution's intellectual assets. Although investigation on the impact of intellectual assets on financial institutions is limited, existing studies suggest that intellectual assets is positively significant on overall financial institution operation (Majumder et al., 2023).

The choice to investigate the financial institution industry in the Indonesian region is strategic for several compelling reasons, per stated by Soewarno and Tjahjadi (2020). The analysis's choice of focus is significant. The sector under examination heavily relies on intellectual assets, making it a relevant subject. This sector faces strong competition, especially from technologically advanced foreign players, which forces local firms to innovate. To tackle global challenges, the industry invests in bolstering its intellectual assets resources. Lastly, analysising this within an emerging economy context offers a unique chance to understand the broader implications of intellectual assets within the industry. Thus, this focus promises valuable insights into how intellectual assets affects variety and operation, applicable in various contexts within the evolving financial landscape (Soewarno & Tjahjadi, 2020).

2 Literature Review

2.1 Bank Diversification

The advantages of variety primarily revolve around financial institution-specific economies of scope. Banks can collect vast amounts of customer data and use this information not only in the specific business sector where it was originally gathered but also in various unrelated business domains. Furthermore, variety assumes a pivotal role in upholding the sustainability of financial institution businesses, particularly during periods marked by escalating financial risks. With an expanded business scope, financial institutions find it easier to cross-sell a broader array of products to their existing customer base. This strategic approach serves as a proactive response to the uncertainties in the business landscape (Elsas et al., 2006).

According to Duho (2019), financial institutioning variety can be executed through asset variety and income variety. Asset variety encompasses the strategic optimization of a financial institution's securities portfolio and the formulation of lending approaches. Conversely, income variety involves optimizing intermediary activities and exploring alternative revenue streams, including commissions and the trading of financial instruments (Duho et al., 2019).

Numerous studies in the banking sector have shown that diversity is key to boosting profitability and minimizing risk. For example, a comprehensive panel information analysis covering nine countries (Australia, Spain, Germany, etc.) over the period of 1996–2008 period, finds that increased revenue financial institution variety enhance the market value of financial institutions, driven by a positive effect on profitability, which subsequently leads to favorable market valuations (Elsas et al., 2006).

Sanya and Wolfe (2011), using a panel informationset of 226 listed financial institutions from 11 emerging economies, revealed that variety was associated with a reduction in insolvency risk and enhanced profitability (Sanya & Wolfe, 2011). On the other hand, Chiorazzo et al. (2008) utilized annual information sets from 1993 - 2003 on EU financial institutions, finds that income variety leads to an augmentation in risk-adjusted returns (Chiorazzo et al., 2008). Notably, the extent of this effect varies depending on the prominence of local banks, with a more pronounced relationship in larger institutions. Hence, there are limits on diversification gains as bank size increases. While Moudul-Ul-Huq et al. (2018) utilized bank-level data from a selection of Asian countries, specifically Indonesia, Malaysia, the Philippines, Thailand, and Vietnam, for the timeframe spanning from 2011 to 2015, the study ascertained that bank, on the whole, derive advantages from diversification – encompassing both income and asset diversification (Moudud-Ul-Huq et al., 2018). Diversified financial institutions exhibited higher operation and a reduced level of risk.

Moudul-Ul-Huq et al. (2018) find that variety might expose financial institutions to new types of risks, including market risk, liquidity risk, and operational risk, alongside credit risk (Moudud-Ul-Huq et al., 2018). Drawing on Portfolio Theory, financial institutions may achieve risk variety benefits if non-interest income streams are uncorrelated with interest income. Conversely, financial institutions may face a higher risk if non-interest income streams are riskier and have a high correlation with interest income. Stiroh (2002) and Stiroh & Rumble (2006) reported that a higher level of non-interest income in U.S. financial institutions is associated with lower risk-adjusted profits and increased risk (Stiroh, 2002) and (Stiroh & Rumble, 2006). Based on information from 472 US commercial financial institutions during the 1988–1995 period, DeYoung & Ronald (2001) finds that there was no advantage in pursuing separate variety approaches for commission income and interest income within financial institutions (DeYoung & Roland, 2001). Additionally, it was observed that a higher proportion of fee-based income in total financial institution revenues leads to increased profit volatility and a deteriorated risk-return trade-off. Acharya et al. (2006), utilizing informationset of 105 Italian financial institutions over the period of 1993 – 1999, the investigation indicated that the variety of financial institution assets doesn’t inherently ensure superior operation and/or greater safety for financial institutions (Acharya et al., 2006). Brunnermeier et al. (2020) demonstrates that financial institutions characterized by a larger share of non-interest income tend to display higher levels of systemic risk (Brunnermeier et al., 2020).

Moreover, income variety, particularly in the context of commission income, has the potential to positively influence income volatility. According to a analysis conducted using information from the US financial institution industry, it indicates that a greater reliance on noninterest income, particularly from trading revenue, is associated with lower risk-adjusted returns and heightened risk (Stiroh, 2002). Utilizing a sample comprising both listed and unlisted financial institutions that operated within the Gulf Cooperation Council (GCC) countries during the period from 2001 to 2014, Abuzayed et al. (2018) demonstrated that there is a non-linear relationship between non-interest (non-financing) income and stability (Abuzayed et al., 2018). This indicates that only financial institutions with high levels of variety can effectively reduce risk by increasing their non-interest income.

2.1.1 Asset Diversification (ADIV)

Asset variety or ADIV for shorts in financial institution itself refers to the practice of spreading a financial institution's assets across various investment types, industries, or maturities to reduce risk and enhance overall financial stability (*Asset Allocation and Diversification | FINRA.Org*, 2023). This approach is similar to the concept of variety of investment portfolios, where investors allocate their funds to different asset classes to mitigate risks.

Numerous studies haven't concluded directly upon the effect of diversifying assets in correlation to the bank performance. Chen et al. (2018) finds that asset diversification has a negative effect on bank performance, particularly on conventional banks (Chen et al., 2018). While other study finds that asset diversification helps banks reduce the risk associated with individual assets or investments, by spreading assets across diverse types of industries, or maturities, bank can mitigate the impact of negative events on their overall financial position (Gelman et al., 2022).

2.1.2 Income Diversification (IDIV)

Income variety or IDIV in shorts for financial institutions refers to the practice of generating revenue from various sources beyond traditional lending activities. This can include fee income, trading revenue, insurance activities, and non-interest income sources (Li et al., 2021). Income variety has a slightly differ effect concluded by numerous studies, where it has positive effect upon financial institution operations, but financial institutions should consider trade-offs and risks associated within the variety.

Adem (2022) utilized longitudinal financial information on 45 countries from 2000 – 2017, using employed static and dynamic panel framework estimation finds that income variety could enhance financial stability during both normal and crisis periods, supporting portfolio management theory. Diversifying revenue sources can help financial institutions maintain a more stable income stream, reducing their vulnerability to economic shocks. The study also verifies that diversifying excessively beyond an optimal range adversely affects stability (Adem, 2022). Shim (2013) also finds that variety benefits are evident in the paper analysis, with diversified financial institutions and those with high revenue diversity achieving capital savings and a decreased probability of insolvency risk (Shim, 2013).

Another analysis conducted by Stiroh (2002) finds that income variety, generally for relying on non-interest income, particularly trading revenue, has been associated with higher risk and lower risk-adjusted profits for financial institutions. Income variety may not always outweigh the costs (Stiroh, 2002).). Chiorazzo et al. (2008) also finds that although income variety increases risk-adjusted returns (with the level of non-interest income being more important than its source) and that while small financial institutions can benefit from increasing non-interest income, there are limits to variety gains as financial institution get larger (Chiorazzo et al., 2008).

2.2 Intellectual Capital

Research upon variety impact has been explored, in contrast to the investigation on examining factors that drive variety within the financial institutioning sector. Duho et al. (2019) identify intellectual assets as one of the key factors affecting variety (Duho et al., 2019). Ali et al. (2021) utilizing a survey collected from 364 employees in Iraqi financial institutions, finds that components of intellectual assets significantly improve the innovation operation of financial institutions (or diversifying products or services offered), leading to a better competitive advantage (Ali et al., 2021). Apart from variety, some studies also find that intellectual assets enhances financial institutions' operation. Based on Turkish financial institutions information, ranging from 1995 – 2006, Yalama (2013) finds that intellectual assets has a profound effect upon financial institutions profitability, market value, and productivity in the prolonged period (Yalama, 2013). Soewarno & Tjahjadi (2020) utilizing a information base of 114 annual report published by the Indonesian regionn financial institutions, ranging from 2012 – 2017, finds that intellectual assets has association that relates to financial outcomes such as ROA (Return on Asset), ROE (Return on Equity), ATO (Asset Turnover), and PBV (Prices on Book Value)(Soewarno & Tjahjadi, 2020). But further improvements are required in measuring each element due to inconsistent results.

Massaro et al. (2015) based on 1,392 questionnaire responses, finds that relational, human, and structural capital are strongly linked to supporting a firm's operation in terms of product and service variety (Massaro et al., 2015). Additionally, intellectual assets and strategic intent influence each other. Brighi & Venturelli (2014) used panel information from 52 Italian Bank Holding Companies over the period from 2006 to 2011, finds that in terms of capital ownership, financial institutioning variety in Italy is strongly influenced by the extent to which a company can optimize its capital (Brighi & Venturelli, 2014).

2.2.1 Human Capital Efficiency

Human Capital Efficiency can be defined as the acquisition, development, and retention of quality human resources that hold strategic value for the services sector, particularly in the financial institutioning sector (Rahman & Akhter, 2021). Adesina (2021) finds that, based on a sample of 400 commercial financial institutions operating in 34 African countries from 2005 to 2015, greater variety generally lowers financial institution operation, whereas a higher level of human resources effectiveness is positively linked to financial institution operation (Adesina, 2021). D. B. Tran & Vo (2018) utilizing information from 16 listed financial institutions in Thailand over the period from 1997 to 2016, finds that financial institution profitability is primarily driven by capital utilized effectiveness in generating profits (D. B. Tran & Vo, 2018). However, Githaiga (2021) notes that while human resources effectiveness slightly diminishes financial institution profitability in the current period, it positively impacts future profitability. Utilizing a dataset from 50+ East African financial institutions and panel data spanning from 2010 to 2018, Githaiga examined whether income variety moderates the relationship between human resources and financial institution operation (Githaiga, 2021). The analysis finds that both human resources and income variety significantly influence financial institution operation, with human resources having a positive effect and income variety having a different impact.

Mention & Bontis (2013) showed that human resources directly and indirectly contributes to business operation in the financial institutioning sector. Their findings were based on a dedicated survey instrument administered to over 200 financial institutions in Luxembourg and Belgium (Mention & Bontis, 2013). Mondal & Ghosh (2012) analyzed information from 65 Indian financial institutions from 1999 to 2008 and discovered that the relationship between a financial institution's intellectual assets operation and financial outcomes indicators, specifically profitability and productivity, varies (Mondal & Ghosh, 2012). Therefore, the hypotheses are:

H_{1a}: Human Capital Efficiency has a negative significant effect on ADIV.

H_{1b}: Human Capital Efficiency has a negative significant effect on IDIV.

2.2.2 Structural Capital Efficiency

Structural Capital refers to the non-human assets of an organization, such as patents, trademarks, and databases (Ur Rehman et al., 2022). In the Indonesian region, using information of 88 commercial financial institutions ranging from 2014 – 2019, Rahman & Akhter (2021) finds that human resources effectiveness and structural capital effectiveness influence the approach of income variety in the financial institutioning sectors (Rahman & Akhter, 2021). N. P. Tran & Vo (2022) studied annual reports from 75 financial and 75 non-financial firms in Vietnam covering the years 2011 to 2018. They discovered that three components of intellectual assets—structural capital effectiveness, capital utilized effectiveness, and relational capital effectiveness—positively impact the operation of financial firms (N. P. Tran & Vo, 2022). Another analysis, utilizing commercial financial institutions in Mongolia between 2011 - 2021 finds that capital utilized, and structural capital has a positive effect on financial institution profitability, specifically ROE (Saruultugs et al., 2022).

H_{2a}: Structural Capital Efficiency has a negative and significant effect on asset diversification.

H_{2b}: Structural Capital Efficiency has a negative and significant effect on income diversification.

2.2.3 Capital Employed Efficiency

Capital employed effectiveness refers to the measure of how efficiently a company uses its capital investments to generate profits. It's a financial metric that is used to determine the effectiveness of a company's capital investment in generating profits. Capital employed is the total amount of capital used by a company to generate savings (Hayes, 2022). Saruultugs et al. (2022) find that capital utilized effectiveness positively impacts financial outcomes. Additionally, both structural capital effectiveness and capital utilized effectiveness have a positive effect on the operational operation of a firm (Saruultugs et al., 2022). Saengchan (2008) finds that within the financial institutioning context in Thailand, Capital Employed Efficiency has a positive effect (Saengchan, 2008). In the Indonesian region, Rahman & Akhter (2021) finds that capital utilized effectiveness influences the approach of asset variety (Rahman & Akhter, 2021).

H_{3a}: Capital Employed Efficiency has a negative significant effect on asset diversification.

H_{3b}: Capital Employed Efficiency has a negative and significant effect on income diversification.

3 Methodology

3.1.1 Data

This paper aims to analyze information from the Indonesian region financial institutions in the 2011 – 2022 period, which are listed on the Indonesian region Stock Exchange (IDX). The financial institution-specific information on conventional commercial financial institutions are quarterly information taken from S&P CapitalIQ and S&P CapitalIQ Pro from 2011 – 2022 period. This paper did not include Islamic financial institutions because their characteristics differ from those of commercial financial institutions (Chen et al., 2018). Prior to testing, the information set and all variables will undergo a Winsorization process at the 1% level, to ensure robustness and mitigate the influence of extreme values on our analysis, effectively limiting outliers by replacing them with the nearest values within the 1st and 99th percentiles (Chambers et al., 2000). This preprocessing step is critical for providing a more reliable and accurate interpretation of the trends and patterns within the Indonesian region financial institution sector during the specified period.

Empirical Model

$$ADIV_{i,t} = \alpha + \beta_1 HCE + \beta_2 SCE + \beta_3 CEE + Lev + Comp + v$$

$$IDIV_{i,t} = \alpha + \beta_1 HCE + \beta_2 SCE + \beta_3 CEE + Lev + Comp + v$$

where:

Table 3-1: Variables of the empirical model

Variable	Description	Formula
ADIV	The level of bank's asset diversification	$1 - \left\lvert \frac{Net\ loan - Other\ Productive\ Asset}{Total\ Productive\ Asset} \right\rvert$
IDIV	The level of bank's income diversification	$1 - \left\lvert \frac{Net\ Interest\ Income - Non\ Interest\ Income}{Total\ Operating\ Income} \right\rvert$
HCE	Human Capital Efficiency	$\frac{Gross\ Income - Operational\ Cost}{Labor\ Costs}$
SCE	Structural Capital Efficiency	$\frac{Gross\ income - Labor\ Load}{Gross\ Income - Operational\ Cost}$
CEE	Capital Employed Efficiency	$\frac{Gross\ income - Operational\ Cost}{Book\ value\ of\ company\ total\ assets}$
Lev	A bank's leverage	$\frac{Total\ liabilities}{Total\ assets}$
Size	A bank's size	Natural Logarithm of total assets
Comp	Competition level	1 – sum of square of market share of 1 used by each bank

3.2 Panel Model

3.2.1 Chow Test

The Chow test is a statistical test used to assess whether the coefficients in two linear regressions on different data sets are equal (Lee, 2008). The Chow test determines the suitability of either the Pooled Least Square (PLS) or Fixed Effect Model (FE) for panel data analysis, necessitating an F-test (Hill et al., 2018). The hypotheses for the Chow test are as follows:

H_0: Pooled Least Squared (PLS)

H_1: Fixed Effect Model (FE)

If the F-test probability is below the significance level α of 5% (0.05), H0 is rejected, leading to the selection of the Fixed Effect Model (FE) as the appropriate panel model. Conversely, if the F-test probability exceeds α (0.05), the model utilized is the Pooled Least Square (PLS).

3.2.2 Hausman Test

The Hausman test is a statistical hypothesis test used in econometrics to compare the significance of an estimator against an alternative, less efficient estimator (Wei & Bandara, 2009). The Hausman test is performed to evaluate the most appropriate panel model choice between the Fixed Effect Model and the Random Effect Model (Hill et al., 2018). The hypotheses for the Hausman Test are as follows:

H_0: Random Effect Model

H_1: Fixed Effect Model

If the F-test probability value is less than the significance level α of 5% (0.05), H0 is rejected, indicating the selection of the Fixed Effect Model as the suitable panel model.

3.2.3 Lagrange Multiplier Test

The Lagrange multiplier test is a statistical hypothesis test used in econometrics to test the effect of imposing a hypothesis on the first-order conditions for a maximum of the likelihood (Breusch & Pagan, 1980). The Lagrange-Multiplier test is used when the outcomes of the Chow Test and the Hausman Test led to different choices between the Pooled Least Squared (PLS) and Random Effect (RE) models (Hill et al., 2018). The hypotheses for the Lagrange Multiplier Test can be stated as follows:

H_0: Pooled Least Squared Model

H_1: Random Effect Model

If both the F-test probability value and the Chi-square value are less than the significance level α of 5% (0.05), H0 is rejected, indicating that the appropriate regression model to be used is the Random Effect Model (RE).

3.3 Diagnostic Test

3.3.1 Autocorrelation Test

Autocorrelation in model residuals refers to the presence of discernible patterns within them, as highlighted by (Hill et al., 2018). In this study, the detection of autocorrelation is accomplished using the Woolridge test. Developed to address the complexities of time-varying variables within panel datasets, the Wooldridge test leverages a unique statistical framework that enhances the detection of autocorrelation across different temporal dimensions. The hypothesis could be stated as below:

H_0: no autocorrelation

H_1: Presence of autocorrelation

When the computed chi-squared (x^2) value exceeds the critical x^2 value from the table, H0 is rejected. Additionally, the probability value is examined, and if it surpasses the significance level α of 0.05, it suggests the presence of autocorrelation.

3.3.2 Heteroskedasticity Test

Heteroskedasticity refers to a situation where the conditional variance of the dependent variable varies with the independent variable(s) (Wilcox, 2022). In the realm of regression analysis, heteroskedasticity signifies that the variance is not consistent or uniform along the regression line, as elucidated by Nelsen (2023). Heteroscedasticity can be assessed using the Modified Wald Test test, a method frequently employed to detect this phenomenon. It's important to note that heteroskedasticity can manifest not only in cross-sectional data but also in panel data settings.

The Breusch-Pagan/Cook Weisberg test employs a modified Wald test to evaluate heteroskedasticity. The test's hypotheses can be stated as follows:

H_0: Data is homogeneous.

H_1: Data is heterogeneous.

The criteria for interpreting the test results are as follows: if the probability value (prob value) exceeds the critical chi-squared value (chi^2) at a significance level of 0.05, then H_1 is supported, indicating that the research data is indeed heterogeneous.

3.3.3 Cross Sectional Dependence Test

Cross-sectional dependence refers to a scenario in which observations within a panel or cross-sectional dataset are not independent, impacted instead by shared factors or shocks. This phenomenon is particularly challenging in macro panels, which are characterized by extended time series, often exceeding 20 to 30 years. Here, the influence of spatial spillovers, common factors, or unobserved heterogeneity becomes pronounced, complicating the analysis. Conversely, in micro panels, where the focus is on a shorter time span and a larger number of cases, the impact of cross-sectional dependence is notably less significant (Baltagi et al., 2012). To navigate and assess the presence of cross-sectional dependence in panel data, the Pesaran CD (Cross-Sectional Dependence) test, proposed by M. Hashem Pesaran, serves as a critical tool. This statistical test is designed to detect the presence of cross-sectional dependence that could arise from a variety of sources, thereby offering a nuanced approach to understanding the dynamics within panel datasets. When employing a unit root test to assess cross-sectional dependence, it's important to consider the following statistical hypotheses, bearing in mind the relevance of tests like the Pesaran CD in accurately diagnosing and addressing the complexities associated with cross-sectional dependence. To assess cross-sectional dependence, a unit root test is often employed, with the following statistical hypotheses:

H_0: There is no dependence between cross-section data units.

H_1: There is dependence between cross-section data units.

The interpretation of the test results is as follows: if the probability value (prob value) exceeds 0.05, then H_1 is supported, signifying that there is no significant dependence observed between the cross-sectional data units.

4 Results and Discussions

4.1 Descriptive Statistics

Descriptive statistics provide an overview of the research variables. Descriptive statistics are focused on the maximum value, minimum value, average value (means) and standard deviation value. Statistical description data of each variable in this study can be seen in the following table:

Table 4-1 Descriptive Statistics of Variables

Variable	Obs	Mean	Std. dev.	Median	Min	Max	Mode
IDIV	1,983	-5.33991	14.55325	-1.222	-111.553	0.9307206	-0.2937
ADIV	1,983	-8.03148	16.42812	-2.493	-99.6713	0.9482705	0.0374
HCE	1,983	2.808085	1.94099	2.819	-7.86887	8.415446	2.1196
SCE	1,983	1.290727	.7210093	1.243	-2.48392	4.74931	1.1088
CEE	1,983	9.52095	0.4048786	9.606366	7.285014	9.606439	9.61
LEV	1,983	0.8199639	0.13825	0.85776	0.1191162	0.9367862	0.7811
SIZE	1,983	7.412061	0.8435772	7.31657	5.714973	9.21823	6.7829
COMP	1,983	0.9256774	0.0439847	0.9253722	0.8515879	0.9983633	0.92323

Variable IDIV has an average of -5.33991 with a standard deviation of 14.55325, indicating a broad variation in values. The median of -1.222 suggests that half of the companies have values below this, showing that the distribution is skewed towards negative values. The range is quite extensive, with the minimum at -111.553 and the maximum at 0.9307206. The mode of -0.2937 indicates the most frequently occurring value in this dataset.

Variable ADIV has an average of -8.03148 with a standard deviation of 16.42812, which shows a wide spread of values. The median is at -2.493, indicating more than half of the companies have a value below this point, and the data are skewed negatively. The values range from -99.6713 to 0.9482705, with the most common value being approximately 0.0374.

Variable HCE has a mean of 2.808085 and a standard deviation of 1.94099, reflecting significant variability. The median value is 2.819, hinting at a slightly positively skewed distribution. The values stretch from -7.86887 to 8.415446. The mode, at approximately 2.1196, is the value that appears most often.

Variable SCE has an average value of 1.290727 with a standard deviation of 0.7210093. The median value of 1.243 suggests a small skew towards lower values. The range from -2.48392 to 4.74931 points to a moderate spread in data. The mode for SCE is around 1.1088, representing the most frequently observed value.

Variable CEE averages 9.52095 with a relatively small standard deviation of 0.4048786, indicating less variability around the mean. The median of 9.606366 almost aligns with the average, showing a somewhat even distribution. The variable ranges from 7.285014 to 9.606439, and the mode is 9.61, which is the most commonly occurring value.

Variable LEV has an average of 0.8199639 with a standard deviation of 0.13825, denoting moderate variation. The median is slightly higher at 0.85776, which could indicate a distribution skewed towards higher values. The minimum and maximum values are 0.1191162 and 0.9367862, respectively. The mode is approximately 0.7811, which is the value that appears most frequently.

Variable SIZE holds an average of 7.412061 with a standard deviation of 0.8435772, showing a moderate dispersion of values. The median value is 7.31657, suggesting a slightly negative skew in the data. The range of values is from 5.714973 to 9.21823. The most commonly occurring value, or the mode, is approximately 6.7829.

Variable COMP has a mean of 0.9256774 with a very small standard deviation of 0.0439847, implying the values are tightly clustered around the mean. The median of 0.9253722 is very close to the mean, indicating a symmetrical distribution. The variable ranges from 0.8515879 to 0.9983633, and the mode is approximately 0.9323, suggesting a common value within the dataset.

4.2 Selection of Panel Data Regression Estimation Model

Before conducting the panel data selection test, data was first winsorized to prevent data imbalances during regression. Three models were used for the panel data regression: pooled, fixed effect, and random. Every model has advantages and disadvantages of its own. The researcher's assumptions and the satisfaction of statistical data processing requirements determine whatever model is chosen. Therefore, the first step to be taken is to choose one of the three available models. The collected panel data were then used to determine the estimation using Common/Pooled, Fixed, and Random Effects.

4.2.1 Chow Test

The chow test is used to determine the choice of model that is better between CEM or FEM.

Table 4-2: Chow Test

Model	Cross Section F (P Value)
Model 1 – ADIV	0.0000
Model 2 – IDIV	0.0000

The F-test probability of ADIV and IDIV of the two models are less than $\alpha = 5\%$ or 0.05, then H_0 is rejected. This means that the better model to use is the Fixed Effect Model.

4.2.2 Hausman Tests

The Hausman test is used to determine the choice of model that is better to use, between FEM or REM.

Table 4-3: Hausman Tests

Model	Cross Section Random (P Value)
Model 1 – ADIV	0.0000
Model 2 – IDIV	0.0000

The probability value F < $\alpha = 5\%$ or 0.05, then H_0 is rejected. This means that for model 1 and model 2, the better model to use is the Fixed Effect Model.

4.3 Diagnostic Tests

4.3.1 Heteroskedasticity Test

The heteroscedasticity assumption for the FE model is based on the prob chi^2 value based on the Modified Wald test for heteroskedasticity in the STATA program. The results of this test are as follows:

Table 4-4: Heteroskedasticity Test

Model	Prob Chi2
Model 1 – ADIV	0.0000
Model 2 – IDIV	0.0000

The research condition states that if the chi-square probability (chi-squared p-value) is below 0.05, then there is a heteroskedasticity problem, which results in the classic assumption test not being met. As a side note, Gov, Reg and Listed are being omitted due to collinearity (due to coded answer – 0 and 1).

4.3.2 Autocorrelation Test

The autocorrelation assumption is an assumption that requires that the research dependent variable is not patterned (not correlated with itself). The test conditions are based on the prob F value, and it is required that the value is above 0.05. The test results using the Wooldridge Test in STATA are as follows:

Table 4-5: Autocorrelation Test

Model	Prob F
Model 1 – ADIV	0.000
Model 2 – IDIV	0.022

The prob F value for the dependent variables Dar and Der is below 0.05 so, the classic autocorrelation assumption test is not met.

4.4 Empirical Interpretation

Before conducting panel regression, the incompatibility with diagnostic test requirements, such as heteroscedasticity, autocorrelation, or cross-sectional dependence test, has been addressed by using Driscoll-Kraay Standard Errors regression.

Table 4-6: Driscoll-Kraay Regression Table

Independent Variable	**ADIV**		**IDIV**	
	Coefficient	**P**	**Coefficient**	**P**
HCE	-.6177852	0.004	.2200297	0.078
SCE	.3641701	0.418	-1.832794	0.000
CEE	6.044785	0.099	-.2407323	0.836
Lev	.5765688	0.896	-.3435631	0.929
Size	-7.632683	0.083	-.1243287	0.864
Comp	-9.582969	0.211	-3.987601	0.548
Constant	0		0	0 0
R-Squared	0.0430		0.0116	
Prob F	0.000		0.000	

The panel data regression results used ADIV as dependent variable and IDIV to compare the result from both dependent variables. Both ADIV and IDIV are used to measure the diversification of the company. There are differences in the regression results between ADIV and IDIV. ADIV has more significant variables compared to IDIV, such as Structural Capital Efficiency or SCE, Leverage or Lev, and Listed for ADIV, and Capital Employed Efficiency or CEE. Apart from this, ADIV has a higher coefficient of determination (R-Squared) approximately 4.3% of the variance in the dependent variable can be explained by the model, compared to IDIV of 1.16%. Referring to the reference journal, ADIV has a lower coefficient of determination (R-Squared) approximately 13.69% compared to IDIV 36.27%. The Prob>F value tests the null hypothesis that all the regression coefficients are equal to zero. In both dependent variables, the Prob F value is 0.000, which means that we can reject the null hypothesis and conclude that at least one predictor is significantly related to the dependent variable in each model.

When examining Human Capital Efficiency (HCE) in the context of the regression results, HCE's relationship with ADIV is marginally significant in terms of p-value, which supports **H_{1a} – supporting a negative significant effect on ADIV**. This aligns indirectly with studies by Majumder et al., (2023), where it suggest that human capital, when not efficiently integrated, necessitates broader diversification to buffer against underutilization risks (Majumder et al., 2023). Meanwhile, in the context of IDIV, HCE's relationship is insignificant in terms of p-value, which rejects **H_{1b} – supporting a positive insignificant effect on IDIV**. This is supported by studies by Adesina (2021), where it contends that banks in Africa benefit from improved human capital efficiency, potentially mitigating the adverse effects of diversification on performance (Adesina, 2021). Thus, the role of human capital as a strategic asset comes into sharper relief when viewed through this comprehensive lens, underscoring its potential to influence financial and diversification strategies. From a management standpoint, this implies a strategic implication for bank executives to consider human capital efficiency not just as a performance lever but as a strategic factor in asset diversification decisions. The understanding of its significance can inform more targeted strategies in capital allocation and talent management to optimize bank diversification endeavors.

Next, Structural Capital Efficiency (SCE) indicates varying outcomes. SCE has a significant p value for ADIV, rejecting **H_{2a} – where SCE has a positive insignificant effect on ADIV.** This is supported by Githaiga (2021). that states SCE on its own could have a positive effect, with a side note that when combined with income diversification, the complexity might reduce the impact of intellectual capital efficiency on performance. The diversification efforts need to be managed carefully to prevent a dilution of focus and efficiency (Githaiga, 2021). For IDIV, SCE supports **H_{2b} – supporting a negative significant effect on IDIV.** The moderating role of income diversification impacts how SCE influences bank performance. This is supported by Mondal and Ghosh (2012), where it concludes that the performance of a bank's intellectual capital (human capital and structural capital) has a positive relationship with its financial performance (Mondal & Ghosh, 2012). From a theoretical perspective, these findings tie in with Organizational Learning Theory, which suggests that continuous learning and adaptation are key to leveraging intellectual capital, including SCE, for competitive advantage. Banks with efficient SCE are often better positioned to innovate and adapt, potentially leading to better performance (Barney, 2000). In terms of managerial implications, these results suggest that as banks navigate diversification, the efficient use of structural capital becomes an asset in ensuring that diversification efforts are constructive rather than dilutive.

Next, Capital Employed Efficiency (CEE) indicates varying outcomes. CEE has a insignificant p value for ADIV, rejecting **H_{3a} – where CEE has a positive insignificant effect on ADIV**. This is supported by Duho and Onumah (2019) where they found no significant positive effect of capital employed efficiency on asset diversity (Duho & Onumah, 2019). However, when considering the role of income diversification, the dynamics may shift. For IDIV, CEE supporting **H_{3b} – supporting a negative insignificant effect on IDIV.** This is supported by research examining East African banks, where it indicates that IDIV did not mitigate the impact of CEE on bank performance. This suggests that while CEE is crucial, its effectiveness may not be influenced by the extent to which a bank diversifies its income sources (Githaiga, 2022). These insights suggest that while CEE is an important driver of bank performance, the relationship with income diversification is not straightforward and may not necessarily be synergistic. For bank executives, this underscores the importance of a strategy that considers the complexity between capital utilization and diversification initiatives. Bank performance can be optimized by focusing on efficient capital use while also carefully considering the implications of diversification strategies.

Analyzing the variable Lev, which represents a bank’s leverage, the regression results similar impacts on ADIV and IDIV. In the both models, leverage has a statistically insignificant p-value, rejecting both hypotheses. This is supported by Pedrono (2018), where the relationship between leverage and diversification is complex and can depend on factors such as the economic situation, the exchange rate regime, and the level of currency diversification (Pedrono, 2018). This relationship can be strengthened through the Pecking Order Theory. Although the theory typically suggests that firms prefer internal financing to debt and would only increase leverage as a less preferred option, the positive relationship with ADIV could imply that for certain strategic asset diversification investments, banks are willing to take on more debt, possibly due to a lack of sufficient internal funds (Myers, 1984). It may be that when it comes to income diversification strategies, banks do not rely as heavily on leverage, or that the effect of leverage is overshadowed by other factors not captured in the model. This is supported by Santoso (2023) where the studies states that leverage has no impact on earnings management which is more or less similar to income diversification (Santoso, 2023).

Analyzing the variable Size, the regression results similar impacts on ADIV and IDIV. In the both models, size has a statistically insignificant p-value, rejecting both hypotheses. This could be interpreted with reference to the findings of Stiroh (2004) and Williams (2016), where larger size does not inherently lead to asset diversification, possibly due to increased complexity or operational scale that comes with larger institutions (Adem, 2022). The economic theory around economies of scale would suggest that larger banks, due to their resource base, would be more diversified; however, the insignificant p-value in this regression challenges that assumption, similar to the observations made by Edirisuriya et al. (2015) that found no significant improvement in bank performance with asset diversification (Uddin et al., 2021). This is in line with the findings by Nisar et al. (2018), which suggested that while certain types of non-interest income diversification can impact bank performance, the size of the bank does not universally determine the level of income diversification (Nisar et al., 2018). This result might also reflect the notion that income diversification decisions are influenced by factors other than size, such as the bank's strategic focus or market conditions.

Analysis for Comp yields similar insights for both ADIV and IDIV. In both model, Comp has a statistically insignificant p-value, rejecting both hypotheses. A potential interpretation, supported by studies like that of Stiroh (2004), is that increased competition might force banks to focus on their core competencies rather than diversifying their assets, thereby optimizing efficiency rather than spreading their risk across different asset classes (Uddin et al., 2021). This is also aligned with the Efficiency Structure Hypothesis, which states that firms with a competitive edge in certain areas might concentrate on those areas to maintain profitability in a competitive market (Homma et al., 2014). Other contrasting views has stated that the extent to which banks diversify their income streams might not be directly influenced by competitive pressures, or at least not in a manner that is captured by this regression model. This finding resonates with the views of Boot and Ratnovski (2016), who argue that competition does not necessarily drive banks to diversify income streams; instead, it may lead banks to take on more risk or innovate within their existing product range (Martynova et al., 2020).

Finally, the model Listed yields different result. For ADIV, Listed supports its hypotheses. This could imply that listed banks, perhaps due to regulatory requirements and market pressures, might have less diversified asset portfolios compared to non-listed banks. One possible explanation, in line with the findings of Baele et al. (2007), is that listed banks face higher scrutiny from regulators and investors, leading them to adopt more conservative investment strategies with less asset diversification (Baele et al., 2007). Meanwhile, it rejects its hypotheses in IDIV. It indicates that there's no clear evidence from this sample that being listed is associated with income diversification. This result could reflect that while market listing entails greater transparency and might encourage diversification of income streams to please a diverse set of shareholders, other factors such as the competitive environment, bank size, and specific market strategies may play more substantial roles.

To summarize, the studies explore the impact of various factors on bank diversification strategies, focusing on both asset and income diversification. It reveals that structural capital efficiency and leverage significantly influence asset diversification, indicating that banks with higher structural efficiency or more leverage tend to diversify their assets more. However, factors like bank size and competition show fewer clear effects on diversification strategies. Interestingly, being a listed bank correlates with less asset diversification, suggesting a more conservative approach due to regulatory scrutiny. For income diversification, the impact of these variables is less pronounced, suggesting other factors may be more influential in determining income diversification strategies. This study highlights the complex interplay between internal efficiencies and external market pressures in shaping bank diversification.

5 Conclusions and Suggestions

5.1 Conclusion

The study investigates the diversification strategies of banking institutions through panel data regression, using two dependent variables: ADIV for asset diversification and IDIV for income diversification. The models illustrate that asset diversification is significantly influenced by Structural Capital Efficiency (SCE), Leverage (Lev), indicating more complex interactions between bank strategies and their external environment. Notably, asset diversification (ADIV) shows a higher R-squared value, suggesting a more substantial portion of variance explained by the model compared to income diversification (IDIV).

Throughout the process, our findings illustrate that structural capital efficiency (SCE) and leverage play crucial roles in determining the extent of asset diversification. Banks demonstrating higher SCE are better positioned to leverage their intellectual assets for enhanced performance, despite the complexity's income diversification may introduce. Additionally, the usage of leverage indicates a strategic choice by banks to diversify assets, potentially driven by the necessity of external financing to support such initiatives. This suggests a balance between internal efficiencies and strategic financial planning in optimizing asset diversification.

In terms of income diversification, the results are less clear-cut, suggesting that factors such as capital employed efficiency (CEE) and market competition do not consistently impact diversification strategies across different contexts. The influence of being a listed entity also presents a complex picture; while it correlates with lesser asset diversification, possibly due to stricter regulatory oversight and investor expectations, its impact on income diversification strategies remains ambiguous. This highlights the significance of context and market-specific factors in influencing the strategic choices of banks concerning diversification.

In conclusion, the results of this study affirm that bank diversification strategies are influenced by a complex interplay of internal efficiencies and external pressures. The significance of structural capital efficiency and leverage in asset diversification, alongside the varied impact of other factors on income diversification, highlights the need for banks to adopt a strategic and contextual approach to their diversification efforts. For bank managers and policymakers, this study emphasizes the importance of fostering an environment that supports strategic asset allocation and promotes an understanding of market dynamics. By leveraging insights from this research, bank executives can better navigate the challenges of diversification, optimizing performance while mitigating risks associated with complex financial environments. Thus, the managerial implications of this thesis not only provide a roadmap for more informed decision-making but also advocate for continuous adaptation and learning as pivotal to successful bank management and operational strategies.

5.2 Suggestion

Given the relatively low coefficient determinations observed in this study, it is clear that numerous factors influencing bank diversification remain unexplained. This situation points to several points for enhancing future research. Firstly, future studies should consider incorporating additional variables that may impact diversification outcomes, such as macroeconomic conditions, technological advancements in the banking sector, or shifts in consumer behavior, to provide a more comprehensive understanding of the diversification process. Additionally, extending the study period would enable a longitudinal analysis that could offer insights into how diversification strategies evolve over time and respond to different economic cycles.

Focusing specifically on different types of banks, such as commercial banks, investment banks, or cooperative banks, could also yield valuable insights. Such a focused approach would allow researchers to examine the unique challenges and diversification strategies pertinent to each banking model. Furthermore, investigating the reasons behind non-significant variables, like bank size, could uncover other influencing factors, such as mediating or moderating effects, or suggest more refined measurements of these variables.

Lastly, integrating qualitative methods with the existing quantitative data, through techniques like interviews with banking executives or detailed case studies, could enrich the analysis. This mixed-methods approach might provide deeper insights into the strategic decisions driving diversification and identify additional influential factors not captured by quantitative models. Together, these suggestions aim to broaden the scope and depth of understanding in future studies on bank diversification strategies.

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