Inclusivity of financial services and regional growth in the Philippines: A panel data estimation approach

Vaneza Jean M. De Tomas[1], **Jennifer E. Hinlo**[1]

[1]*College of Applied Economics, University of Southeastern Philippines, Davao City, Philippines*

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corresponding authors: jennifer.hinlo@usep.edu.ph

Abstract

The accessibility in basic financial services is a vital component in the growth of regional economies in the Philippines. However, there are certain barriers that hindered the effective and efficient access, as well as utilization of Filipinos to rudimentary services in the financial sector. With this dilemma, we examined how inclusivity in the financial sector affects regional growth of economies thorough a panel regression analysis approach using yearly data (2015-2020). Based on our findings, regional financial inclusion disparities are prevailing amongst urban and rural regions. Moreover, results have shown that inclusivity of the financial sector have a positive influence on growth of regional economies. Significant findings serve as an input for policies that will strengthen public-private partnerships in sustaining and strengthening the financial services in the regions.

Keywords: Financial inclusion; regional economic growth; panel data; Philippines

JEL Classification Codes: C33, C43, G21

1. Introduction

The availability of useful services and products in the financial sector, like insurance, savings disbursements and credit, that are given in a moral and sustainable manner is referred to as financial inclusion or inclusivity of the financial sector (Van *et al.*, 2021). Survey of Financial Inclusion (BSP, 2019) reports that only 29% of Filipinos have a formal bank account. With this, 7 out of 10 Filipinos are not actively engaged in formal financial access and usage. The underserved Filipino population continues to experience financial hardship because of limited accessibility to basic services in the financial sector. Therefore, a thriving financial environment is a prerequisite for development and a sign that the nation, particularly in its many areas, has a thriving economy.

Given this situation, an evaluation of financial inclusivity in the various Philippine regions is essential, in order to examine how this impacts regional economic growth. Currently, studies about financial inclusion are limited (Camara & Tuesta, 2014) and there are still prevailing issues on its robust measurement. There were relevant findings from Africa, Nepal, India and Indonesia, reporting that economic growth and financial inclusivity has a substantial direct relationship (Musembi and Chun, 2020; Ratnawati, 2020; Gajurel, 2022; Ifediora *et al.*, 2022;). However, most of these studies were analyzed on a national scale and domestic regional analysis using panel data regression are rarely attempted. In the Philippines, financial inclusion index was constructed and analyzed using 2012 data (Mojica & Mapa, 2016), but it was not able to compare indices across time and regions and investigate how it will influence growth in the economy.

With this research gap, the study's primary objective is examining an impact of inclusivity of financial services to the expansion of regional economies in the Philippines using panel data regression analysis, using pooled data of 17 regions over a time period of 6 years (2015-2020). Hence, the preliminary goal is to develop a regional financial inclusion index and used this as a predictor in evaluating the regional economic changes over time and across regions. Secondly, empirical estimation employed two models in the analysis. The first model used the overall index as the explanatory variable with employment rate as control variable. Meanwhile, the second model employed the raw indicators of financial inclusion as regressors, which describes access, usage and barriers, and employment rate is still indicated as control variable.

Based on economic theory and related literature, it is expected having direct effect of inclusion in financial services to regional growth of economies. Moreover, indicators of financial access (ATMs and FIs) and usage (loans) is expected to have a direct linkage in the improvement of economic growth in the regions. Henceforth, data on financial barriers have unique effects because functional literacy rate is assumed to represent human capital and will positively affect regional economic growth, while poverty gap will have an inverse effect. The findings revealed that regional financial inclusion indices in the urban areas are relatively higher compared to rural ones. Moreover, there exist a direct relationship of inclusivity of financial services and growth of regional economies, which is highly significant, as exhibited by the Fixed Effect (FE) - Least Squares Dummy Variable Model (LSDVM).

With these results, this study will aid policymakers in crafting appropriate development plans, programs and policies that will boost the local financial sector. This leads in the substantial growth of economies in various regions in the country. This study is also pertinent because the nation is currently going through an economic recovery from the pandemic. This study has a comprehensive analysis and aligns its discussion with the current economic recovery program of the government, which will contribute in strengthening the financial inclusion initiatives in leveraging on financial technology, research and literacy (NEDA, 2020).

2. Data and Methodology

This study made use of publicly available data from numerous agencies. The Bangko Sentral ng Pilpinas (BSP) is the source for access data like the quantity of bank branches, as well as, ATMs in each region for the regional financial inclusion index (RFII). Utilization indicators include the number of deposits from the Philippine Deposit Insurance Commission (PDIC) and the quantity of loans sourced from BSP. Financial barrier measures, as well as, regional gross output and rate of employment are gathered from BSP and Philippine Statistics Authority (PSA). The study used a balanced short panel data from 17 regions from year 2015 to 2020. This is considered a short panel data because the cross-section of 17 regions are greater than the 6 time periods (Gujarati, 2011).

The RFII is a multi-dimensional index that is composed of 3 dimensions, which describes the usage, access and barriers in financial services. Specifically, usage refers to how financial services are utilized and adopted. Meanwhile, access described the capability of people to utilize banking services. Particularly, factors that preventing participation in the monetary segment are represented as barriers. Given the three dimensions in measuring the RFII, the Table 1 conveys the specific indicators.

Table-1. The specific indicators

Dimensions	Abbreviations		Indicators
Usage	*use*	D_{it}	Deposit per 10k pop./region
		DA_{it}	Deposit accnt. per 10k pop./region
		LO_{it}	Loans per 10k pop./region
Access	*fa*	FIP_{it}	Financial Institutions per region for every10,000 population
		FIK_{it}	Quantity of Financial Institutions per 100 square kilometers per regions
		ATM_{it}	Quantity of ATMs in every region for every 10,000 population
Barriers	*barr*	LR_{it}	Rate of functional literacy in every region
		PG_{it}	Gap of poverty in every region

In constructing the index, the study adopted the non-parametric index method developed by Sarma (2012), in computing for the three dimension index, and Huang and Zhang (2020) in the aggregation method to construct an aggregate index for regional financial inclusion index. The calculated index is per region and per year.

This is the index formula for the indicators in usage, access and barriers:

$$d_{it} = \frac{A_{it} - Min_t}{Max_t - Min_t} \quad (1)$$

where:
d_{it} = the computed indicator index from each financial inclusion dimensions ($D_{it}, DA_{it}, LO_{it}, FIP_{it}, FIK_{it}, ATM_{it}, LR_{it}, PG_i$)
A_{it} = Actual value of indicator in region i at time t
Min_t = minimum value among regional indicators at time t
Max_t = maximum value among regional indicators at time t

After computing the indices per indicator in (1), this shall be aggregated to form the financial inclusion dimension indices for usage, access and barriers:

$$Use_{it} = \frac{1}{2}\left[\frac{\sqrt{(D_{it})^2+(DA_{it})^2+(LO_{it})^2}}{\sqrt{(w_1{}^2+w_2{}^2+w_3{}^2)}} + \left(1 - \frac{\sqrt{(w_1-D_{it})^2+(w_2-DA_{it})^2+(w_3-LO_{it})^2}}{\sqrt{(w_1{}^2+w_2{}^2+w_3{}^2)}}\right)\right] \quad (2)$$

$$FA_{it} = \frac{1}{2}\left[\frac{\sqrt{(FIP_{it})^2+(FIK_{it})^2+(ATM_{it})^2}}{\sqrt{(w_1{}^2+w_2{}^2+w_3{}^2)}} + \left(1 - \frac{\sqrt{(w_1-FIP_{it})^2+(w_2-FIK_{it})^2+(w_3-ATM_{it})^2}}{\sqrt{(w_1{}^2+w_2{}^2+w_3{}^2)}}\right)\right] \quad (3)$$

$$Barr_{it} = \frac{1}{2}\left[\frac{\sqrt{(FIP_{it})^2+(FIK_{it})^2}}{\sqrt{({w_1}^2+{w_2}^2)}} + \left(1 - \frac{\sqrt{(w_1-FIP_{it})^2+(w_2-FIK_{it})^2}}{\sqrt{({w_1}^2+{w_2}^2)}}\right)\right] \tag{4}$$

From the computed dimension indices in formula (2), (3) and (4), the results shall be aggregated again to form the final regional financial inclusion index using this formula (5) for each region per year:

$$RFII_{it} = \frac{1}{2}\left[\frac{\sqrt{(Use_{it})^2+(Fa_{it})^2+(Barr_{it})^2}}{\sqrt{({w_1}^2+{w_2}^2+{w_3}^2)}} + \left(1 - \frac{\sqrt{(w_1-Use_{it})^2+(w_2-Fa_{it})^2+(w_3-Barr_{it})^2}}{\sqrt{({w_1}^2+{w_2}^2+{w_3}^2)}}\right)\right] \tag{5}$$

where:
Use_{it} = dimension index for financial usage in each region i at time t
Fa_{it} = dimension index for financial access in each region i at time t
$Barr_{it}$ = dimension index for financial barrier in each region i at time t
$RFII_{it}$ = financial inclusion overall index for region i at time t
w_u = dimension indices weights

$$w_u = \frac{V_u}{\sum_{u=1}^{v} V_u} \quad , u = 1,2,3 \tag{6}$$

V_u= index of coefficient variance u, measured by the standard deviation over the average value

The RFII score values only range from 0 to 1, one being the highest value and 0 lowest value. These index scores are categorized into three which is high, medium and low (Table 2). When a region has the highest score, it does not entail a full inclusivity of financial services, because it is only described as the best region of financial inclusion relative to the country and this is also true to those with lowest scores. The values can be interpreted as percentage of financial inclusion in a particular locality (Sarma, 2012).

Table-2. Scaling of RFII scores

High	Medium	Low
0.60 to 1.00	0.30 to 0.59	0.29 and below

After the construction of the RFII in each region per year, this was used as an explanatory variable in predicting the changes in regional gross domestic product, serves as proxy for growth in regional economies. Table 3 present variables employed in the empirical model and also presented here are the data sources and research hypothesis/expected signs of the estimated coefficients with reference to past literatures. All regressors are hypothesized to be positively related to regional economic growth, except for poverty gap.

Table-3. Data description of variables in the empirical model

Financial Inclusion Dimensions	Variable	Data Description	Source	Hypothesis (Expected signs of coefficients)	Related Literatures
Overall	$RFII_{it}$	Regional Financial Inclusion Index score in region *i* at time *t*	Constructed in this study	**(+)** If $RFII_{it}$ increases $GRDP_{it}$ increases	(Musembi & Chun, 2020)
Usage	LO_{it}	Total Amount of Loans in pesos at time *t* for region *i*	BSP	**(+)** If LO_{it} increases $GRDP_{it}$ increases	(Gajurel, 2022)
Access9	ATM_{it}	Automated Machine Tellers at time *t* for region *i*	BSP	**(+)**If ATM_{it} increases $GRDP_{it}$ increases	(Ifediora et al., 2022)
	FI_{it}	Number of Bank and Non-Bank Financial Institutions at time *t* for region *i*	BSP	**(+)** If FI_{it} increases $GRDP_{it}$ increases	(Ratnawati, 2020)
Barriers	LR_{it}	Literacy rate, percentage of the population from 10 years old and up who are able to comprehend in reading and writing, at time *t* for region *i*	PSA	**(+)** If LR_{it} increases $GRDP_{it}$ increases	(Hossain, 2022)
	PG_{it}	Poverty gap, percentage of the population who have income deficiency, at time *t* for region *i*	PSA	**(-)**If PG_{it} increases $GRDP_{it}$ decreases	(Erlando *et al.*, 2020)
$GRDP_{it}$		Gross Regional Domestic Product accounts for economic output in million pesos at time *t* for region *i*	PSA	**(+)**If ER_{it} increases $GRDP_{it}$ increases	(Vaceanu, 2014)
ER_{it}		Employment Rate is the percentage of employed labor force at time *t* for region *i*	PSA		

In order to check the values, specific unit of measurements and scaling for each data sets, the variables' summary statistics are shown (Table 4). It is evident that there are varied scaling of data to be used in the empirical model. Specifically, $RFII_{it}$ are presented in index scores, with value from 0 to 1. Meanwhile, $GRDP_{it}$ are in million pesos and LO_{it} are in actual peso loan amounts. On the other hand, ATM_{it} and FI_{it} are presented as a discrete number of the quantity of ATMs and banking and non-banking financial institutions. The other variables like ER_{it}, LR_{it} *and* PG_{it} are in percentage values. Given the diverse units and scales of the variables to be estimated, the study transformed these variables into logarithmic form so that it is unitless and can be interpreted as elasticities. This data log transformation is widely explored in statistical analysis in order to reduce skewness and standardized the data sets (West, 2022).

Table-4. Sample statistics of the data set

Indicators	N	Mean	S.D.	Minimum	Maximum
$RFII_{it}$	102	0.33	0.16	0.04	0.78
$GRDP_{it}$	102	1013.75	1292.71	192	6224
ER_{it}	102	94.48	1.84	87.6	97
ATM_{it}	102	119.28	1849	33	8453
FI_{it}	102	1640.09	1582.09	152	7585
LO_{it}	102	1.89E+14	1.14E+15	1.59E+09	8.32E+15
LR_{it}	102	89.15	6.02	71.6	97.2
PG_{it}	102	4.76	3.63	0.22	15.08

2.1 Empirical Method

In the empirical method of the analysis, the study estimated possible panel data models and conducted a test to select the best fit model. After that, diagnostic tests and remedial measures were done to satisfy the assumptions for autocorrelation and heteroscedasticity, in order to produce robust results.

This study utilized the panel data regression models which consider similar groups of units (companies, households, cities, provinces, countries, etc.) over a certain period of time (daily, monthly, quarterly, annually, etc.) These models are different from the usual cross-section or time-series regression because it considers heterogeneity effects of specific units over a certain period of time, which is often not observed (Gujarati, 2011). Hence, the approaches in panel data analysis includes heterogeneity overtly into the model by adding the unit-specific predictors. Moreover, when the cross-sectional samples are pooled together over time, the panel data will provide more information about the data set, it is more varied, more efficient, collinearity is smaller, and there are greater degrees of freedom among predictors (Baltagi,2005). This is the general panel data model described in equation (7), which is a classical regression model (Greene, 2003):

$$Y_{it} = \beta_0 + \sum_{j=2}^{k} \beta_j X_{jit} + \sum_{p=1}^{s} \gamma_p Z_{pi} + \delta Time + \varepsilon_{it} \quad t=1,\dots,T. \quad i=1,\dots,N; \tag{7}$$

description:

i = represents the cross-section dimensions *i.e.* regions, countries, households, companies, etc.

t = represent time period dimension
X_{jit} = variables of interest, with observed characteristics
Z_{pi} = variables that cause unobserved heterogeneity as a whole are an inconvenient part of the model.
j,p = used to differentiate between observed *Xs* and unobserved *Zs* regressors
β_j = parameters of observed regressors
γ_p = parameters of unobserved regressors
β_0 = intercept
ε_{it} = residuals
time = trend variable, enables the intercept to vary over time, if treated as time dummy or measures trend in Y over time
time = {1 if data belong to panel 1, otherwise 0 if data does not belong to panel 1}

In equation (7), the Z's of the unobserved heterogeneity are assumed to be constant across time that's why it has no time subscript. These *Z* variables are some unobserved characteristics like skills or preferences that are assumed to be constant over time periods. Moreover, there are unimportant unobserved qualities if the *Xs* variables are so comprehensive that they capture every relevant aspect of the person. If Z_{pi} can be seen for all observations, then the whole model is analyzed as an ordinary linear model and can be fitted by least squares method (Greene, 2003). With this, there are three distinct methods for panel data models considered and tested for significance in this study.

A. Pooled Ordinary Least Square (POLS): The POLS ignores the panel data and treat all data as one pooled sample. This is also referred to as *constant coefficient model*, because coefficients are presumed to be uniform given the time and cross-sectional units (Gujarati, 2011). In this model, all data are combined regardless of whether the observations belong to different time periods. If Z_{pi} has an intercept term only, then POLS gives efficient and consistent estimates of the common γ_p and the β_j parameters (Greene, 2003).
B. Fixed Effect model (FEM): FEM captures heterogeneity through a constant term that does not vary (fixed) with time but is still variable within the group of observations. There are three techniques in forming the FEM, namely: 1) within groups (WG), 2) first difference (FD) and 3) least squares dummy variable (LSDV). The WG and FD methods ignores the unobserved effects while LSDV recognized heterogeneity effects but only through the intercept of the model (Greene, 2003). In this study, the LSDV method was implemented in forming the FEM. Specifically, three (3) LSDV models were formed: LSDV1 (with region dummies), LSDV2 (with time dummies) and LSDV3 (with time region and time dummies).

C. Random Effects Model (REM): REM also captures heterogeneity through the β_j of Xs or error term of the model. This model has random parameters and compound error term. It is considered that the intercepts of the observations are random drawings taken from a bigger population of cross-sectional units (Gujarati, 2011). The REM approach has a compound disturbance term (w_{it}), which is equivalent to $\varepsilon_i + u_{it}$, that captures the composite error term and merged with the cross-section and time-series error component (Greene, 2003).

The study considered two main economic models. The first economic model used the overall index, RFII, as variable for financial inclusion, and ER as control variable. Specifically, the second economic model, utilized the individual financial inclusion indicators as regressors (ATM, FI, LO, LR, PG) and ER as control variable. From these main models, ten (10) empirical models, in double-log linear functional form, were formed applying the panel data models of POLS, FEM-LSDV and REM, shown in Table 5. The logarithmic form was used in order to standardize the data which has varied units of measurements and scales. All of these models were estimated using the STATA Version 17 software. The study followed the sequential procedures in testing the different panel data models. In addition, several hypothesis tests were implemented in order to check if the models are significant and is fitted to analyze the panel data set (Table 6).

Table-5. Empirical model estimation results

Panel Data Models			Estimation Equation
POLS	RD: wo TD: wo	Model 1	$LGRDP_{it} = \beta_0 + \beta_1 LRFII_{it} + \beta_2 LER_{it} + \varepsilon_{it}$
		Model 2	$LGRDP_{it} = \beta_0 + \beta_1 LATM_{it} + \beta_2 LFI_{it} + \beta_3 LLO_{it} + \beta_4 LLR_{it} + \beta_5 LPG_{it} + \beta_6 LER_{it} + \varepsilon_{it}$
FEM-LSDV1*	RD: w TD: wo	Model 1	$LGRDP_{it} = \beta_{0i} + \beta_1 LRFII_{it} + \beta_2 LER_{it} + \beta_3 D_{2i.} \dots\dots\dots + \beta_{19} D_{17i} + \varepsilon_{it}$
		Model 2	$LGRDP_{it} = \beta_{0i} + \beta_1 LATM_{it} + \beta_2 LFI_{it} + \beta_3 LLO_{it} + \beta_4 LLR_{it} + \beta_5 LPG_{it} + \beta_6 LER_{it} + \beta_7 D_{2i} \dots\dots\dots + \beta_{23} D_{17i} + \varepsilon_{it}$
FEM-LSDV2*	RD: wo TD: w	Model 1	$LGRDP_{it} = \beta_{0t} + \beta_1 LRFII_{it} + \beta_2 LER_{it} + \beta_3 D_{2016t} \dots\dots\dots + \beta_8 D_{2020t} + \varepsilon_{it}$
		Model 2	$LGRDP_{it} = \beta_{0t} + \beta_1 LATM_{it} + \beta_2 LFI_{it} + \beta_3 LLO_{it} + \beta_4 LLR_{it} + \beta_5 LPG_{it} + \beta_6 LER_{it} + \beta_7 D_{2016t} \dots\dots\dots + \beta_{12} D_{2020t} + \varepsilon_{it}$
FEM-LSDV3*	RD: w TD: w	Model 1	$LGRDP_{it} = \beta_{0it} + \beta_1 LRFII_{it} + \beta_2 LER_{it} + \beta_3 D_{2i} \dots + \beta_{19} D_{17i} + \beta_{20} D_{2016t} \dots + \beta_{36} D_{2020t} + \varepsilon_{it}$
		Model 2	$LGRDP_{it} = \beta_{0it} + \beta_1 LATM_{it} + \beta_2 LFI_{it} + \beta_3 LLO_{it} + \beta_4 LLR_{it} + \beta_5 LPG_{it} + \beta_6 LER_{it} + \beta_7 D_{2i} \dots + \beta_{23} D_{17i} + \beta_{24} D_{2016t} \dots + \beta_{29} D_{2020t} + \varepsilon_{it}$
Random Effects Model (REM)		Model 1	$LGRDP_{it} = \beta_{0it} + \beta_1 LRFII_{it} + \beta_2 LER_{it} + w_{it}$
		Model 2	$LGRDP_{it} = \beta_{0it} + \beta_1 LATM_{it} + \beta_2 LFI_{it} + \beta_3 LLO_{it} + \beta_4 LLR_{it} + \beta_5 LPG_{it} + \beta_6 LER_{it} + w_{it}$

Note: *Fixed Effects Models (FEM) - Least Squares Dummy Variable Models (LSDV); RD (Region Dummies); TD (Time Dummies); w(with): wo (without)

where:

$LGRDP_{it}$	= log of gross regional domestic product at time *t* for region *i*
$LRFII_{it}$	= log regional financial inclusion index score at time *t* for region *i*
LO_{it}	= log of the total amount of loans at time *t* for region *i*

$LATM_{it}$	= log of the number automated machine tellers at time *t* for region *i*
LFI_{it}	= log of the number bank and non-bank Financial Institutions at time *t* for region *i*
LR_{it}	= log of literacy rate at time *t* for region *i*
LPG_{it}	= log of poverty gap at time *t* for region *i*
LER_{it}	= log of employment rate at time *t* for region *i*
$D_{2i} \dots \dots D_{17i}$	= cross-section dummies from region 2 to region 17, region 1 as the base/reference category
$D_{2016t} \dots \dots D_{2020t}$	= time dummies from year 2016 to year 2020, year 2015 as the base/reference category
β_{0i}	= time-invariant intercept
β_{0it}	= time-variant intercept
ε_{it}	= cross-section specific error component
w_{it}	= $\varepsilon_i + u_{it}$, composite error term, merged cross-section and time-series error component

In Table 6, the sequential procedure for testing the empirical models are presented. Specifically, the F-test for linear restrictions tested the significance of the restricted versus the unrestricted model. The restricted model is POLS, since it does not consider heterogeneity effects and only treats the observation as a pooled sample. On the other hand, the unrestricted models of LSDV1, LSDV2 and LSDV3, describes the inclusion of heterogeneity effects through time and region dummies. If these tests are significant, the appropriate model is the unrestricted one. These tests were done after two models were estimated in STATA and the *testparm* command was used by specifying the dummies included in the unrestricted model. After that, we used the Lagrange multiplier (LM) test to analyze random effects while the F-statistic is implemented for the analysis of fixed effects (Breusch and Pagan, 1980). The following steps are official tests to look at individual, group, or/and impacts of time. Preference is given to FEM over a OLS pooled model if there is rejection in the F-null hypothesis. A REM is preferable over pooled OLS if there is rejection of null hypothesis for LM test. Pooled OLS is preferred if neither of the null hypotheses is disproved. When the LM and F test results are not favorable, the procedure only then moves on to the Hausman test (Park, 2011). To assess whether FEM or REM is more suitable for the data, the Hausman test was utilized. Either the unique errors (u_i) are not associated with the null hypothesis of the regressors, or the model of preference is REM as opposed to FEM. In the event that this theory is incorrect, it is concluded that fixed effects are preferable to random effects (Torres-Reyna, 2007).

Table-6. Significance tests of panel data models

Model Tests	Test Statistic	Hypothesis Tests	Interpretation
POLS vs LSDV1	F-test for linear restrictions (Gujarati, 2011): $F = \frac{(R_{UR}^2 - R_R^2)/m}{(1-R_{UR}^2)/(n-k)}$ (7) where: F=test statistic value $R_{UR}^2 = R^2$ of the unrestricted model $R_R^2 = R^2$ of the restricted model n=number of observations k=number of parameters m=number of restrictions	Ho: $POLS_R$ Ha: $LSDV1_{UR}$	Significant: LSDV1 Not Significant: POLS
POLS vs LSDV2		Ho: $POLS_R$ Ha: $LSDV2_{UR}$	Significant: LSDV2 Not Significant: POLS
LSDV1 vs LSDV3		Ho: $LSDV1_R$ Ha: $LSDV3_{UR}$	Significant: LSDV3 Not Significant: LSDV1
LSDV2 vs LSDV3		Ho: $LSDV2_R$ Ha: $LSDV3_{UR}$	Significant: LSDV3 Not Significant: LSDV2
POLS vs LSDV3		Ho: $POLS_R$ Ha: $LSDV3_{UR}$	Significant: LSDV3 Not Significant: POLS
POLS vs REM	B&P LM Test for REM (Wooldridge, 2002): $LM = \frac{IT}{2(T-1)}\left[\frac{\sum_{i=1}^{I}\left(\sum_{t=1}^{T}\hat{\sigma}_{it}\right)^2}{\sum_{i=1}^{I}\sum_{t=1}^{T}\hat{\sigma}_{it}{}^2} - 1\right]$ (8) where: LM=test statistic value I= units of cross sections T=periods of time $\hat{\sigma}_{it}$=estimated standard deviation of errors in *i* at time *t* $\hat{\sigma}_{it}{}^2$= estimated variance of errors in *i* at time *t*	Ho: $\sigma_\varepsilon^2 = 0$ Ha: $\sigma_\varepsilon^2 \neq 0$	Significant: REM Not Significant: POLS
FEM vs REM	Hausman Test (χ^2)(Greene, 2003): $\chi^2 = \Sigma \frac{(\beta_{FE}-\beta_{RE})^2}{Var(\beta_{FE})-Var(\beta_{RE})} \sim \chi_\beta^2$ (9) where: χ^2 = test statistic value β_{FE} =coefficients of the FEM β_{RE} = coefficients of the REM $Var(\beta_{FE})$ = variance of FEM $Var(\beta_{RE})$ = variance of REM χ_β^2 = test statistic has a chi-square distribution	Ho: REM Ha: FEM	Significant: FEM Not Significant: REM

The ordinary least square (OLS) was utilized to calculate the predictors in the multiple linear regression model using panel data. The total squared distance of the observed responses of the data and those anticipated by approximation of linearity is reduced when this technique is implemented. The y-intercept and slope of the relationship are represented by the parameters 0, 1 to *n*, respectively. The following presumptions need to be true in order for the parameter estimations to be BLUE (Best Linear Unbiased Estimator). The first presumption suggests that the error term's mean is zero. The errors in the second have a common variance, which is a homoscedasticity feature. The third premise is that there is no autocorrelation, *i.e.*, no serial connection between errors. Heteroscedasticity and autocorrelation are the potential issues in the OLS. The Best Linear Unbiased Estimator (BLUE) will no longer be valid if one of these presumptions is broken (Gujarati, 2021): 1) E $(\varepsilon_t)= 0$; 2) E $(\varepsilon_t^2)=$ var $(\varepsilon_t) = \sigma^2$ and 3) Cov $(\varepsilon_i\varepsilon_j)= 0$, $i \neq j$.

In order to yield BLUE, the following are the diagnostic tests conducted to detect heteroscedasticity and autocorrelation:

a. In detecting autocorrelation in the model, the Wooldridge autocorrelation test for panel data was employed. First, this test is done by running the same panel data regression in first differences, save the residuals and run the auxiliary regression of residuals and lagged residuals (shown in equation 8 and 9). In the test for hypothesis, the null of correlation coefficient being close or equal to -0.50, if rejected then serial correlation exist significantly. This result can easily be generated using the *xtserial* command in STATA. This test carries out the existing autocorrelation where errors are idiosyncratic in panel data linear models. Moreover, this test is evidently having better size and power properties in sensible sample sizes (Drukker, 2003).

$$y_{it} - y_{it-1} = (x_{it} - x_{it-1})\beta_1 + \varepsilon_{it} - \varepsilon_{it-1} \quad (10)$$

$$\Delta y_{it} = \Delta x_{it}\beta_1 + \Delta\varepsilon_{it} \quad \text{where: } \Delta = \text{first-difference operator} \quad (11)$$

Hypothesis Test: Ho: $\mathrm{Corr}(\Delta\varepsilon_{it}, \Delta\varepsilon_{it-1}) = -0.50$
Ha: $\mathrm{Corr}(\Delta\varepsilon_{it}, \Delta\varepsilon_{it-1}) \neq -0.50$

b. Meanwhile, the groupwise heteroskedasticity was done to test if there are significant differences in the variances of the model using Wald Test (modified). This test is under constant variance null hypothesis (homoscedastic) with an alternative of groupwise heteroscedasticity (Greene, 2003). This can be generated using the *xttest3* after estimating the FEM. There is groupwise heteroskedasticity in the panel data if the test is significant.

$$W' = \sum_{i=1}^{n} \frac{\left(\hat{\sigma}_i^2 - \hat{\sigma}^2\right)^2}{\frac{1}{T}\frac{1}{T-1}\sum_{t=1}^{T}\left(e_{it}^2 - \hat{\sigma}_i^2\right)^2} \quad (12)$$

Hypothesis Test: Ho: $\sigma_\varepsilon^2 = 0$
Ha: $\sigma_\varepsilon^2 \neq 0$

The study implemented a remedial measure to treat the effects of heteroscedasticity and autocorrelation in the panel data model through application of the robust standard error estimation. This is generated by adding the robust option in the *reg* and *xtreg* commands in

STATA. Specifically, the standard errors that are consistently heteroscedastic, are utilized in order to fit a model which do not have error terms that are heteroscedastic. If the u_i residuals of the regression are not dependent, but there is presence of different variances σ_i^2 , then the summation of diagonals in the variance-covariance matrix (σ_i^2,…….. σ_n^2) can be estimated with $\hat{\sigma}_i^2 = \hat{\varepsilon}_i^2$. Hence, this will provide the estimator derived by White (1980) which is also called the HCE or the heteroscedasticity-consistent estimator:

$$\vartheta_{HCE}\left[\hat{\beta}_{OLS}\right]\frac{1}{n}\left(\frac{1}{n}\sum_i X_i X_i^T\right)^{-1}\left(\frac{1}{n}\sum_i X_i X_i' \hat{u}_i^2\right)\left(\frac{1}{n}\sum_i X_i X_i^T\right)^{-1} \tag{13}$$

where:

$\vartheta_{HCE}\left[\hat{\beta}_{OLS}\right]$ = heteroscedasticity-consistent estimators
n = number of observations
u_i = residuals of the regression
X = vector of variables in the model

3. Empirical Results

3.1 Regional Financial Inclusion Index (RFII) Scores

The study's preliminary aim is to create the index scores and compare them across different regions from 2015 to 2020. Figure 1 presents the RFII scores for 6 years across different regions. The highest financial inclusion index from 2015 to 2020 is seen in National Capital Region (NCR), because it is a highly urbanized region where active economic activities are present which boosted the regional usage and access of services in the financial sector. NCR's RFII is consistently high with scores ranging from 0.7752 to 0.7793. In contrast, the rural area of Autonomous Region of Muslim Mindanao (ARMM) got the bottommost values of 0.0388 to 0.1019. Generally, there is higher RFII in urbanized areas compared to rural places.

The regions classified with medium RFII scores are: Ilocos, Cagayan Valley, Central Luzon, Calabarzon, Western Visayas, Central Visayas and Davao, respectively. The regions with medium RFII scores are mostly urbanized regions which showed a rise in the availability of products and services in the financial sector.

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http://doi.org/10.31039/jomeino.2024.8.1.2

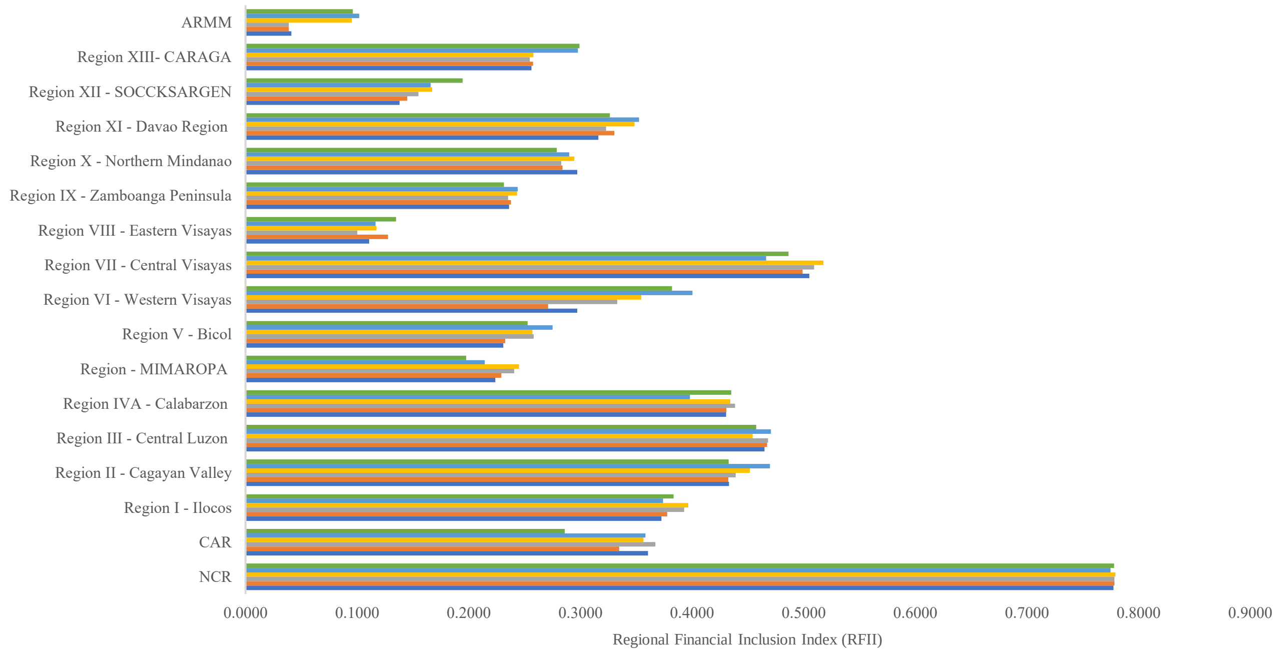

Figure-1. Regional Financial Inclusion Index (RFII) Scores in the Philippines, 2015-2020 (computed in this study).

The average index for financial access, which is 30% while financial usage has reached 44%, however the average barrier is 49%. Central Luzon and Calabarzon are regions adjacent to NCR, are top three and two, respectively, in accordance with bank networks and having larger populations. The regions are leaning closer to the bottommost value of RFII despite being in the medium level. Particularly, regions with low RFII scores comprise mainly of rural regions: MIMAROPA, CAR, Bicol, Zamboanga Peninsula, Eastern Visayas, CARAGA, Northern Mindanao, SOCCKSARGEN and ARMM. Eastern Visayas, SOCCSKARGEN and ARMM, are regions which are highly rural having a minimum quantity of banks/10k adults (Llanto and Rosellon, 2017). Out of 17 regions, only 1 has a high RFII, 8 regions with medium and low indices, respectively.

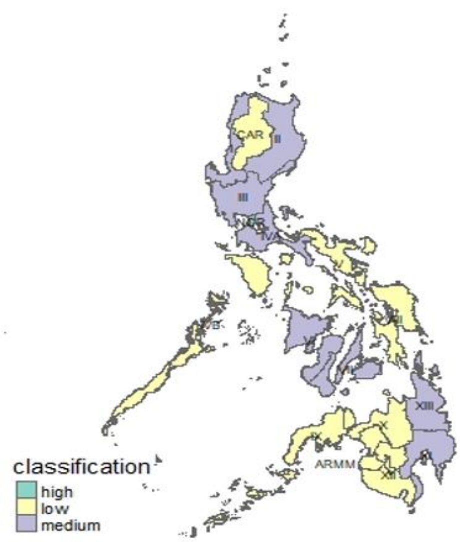

Figure-2. Choropleth map of RFII in the Philippines, 2020.

Figure 2 presents the diagram of 2020 RFII classifications. Geographic clumping is evident on the map, with each region's RFII values being comparable to that of its surrounding regions.

3.2 Panel Data Estimation Results

The study's second goal is to utilize panel data across 17 regions over a 6-year period, and analyze how financial inclusion affects regional economic growth (2015-2020). This was done using two models, with the first having the overall RFII as a predictor variable and the second using the individual financial inclusion indicators, with both having employment rate as control variable. The study performed model significance tests to check the best fit model for the panel data, conducted diagnostic testing for autocorrelation and heteroscedasticity, and applied remedial measures in order to have robust estimates that are consistent and efficient.

The diagnostic test results of the Wooldridge test for autocorrelation and the Wald test (modified) for heteroskedasticity is conveyed in Table 7. There is proof of autocorrelation and heteroscedasticity in both models as a result of the tests being highly significant at the 1% level. Given this, the robust estimation was performed to produce the best unbiased estimators (Table 9).

Table-7. Results of panel data diagnostic tests

Panel Data Diagnostic Tests	Model 1	Model 2
Wooldridge test for autocorrelation	F(1, 16) = 68.025***	F(1, 16) = 50.925***
Modified Wald test for heteroskedasticity	chi2 (17) = 204.89***	chi2 (17) = 437.20***

Legend: ***,**,* shows significance level at 1%, 5% and 10%, correspondingly.

In testing the significance of the panel data estimation models, Table 8 shows that the fixed effects (LSDV1, LSDV2, LSDV3) and random effects models revealed to be significant against the pooled ordinary least squares (POLS) in both models. In terms of finding the appropriate model for the panel data estimation, LSDV3 appeared to be the fit model. This model was used in interpreting the results.

Table-8. Panel data model significance tests results

Tests			Model 1	Model 2	Appropriate Model
POLS	vs	FEM-LSDV1	F(16, 83) = 270.04***	F(16, 79) = 237.31***	LSDV1
POLS	vs	FEM-LSDV2	F(5, 94) = 2.42**	F(5, 90) = 3.30***	LSDV2
POLS	vs	FEM-LSDV3	F(21,78) = 6200.18***	F(21, 74) = 1293.60***	LSDV3
FEM-LSDV1	vs	FEM-LSDV3	F(5, 78) = 475.52***	F(5, 74) = 96.24***	LSDV3
FEM-LSDV2	vs	FEM-LSDV3	F(16, 78) = 7207.94***	F(16, 74) = 1433.75***	LSDV3
POLS	vs	REM	chibar2(01) = 170.23***	chibar2(01) = 137.51***	REM
FEM-LSDV3	vs	REM	chi2(2) = 17.15	chi2(6) = 178.91	REM

Legend: ***,**,* shows significance level at 1%, 5% and 10%, correspondingly.

In estimating the two models, FEM - LSDV3 revealed to be the appropriate model for analyzing the relationship of RFII to regional growth of economies for both Models 1 and 2 (Table 9). In checking the heterogeneity effects, results revealed that both time and regional dummies (employed in both models) are highly significant in explaining the variations in regional economic growth. The results of Model 1 clearly show that on average a 10% increase in the index will contribute to a miniscule but significant positive effect of 0.49% to economic output in the regions, ceteris paribus. It is expected that inclusivity of the financial sector does not have a large influence on growth of regional economies, because there are other factors that may affect its deviations. However, results revealed how financial inclusion contributes to growth and this is a relevant information for the current efforts of the government to intensify financial literacy, usage, and access (NEDA, 2020). This result is consistent with theory that financial activities will strengthen economic activities (Levine, 1997), and is also aligned with the results of previous studies (Musembe and Chun, 2020; Ratnawati, 2020).

Meanwhile in Model 2, all of the estimated coefficients are significant in affecting the changes in regional economic growth, except for the functional literacy rate. The coefficients of ATM_{it}, FI_{it}, PG_{it} and ER_{it} are all highly significant (at 1 percent level), while LO_{it} is significant (at 5 percent level), ceteris paribus. Specifically, a 10% increase in the number of ATMs will contribute to a 2.45% increase in regional economic growth, holding other things constant. This is expected as ATMs are the main channels in accessing financial services outside of banking offices (Ifediora *et al.*, 2022). Meanwhile, a 10% increment in the quantity of financial establishments significantly affects the increase in regional economic output by 1.05%. In theory, as financial institutions increases, the access to financial services will improve because it strengthens the productive activities of different economic sectors in the region (Van *et al.*, 2021). On the other hand, one important indicator of financial usage is the amount of loans disbursed, on average a 10% increase in the amount of loans availed will significantly affect regional income by 0.05%. Most of the bank's income comes from interest from loans (availed by their clients) and this result reveals that most people availed of loans to invest in productive activities or purchase goods and services, that in turn will contribute to the regional economy (Gajurel, 2022). Moreover, in terms of barriers affecting financial inclusion, poverty gap in the regions explicitly shows that when there is a 10% increase in poverty, it will significantly contribute to a decrease in regional economic growth by 1.26%. When average income of the population decreases, this impacts the flow of activities in the regional economies, resulting to a germane influence on growth in regional economies (Erlando *et al.*, 2020). Considering the variations in regional economic growth, the R-square reveals a 99.97% (Model 1) and 75.59% (Model 2) coefficient of determination, which means that the models strongly explain how financial inclusion significantly affects regional economic growth.

Table-9. Estimation Results of Panel Data Regression Analysis

Indicators	1st Model	2nd Model
$LRFII_{it}$	0.0491*** (0.0132)	0.2445*** (0.0829)
LER_{it}	0.7513*** (0.1774)	1.7898*** (0.2903)
$LATM_{it}$		0.2445*** (0.0829)
LFI_{it}		0.1048*** (0.0332)
LLO_{it}		0.0047** (0.0022)
LLR_{it}		0.0110 (0.4584)
LPG_{it}		-0.1255*** (0.0354)
D_{R2}	-2.9369*** (0.0155)	-2.9554*** (0.1151)
D_{R3}	-2.2570*** (0.0131)	-2.2824*** (0.1001)
D_{R4}	-2.7212*** (0.0144)	-2.7308*** (0.0870)
D_{R5}	-1.0535*** (0.0116)	-1.0546*** (0.0615)
D_{R6}	-0.7602*** (0.0121)	-0.7962*** (0.0883)
D_{R7}	-2.7335*** (0.0196)	-2.7758*** (0.1107)
D_{R8}	-2.3745*** (0.0181)	-2.4225*** (0.0995)
D_{R9}	-1.8984*** (0.0153)	-1.9215*** (0.0843)
D_{R10}	-1.6035*** (0.0116)	-1.6458 (0.0856)
D_{R11}	-2.5141*** (0.0272)	-2.6083*** (0.1163)
D_{R12}	-2.6908 (0.0192)	-2.7422*** (0.1103)
D_{R13}	-1.9388*** (0.0170)	-1.9925*** (0.0965)
D_{R14}	-1.9312*** (0.0154)	-1.9763*** (0.0964)
D_{R15}	-2.5112*** (0.0237)	-2.5994*** (0.1130)
D_{R16}	-2.9626*** (0.0173)	-3.0238*** (0.1199)
D_{R17}	-3.1228*** (0.0354)	-3.2296*** (0.1848)
D_{2016}	0.0597*** (0.0056)	0.0580*** (0.0071)
D_{2017}	0.1282*** (0.0055)	0.1263*** (0.0089)
D_{2018}	0.1839*** (0.0058)	0.1927*** (0.0127)

Indicators	1st Model	2nd Model
D_{2019}	0.2419***	0.1336
	(0.0057)	(0.1169)
D_{2020}	0.1797***	0.0719
	(0.0069)	(0.1147)
Constant	5.0998***	-3.9982***
	(0.8020)	(2.7053)
N	102	102
R-square	0.9997	0.7559

Legend: ***,**,* shows significance level at 1%, 5% and 10%, correspondingly. Values in ( ) are standard errors.

Furthermore, in analyzing the effect on employment (as a control variable) has a direct significant link to changes in regional economic growth. In particular, a 10% increase in regional employment rate will significantly affect the gross output by 7.5% and 17.9%, in Model 1 and 2, respectively. This result clearly defines the importance of human capital in the regions, because if majority of the labor force are employed, they can have more access and usage to financial services, and in the long run this will significantly improve the regional output (Vaceanu, 2014).

4. Conclusions and Recommendations

In summary, the indicators for inclusivity of the financial sector influences growth in regional economies based on panel data estimation results. The study is the first to attempt a domestic regional analysis for financial inclusion and growth, for the purpose of comparing them across time and regions in the Philippines. Given that most studies on this topic were analyzed on a country and national level, the relevant findings of this research will significantly contribute to additional knowledge on domestic regional analysis of inclusivity of the financial sector and growth of regional economies. The findings are relevant to current economic recovery program of the government. Hence, this will contribute to strengthening the financial inclusion initiatives in leveraging on financial technology, research and literacy in the regional level (NEDA, 2020). In particular, the study's findings led to the following conclusions:

1. There are disparities in the Regional Financial Inclusion Indices (RFII) between urban and rural regions. Thus, it can be seen that highly urbanized areas have greater financial inclusion compared to rural localities. This is evident because NCR got the highest index score, ranging from 0.7752 to 0.7793, which is a highly urbanized area in the country. In contrast, the index score of ARMM, a dominantly rural area, is very low with scores only ranging 0.0388 to 0.1019. On average out of 17 regions, only 1

region got a high index score, while the remaining 16 regions are equally distributed to medium (8 regions) and low-indexed (8 regions) regions.

2. RFII has a direct effect to regional economic growth. In the primary model, it is apparent that the overall RFII significantly affects regional economic growth. Meanwhile, the second model revealed that usage and access of financial services, as described by ATM quantities, financial institutions and amount of loans, exhibits a direct effect to growth in regional economies. Furthermore, significant barriers to financial inclusion are poverty gap, which negatively affects regional growth. In addition, the employment rate control variable appeared to be highly significant in both models. In the estimation of results, it was revealed that the Fixed Effect (FE) - Least Squares Dummy Variable Model (LSDVM) with region and time dummies, is the appropriate model for the panel data analysis. Hence, both time and regional dummies (employed in both models) appeared to be highly significant in explaining the variations in regional economic growth.

Considering the conclusions discussed in this study, the following are the specific policy recommendations:

1. With the evident inequality of RFII across regions, it is essential to thoroughly review and assess the existing situation of the local financial sector, in order to identify the factors affecting their access and usage of financial services. In addition, local policymakers and leaders should also evaluate the current condition of farm to market road infrastructures, as well as, telecommunication and internet facilities, especially in the rural areas because this will help boost financial activities and encourage digital transactions in different regions.
2. Given the significant effects of inclusivity of the financial sector to growth in regional economies, this study is a great input to the public and private sectors (financial sectors) in initiating public-private partnerships in sustaining and strengthening the financial services in the regions. Specifically, local governments in the different regions may need to review certain policies that will promote the ease of doing business (Romero *et al.*, 2019) that will encourage the local financial sector to develop infrastructures and improve their services that will strengthen the regional financial inclusion. Thus, this move will significantly boost economic activities, especially in the rural regions.

Given the scope and limitations of the study, there are still areas that needs further research:

1. It can be seen in the map of RFII results that there is geographical clumping, with each region's RFII values being comparable to that of its surrounding regions. With this, there is a possibility of existing spatial dependence in regional inclusivity of the financial sector and growth of regional economies. Thus, a further study that will dwell on spatial econometrics analysis is a good venture to further analyze the spill-over effects and contiguity effects of neighboring regions.
2. Furthermore, financial inclusion studies on a micro-level (provincial, municipal or city) are also a relevant future research in order to draw specific policy recommendations and to further identify which provinces/municipalities/cities are the growth poles and growth centers that initiates that spilling-over effects of financial inclusion to other areas (which contributes to the whole region's economic growth). This future research will contribute significant information that will help develop rural areas with low financial inclusion.

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