
Technical Report

The Eighth **Research Dive** on
Financial Inclusion

December 2018

Executive Summary

Indonesia scored around 50 per cent on the Global Financial Inclusion Index in 2017, which means that half of the Indonesian adult population did not access formal financial services. In addition to factors such as geographic coverage and lagging regional infrastructure that inhibit the pace at which cohorts within the population become financially included, other knowledge gaps remain. Across the country, new data are being generated that provide opportunities for financial institutions and those in the policy-making domain to understand the needs of different communities to accelerate financial inclusion.

To support the Government of Indonesia's national strategy on financial inclusion, Pulse Lab Jakarta organised a data dive to ascertain insights on the various dimensions of financial inclusion, their importance for the Indonesian society, as well as the progress made and challenges that are ahead. Focused on analysing new sources of data in tandem with traditional data sets, a cadre of researchers and data analysts from academia, government and the private sector convened at the Lab for the three-day Research Dive event held on 25-28 November 2018.

Four research areas were outlined to help answer pressing policy and development questions: 1) measuring financial awareness and financial literacy through social media; 2) measuring financial access through formal financial and non-financial institutions; 3) modelling gender-based differences in financial inclusion; and 4) assessing the impact of digital opportunity on financial inclusion.

This report outlines the research findings from the research and is structured as follows:

1. The first paper describes the data sets that were assigned to the participants.
2. The second paper explores the potential of using social media data to measure financial awareness, more specifically by developing a model to process public tweets that contain keywords with the goal of predicting the level of financial awareness in a few Indonesian cities.
3. The third paper examines the supply side measurement of financial inclusion, in particular the possibility of extending the calculation of the Financial Inclusion Index to the village level (in Pontianak) using non-financial channels as well as mapping their geographical proximity.
4. The fourth paper looks on modelling gender-based differences in financial inclusion to understand the extent of financial inclusion disaggregated by gender in rural areas and to quantify the probability of being financially included based on gender in rural areas.
5. The fifth paper investigates whether the growing adoption of digital technology can accelerate financial inclusion. Using 2017 Susenas data and about 90 million anonymised tweets from 2014, the team worked to model Financial Inclusion from this perspective.

Pulse Lab Jakarta is grateful for the cooperation of the Indonesian Financial Services Authority (OJK), Microsave Indonesia, Universitas Airlangga, Universitas Brawijaya, Universitas Gadjah Mada, Universitas Indonesia, Universitas Multimedia Nusantara, Universitas Padjajaran, Universitas Pertamina, Universitas Wahid Hasyim, Institut Teknologi Bandung, Institut Teknologi Kalimantan, Institut Teknologi Sepuluh Nopember, Indonesia Research Institute, Data Science Indonesia, OpenStreetMap Indonesia and Sekolah Tinggi Manajemen Informatika dan Komputer Pelita Nusantara Medan. We are thankful for the support we received from the Australian Department of Foreign Affairs and Trade (DFAT).

Advisor Note

Data Analysis Needs Creativity

Creativity is needed when conducting data analysis because of constraints related to context, availability of resources such as time and tool, as well as other factors that are outside a given data set. For instance, the context of a problem influences how we frame a research question, how we translate it into a data problem, and how we go about collecting relevant data. A data analyst will likely also have to work under resource constraints, therefore limiting what can be done with the data. If resources are limited, the analyst must be adaptable and that's where creativity kicks in.

During this research dive, the participants put their creative skills to the test. Despite limited time and tools, they did well. In the final presentations, each group exemplified their creativity - despite having software, hardware and data constraints. Thank you Pulse Lab Jakarta for the invitation.



Prof. Edi Winarko
Data Science Advisor

Edi Winarko received his doctorate in Computer Science from Flinders University. He is currently an Associate Professor in the Department of Computer Science, Faculty of Mathematics and Natural Sciences at Universitas Gadjah Mada. He is interested in text mining, spatio-temporal mining, information retrieval, information extraction and natural language processing.

Geospatial Data for Financial Inclusion

A platform using GIS mapping can help regulators and governments to visually understand information, such as where financial access points are and citizens' mobility. For this Research Dive, I presented on how mapping financial access points using geospatial data can help to highlight groups with limited access to financial service providers.

PLJ's Research Dive is a great opportunity for researchers from different backgrounds to collaborate on research. This was my first time participating in research activities

with practitioners from the humanitarian sector. The event challenged me to think outside my comfort zone. The research introduced me to new perspectives of what financial inclusive entails and how big data can be used to improve financial literacy and access to financial services. I enjoyed every session, especially sharing and receiving feedback to refine the research approach. Thank you Pulse Lab Jakarta for giving me the opportunity to partake in this event.



Adityo Dwijananto
Geographic Information System Advisor

Adityo Dwijananto graduated from the University of Indonesia with a bachelor's degree in Geography. He now coordinates a team that uses Geographic Information systems (GIS) applications at OpenStreetMap. He is passionate about using open source applications and web-based applications to develop mapping systems for development programmes.

Advisor Note

Spatial Econometrics Modelling for Financial Inclusion

An effective welfare scheme can have a positive impact on financial inclusion. Research and development can help governments better target welfare programmes, particularly by leveraging advanced tools and methods to gather accurate information for developing a useful financial inclusion index. The importance of having reliable and accessible geospatial data was something that stood out during the Research Dive, as well as the value of having

neat visualisations that policy makers can interpret. I am optimistic about the use of this research approach to further understand financial inclusion. I am ready to participate in future research initiatives that will allow me to apply my skills in this area.



Rahma Fitriani
Statistician

Rahma Fitriani is a lecturer in the Department of Statistics at Universitas Brawijaya. She teaches mathematical statistics, econometrics, microeconomics, research methods and simulation methods. She has a PhD in engineering mathematics from the University of Sydney.

Promoting Financial Inclusion Research Collaboration

The term financial inclusion has grown popular in Indonesia; however insights from grassroots research are still struggling to reach in the hands of some policy makers. In Indonesia, it is evident that more research is still needed to understand the quantitative and qualitative aspects of financial inclusion. Separate from helping citizens to access formal loan services, financial inclusion programmes should also encourage savings and investments.

This means the Government should consider how informal financial service providers can help to accelerate financial inclusion. This Research Dive provided academics and practitioners an opportunity to go beyond discourse to find inter-disciplinary solutions as knowledge brokers. I was delighted to be part of this initiative focused on accelerating financial inclusion.



Chaikal Nuryakin
Financial Inclusion Advisor

Chaikal Nuryakin is currently the head of Economics Study in the Department of Economics, Faculty of Economic and Business, University of Indonesia. He is also the head of digital economics research and behavioral economics at the Institute of Economics and Social Research (LPEM) University of Indonesia. He is interested in experimental and behavioral economics, banking and finance, econometrics and modelling. He received his PhD in economics from the National Graduate Institute for Policy Studies (GRIPS) in Tokyo..

Research Dive Advisors and Participants

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Task 3 - Modelling Gender-Based Differences in Financial Inclusion

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Data Description for Research Dive Financial Inclusion

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ABSTRACT

Financial inclusion has several nuances. Within the development sector in Indonesia, for instance, the term is understood from the standpoint of access, availability, usage and quality in relation to financial products and services offered. In general though, by becoming financially included, citizens can withstand the shocks and strains typically brought on by financial crises. The digital revolution continues to generate an abundance of data that is providing more opportunities for policy makers to gain insights on financial inclusion, particularly on progress that has been made and gaps to be addressed. In line with the Government of Indonesia's national strategy on financial inclusion, Pulse Lab Jakarta invited a group of researchers to the Lab to analyse various new and emerging data sources alongside traditional datasets with a view to answering relevant policy questions. For the event, Pulse Lab Jakarta provided the datasets with the support of Indonesia's Central Statistics Bureau, the Indonesian Financial Services Authority, and the National Team for Alleviating Poverty. Datasets included: social media data, the national socio-economic survey (Susenas) data, the national survey on financial literacy and financial inclusion data, household survey data, as well as geographic location data on bank branches, mini markets and post offices. This paper briefly describes the datasets to contextualise the related technical papers.

KEYWORDS

digital revolution, financial inclusion, household data, social-economic

1 INTRODUCTION

Financial inclusion is interpreted differently across institutions. From some, the term is viewed through the lens of access and availability, while for others it is more about quality and usage. Based on research, such as one conducted by Won Kim et.al., financial inclusion is a critical ingredient for economic growth[3]. Whenever an individual or business can access useful and affordable financial products and services to meet their needs, this is considered as financial inclusion. These products and services may include payment transactions, savings, credit and insurance. Whenever an individual or business can access useful and affordable financial products and services to meet their needs, this is considered as financial inclusion. These products and services may include payment transactions, savings, credit and insurance¹. At a global level, efforts to accelerate financial inclusion complement the UN Sustainable Development Goals, specifically goals and targets related to eliminating poverty, creating jobs, achieving gender equality, and

accessing good health services². People who have access to financial services tend to be more secure financially, therefore helping with poverty reduction (such as in Nepal, among women who have bank accounts³).

The Government of Indonesia has been working to get more of the population financially included, with the expectation that this will boost economic growth. To accelerate financial inclusion in Indonesia, Bank of Indonesia together with the National Team for the Acceleration of Poverty Alleviation (TNP2K) and the Ministry of Finance designed a six-point national strategy for financial inclusion. These points include financial education, public finance facility, financial information mapping, and supporting policy, facilities on intermediation and distribution channel, and consumer protection.

One of the challenges in the global financial sector is that there's insufficient data, especially on the extent of financial inclusion and to the of degree on groups such as women, the poor, and youth [2]. World Bank made one of the early attempts at collecting proxy indicators of financial inclusion, by including the measurements on the total number of bank branches, ATM locations, as well as the number of loan and deposit accounts [1]. In addition, World Bank continues to develop the Global Financial Inclusion (Global Findex) which is constructed through survey data from interviews. In Indonesia, the Financial Services Authority conducted similar surveys on financial literacy and financial inclusion in 2013 and 2016. The results of which indicated that financial literacy increased between 2013 and 2016 from 21.84% to 29.66%, respectively. While financial inclusion increased from 59.74% in 2013 to 67.82% in 2016⁴.

Pulse Lab Jakarta conducted a Research Dive on financial Inclusion, focusing on four research questions that sought to understand the extend of financial inclusion across Indonesia, including access, Indonesians' readiness from a financial literacy perspective, gender equality and the impact of new digital technologies.

2 DATA SETS

This section explains briefly the types of data used by the participants.

2.1 Social Media Data

PLJ provided anonymous information based on tweets from users located in Indonesia. Based on this data, we aggregated geo-spatial data for Administrative Boundaries shapefile. This provided more detail from the province level to district level.

² <https://www.cgap.org/blog/financial-inclusion-has-big-role-play-reaching-sdgs>

³ <https://www.cgap.org/blog/financial-inclusion-has-big-role-play-reaching-sdgs>

⁴ <https://www.ojk.go.id/id/berita-dan-kegiatan/siaran-pers/Documents/Pages/Siaran-Pers-OJK-Indeks-Literasi-dan-Inklusi-Kuangan-Meningkat/17.01.23%20Tayangan%20%20Presscon%20%20nett.compressed.pdf>

¹ <https://www.worldbank.org/en/topic/financialinclusion/overview>

Table 1: Information collected on each tweet

Column name	Column description	Example of value
tweet_id	Tweet id	422199748800430081
user_id	User id	67231176
lon	Longitude	106.72679883
lat	Latitude	-6.55841106
prov	Province id	32
kab	Region id	3201
kec	District id	3201060
gender	Gender	
Content	Content	Seru hari ini :))
datetime	Local datetime of tweet	Sun, 12 Jan 2014, 02:53:58
timestamp	Timestamp of tweet	1389470038
source	Source of tweet	Twitter for Android
kab/kota	Location of Tweet	Ciampea, Bogor

2.2 National Socio-Economic Survey (Susenas)

The National Socio-Economic Survey or Susenas contains basic data to support the Government’s development agenda and is carried out by the Central Statistics Bureau (BPS). In this Research Dive, we used the 2017 Susenas data and selected variables that were most related to the research. All provinces, regencies, and districts were classified into rural and urban levels. Some of the variables from Susenas datasets included: summary of family members, birth certificate, education, using technology tools, accessing internet, employment, health, food access, social protection, financial services, goods ownership, and household source income.

2.3 National Survey on Financial Literacy and Financial Inclusion

The Indonesian Financial Services Authority (OJK) (table 3) conducted a national survey on financial literacy and financial inclusion in 2016. In this year, 9.680 respondents across 64 regions and cities within 34 provinces participated. The OJK survey used multistage stratified random sampling based on respondent classification.

2.4 Geographic Location Data on Bank Branches, Mini Markets, and Post Offices

These datasets supported the team that examined financial access through different channels, which covered bank branches in all provinces specifically in 2014, Indomaret and Alfamart store locations in Pontianak in 2016, and post offices location in Pontianak updated as of 2018. The data was crawled from OpenStreetMap APIs. Though details on latitude and longitude were not provided for these locations, we relied on Google Maps to verify their specific positions.

2.5 2015 Basis Data Terpadu (BDT)

PLJ provided the 2015 Basis Data Terpadu (BDT) from the National Team for Alleviating Poverty (TNP2K), including household and individual data. The data is anonymised.

3 DATA AND TASK MAPPING

We defined four research questions and assigned a different dataset for each question. The first task used Twitter and Susenas Data to measure financial literacy and financial inclusion. The second task used geo-location data to measure financial access. The third task used socio-economic survey data and BDT data to model gender-based differences, and the fourth task used Twitter and Susenas data to assess the effect of digital opportunity.

REFERENCES

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- [3] Dai-Won Kim, Jung-Suk Yu, and M. Kabir Hassan. 2018. Financial inclusion and economic growth in OIC countries. *Research in International Business and Finance* 43, C (2018), 1–14. <https://doi.org/10.1016/j.ribaf.2017.07.1>

Table 2: Sample of 2017 Susenas Data for Research Dive

Column name	Column description	Example of value
kab_kota	Region id (refer to BPS)	8
use_phone_within_last3m	Do (a family member) use phone for last 3 months?	1
n_art	Number of family member	3
type_of_job_during_last_week	Type of job for the past week	7
health_ins_a	Ownership type of health insurance A (BPJS Kesehatan as beneficiary)	A
recv_or_buy_raskin	For the last 4 months, did the family buy/receive beras miskin / beras sejahtera	1
art_recv_bank_loan	For the last year, did (any family member) receive loan from bank?	5

Table 3: Sample of National Survey on Financial Literacy and Financial Inclusion

Variable data	Column
Pengenalan Lembaga Jasa Keuangan	
Perbankan (Konvensional)	perbankan_k
Perbankan (Syariah)	perbankan_s
Perasuransian (Konvensional)	perasuransian_k
Perasuransian (Syariah)	perasuransian_s
Dana Pensiun (Konvensional)	dana_pensiun_k
Dana Pensiun (Syariah)	dana_pensiun_s
Perusahaan Efek/Sekuritas (Konvensional)	sekuritas_k
Perusahaan Efek/Sekuritas (Syariah)	sekuritas_s
Manajer Investasi (Konvensional)	manajer_investasi_k
Manajer Investasi (Syariah)	manajer_investasi_s
Perusahaan Pembiayaan (Konvensional)	multifinance_k
Perusahaan Pembiayaan (Syariah)	multifinance_s
Modal Ventura (Konvensional)	modal_ventura_k
Modal Ventura (Syariah)	modal_ventura_s
BPJS Kesehatan (Konvensional)	bpjs_kesehatan_k
BPJS Kesehatan (Syariah)	bpjs_kesehatan_s
BPJS Ketenagakerjaan (Konvensional)	bpjs_ketenagakerjaan_k
BPJS Ketenagakerjaan (Syariah)	bpjs_ketenagakerjaan_s
Lembaga Keuangan Mikro (Konvensional)	lembaga_keuangan_mikro_k
Lembaga Keuangan Mikro (Syariah)	lembaga_keuangan_mikro_s
Koperasi (Konvensional)	koperasi_k
Koperasi (Syariah)	koperasi_s
BMT (Syariah)	bmt_s

Table 4: Sample of Household Survey Data

Variable data	Column
Jumlah keluarga	jml_keluarga
Jumlah anggota rumah tangga	jml_art
Keterangan perumahan	
Milik sendiri	sta_bangunan1
Milik orang lain	sta_bangunan2
Luas bangunan	luas_bangunan (rata-rata)
Jenis lantai terluas	
Marmer/granit	jns_lantai1
Kepemilikan aset dan keikutsertaan program	
Rumah tangga dan aset bergerak	
Tabung gas 5,5 kg atau lebih	gas_55
Kepemilikan aset tidak bergerak	
Lahan	lahan (luas lahan = rata-rata)
Rumah di tempat lain	rumah_lain
Kepemilikan kartu pintar, sejahtera, dan lainnya	
kartu keluarga sejahtera (KKS)/ kartu perlindungan sosial (KPS)	kartu_bansos1
kartu indonesia pintar (KIP)/ bantuan siswa miskin (BSM)	kartu_bansos2

Measuring Financial Literacy and Financial Inclusion through Social Media

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ABSTRACT

The aim of this study is to measure financial literacy and inclusion of 7 cities in Indonesia by using social media data. This study used data cleaning, data processing, and keyword scoring measured by financial tweet and user in each city based on attributes criteria. Financial attributes are categorized into 7 group, which are banking, insurance, pension fund, financial institutions, pawn shop, capital market, and others. Results show that Jakarta achieved highest financial tweets ratio followed by Bandung, Banten, Makassar, and Medan. On the other hand, in terms of financial users, Makassar shows the highest results, followed by Jakarta and Medan. Majority of cities showed increasing financial tweets and users trend. In contrast to the majority, DIY Yogyakarta showed stationary trend and ranked as the lowest on both measures. We also showed that each city had different characteristics using word cloud visualization. Our results give insights are potential to be used by authorities to formulate relevant policies in order to increase financial literacy and inclusion in Indonesia.

KEYWORDS

Financial Literacy, Financial Inclusion, Social Media

1 INTRODUCTION

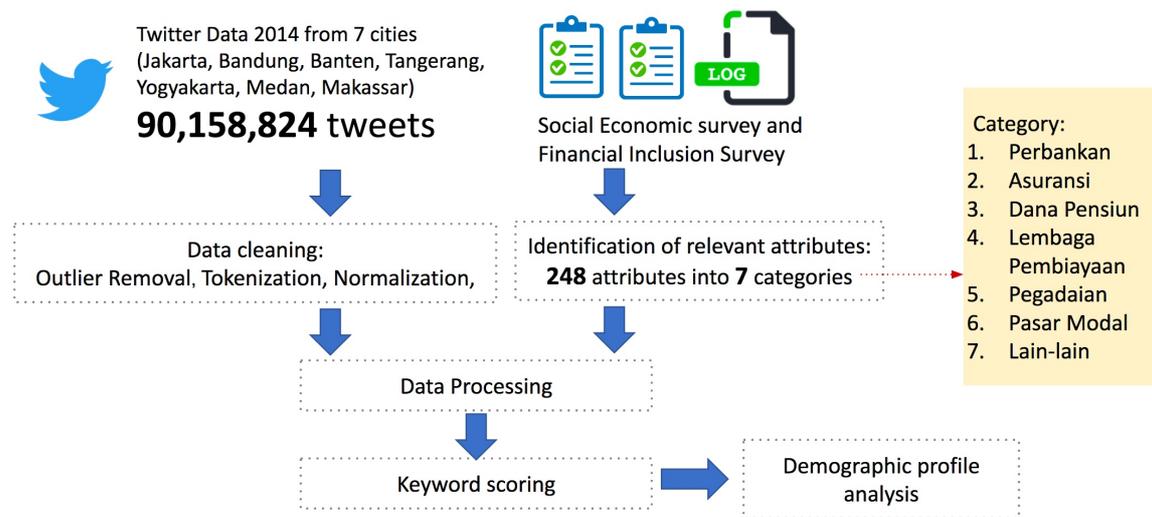
Recently financial inclusion is one of important issues in the global economy. The Global Findex Database 2017 shows financial inclusion has many matters for development. Saving account has the highest percentage based on OJK Financial Inclusion Survey in 2016 and the Global Findex Database 2017 by World Bank. From 2014 to 2017, the adults that have an account increased only 7%. Indonesia National Survey conducted by Indonesian Financial services Authority in 2016 shows that the rate of financial inclusion is 67.8% and it is quite wide gap to fulfill the target in 2019. Despite that, BKPM (Indonesian Investment Coordinating Board) statistic in 2018 showed that growth of investment in Indonesia are going positive and in line the target. Moreover, development of International Financial Integration (IFI) also makes an impact on global economy to the extent which an economy does not limit cross-border transactions.

Increasingly complex and interrelated financial markets caused increasing uncertainty of the global economy make the role of financial literacy more important in society, especially in terms of making sound investment decisions. Financial literacy dimension

is not only characterized by financial knowledge, but also other factors, such as financial awareness. Financial awareness identified by people involvement in discussions on financial topics [6]. Financial awareness is an important factor in financial literacy, which influences decision making related to financial activities. Furthermore, financial awareness is one of the elements needed to create financial inclusion. The effects of high financial literacy can strengthen financial inclusion [3]. In general, people with high financial awareness will have a beneficial effect on the financial systems because those people are smarter in making investment choices and financial products. At the end, it will also has impact to financial inclusion growth.

As a digital communication tool, social media has fostering the dissemination of information on social networks. Twitter messages that are emotionally charged tend to be re-tweeted more often and faster than neutral ones [10]. Lampos et.al and Mislove et.al. [4, 9] conducted mapping social media users with users profiles to finds demographics of twitter user and classify based on socioeconomic status. Michelson et.al [8] has also examined topics of interest to Twitter users based on their "tweets" posts as profile topics, which characterize the topic of user interest, by distinguishing which categories often appear and closing entities. Interesting findings prove that Twitter users can be grouped by topic their interest using approach knowledge base to disambiguate and categorize the entities in the Tweets, such as measure vote intention in governance election or political preference [5, 7], predict disease surveillance [1], health related [12], financial indexes [2], and impact on future stock return [11]. Online information from social media also used to model financial indexes, such as to predict the stock market using the text content of daily Twitter to measure experience mood states that affect their decision making [2].

Recent fast growth adoption of technology in Indonesia makes online information are very promising. Suggested by aforementioned previous studies, Twitter is one of the online information that can be used to model financial indices such as the financial awareness index because it can represented a broad set of features reflecting users and also population behaviors to improves decision making. This analysis uses a collection of online social networking media data collected by Twitter where users create profiles online and communicate with each other by sharing interests, ideas, activities, problems, particularly related to financial issues to show their financial awareness.



(a) Demographic Profiling

1. Creating the data



2. Data Preprocessing



3. Build Classifier/ Modelling

Classifier Naive Bayer: 74.89%
 Classifier SVM: 79.15%
 Classifier RandomForest: 83.07%

Testing Sample of Unseen Data

- 'meneher investasi gt pimamanggala satu lagi teman yang sukses diracuni untuk invest di reksadana kalau agen udah banyak nih komisinya',1
- 'alhamdulillah 1 emas 1 perunggu with pdbi at asrama haji bekasi islamic center',0
- 'spending money was so happy',0
- 'suku bunga bank bi tetap 7 5 inflasi kenaikan bbm masih gangerti maksudnya apaan yang kecil makin terkucil yang besar makin lapar',1

(b) Relevant Tweet Data Classification

Figure 1: Research Methodology

2 DATA & METHODOLOGY

The dataset used in this study included Twitter data in 2014 from seven cities in Indonesia, which are:

- Medan
- Jakarta
- Bandung
- DI Yogyakarta
- Surabaya
- Tangerang
- Makassar

We also used additional data, which are:

- Financial inclusion survey data from Otoritas Jasa Keuangan Indonesia (OJK)
- Financial service authority from Biro Pusat Statistik (BPS)
- Household data survey from Badan Pusat Statistik (BPS)

The Twitter contained 90,158,824 tweets posted in 2014. The OJK's survey data encompassed the results of financial literacy and inclusion national survey in 2016, while the data from BPS provided annual basis data of household and demographic profile in Indonesia.

Figure 1a shows demographic profiling methodology. We employed Twitter dataset processing, keyword scoring, classification, and data visualization. Twitter data was extracted by performing

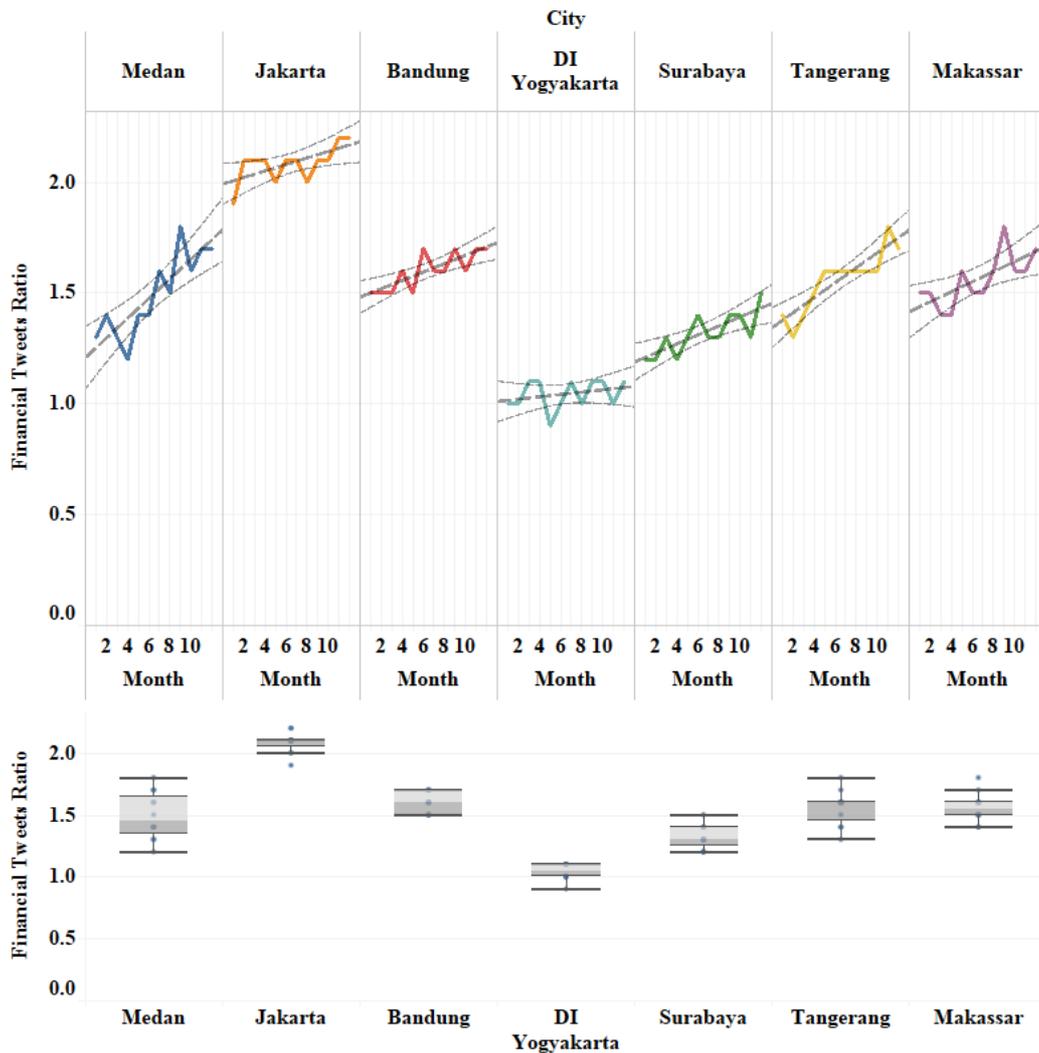


Figure 2: 2014 Financial Tweets Trend

outlier removal, keyword filtering, and relevant tweet classification. Twitter data can be categorized as noisy data because of the unstructured format of its content. Relying to keyword filtering can not guarantee all the tweets are related to financial literacy and inclusion as research topic. To ensure filtering phase gives related tweets better, initialization of text classification approach was applied. About 1000 tweets is normalized to reduce the huge number of features used for next classification steps. For example word "krtu" is transformed into its normal form "kartu". This technique prevent same word with different form was seen as different features. After normalization step, the data is labeled manually by expert in financial inclusion fields by defining its category (7 classes) and its relevance to research topic (0/1 class).

Next step was to identify the relevant attributes to filter the Tweet data that related to financial topics. Attributes identification

contained 248 attributes in 7 categories, i.e., Perbankan (Bank), Asuransi (Insurance), Dana Pensiun (Pension Fund), Lembaga Pembiayaan (Financial Institutions), Pegadaian (Pawn shop), Pasar Modal (Capital Market), and Lain-lain (Others). Table 1 shows samples of keyword used in this studies. Next step was to perform data processing using the results from the Twitter extraction and the attributes identification. Last step was to score the keywords to measure the financial literacy and inclusion in seven cities.

We developed two metrics to measure financial literacy and inclusion, which are:

- **Financial tweets ratio** is defined as number of tweets which contain financial attributes divided by all tweets in a city.
- **Financial users ratio** is defined as a number of financial aware users (posted financial attributes tweet) divided by all users in a city.

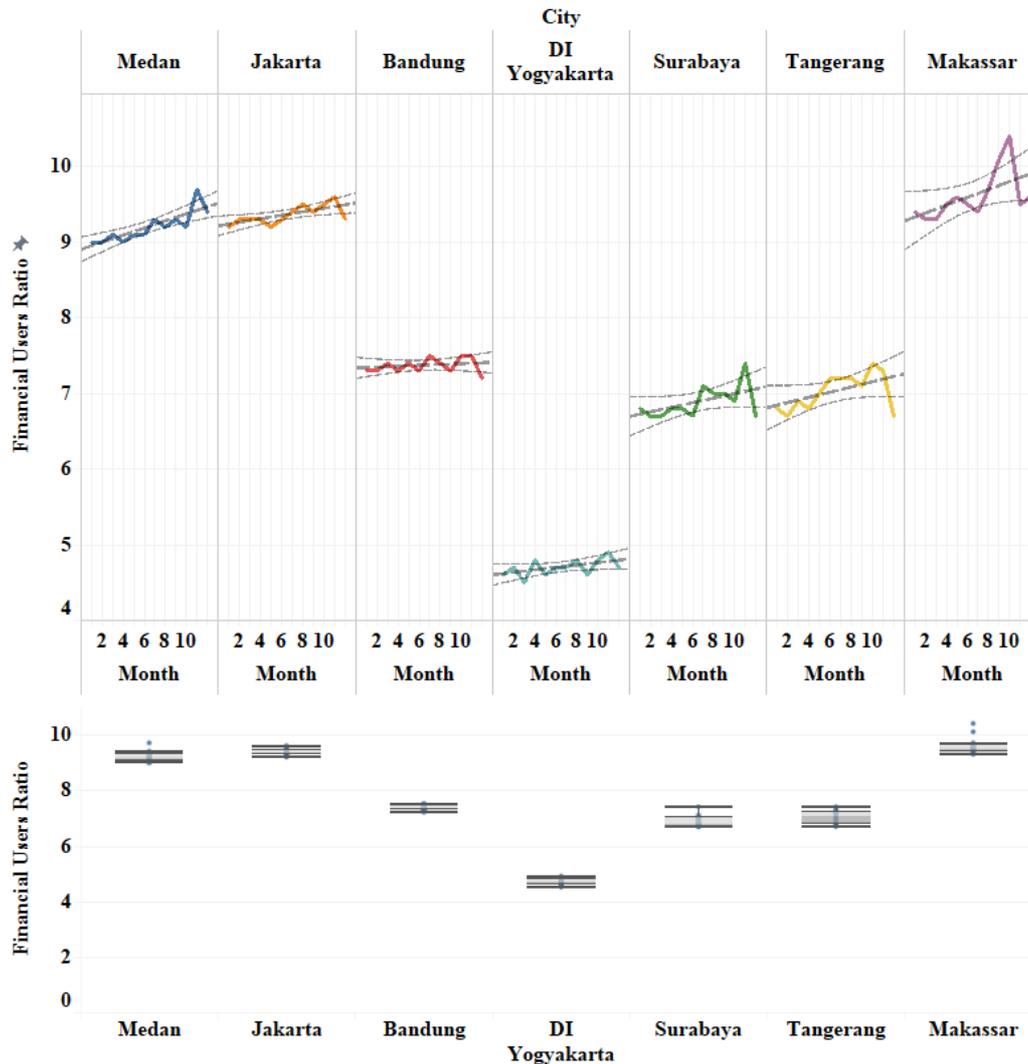


Figure 3: 2014 Financial Users Trend

Twitter data can be categorized as noisy data because of the unstructured format of its content. Relying to keyword filtering can not guarantee all the tweets are related to the financial inclusion and financial literacy as research topic. To ensure filtering phase gives related tweets better, we develop text classification approach as shown in Figure 1b. In first classification step, tweet content can be seen as set of words was transformed into vector representation. Each word acts as a feature that contributes to the classification results. Dataset has an issue about imbalanced data and balanced using SMOTE algorithm. We explored 3 algorithm as classifier, which are naive bayes, SVM (Support Vector Machine), and random forest. 10-fold cross validation are used to measure each classifier performance. Using default configuration, random forest gives best performance (83.07% accuracy) to classify related tweets to the financial inclusion and literacy.

3 RESULTS AND FINDINGS

Figure 2 and 3 show financial awareness trend in seven cities during 2014. We measured financial awareness by using two metrics, financial tweets and financial users ratio. Jakarta achieved the highest financial tweet ratio ($\bar{x} = 2.1$), followed by Bandung and Tangerang ($\bar{x} = 1.6$), Makassar ($\bar{x} = 1.55$), Medan ($\bar{x} = 1.45$), and Yogyakarta ($\bar{x} = 1.05$). Second demographic results shown in Figure 3 showed trend of users who posted financial tweets in seven cities. Makassar achieved the highest financial users ratio ($\bar{x} = 9.5$), followed by Jakarta ($\bar{x} = 9.3$), and Medan ($\bar{x} = 9.15$). Majority of the cities exhibited increasing trend. On the other hand, Yogyakarta ($\bar{x} = 4.7$), who also had the lowest financial users ratio.

We performed analysis on given financial tweets and users trend by using Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for stationary

Table 1: Keyword Samples

No	Keyword	Category
1	bank	Bank
2	deposito	
3	kartu kredit	
4	asuransi	Insurance
5	bpjs	
6	insurance	
7	taspen	Pension Fund
8	dana pensiun	
9	dplk	
10	koperasi	Financial Institutions
11	baitul maal wat tamwil	
12	lembaga keuangan mikro	
13	tabungan emas	Pawn shop
14	pegadaian digital	
15	gadai emas	
16	capital market	Capital Market
17	mutual fund	
18	obligasi	
19	fintech	Others
20	tax	
21	ojk	

Table 2: Stationary Trend Tests

Province	Monthly Financial Tweets		Monthly Financial Users	
	KPSS statistics	Theil-Sen slope	KPSS statistics	Theil-Sen slope
Medan	0.95**	0.05**	0.86**	0.04**
Jakarta	0.45*	0.01*	0.66*	0.03**
Bandung	0.79**	0.02*	0.12	0.01*
DI Yogyakarta	0.14	0	0.35	0
Surabaya	0.73**	0.02*	0.41	0.04**
Tangerang	0.96**	0.03**	0.48*	0.05**
Makassar	0.69**	0.03**	0.52*	0.05**

*** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

trend test and Mann-Kendall to assess upward-downward trend. Table 2 shows trend test results. Interesting insights are shown as majority of the cities exhibited non-stationary increasing trend. Medan got highest results (Theil-sein slope=0.05) compared to other cities in terms of financial tweets. Both Tangerang and Makassar shared similar results (Theil-sein slope=0.05) in financial users which highest compared to others. Yogyakarta, who achieved lowest financial tweet and users ratio compared to other 6 cities, are also showed a stationary trend which imply stagnant monthly financial tweets and users growth. It is worth to mentioned that Bandung and Surabaya got stationary results on financial users monthly growth.

We used word cloud visualization as a tool for text analytics of social media "twitter". We used the word cloud to visualize the financial topics in 7 cities in Indonesia. As shown in Figure 4, it can be observed that each city have different financial awareness

characteristics. The most frequent words of text document in the "tweets", we can quickly spot common words from the category of banking, such as bank, Permata, Mandiri most often mentioned in almost cities. Category Bank is the most frequent words of tweets text document. This results support the OJK Financial Inclusion Survey in 2016 and the Global Findex Database 2017 by World Bank, that banking has the highest percentage of financial inclusion and financial literacy. High intensity of social media activity "tweet" that discuss about finance, is a indicator that can used to measure of financial awareness. Financial awareness might provide insight about the financial inclusion and financial literacy and further potential to be used by financial authorities to formulate relevant policies in order to increase the local and national financial inclusion. Methodology can be applied to wider or more specific geographical areas.

4 CONCLUSION

We showed that social media analysis can reveal hidden insights of financial literacy and inclusions. Compared than traditional survey and field observation approaches, social media analysis offers higher spatial and temporal resolutions makes more accurate and real-time information. Social media insights about the financial inclusion and financial literacy are promising to be used by financial authorities to formulate relevant policies in order to increase the local and national financial inclusion. Despite the promises, validity of the keywords and model needs to be more evaluated to better capture financial literacy and inclusion insights.

ACKNOWLEDGMENT

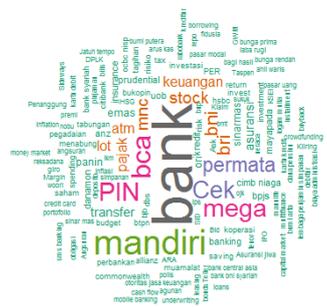
The authors would like to acknowledge Pulse Lab Jakarta of United Nation's Global Pulse for the initiation of Research Dive 8 "Financial Inclusion".

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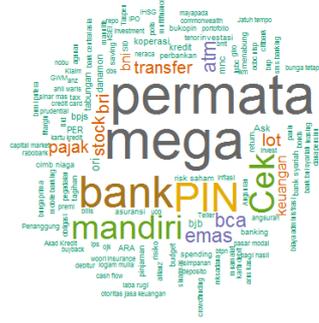
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(a) Medan



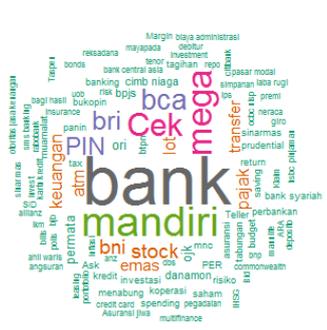
(b) Jakarta



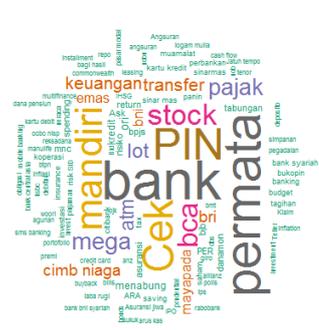
(c) Bandung



(d) DI Yogyakarta



(e) Surabaya



(f) Tangerang



(g) Makassar

Figure 4: Word Cloud of 2014 Financial Tweet

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Supply-Side Measurement of Financial Inclusion

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ABSTRACT

This paper proposes a novel model on measuring financial inclusion from the supply side, by harnessing the combination of location data of financial channel and population density. We extend the channel of formal financial service provider such as bank to formal non-financial institutions that provide partial financial services, such as post office and two most Indonesian popular chain convenient stores, Alfamart and Indomaret. The proposed model is implemented and evaluated in Pontianak city, and can be generalized to other cities in Indonesia. It measures the score of financial inclusion index in population within predefined area by taking the ratio between the number of financial channels over the population aged 15 years old and older. Moreover, the financial inclusion index is weighted by the geographic distance between the center of area and the channels. The financial inclusion index based on the proposed approach seems to relatively follow the pattern of local economics, where the majority of channels are located on the areas known to be traditionally wealthier or growing business districts. This evidence is a supporting proof that the proposed model is decent as proxy of financial inclusion index generated by official survey.

KEYWORDS

financial inclusion, supply side, proximity, distance

1 INTRODUCTION

Financial inclusion implies expanding access to financial services to the people who are currently do not have access to them. This paradigm becomes more important in the developing countries [14] as the financial inclusion enhances economic growth, financial stability, poor reduction, and economic disparity. Financial access is further believed as a tool to increase household welfare through increasing the economic capability and financial planning.

Indonesia has launched National Strategy for Financial Inclusion in 2011, and it becomes an official policy with Presidential Act No 82/2016. The President of Republic Indonesia leads the programme committee directly, with Vice President as the deputy. It reflects the great importance and commitment to the financial inclusion programme in Indonesia. As the result, the financial inclusion programme in Indonesia has made the most progress across East Asia and the Pacific in bringing its citizens into the formal financial

system in the 2014-2017 period. Indonesia also boasts a strong use of accounts for saving, registering ten percentage points higher than the comparable world average, where 42 percent of account owners in Indonesia save at a formal financial institution such as a bank or micro-finance institution¹.

Financial inclusion can be seen using two ways, supply side perspective as well as demand side perspective. Reference [14] mentioned the existence of the supply-side and demand-side barriers. The supply-side barriers include physical barriers, lack of suitable products and documentation requirements. The demand side barriers include psychological, cultural and financial illiteracy. It is important to measure not only the usage (demand-side), but also barriers to access (supply-side), in order to understand and put effort in expanding financial inclusion [2].

Physical barriers can be resolved by providing the sufficient number of financial services. Global Financial Inclusion Index by the World Bank implies that 33 percent of the un-banked people cited distance as a key reason for not having an account. Therefore, the availability and accessibility is the important aspect to solve financial inclusion issues. Indonesia Financial Service Authority (Otoritas Jasa Keuangan, OJK) puts in availability as an indicator apart from access, usage and quality in the financial inclusion dimensions.

This study proposes a novel model on measuring the financial inclusion index from the supply side. The study focuses in the city of Pontianak, West Kalimantan, Indonesia, to:

- (1) delineate the mapping of the availability of financial services and
- (2) analyze the population density and geographical proximity of the financial channels within the area to calculate the FI index from the supply-side.

The availability of financial services includes bank branches, ATMs, post offices and retailer store networks (Indomaret and Alfamart). By definition, bank branches and ATMs are formal financial institutions that clearly provides financial services. Consequently, post offices and retailer stores that support financial services are defined as formal non-financial institution in this study.

¹<http://fintechnews.sg/19095/indonesia/world-bank-global-findex-financial-inclusion-unbanked/>

2 FINANCIAL INCLUSION: SUPPLY-SIDE

There are some definitions of the financial inclusion. One of them is that financial inclusion as the delivery of financial services at an affordable cost to vast sections of disadvantaged and low-income group of the society, including households, enterprises, traders, etc. The term financial services includes savings, credit, insurance, remittance facilities, etc. [7]. Meanwhile, the World Bank briefly defines financial inclusion as access to and use of formal financial services [4]. Inclusive financial systems is meant as allowing people to obtain broad access to financial services, without price or non-price barriers to their use, especially for poor people and other disadvantaged groups [3]. Ultimately, The Indonesia Financial Authority (OJK) as cited in Presidential Act 82/2016 describes financial inclusion as conditions when each member of the community has access to various formal quality financial services in timely, fluently and safe manner with affordable costs in accordance with needs and capabilities within order to improve people's welfare.

The opposite of financial inclusion is financial exclusion. Reference [6] stated that financial exclusion comprises a number of aspects. First, access exclusion, refers to a restriction of access to financial services which may be due to factors such as branch closures or unfavourable risk assessments. Second, condition exclusion is where individuals are excluded from financial services due to conditions attached to the products offering. Third, price exclusion refers to a situation where certain individuals cannot afford financial services or products at the offered price. And the last, marketing exclusion that overlooks of certain groups during the marketing activities of financial services firms [5].

Access and condition exclusion are related to the physical distance. The farther the distance, the more exclusive the access and the condition to financial service. Therefore, it is important to analyze the availability and the distance of financial service facilities in each region, in order to compute the financial inclusion index that considers the formal non-financial channels and their geographical proximity.

Reference [1] proposed a multidimensional index with both demand and supply-side information to measure the extent of financial inclusion at country level for eighty-two developed and less-developed countries. Using a two-stage Principal Component Analysis (PCA), financial inclusion is determined by three dimensions: usage, barriers and access to financial inclusion.

Reference [14] explained that the supply side barriers such as the physical barrier stemming from distance to formal financial services. The other barriers are lack of appropriate financial products and documentation requirement. The terms and conditions offered by banks are not suitable for low income groups because the minimum balance required to open accounts is unaffordable. Then, some people can not open bank accounts due to incomplete documents required by bank regulation. Also, some accounts are closed by banks due to infrequent use.

This paper focused on the financial inclusion index calculation from supply-side perspective that focuses on the financial services provider. It is important to note that financial service providers are not only bank and other formal financial institution, but also the formal non-financial channels such as retailer and postal office that provide alternative financial services. In addition, the geographical

proximity, i.e. the distance from each financial channels to the center of villages, is also considered in calculating the financial inclusion index.

3 DATA

The focus of the study is on Pontianak city simply for the data availability reason. The data consist of geographical location (GL) on the map (longitudes and altitudes) of the four aforementioned financial channels (i.e. banks, ATMs, retail/minimarket store (Indomaret and Alfamart) and post office within the vicinity of Pontianak city), Village Potential (Potensi Desa-Podes) data from Indonesia's Central Bureau of Statistics (BPS), and population data in each village from National Board for Disaster Management (BNPB). The longitudes and the altitudes are collected by manually copied the GL values from Google maps where the intended channels are located by Google. The GL are then processed by calculating imaginary straight line (Euclidean distance) from the financial service channels to the center of each villages to estimate the relative distance between the channels and the villages (Section 3.1). In total there are 378 points of GL from: 132 banks and ATMs, 91 Indomaret, 62 Alfamart, and 93 post offices. Thus, there 378 distances from each channel to each village center. These distances will used as a weight, so-called a geographical proximity, when calculating the supply-side financial inclusion index proposed in this research.

As an additional information, the Podes data provides information about formal financial services such as state-owned bank (*Bank BUMN/Pemerintah*), Commercial Banks (*Bank Swasta*), rural banks (*Bank Perkreditasi Rakyat*) and various kinds of cooperatives. These financial channels are not considered in our proposed approach because the Podes data does not provide their GL information. Therefore, the geographical proximity considered in our approach is not available for these channels. If the GL is available, it can be done for further research, then these formal financial services can be easily accommodated in our method by updating the number GL channel (there are 378 points for current report).

3.1 Data processing

The GL points are distributed into 29 groups correspond to 29 villages in Pontianak. We exclude 31 GL points since they are located outside the administrative border of Pontianak such that we assume that they are irrelevant, even in practice those channels may be utilized by people to do financial transactions. However, some of points out of 31 GL points are very far from the border (automatically far from the village center) such that these outliers will introduce bias to our financial inclusion index.

3.2 Proposed index

The distance $D(v_i, c_j)$ between village centroid v_i to each financial channel with specific GL point c_j ² are measured as the distance managed by vehicle acquired from Open Street Map. Then, the supply-side financial inclusion for village i denoted as $FI^{SUP}(v_i)$ is calculated by taking the ratio of the number of channels $|c_i|$ within the village i that serve population aged 15 years old and above ($|P15|$). The ratio is weighted by the the average distance of village's centroid to all channels (\bar{D}) over the population aged

²<https://www.openstreetmap.org/map=5/-2.546/118.016>

15 years old and above ($P15$) at each village. The mathematical formulae is defined in Equation (1).

$$FI^{SUP}(v_i) = \frac{|c|_i}{|P15|_i} \times \frac{1}{\bar{D}_i |P15|_i} \quad (1)$$

The first term in equation (1) is equivalent with formal definition of financial inclusion, i.e. number of bank account ownership over the population aged 15 years old and above. Our proposed formulae extends the calculation of financial inclusion index based on the intensity of channel that provides financial service. In addition, the proposed financial inclusion index is weighted by the geographical proximity as imposed at the second part.

4 RESULTS

The distribution of all financial service channels in Pontianak can be seen in Figure 1. The bank are marked with red, the ATMs are also marked with red with additional border, the Indomarets and Alfamarts are colored with blue and green, respectively, and post office in orange colour. The more points the more intensity of financial channel within the area.

The picture depicts the unbalance distribution of financial channels, especially banks. The location of banks centered on the middle of the city. Most of the other financial channels are in southern of the Pontianak City. The northern of the city which is bordered by the river seems lack of financial service channels. The non-financial institution like retail store and post office seem to have more balance spatial distribution than formal financial service like banks. This means that non-financial institutions that provide financial services such as retail store and post office can be an alternative channel, particularly as complement, for calculating the financial inclusion index in addition to the formal financial institutions like banks.

Concerning the population density area, it seems that the locations of financial channel do not always in the populous area as can be seen in Figure 2. The darker area represents the more densely populated area. It might be that other factors play key role, such as economic activities.

The result of $FI^{SUP}(v_i)$ index for each village as calculated using Equation (1) is displayed in Figure 3. The larger value of the financial inclusion index means that the corresponding village is more inclusive financially. The value of the supply-side financial inclusion index is not laying between zero and one. The scaling transformation such that the range value of the supply-side financial inclusion index is in $[0,1]$ will be considered for the future work. Once the $[0,1]$ -scale is provided, the the proposed financial inclusion index can be compared with the existing financial inclusion index.

The financial inclusion index seems to relatively follow the pattern of local economics, where the majority of channels are located on the areas known to be traditionally wealthier or growing business districts. Data from stipulated property tax as the proxy to local economics in 2017 suggests the top six villages in Pontianak city are Benua Melayu Darat (1st), Akcaya (2nd), Parit Tokaya (3rd), Bangka Belitung Laut (4th), Darat Sekip (5th) and Sungai Bangkong (6th) [9], [12], [10], [8], [13], [11]. Four of them: Sungai Bangkong (1st), Benua Melayu Darat (2nd), Akcaya (4th) and Darat Sekip (5th), appeared in the top six financial inclusion index list as indicated

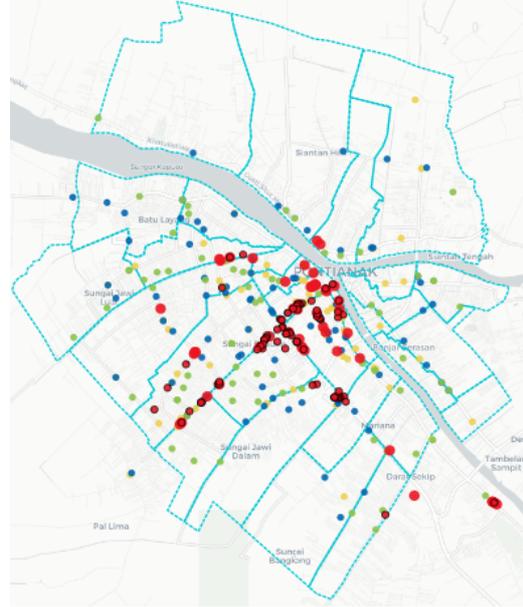


Figure 1: Plots of Geographical Location of Financial Service Channels

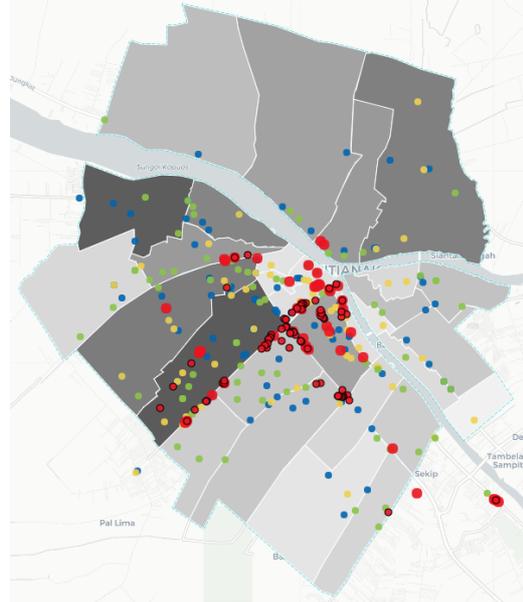


Figure 2: Plots of Financial Service Channels with Population Density at Each Village

in Figure 3. Sungai Jawi, the third place in the financial inclusion index, instead shows population density as the more significant contributing factor. Further, together with Parit Tokaya that in sixth place, they shares borders and main roads with Sungai Bangkong, the most densely populated village in town.

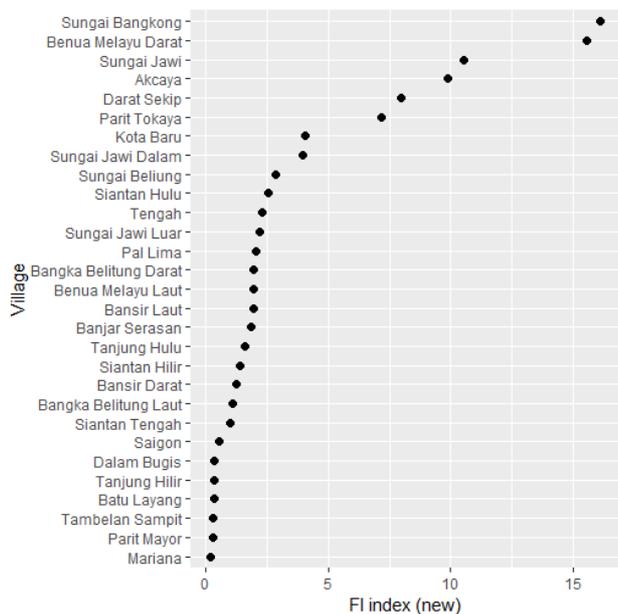


Figure 3: The Supply-side Financial Inclusion Index for Each Village

5 CONCLUDING REMARKS AND POLICY IMPLICATION

From the results above, we conclude the discussion with some suggestions as follows:

- (1) Two essential factors for the existing spatial distribution of financial services channels in Pontianak city are population density and local economies.
- (2) Related to the first point, location of the formal financial institution like banks need to be arranged not only by the proposal of each bank, but also need intervention from regulator in order to make the spatial distribution of banks and other financial institutions becomes more balance, relatively to the population, over the region such that they can give financial service for broader area and more population. The can be expected to increase the number banked people such that the financial inclusion index also increase.
- (3) The proposed formula to calculate the supply-side financial inclusion index, that also consider the geographical proximity of financial channel, provides the make-sense results compared with the real condition of each corresponding village.
- (4) The formal non-financial institution can provide financial services that can not be reached by formal financial institution. This fact can be used to extend the calculation of the financial inclusion index particularly from the supply-side.

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Modelling Gender-Based Differences in Financial Inclusion

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ABSTRACT

At the end of 2019, National Strategy of Financial Inclusion - SNKI (2016) commanded that financial inclusion index still needs to be more highly targeted by 75 percent. It means that 75 percent of adult population will have access to financial services offered by formal institutions. Dozens of national stakeholders have convinced a positive effect of financial inclusion to solve poverty-alleviation and inequality gap-issue especially in rural area. The objective of this research is to examine the extent of inclusiveness on finance based on gender differences. To define this model, we use Generalized Linear Latent Variable Models (GLLVM). GLLVM is an extended version of ordinary regression model where multivariate-correlated responses are modeled through a single-joint model and are a powerful class of models for understanding the relationships among multiple, correlated responses. The result is rural-based female adults are more likely to be formally served, and specifically more likely to be banked through the facilities of non-bank credit and bank saving than males, with a difference of 5% to 10%.

KEYWORDS

Gender, GLLVM, financial inclusion, rural

1 INTRODUCTION

By 2030, Sustainable Development Goals (SDGs) has been set to be achieved through a set of 17 goals that range from eradicating poverty and hunger to promoting gender equality. Reflecting the integrated and interconnected goals, the framework sets out a wide range economic, social and environmental objective [1]. For Indonesia, however, we are encountering at a time of immense challenges to sustainable development. There are enormous inequalities within and among provinces, specifically the level of poverty between rural and urban areas. In 2017, extreme poverty in rural area is higher than in urban area by 13.47 percent and 7.26 respectively [2].

To solve poverty-alleviation and inequality-gap issues, the government of Indonesia concerns to improve financial services as the core of development agenda (Bank Indonesia, 2014). The poor may find themselves in poverty trap if financial barriers are not removed [3]. Dozens of national stakeholders have convinced the positive impact of financial inclusion on high economic growth, financial stability, poverty alleviation, and regional divergences. Surely, it is in line with the objective of SDGs.

To do this, they have continuously held a range of financial education and inclusion programs. As a result, the score of Global Financial Inclusion Index (Findex) for Indonesia has gradually increased to 49 percent in 2017 [4]. If we compared, this number is lower than the result from the National Survey on Financial Inclusion [5] which is up to 67.82 percent. Despite these significant different figures, National Strategy of Financial Inclusion - SNKI commanded that financial inclusion index still needs to be more highly targeted by 75 percent of adult population will have access to financial services offered by formal institutions at the end of 2019. It means the number needs to be boosted for the next year.

As part of its efforts to boost financial inclusion outreach, SNKI (2016) has listed the most targeted participants, namely women, MSMEs, students, people in underdeveloped areas, and Indonesian migrants. It is believed that gender affects financial inclusion. Enable females to develop skills in household financial management could lead to their empowerment and household financial involvement [6]. A number of recent studies have reported the existence of women exclusion from financial services, especially for those who live in rural area [7]; [4]. For Indonesia, it is interesting whether the gender gap and region inequality are really worrisome issues.

Numerous approaches have been made to analyse this inclusive financing issue. In general, the inclusivity in finance are measured through supply side and demand side. Most studies discuss merely on supply side through how the inclusivity relies on infrastructure availability (top-down approach). In fact, this approach cannot capture the perspective from the specific characteristics of the people, especially from gender gap. There is, thus, an urgent need to assess the financial inclusion from demand side (bottom-up approach), especially in Indonesian rural area. This will enable policymakers and researchers to construct and evaluate policies in accordance with evidence-based research. Therefore, this paper tries to fulfill three objectives. First, examine a significance of gender on individual preferences for financial services. Second, this paper also aims to study how individual characteristics for each gender affect the financial inclusion indicators. Last, find the correlation among financial services for males and females.

2 DATA AND CONCEPTUAL FRAMEWORK

The study uses the data from the second National Survey on Financial Literacy and Inclusion (SNLIK) that the Financial Service Authority (OJK) conducted in 2016 [5]. The survey involved 9,680

respondents from 34 provinces that spread over 64 cities across Indonesia. This database documents financial literacy and usage across gender, age, educational level, geographic regions and income level. Since the focus of this paper only for the rural area, thus we excluded the data of urban area. There are data of 1340 respondents from rural area used in this study.

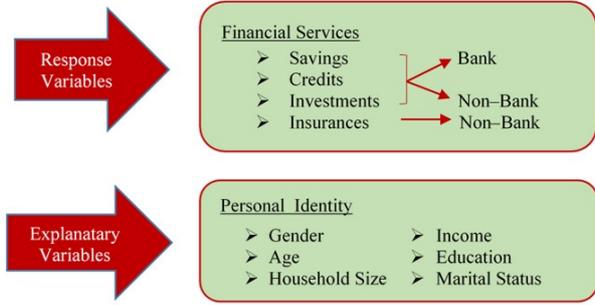


Figure 1: Data Framework.

In here, we use 7 (seven) types of financial services as the response or dependent variables, namely bank savings, non-bank savings, bank credits non-bank credits, bank investments, non-bank investments, non-bank insurances. From the demand sides, we use 6 (six) personal identities as the explanatory or independent variables, namely gender, age, household size, marital status, incomes (lower, middle and upper incomes based on grouping from OJK survey) and education level (primary, secondary and higher educations). In short, Figure 1 depicts the data framework in this study. As the preliminary study, this paper only uses the data from the rural area for both variables.

3 METHODOLOGY

Generalized Linear Latent Variable Models (GLLVM) is the common method used in ecological analysis ([8]; [9]). To the best of our knowledge, this study is the first unified study in using GLLVM on the economic topic. A latent variable model or more common GLLVM is an extended version of ordinary regression model where multivariate-correlated responses are modeled through a single-joint model. In general, the equation of GLLVM is given as follow:

$$g(\mu_{ij}) = \eta_{ij} = \tau_i + \beta_{0j} + x_i^T \beta_j + u_i^T \lambda_j.$$

where $g(\cdot)$ is the link function that explain the relationship of between linear predictor η_{ij} and the mean response, β_j is regression parameters of corresponding explanatory variables. u_i is a latent variable assumed to be independently-normally distributed with zero mean and constant variance; also refers to missing predictors. The latent variable is also used to incorporate the correlation among responses; in our case, we assumed correlated responses as multiple indicators are collected from a single person. Factor loadings λ_j are used to explain the such correlation in the model. See [10] and [11] for more details of GLLVM and GLM. In short, GLLVM could be depicted as shown by Figure 2.

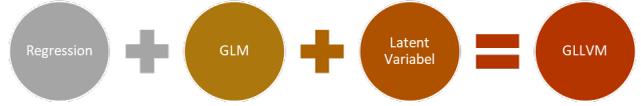


Figure 2: Generalized Linear Latent Variable Models (GLLVM).

Binomial distribution is assumed for our model since the response is binary. Hence the link function used in the model is a logit function. We used six personal identities above where all categorical variables are treated as factors (dummy variables). The analysis is conducted in software R using package of GLLVM [12]. Since the aim of analysis to explain mean-variance relationship, the goodness of fit is assessed through the model residuals instead of testing the accuracy of prediction.

4 FINDINGS AND DISCUSSION

In this section, we analyze three model of gender-based differences in financial inclusion. Credible analysis on the financial lives of people is provided in this section to have unified-evidence for developing appropriate financial products in terms of key demographics-gender. The analyses are presented as follows:

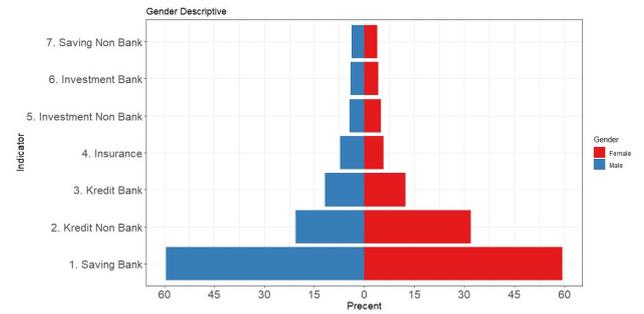


Figure 3: Account Ownership at Formal Financial Institutions by Gender in Rural Area.

4.1 Gender-Based Differences in Individual Financial Services

Figure 3 depicts the percentages of seven indicators for males and females in rural area. There is no major difference between males and females in financial inclusion in rural area looking at from various financial services. Credit from non-bank institutions, however, shows a higher figure for females, reaching over 30% while males only have access to credit from non-bank institutions at below 20%. Beside that, if we compared the financial facilities between bank and non-bank, the largest gap occurs on savings and credits. For saving, both males and females prefer to use bank-savings than non-bank savings. This could happen since the formal bank gives more satisfied saving facilities in terms of interest rate, security, easiness etc. For credit, the highest proportion of adults borrow through non-bank institutions. Perhaps, those who borrow the money from

non-bank credit facilities consider it very easy to do so and feel that they can trust the institution.

To test our hypothesis whether gender has a significant effect on individual financial inclusion in rural area, a latent variable model is used for modeling. Seven financial inclusion indicators as explained in previous section are used in the model as dependent variables, and six individual characteristics as explanatory variables. Binomial distribution is assumed for our model since the response is binary. We look more detail on other independent variables for separate model between males and females. The remaining six indicators, except non-bank credit services, do not receive any significant effect indicating no major difference between males and females in terms of the probability of being financially inclusive.

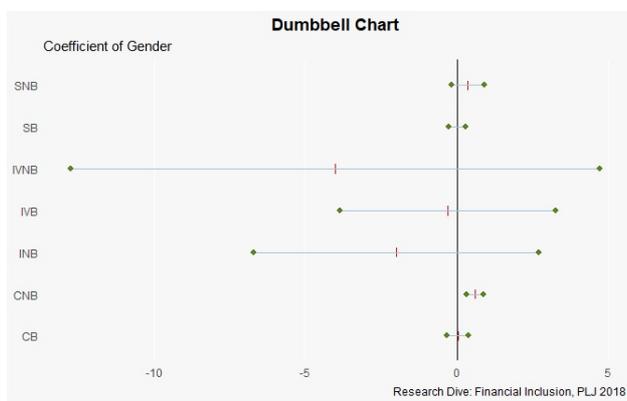


Figure 4: Generalized Linear Latent Variable Models (GLLVM).

The results found that only credit from non-bank institutions has a positive significant effect from gender as the confidence interval of corresponding parameter does not contain zero in its interval. The odds ratio of gender on credit from non-bank institutions is about 2 meaning that females are almost twice higher than males to get financially inclusive based on this indicator. This finding is also relevant with Figure 3. The fact that more females access non-bank credits shows that non-bank institutions serve as a better alternative route to females than males. This surprising finding is in line with [4], the gap between men and women to have account ownership in Indonesia is -5 (minus five). A negative value indicates that Indonesia has a larger share of women than men in having an account.

4.2 Gender-Based Relationship between Financial Service Indicator and Personal Identity

To study how individual characteristics for each gender affect the financial inclusion indicators, we build separate model for males and females using a latent variable model. Figure 4 presents the parameter testing for both genders. A box with cross sign indicates insignificant p-values for corresponding independent and dependent variables. In here, the significant effects will be our concern. By looking at the figure 4, there seems a positive-significant effect

from age to credit from non-bank institutions on females in rural area. Positive parameters indicate positive-multiplicative effect of the odds ratio. The estimated odds ratio of this parameter explains that the higher age in females the higher the probability to have access to credit from non-bank institutions. Moving to the next significant variable, marital status where we assign 1 for being married and 0 otherwise. In females, we found that credit from non-bank institutions indicators receives positive effect from marital status where married females have higher chance to be financially inclusive, having more chance to access credit from non-banks. On the other hand, males show major difference in marital status for having non-bank saving where married males have higher probability to have saving at non-bank institutions.

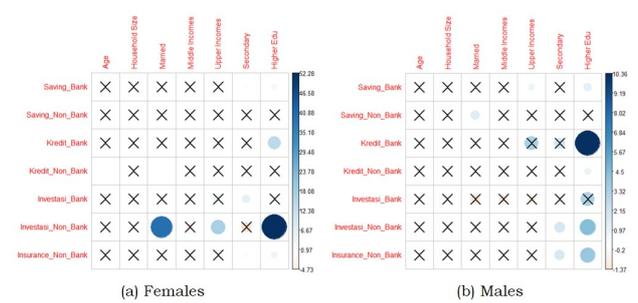


Figure 5: Results of Significance Test between Dependent and Independent Variables.

The last two variables are incomes and education. We divide incomes into three categories: lower, middle and upper incomes where lower incomes are set as reference code (equal to 0). The results found that there is no major difference between middle and lower incomes in terms of chances of being financially inclusive for both genders. Upper incomes, however, give some positive effects on particular indicators. The financial status of females, especially non-bank investment (the only significant variable) is positively influenced by upper incomes indicating upper income females strongly have more chance to access the investment from non-bank institutions. However, males of upper incomes have small p-values for bank saving indicator meaning that the probability in owning bank saving is higher for upper incomes than males of lower incomes. It means that wealthier segments, for both males and females, have the highest likelihood of being banked, compared with those in poorer segments are more likely to be financially excluded.

The surprising and most varied finding are on education. We also divide the education into three levels: primary, secondary and higher education where we put primary level as reference code (assigned to be zero). For secondary level, the financial inclusion indicators that receive strong effect are non-bank investment and non-bank insurance for males while in females are bank saving, bank investment and non-bank insurance. All of parameters are positive meaning that secondary level has bigger chances to have access on those financial inclusion indicators than primary level. For higher education, more indicators have more lower p-values

as an indication of significant variables. From females, we found four out of seven indicators are receiving significant effects, those are bank saving, bank credit, non-bank investment and non-bank insurance. Non-bank investment has the highest odd ratio, bigger than 100. From males, higher education affects positively five out of seven indicators: bank saving, bank credit, non-bank credit, non-bank investment and non-bank insurance. Credit from formal bank has the highest odd ratio of greater than 100. From findings above, we can conclude that if we use the definition of being financially inclusive is to own basic saving at bank institutions, then level of education is the most contributing variable for females in rural area to own accounts at bank. For males only upper incomes and higher education are the two matter factors influencing account ownership.

4.3 Gender-Based Correlation among Financial Service Indicator

Finally, we are also interested to find the correlation among seven dependent indicators for males and females after controlling the effects of age, household size, marital status, incomes and education levels. Findings shows that females who own saving at bank have strong dependence with females of having access to other indicators meaning that females who have access at bank saving tend to strongly have access in other financial indicators.

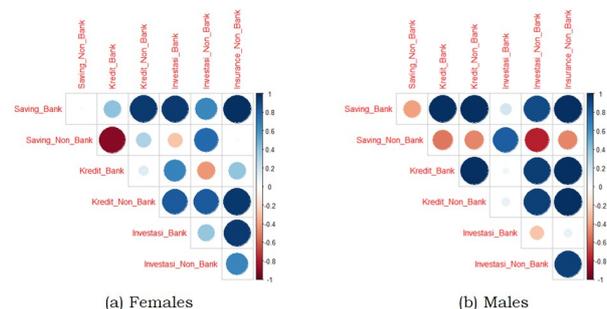


Figure 6: Result of Correlation Test among Financial Service Indicators.

Figure 6 shows the similar pattern also occurs on males where in males there is a negative association between saving at bank and non-bank institutions meaning that males who have saving at bank would likely not have saving from non-bank institutions. In females, many correlations are strongly positive while in males a few indicators have negative relationship such as non-bank saving and other indicators that indicates when males have non-bank saving, they tend not to own other financial services. On the other hand, if the value of correlation is close to zero (white colour) the association between the indicators is random, no particular pattern.

Since the aim of analysis to explain mean-variance relationship, the goodness of fit is assessed through the model residuals instead of testing the accuracy of prediction. The finding shows that no particular pattern appears on the residuals and the residuals lies closely to the normal distribution line with no major outliers. This indicates no sign of lack of fitting in our model.

5 CONCLUSION AND POLICY RECOMMENDATION

The study conclude that rural-based female adults are more likely to be formally served, and specifically more likely to be banked through the facilities of non-bank credit and bank saving than males, with a difference of 5% to 10%. Surprisingly, no major difference between males and females in terms of the probability of being financially inclusive in rural area in general except for having access to non-credits. We also found that for females, non-bank credit is positive-significantly determined by age, marital status, and income. The most varied finding is on higher level of education where it becomes the significant factor to boost the usage of saving account both males and females in rural area. Finally, many correlations are strongly positive in females while in males a few indicators have negative relationship in financial inclusion. Both male and female ownership insurance have the highest correlation with others of indicators in financial inclusion; on the other hand, saving at the bank has the lowest correlation.

The recommendation from this study includes: for policymakers review and explore ways to strengthen financial literacy programmes and developing programmes for differentiated target groups based on age, marital status, income and educational level. And for financial service providers, strengthen linkages with formal non-bank providers of credit, to capitalise on the specific strengths and advantages of both bank and non-bank institutions and to improve the provision of credit services without excessively increasing the transaction costs for the end-users.

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Assessing the Impact of Digital Opportunity on Financial Inclusion

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ABSTRACT

Indonesian government has targeted the financial inclusion index in 2019 reaches 75 percent. Meanwhile, in 2017, according to Indonesia Financial Services Authority (OJK), the index is at 69 percent. There is quite wide gap to fulfill 2019 target with only about 1 year left. On the other side, the adoption of technology in Indonesia is growing rapidly. Based on data released by Statistics Indonesia, the percentage of people having mobile phone is 58.3 percent. Therefore, this research aims to measure the effect of digital opportunity to financial inclusion. This research analyzes data from two different sources which are 2017 National Socio-Economic Survey (SUSENAS) and 2014 Twitter data. The main methodology used in the research is logistics regression. In addition, descriptive statistics with visualization is utilized to provide further analysis. This study found that digital opportunity has positive impact to financial inclusion. The ownership of computer and phone is expected to improve financial inclusion. Moreover, high intensity of social media activity correlates with financial inclusion.

KEYWORDS

Financial Inclusion, Digital Opportunity, Information Technology (IT) adoption, Twitter

1 INTRODUCTION

Financial inclusion has become a major policy concern after the 2008 financial crisis which mainly impacted the bottom of the pyramid (those with low and irregular income, living in remote areas, disabled people, those who do not have legal documents, and other marginalized groups) who are generally unbanked and majority of them are from developing countries. Since then, many international organizations have focused their activities on financial inclusion such as World Bank, Asian Development Bank, and others, including developing countries such as Indonesia [3].

According to the World Bank, the Indonesia Financial Inclusion Index in 2017 is 48.9 percent. This shows that the number of population aged more than 15 years old that have formal saving account is 48.9 percent of such population category. In addition, based on financial literacy and inclusion survey conducted by Financial Services Authority of Indonesia (OJK), the index in 2017 is recorded at 69 percent. Meanwhile, the government has targeted the financial inclusion index in 2019 is 75 percent [6]. There is quite wide gap to

fulfill 2019 target with only about 1 year left. Therefore, in order to achieve the target government should not take "business as usual" approach. One way to accelerate the financial inclusion index is by adopting the use of technology.

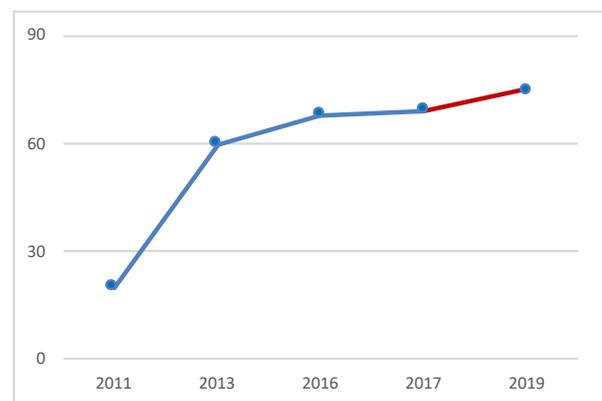


Figure 1: Indonesia Financial Inclusion Index 2011 - 2019 (Target)

The adoption of technology in Indonesia is growing rapidly. Based on the data released by Statistics Indonesia, the percentage of people having computers in 2016 reaches 19,14 percent, while the percentage of people having mobile phone is 58.3 percent. More than half of Indonesia population have mobile phones. This is a good achievement even though the ownership it is still dominated by resident in urban areas. Still, the figure shows Indonesian people are familiar with the use of technology [1]. Furthermore, this number shows vast potential of financial service delivery through the adoption of technology.

Moreover, financial inclusion means that individuals and businesses have access to useful and affordable financial products and services that meet their needs such as transactions, payments, saving, credit and insurance delivered in a responsible and sustainable way [2]. There are three dimensions of financial inclusion: access, availability, usage, and quality.

One of the financial dimensions to support spread of financial inclusion, access, has become important component. In this Industrial

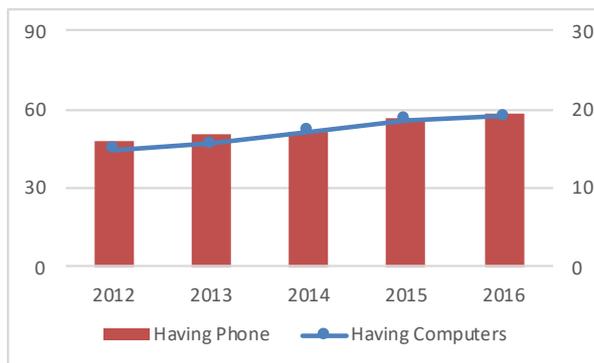


Figure 2: Percentage of Population having phone and computer

Revolution 4.0 era, the financial access delivery should be compatible with user behaviour. Several digital-based Financial Technology (fintech) have begun to be developed. Majority of their services is accessed through computer and mobile phone. Based on data released by OJK, there are 64 Financial Technology Companies licensed by OJK [5]. With such high target of financial inclusion level set by the government and the vast potential of Indonesian adoption of technology, therefore, this research aims to measure the effect of digital opportunity to financial inclusion.

2 METHODS

This research analyzes data from two different sources which are 2017 National Socio-Economic Survey (SUSENAS) and 2014 Twitter data. SUSENAS is a survey conducted by Statistics Indonesia having aims to describe social and economics conditions of Indonesia citizens whereas anonymized Twitter’s data consists of the tweet itself, location, and date.

2.1 Pre-Processing

SUSENAS data is obtained through survey of individual at household level. It is one of the largest survey in Indonesia and has a broad coverage representing almost all of cities in Indonesia. It covers 30 provinces, 465 cities, 297,276 households, and 1,132,749 individuals. SUSENAS data generally are can be analyzed as deep as individual level or at minimum at household level depends on the variable. Meanwhile, the tweeter’s data cannot be analyzed to household level, the feasible analysis can be done at city level. In addition, only covers 16 cities in Indonesia which are Medan, Kepulauan Seribu, South Jakarta, East Jakarta, Central Jakarta, West Jakarta, Bogor Regency, Bandung Regency, Bekasi City, Yogyakarta City, Surabaya, Tangerang City, Tangerang Regency, West Tangerang City, and Makasar City.

Because of the data level differencies, in the descriptive statistics analysis and visualization, we grouped by SUSENAS individual data into city level. In addition, we also make adjustment to the ratio of household saving account ownership considering that age group division in SUSENAS is available at number of household members aged more than 10 years old whereas both World Bank and OJK financial inclusion indexes measured people who are older than

15 years old. Therefore, for logistics regression analysis, we adjust saving account ownership ratio from age group of more than 10 years old to age group of more than 15 years old based on Indonesia Statistics population pyramid.

To measure the effect of digital opportunity to financial inclusion, the framework used in this research is shown on figure 3. There are 2 (two) methods implemented in this study. The first model utilizes only SUSENAS data by implementing logistics regression, whereas the second method utilizes both SUSENAS data and Twitter data by analyzing through descriptive statistics with visualization. The dependent variable (response variable), also as a proxy for financial inclusion measurement, of the first method is similar to measurement used by World Bank and OJK which is ratio of adult population having formal saving account, whereas the independent variables (predictor variables) are computer/laptop ownership, phone ownership, and city/rural classification.

Regarding the second method there are two independent variables at the city level i.e. ratio of adult population having formal saving account and ratio of adult population obtained loan within the last year from at least one of these formal institutions: people business credit program (Kredit Usaha Rakyat / KUR), banks other than KUR, rural banks (Bank Perkreditan Rakyat), cooperatives, pawn shops, leasing companies, joint business group (Kelompok Usaha Bersama), and village owned enterprise (BUMDes). In addition, the independent variables for the second method comprised from two data sources at city level which are mobile phone ownership and having access to internet from SUSENAS data and number of twitter accounts and number of tweets from Twitter data. Furthermore, all of the variables and the flow of analysis is displayed in Figure 3.

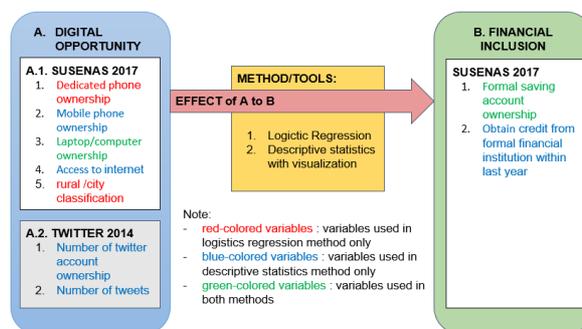


Figure 3: Research Framework

2.2 Methods of Analysis and Data Collection

This research utilizes two methods in order to measure effect which are logistics regression and descriptive statistics with visualization. Logistics regression is used to measure the impact of digital opportunity on probability of household to be financially included. A household is categorized as financially included household if its ratio of formal saving account ownership reaches the government financial inclusion index level, 75 %. Household with 75% level of financial inclusion index implies that 75% of household members aged more than 15 have formal saving account.

Furthermore, logistics regression is a statistical method for analyzing a dataset in which there are one or more independent variables that determine an outcome. The outcome is measured with a dichotomous variable (in which there are only two possible outcomes). Logistic regression generates the coefficients (and its standard errors and significance levels) of a formula to predict a logit transformation of the probability of presence of the characteristic of interest [4]. Moreover, the logistics regression equation in this research is as follow:

$$y_p = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (1)$$

Where:

Y_p : The Probability of Households to be Financially Included (1 = Saving Account Ratio >= 75%, otherwise = 0)

X_1 :1 = Household owns computer/laptop, otherwise = 0

X_2 :1 = Household owns dedicated phone, otherwise = 0

X_3 :1 = Household is located in rural area, otherwise = 0

The logit transformation is defined as the logged odds:

$$Odds = \frac{p}{1-p} \quad (2)$$

$$Odds = \frac{\text{probability of households in financially included}}{1 - \text{probability of households in financially included}} \quad (3)$$

and

$$\text{logit}_p = \ln\left(\frac{p}{1-p}\right) \quad (4)$$

Moreover, descriptive statistics analysis is used to generally describe the aggregation results of SUSENAS and tweeter data at city level regarding depth of digital opportunity and level of financial inclusion as well as finding relationship between them. In addition, the analysis is equipped with visualization through maps and charts for better understanding and interpretation.

3 RESULTS

3.1 Logistics Regression at Household

There are 297,276 households that is analyzed using logistics regression with minimum value of saving account ratio for family members aged more than 15 years old is 0% and the maximum value is at 100%. Interestingly, the mean of the ratio is at 35.2%. By applying definition of World Bank and OJK financial inclusion index, that mean can be classified as financial inclusion index implying that the index at household level is at 35.2%. This figure is far below OJK 2017 financial inclusion index which is at 69%. Although it is still lower, it is closer to World Bank estimation which recorded financial inclusion index at 48.9%.

Table 1. Summary of Financial Inclusion at Household Level

Number of Observation	297,276
Min. Value of Saving Account Ratio for family member aged > 15 years old	0 %
Max value saving account ratio for family member aged > 15 years old	100 %
Mean of saving account ratio for family member aged > 15 years old	35.2%

Furthermore, the logistics regression result and its odds ratio is presented in Table 4 as follow:

Table 2. Summary of Financial Inclusion at Household Level

Independent Variable	Logit Coefficient	Odds Ratio	P-Value
Own computer/laptop	1.37	3.93	0.000
Own dedicated phone	0.66	1.94	0.000
Located in rural area	-0.84	0.43	0.000
Prob > chi2	0.000		
LB chi2 (3)	21769.87		

As we can see from Table 4, all of the coefficient p-value are less than 0.01 meaning that all of independent variables have significant impact to 99% confidence level. Furthermore, in order to provide better understanding we can look at logit coefficients and odds ratio values which their interpretation is as follow:

Example of logit coefficient interpretation:

If the status of a family change from do not have phone to have a phone than the probability to be financially inclusive is increased by 66%.

Interpretation of odds ratio:

- (1) The probability of a family that has at least a computer/laptop to be financially inclusive is 3.93 times higher than a family that does not own it
- (2) The probability of a family that has a dedicated phone to be financially inclusive is 1.94 times higher than a family that does not own it
- (3) The probability of a family in urban area to be financially inclusive is 2.32 (1/0.43) times higher than a family in rural area

3.2 Descriptive Statistics at City Level

Based on the results of data processing, the results show that ratio of people having mobile phone at city level in 2017 is 69.76 percent. In addition, the ratio of people connected to internet in 2017 is 26.82%. This ratio is quite far below the results of survey conducted by Association Indonesia Internet Service Provider (APJII). APJII released ratio of internet users in Indonesia is 54.68% [1].

Two characteristics of data that describe financial inclusion in this study are the ratio of adult population having formal saving account and ratio of population received credit from formal financial services. Based on the result of data processing, ratio of population that received credit is 22.7% whereas the ratio of saving account ownership is 22.10% (Table 5).

Table 3. Descriptive Statistic

Variables	Mean
Mobile phone ownership ratio	0.697657
Internet access ratio	0.268283
Loan ratio	0.227628
Saving account ratio	0.220694

Furthermore, for better understanding, the result of each city in Indonesia is visualized in form of Indonesian map in Figure 4 and 5. From those figure, we can see that cities with high digital opportunity measurement (high mobile phone ownership ratio and internet access ratio) tend to have high financial inclusion level (loan ratio and saving account ratio). In addition, another finding

to note is we can see that there is distinct differences between western part and eastern part of Indonesia both in terms of digital opportunity and financial inclusion level. It means that, digital divide, the gap between demographics and regions that have access to ICT and those that do not or have restricted access, happens in different parts of Indonesia. Similar gap also applies in terms of access to financial services.

In detail, based on those figures, high level of mobile phone ownership and access to internet ratio are dominated by cities in Java, Bali, North Sumatra, West Kalimantan and South Sulawesi. In contrast, cities in eastern Indonesia such as Papua, NTT, Maluku the ratio of them are generally low. Similar to the digital opportunity measurement, the distribution of high level of financial inclusion ratio is dominated by cities in Java, Bali, South Kalimantan and South Sulawesi. This shows that there is a positive correlation between the ratio of internet users and phone users (digital services/opportunity) to the ratio of formal saving accounts and loan ratio of access to loan (financial inclusion).

All of methods implemented by using SUSENAS data shows that digital opportunity have significant and positive impact to financial inclusion. However, regarding the use of twitter data as digital opportunity does not imply the same relationship. Based on twitter data of 16 cities, from Figure 7, we can see that the financial inclusion level does not move in the same direction with number of tweets. This is likely because SUSENAS data consist of far more comprehensive data representing almost all provinces and cities in Indonesia, whereas Twitter data only originated from 16 cities.

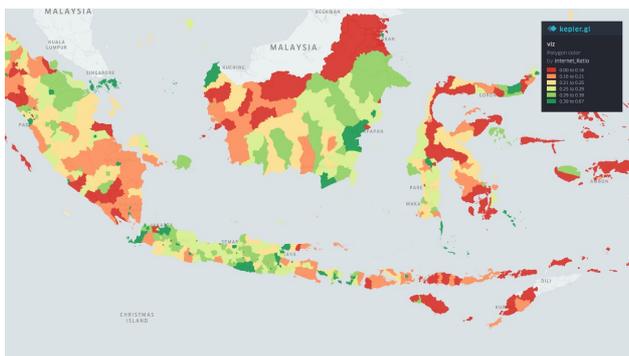


Figure 4: Internet Usage Ratio by Cities

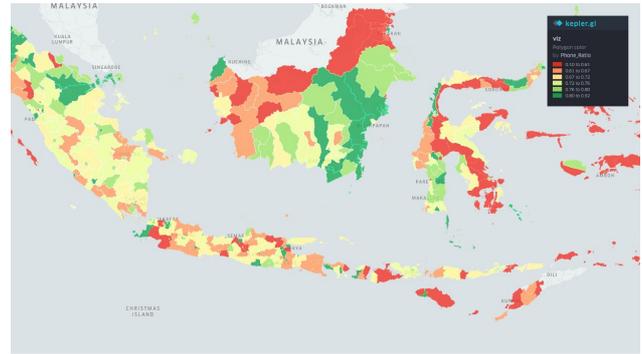


Figure 5: Phone Uses Ratio by Cities

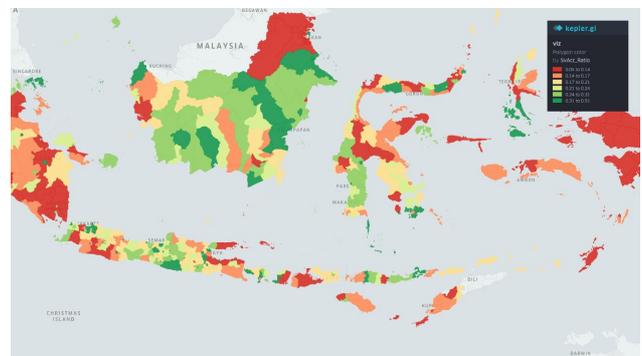


Figure 6: Formal Saving Account Ratio by Cities

Table 4. Identity and Name of Cities

City ID	City Name
1275	Medan
3101	Kepulauan Seribu
3171	South Jakarta
3172	East Jakarta
3173	Center Jakarta
3174	West Jakarta
3201	Bogor Regency
3204	Bandung Regency
3275	Bekasi
3276	Depok
3471	Yogyakarta
3578	Surabaya
3603	Tangerang Regency
3671	Tangerang City
3674	South Tangerang
7371	Makassar

4 CONCLUSION AND POLICY RECOMMENDATION

In general, digital opportunity has a significant and positive impact to financial inclusion. The use of computer, phone, and access to internet is expected to improve financial inclusion. However, in

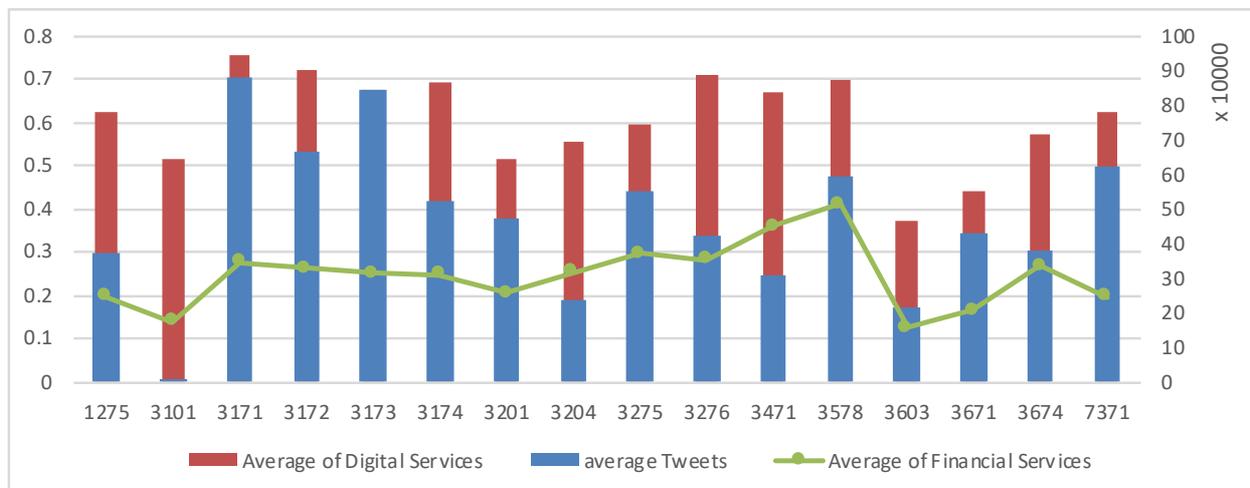


Figure 7: Graph of average Digital services, financial inclusion and tweets in 16 cities

terms of Twitter data high intensity of social media activity (tweet) does not correlate directly with financial inclusion that is likely because Twitter data is not as comprehensive as SUSENAS data which covers almost all of cities and provinces in Indonesia. Based on the result, in order to accelerate financial inclusion in Indonesia we propose two recommendations which are:

- Reduce digital divide between eastern and western part of Indonesia as well as urban and rural area by improving internet and telecommunication infrastructure and access in those disadvantaged area as well as introducing the adoption of technology for those who are technology-illiterate
- It is better for the government to distribute social fund like Program Keluarga Harapan through payment system fintech that provide e-wallet using cellphone particularly to the largest cellular provider in Indonesia, Telkomsel, by using their digital wallet which is T-Cash. By using their services, the use of financial services can be accelerated considering that they have the largest subscribers and cellular coverages in almost all of Indonesia geographic location.

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