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PRE

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Nowcasting domestic liquidity in the Philippines using machine learning algorithms

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This study utilizes a number of algorithms used in machine learning to nowcast domestic liquidity growth in the Philippines. It employs regularization (i.e., Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net (ENET)) and tree-based (i.e., Random Forest, Gradient Boosted Trees) methods in order to support the BSP's current suite of macroeconomic models used to forecast and analyze liquidity. Hence, this study evaluates the accuracy of time series models (e.g., Autoregressive, Dynamic Factor), regularization, and tree-based methods through an expanding window. The results indicate that Ridge Regression, LASSO, ENET, Random Forest, and Gradient Boosted Trees provide better estimates than the traditional time series models, with month-ahead nowcasts yielding lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Furthermore, regularization and tree-based methods facilitate the identification of macroeconomic indicators that are significant to specify parsimonious nowcasting models.

JEL classification: E40, E47, E50
Keywords: nowcasting, domestic liquidity, machine learning, ridge regression, LASSO, elastic net, random forest, gradient boosted trees

1. Introduction

1.1. Background of the study

Timely estimates or forecasts of different macro and socioeconomic indicators are needed to monitor developments in numerous sectors of the economy (e.g., households, depository corporations) and formulate appropriate policy (e.g., fiscal, monetary) responses. A reliable dataset allows assessment of an economy's overall condition and monitoring of situations that suggest imbalances or potential vulnerabilities. Some recent developments can allow policymakers to improve their ability to implement these forecasts and assessments.

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One is the increased access to larger and more granular datasets that can potentially offer new insights (e.g., transactions level data in finance), and two is the use of modern data analysis techniques, including machine learning techniques, that are particularly suited for analyzing large and complex datasets [e.g., Carriere-Swallow and Haksar 2019].

However, management and analysis of economic data pose challenges. For example, certain types of official statistics, such as the Gross Domestic Product (GDP), may be hard to produce promptly and accurately (Dafnai and Sidi [2010]; Bragoli and Modugno [2016]; Chikamatsu et al. [2018]; Richardson et al. [2018]). The reasons may include the complex process of adequately classifying accounts, changes in the overall compilation framework, and inevitable delays in receiving source documents (Dafnai and Sidi [2010]; Chikamatsu et al. [2018]). As a result, policymakers from some countries are forced to formulate policies and address economic phenomena (e.g., inflation, business cycle) using outdated or lagged datasets [Richardson et al. 2018].

Nowcasting has been proposed as a tool to address some of these data challenges by International Financial Institutions (IFIs) (e.g., International Monetary Fund, World Bank), National Government Agencies (NGAs), and central banks from various countries. The objective of nowcasting is to provide estimates that could serve as early warning signals (EWS) to monitor the growth or development of certain indicators. Nowcasting, however, mainly aims to predict specific information or scenarios in the short run or in real-time (Bańbura et al. [2013]; Tiffin [2016]).

The International Monetary Fund (IMF), World Bank (WB), and Asian Development Bank (ADB) are among the IFIs that conduct comprehensive studies regarding the use of nowcasting in different fields of study (e.g., economics, finance). Meanwhile, the central banks of Indonesia, Japan, and New Zealand have implemented research that attempted to use nowcasting to estimate their respective GDP growth in the short run.[1]

1.2. Economic nowcasting, big data, and machine learning

Forecasts of the overall growth of an economy, quantitative analyses of the progress of a particular economic sector, or the transmission mechanism of policies have been commonly performed by using time series analysis, particularly univariate (e.g., Autoregressive Integrated Moving Average or ARIMA) and multivariate (e.g., Vector Autoregression (VAR), Dynamic Factor) models. These traditional methods are widely used due to their straightforward approach and ability to decompose the factors that mainly contribute to the movement of a particular target variable of interest.[2]

[1] See Dafnai and Sidi [2010], Chikamatsu et al. [2018], Richardson et al. [2018], and Tamara et al. [2020].

[2] Impulse Response Functions (IRFs) and Variance Decomposition are among the main characteristics of VAR.

However, in most cases, time series models depend on the timeliness of data or information. The publication delay of variables included in a particular model could hamper the attempt to estimate the future condition of the target output. For instance, to estimate the GDP for Q2:2020 using a simple AR(1) model, GDP as of end-Q1:2020 is needed.[3] In a typical situation, the publication of GDP for Q1:2020 is not released exactly at the end of said period. The latest figure is usually posted within one or three months after the reference date (e.g., GDP for Q2:2020 is published in August 2020, rather than end-June 2020).[4] Therefore, an individual or institution that aims to forecast the economic growth for Q2:2020 using an AR(1) model should wait until the data for GDP at the end-Q1:2020 is published.

The presence of lags in data availability is one of the main reasons for the adoption of nowcasting in economics. The advantage of nowcasting models (e.g., Mixed Data Sampling, Ridge Regression) is that they can use real-time information or higher-frequency data (e.g., daily financial data, survey results) in order to estimate a particular macro or socioeconomic variable (Bańbura et al. [2013]; Chikamatsu et al. [2018]; Richardson et al. [2018]). Hence, in contrast to a typical time series model used in economic forecasting, nowcasting models can also estimate the current state of a target variable of interest using data or information with different granularity levels [Tiffin 2016]. Moreover, since most conventional macroeconomic indicators are published with lags and frequent revisions, nowcasting has become an essential tool for policymakers to minimize the usual approach of attempting to estimate an economic variable using outdated or lagged data [Richardson et al. 2018].

Lastly, the emergence of nowcasting has been supported by recent trends favoring the use of big data and machine learning. This is mainly due to the potential of big data to provide supplementary information regarding current macro and socioeconomic data that may not be available yet. At the same time, machine learning can process the immense and sometimes difficult to manage information provided by big data (Hassani and Silva [2015]; Baldacci et al. [2016]; Richardson et al. [2018]).

1.3. The Philippines and domestic liquidity

Domestic liquidity (M3) is the total amount of broad money available in an economy, usually determined by a central bank and banking system. In the IMF's Monetary and Financial Statistics Manual (MSFM), this monetary indicator is similarly defined as the sum of all liquid financial instruments held by money-holding sectors, such as Other Depository Corporations (ODCs).

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[3] Autoregressive Model of Order 1 or AR(1) model is defined as $y_t = \alpha_0 + \alpha_1 y_{t-1} + \epsilon_t$.

[4] Depending on the statistical calendar (or advance release calendar) of a specific country.

It can be categorized as an instrument widely accepted as (1) a medium of exchange or (2) a close substitute for the medium of exchange with a reliable store value [IMF 2016: 180].[5,6]

The change in its overall growth is considered an essential dynamic that most central banks closely monitor mainly because it is an essential element to the transmission mechanism of monetary policy, particularly its influence on aggregate demand, interest rates, inflation, and overall economic growth. For this reason, policymakers from different central banks diligently observe its expansion or contraction to formulate an effective and timely monetary policy response, especially when there are predicaments that require them to adjust policy rates to impede the negative implication of increasing inflation rates.

In the Philippines, domestic liquidity likewise plays an important role in an economy with a fractional-reserve banking system (e.g., US, Japan).[7] The Bangko Sentral ng Pilipinas (BSP) monitors its level and growth because the main components of this monetary aggregate are primarily used to measure liquidity in the country, input for early warning systems (EWS) models on the macroeconomy, and indicators to formulate and implement timely monetary policy, among others.[8,9]

The BSP announces domestic liquidity statistics in the Philippines on a monthly basis. Its Department of Economic Statistics (DES) consolidates the balance sheet of the BSP and ODCs to calculate this monetary indicator in a given period. However, for the domestic liquidity to be released promptly, the DES and Department of Supervisory Analytics (DSA) of the BSP need to ensure that punctual submission of bank reports (e.g., Financial Reporting Package for Banks) is observed.

1.4. Statement of the problem

Delay in data publication is one of the most common difficulties government institutions encounter. This scenario, unfortunately, is also observed in producing domestic liquidity statistics in the Philippines. Even though the BSP may meet the deadline to announce its latest available figure based on their advance release calendar (ARC), the publicly shared data on domestic liquidity are not based on real-time position. As seen in Table 1, data from the Depository Corporations Survey (DCS) dated November 15, 2021 actually refers to domestic liquidity statistics at end-September 2021 (e.g., the current release has lags of four to six weeks).

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[5] The MFSM is the official guideline of IMF member countries in the compilation of monetary statistics.

[6] ODCs refer to financial corporations (other than the central bank) that incur liabilities included in domestic liquidity [IMF 2016: 405].

[7] Fractional-reserve banking system refers to a system in which banks retain a portion of their overall deposits on reserves [Mankiw 2016: 620].

[8] Based on the DCS conducted by the BSP, domestic liquidity in the Philippines is mainly composed of currency in circulation and transferable deposits (M1), other deposits such as savings and time deposits (M2), and deposit substitutes such as debt instruments. The DCS is a consolidated report based on the balance sheets of BSP and ODCs, such as universal and commercial banks, thrift banks, rural banks, non-stock savings and loan associations, non-banks with quasi-banking functions [BSP, 2018].

[9] See BSP [2018].

Aside from this concern, the official data on domestic liquidity is also subject to revisions. Based on the publication policy of the BSP, the latest statistical reports (which include the DCS) are treated as preliminary information (Table 1).

The initial publication is revised within two months to reflect any changes in the reports submitted by the banks under its jurisdiction.[10] This procedure also applies to the other key statistical indicators produced by the said institution, such as the balance of payments (BOP) and flow of funds (FOF), to name a few. However, the preliminary and revised data have significant numerical discrepancies in some cases.

This study aims to mitigate these issues and concerns by investigating the use of different machine learning algorithms to estimate domestic liquidity growth in the Philippines. This research primarily intends to formulate a quantitative model that could support the BSP's suite of macroeconomic models used in forecasting (e.g., GDP, inflation, domestic liquidity) and policy analysis.

1.5. Significance of the study

For the past years, an increasing number of studies have focused on utilizing time series models and machine learning techniques to estimate different macro and socioeconomic indicators. The studies of Rufino [2017], Mapa [2018], and Mariano and Ozmucur [2015; 2020] are among the recent ones that have established the use of these methods to nowcast GDP and inflation in the Philippines. However, none of these published studies has explored the usefulness of nowcasting in monetary policy, particularly in using machine learning algorithms to estimate domestic liquidity growth in the country. This study contributes to the growing body of literature regarding the application of time series and machine learning models in economic forecasting or nowcasting.

In addition, although the BSP shifted to inflation targeting, domestic liquidity remains a critical indicator in monetary policy formulation. Liquidity forecasting is currently part of the institution's Multi-Equation Model (MEM) [Abenoja et al. 2022].[11] Therefore, the output of this study could serve as a supplementary tool to estimate domestic liquidity growth and input for MEM. The BSP is conducting MEM as part of its scenario-building and policy simulations.

Further, during a period of unstable inflation and significant change in the monetary policy transmission mechanism, a better understanding of how certain monetary variables, such as the behavior of domestic liquidity, could help formulate timely monetary policy.

[10] See https://www.bsp.gov.ph/SitePages/Statistics/Financial%20System%20Accounts.aspx?TabId=2.
[11] Multi-equation Model (MEM) is part of the suite models of the BSP to capture the impact of main monetary policy transmission channels on inflation.

TABLE 1. Depository corporations survey SRF-based* (in million pesos)

	Levels (as of end period)				Changes in levels			Percent change		
					m-o-m	y-o-y		m-o-m	y-o-y	
	Aug-20	Sep-20	Aug-21[r,p]	Sep-21[p]	Sep 21-Aug21	Aug 21-Aug 20	Sep 21-Sep20	Sep 21[p]	Aug 21[r,p]	Sep 21[p]
1. Net foreign assets	**5,824,130**	**5,820,825**	**6,389,895**	**6,478,202**	**88,306**	**565,765**	**657,377**	**1.4**	**9.7**	**11.3**
A. Central bank	4,810,018	4,876,070	5,403,016	5,449,416 a	46,400	592,998	573,346	0.9	12.3	11.8
Claims on non-residents	4,886,081	4,952,171	5,620,943	5,670,102	49,159	734,862	717,931	0.9	15.0	14.5
Less: Liabilities to non-residents	76,063	76,101	217,927	220,686	2,759	141,864	144,585	1.3	186.5	190.0
B. Other depository corporation	1,014,112	944,755	986,880	1,028,786	41,906	-27,233	84,031	4.2	-2.7	8.9
Claims on non-residents	1,824,329	1,780,523	1,832,284	1,869,384	37,099	7,955	88,860	2.0	0.4	5.0
Less: Liabilities to non-residents	810,217	835,769	845,404	840,598	-4,806	35,187	4,829	-0.6	4.3	0.6
2. Domestic claims	**13,395,104**	**13,419,434**	**14,298,755**	**14,453,939**	**144,777**	**903,652**	**1,024,098**	**1.0**	**6.7**	**7.6**
A. Net claims on central government	2,734,907	2,795,251	3,374,427	3,475,636	101,209	639,520	680,385	3.0	23.4	24.3
Claims on central government	4,492,141	4,212,202	5,545,403	5,704,164	158,761	1,053,262	1,491,962	2.9	23.4	35.4
less: Labilities to central government	1,757,234	1,416,951	2,170,977	2,228,528	57,552	413,743	811,577	2.7	23.5	57.3
B. Claims on other sectors	10,660,197	10,624,183	10,924,329	10,967,896	43,567	264,132	343,713	0.4	2.5	3.2
Claims on other fnancial corporations	1,170,415	1,177,373	1,163,359	1,184,593	21,234	-7,056	7,220	1.8	-0.6	0.6
Claims on state andlocal government	98,124	98,663	114,742	116,642	1,901	16,618	17,979	1.7	16.9	18.2
Claims on public nonfinancial corporations	231,711	231,854	265,915	268,356	2,441	34,205	36,502	0.9	14.8	15.7
Claims on private sector	9,159,948	9,116,293	9,380,313	9,398,304	17,992	220,365	282,011	0.2	2.4	3.1

TABLE 1. Depository corporations survey SRF-based* (in million pesos) (continued)

	Levels (as of end period)				Changes in levels			Percent change		
					m-o-m	y-o-y		m-o-m	y-o-y	
	Aug-20	Sep-20	Aug-21 r,p	Sep-21 p	Sep 21-Aug21	Aug 21-Aug 20	Sep 21-Sep20	Sep 21 p	Aug 21 r,p	Sep 21 p
3. Liquidity aggregates										
M4 (M3 + 3.e)	15,603,502	15,583,711	16,591,084	16,785,106	194,022	987,382	1,201,395	1.2	6.3	7.7
M3 (M2 + 3.d)3	13,510,788	13,498,470	14,446,660	14,610,565	163,905	935,871	1,112,094	1.1	6.9	8.2
M2 (M1 + 3.c)	12,773,018	12,832,393	13,802,137	14,003,725	201,587	1,029,120	1,171,332	1.5	8.1	9.1
M1 (3.a + 3.b)	5,004,217	5,028,958	5,682,135	5,758,369	76,233	677,918	729,411	1.3	13.5	14.5
3.a Currency outside depository corporations	1,540,227	1,533,370	1,657,808	1,680,864	23,056	117,581	147,494	1.4	7.6	9.6
3.b Transferable deposits included in broad money	3,463,991	3,495,587	4,024,327	4,077,504	53,177	560,337	581,917	1.3	16.2	16.6
3.c Other deposits included in broad money	7,768,800	7,803,435	8,120,002	8,245,356	125,354	351,202	441,921	1.5	4.5	5.7
Savings deposits	5,340,769	5,396,116	5,983,301	6,075,436	92,135	642,532	679,320	1.5	12.0	12.6
Time deposits	2,428,032	2,407,319	2,136,701	2,169,921	33,219	-291,330	-237,398	1.6	-12.0	-9.9
3.d Securities other than shares included in broad money	737,771	666,078	644,522	606,840	-37,682	-93,249	-59,238	-5.8	-12.6	-8.9
3.e Transferable and other deposits in foreign currency (FCDs-residents)	2,092,714	2,085,240	2,144,425	2,174,541	30,116	51,711	89,301	1.4	2.5	4.3
4. Liabilities excluded from broad money	**3,615,732**	**3,656,548**	**4,097,567**	**4,136,628**	**39,061**	**481,834**	**480,080**	**1.0**	**13.3**	**13.1**

Source: BSP (accessed on November 15, 2021)

2. Review of related literature

2.1. Regularization methods[12,13]

Tiffin [2016] and Dafnai and Sidi [2010] used regularization methods to formulate nowcasting models that could accurately estimate GDP growth in Lebanon and Israel, respectively. To address data publication lags, the studies by these authors show how current economic growth can be estimated, despite data lags, to improve policy decisions. Their attempt to formulate nowcasting models also aimed to address the difficulty of their stakeholders from the domestic (e.g., NGAs, central banks) and international (e.g., IFIs, bilateral partners) landscape in assessing the overall economic health of their respective countries (Tiffin [2016]; Dafnai and Sidi [2010]).

The authors used higher-frequency data as explanatory variables to their corresponding GDP nowcasting models. Tiffin [2016] used 19 monthly macroeconomic variables (e.g., customs revenue, tourist arrivals) to observe economic growth in Lebanon.[14] Through regularization methods, the author found that the Elastic Net (ENET) is the most suitable machine learning algorithm to estimate the short-run economic development of Lebanon. Mainly because the result (i.e., in-sample, out-of-sample) systematically traces the cyclical movement of Lebanon's GDP with a small Root Mean Square Error (RMSE).

Dafnai and Sidi [2010], on the other hand, used 140 domestic indicators and 15 global indicators as input variables to nowcast the GDP in Israel.[15] The authors found that ENET is the most comprehensive method to forecast the country's economic growth. Furthermore, compared to other regularization models used in their study, Dafnai and Sidi [2010] argued that ENET is the only model that successfully captured the timing and magnitude of Israel's economic cycle while generating a low Mean Absolute Forecast Error (MAFE).

Hussain et al. [2018] used similar machine learning algorithms to nowcast the short-run growth of Large-Scale Manufacturing (LSM) in Pakistan to compensate for lags in the publication of official GDP data. The authors also used high-frequency data or information as explanatory variables to nowcast LSM, including monthly data regarding financial markets, confidence surveys,

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[12] Regularization methods constrain coefficient estimates to reduce their variance with the intention to improve the overall model fit. Moreover, these approaches incorporate penalties to their regression coefficient(s) to address the issue of bias-variance tradeoff [James et al. 2013].

[13] Among the regularization methods used in this study are (1) Ridge Regression, (2) LASSO, and (3) ENET. Ridge Regression imposes a penalty to their regression coefficient(s) which shrink all of them towards zero. This is also the case for LASSO. However, it forces some of its coefficient estimates to be exactly equal to zero when parameter is large. ENET contains both properties of Ridge Regression and LASSO [James et al. 2013]. Equations of these methods are presented in Section 4 of this paper.

[14] See page 10 of Tiffin [2016].

[15] See Annex of Dafnai and Sidi [2010].

interest rate spreads, credit, and the external sector in Pakistan.[16] Hussain et al. [2018] concluded that regularization methods such as Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), and ENET are useful quantitative tools for estimating the overall growth of LSM. These models are able to observe trends and cyclical movement of LSM with minor forecast errors. However, LASSO had the lowest RMSE [Hussain et al. 2018].

Regularization methods were likewise used by Cepni et al. [2018] as well as Ferrara and Simoni [2019]. These authors utilized the said concepts to formulate models that could accurately nowcast the GDP of emerging economies (i.e., Brazil, Indonesia, Mexico, South Africa, Turkey) and the US, respectively. Again, similar to the previous studies discussed, numerous high-frequency data or information were used as explanatory variables to estimate the economic growth of said countries.

Cepni et al. [2018], in particular, utilized country-specific macroeconomic indicators such as industrial production, demand, and consumption indices and survey data from Market Purchasing Managers' Index (PMI).[17] On the other hand, Ferrara and Simoni [2019] used a large set of data from Google (e.g., Google Trends) to nowcast GDP in the US.[18] The former authors notably used LASSO to augment the nowcasting activity through DFM. Meanwhile, the latter authors utilized Ridge Regression and compared it with their bridge equation benchmark model since numerous variables were included in their model.

Both studies have concluded that these machine learning models give an empirically accurate estimate of the short-run growth of GDP. This is because Ridge Regression and LASSO provide a parsimonious set of nowcasting models with accurate results (Cepni et al. [2018]; Ferrara and Simoni [2019]).

2.2. Tree-based methods[19]

Biau and D'Elia [2010] used the Random Forest (RF) algorithm to forecast short-term GDP growth in Europe. The authors used numerous datasets—under the European Union Business and Consumer Survey—to improve prediction accuracy.[20] Based on this approach, the authors concluded that the particular tree-based machine learning algorithm estimates the short-term growth of GDP in Europe more accurately than the univariate autoregressive (AR) model and is somehow tantamount to the quarterly projections of the *eurozone economic outlook*.[21] This is mainly due to the RF's low forecast error,

[16] See page 13 of Hussain et al. [2018].
[17] See page 2 of Cepni et al. [2018].
[18] See page 7 of Ferrera and Simoni [2019].
[19] Tree-based methods are non-parametric techniques that do not require underlying relationship between dependent and independent variables. It involves stratifying or segmenting the predictor space into a number of simple regions. Hence, the mean or mode of the (training) dataset is used in the region to which it belongs to estimate a given observation [James et al. 2013: 303].
[20] See page 6 of Biau and D'Elia [2010].
[21] Official economic expectation/forecast of Eurosystem.

which only generated an MSE of 0.43. Meanwhile, the univariate and official economic outlook produced 0.64 and 0.15 MSE, respectively. Supplemental to this result, the machine learning-based GDP forecast for Europe specified a parsimonious model by identifying which predictive variables included in their model are useful [Biau and D'Elia, 2010].

Drawing on the methodology of Biau and D'Elia [2010], Adriansson and Mattsson [2015] also used RF to estimate Sweden's quarterly economic growth. The authors support this objective by using the data from the Economic Tendency Survey—conducted by the National Institute of Economic Research (NIER)—as inputs for their tree-based nowcasting. Based on this research framework, Adriansson and Mattsson [2015] found that RF provides a better prediction performance (RMSE 0.75) against the ad hoc linear model and ARIMA (RMSE 0.79 and 0.95, respectively) in forecasting the GDP growth of Sweden [Adriansson and Mattsson 2015].

Aside from RF, Adaptive Trees (AT)—based on Gradient Boosted Trees (GBT)—was also used as a primary machine learning technique in forecasting. This is because of its ability to deal with nonlinearities and structural changes, among others (James et al. [2013]; Woloszko [2020]). The paper of Woloszko [2020] was one of the recent studies that specifically used AT to provide a 3- to 12-months ahead GDP growth forecast for the Group of Seven (G7) countries.[22] In this study, the author employed country-specific information (e.g., expectation surveys, consumer confidence) and macroeconomic data (e.g., housing prices, employment rate) as explanatory variables to the tree-based forecasting model.[23]

Based on the forecast simulations, Woloszko [2020] concluded that the RF algorithm is a valuable tool in economic forecasting, yielding more accurate prediction results than the traditional time series models. In contrast to univariate models, the 3- and 6-months ahead GDP growth forecast for the US, UK, France, and Japan using AT displayed lower RMSEs. However, the forecasting performance of AT worsened for the 1-year-ahead forecast. Woloszko [2020] therefore argued that despite having the advantage of handling a large number of variables in economic forecasting, AT might not be a suitable model to predict long-run effects.

Other empirical studies utilized both RF and GBT as models to forecast economic growth. Among these were the papers of Boluis and Rayner [2020] as well as Soybilgen and Yazgan [2021]. In particular, these authors used the said methods to forecast the GDP growth in Turkey and the US, respectively.

Similar to the previous studies discussed in this section, these authors aimed to determine the best-performing tree-based method to estimate economic growth using higher-frequency data or information, similar to the previous studies discussed in this section. In particular, the study of Boluis and Rayner [2020] used 234 country-specific and global indicators from Haver Analytics. This includes

[22] Canada, however, was not included in the analysis of Woloszko [2020].
[23] See page 11 of Woloszko [2020].

macroeconomic indicators regarding the financial, labor, and external sectors.[24] Meanwhile, Soybilgen and Yazgan [2021] utilized more than 100 financial and macroeconomic variables, including the labor market, money and credit, and stock market data.[25]

Using these input variables, Boluis and Rayner [2020] as well as Soybilgen and Yazgan [2021] concluded that the tree-based methods provide superior forecasts than the benchmark models. This is due mainly to low forecast errors of tree-based methods against DFM. Specifically, Boluis and Rayner [2020] mentioned that RF and GBT respectively registered RMSE of 1.26 and 1.29 compared to the benchmark models, which displayed an RMSE of 1.66.[26] Aside from their outstanding individual accuracy, these authors also cited that the tree-based methods can estimate economic volatility and determine which variables included in the forecasting model are better predictors.

2.3. The utilization of two approaches

Several studies also utilize the strengths of both regularization and tree-based methods to perform forecasting or nowcasting. Authors of these studies have considered this approach in order to distinguish the accuracy of each machine learning algorithm in estimating the growth of a particular macroeconomic indicator or phenomenon and assess the overall fit (e.g., linear, nonlinear) of the variables in a particular model (Richardson et al. [2018]; Aguilar et al. [2019]; Tamara et al. [2020]).

Richardson et al. [2018] used regularization and tree-based methods to formulate a model that could accurately predict the movement of GDP growth in New Zealand. The goal was to reduce the reliance on non-related, outdated, or lagged data in policymaking. To attain this objective, the authors used several higher frequency macroeconomic and financial market statistics as explanatory variables to their simulated nowcasting models. These include data from business surveys, consumer and producer prices, and general domestic activity production, among others.[27]

By using these as regressors for the different models, Richardson et al. [2018] concluded that regularization and tree-based methods could both be used as the primary methods to nowcast the economic growth in New Zealand because of lower forecast errors than traditional time series models. In particular, the authors found that LASSO, GBT, and Ridge Regression had RMSE of 0.45, 0.47, and 0.57, respectively, lower than time series models, such as ARIMA, DFM, and Bayesian VAR.

Tamara et al. [2020] also used regularization and tree-based methods to forecast Indonesia's GDP growth. The authors correspondingly used 18 predictor variables, including quarterly macroeconomic (e.g., consumption expenditure,

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[24] See Tables A5.1 and A5.2, pages 24-25 of Boluis and Rayner [2020].
[25] See Appendix 1, page 23 of Soybilgen and Yazgan [2021].
[26] See Table 1 and 2, page 13 of Soybilgen and Yazgan [2021].
[27] See page 8 of Richardson et al. [2018].

current account) and financial market statistics (e.g., change in stock price) data.[28] Using these indicators as explanatory variables, the authors concluded that regularization and tree-based methods provide better results in estimating the short-run GDP growth of Indonesia, as shown by low RMSE and Mean Average Deviation (MAD). The authors also found that regularization and tree-based methods reduced the average forecast errors from 38 to 63 percent relative to ARIMA. Furthermore, Tamara et al. [2020] find that RF and ENET have the lowest average forecast errors, at 1.27 and 1.31, respectively.

3. Data

3.1. Target variable

The target variable in this study is the monthly data on domestic liquidity growth in the Philippines. This monetary indicator represents the total amount of money available in the economy. The numerical figures (i.e., level, growth rate) of domestic liquidity are acquired from the monthly DCS that the BSP published on its website from January 2008 to December 2020.[29]

3.2. Input variables

Like previous nowcasting studies that use machine learning algorithms, higher-frequency data are used as explanatory variables in this research. These comprise daily or weekly (1) monetary, (2) financial, and (3) external sector indicators.[30] In addition, to capture other determinants that could also influence domestic liquidity growth (i.e., heterogeneity), lagged value of the domestic liquidity is considered an input variable in this study. Data for input variables also cover January 2008 to December 2020 (Table 2).

3.3. Averaging and interpolation[31]

Averaging and interpolating are conducted to correctly align the frequency of all the data used in this study. The former was performed on variables with a daily and weekly frequency. In particular, these data were aggregated and

[28] See Appendix of Tamara et al. [2020].
[29] To ensure that the data on domestic liquidity are not subject to any revisions, the last figure used in this study was as of end-December 2020.
[30] Monetary indicators are composed of available reserves, reserve money, central bank claims on national government, and central bank claims on other sectors of the economy. Financial indicators comprise Weighted Money Operations Rate (WMOR), BSP discount rate, CBOE volatility index, CDS spread, LIBOR, SIBOR, PHIREF, Government Bond Rate, Interbank Call Loan Rate, bank prime rate, treasury bill rate, promissory note rate. External indicators are consisted of foreign portfolio investment and foreign exchange rate.
[31] Averaging and interpolation were conducted to maximize each input variable with a higher frequency (i.e., daily data) to solve the problem caused by the "curse of dimensionality" or fat regression (i.e., various input variables with limited observations).

averaged into two numerical values in a month. The first value is the average from the first until the 15th day of the month, while the other half is the mean from the 16th until the last day of the month (e.g., available reserves data from January 1 to 15 and January 16 to 31 are averaged, respectively). On the other hand, explanatory variables with weekly frequency are averaged. Meanwhile, the latter was implemented on the variables with low frequency (i.e., monthly), such as domestic liquidity, BSP liabilities on NG, and BSP claims on other sectors. The data points between each period of averaged input variable data (e.g., mid-month data) are considered missing values and interpolated using a spline interpolation method commonly used for nonlinear data estimation.

TABLE 2. List of data

No.	Variable	Type	Frequency	Publication delay (days after ref. date)
1	Domestic Liquidity (M3) Growth	Target Variable	Monthly	30
2	M3 Growth (T-1)	Input Variable	Monthly	-
3	BSP Liabilities on National Government	Input Variable	Monthly	15
4	BSP Claims on Other Sectors	Input Variable	Monthly	15
5	Foreign Portfolio Investment (In)	Input Variable	Weekly	30
6	Foreign Portfolio Investment (Out)	Input Variable	Weekly	30
7	Available Reserves	Input Variable	Daily	1
8	Reserve Money	Input Variable	Daily	1
9	CBOE Volatility Index	Input Variable	Daily	1
10	Credit Default Swap	Input Variable	Daily	1
11	London Interbank Reference Rate	Input Variable	Daily	1
12	Singapore Interbank Reference Rate	Input Variable	Daily	1
13	Philippine Interbank Reference Rate	Input Variable	Daily	1
14	Philippine Government Bond Rate	Input Variable	Daily	1
15	BSP Discount Rate	Input Variable	Daily	1
16	Bank Savings Rate	Input Variable	Daily	1
17	Bank Prime Rate	Input Variable	Daily	1
18	Money Market Rate (Promissory Note)	Input Variable	Daily	1
19	Treasury Bill Rate	Input Variable	Daily	1
20	Interbank Call Rate	Input Variable	Daily	1
21	Philippine Peso per US Dollar (FOREX)	Input Variable	Daily	1
22	Weighted Monetary Operations Rate	Input Variable	Daily	1

4. Research methodology

4.1. Models

Two types of models are used in this study. First, as a benchmark, univariate (i.e., ARIMA, Seasonal ARIMA, Random Walk) and multivariate (i.e., DFM) time series models are estimated. Second, machine learning algorithms, namely regularization (i.e., Ridge Regression, LASSO, ENET) and tree-based (i.e., RF, GBT) models, are estimated as alternatives. The objectives are: (1) to establish which quantitative models could accurately estimate the monthly growth of the monetary indicator; and (2) to determine how well recent regularization methods applied to machine learning nowcast vis-à-vis traditional time series models.

4.1.1. Autoregressive Integrated Moving Average (ARIMA)

The forecasting equation using ARIMA is structured as follows:

$$\hat{y}_t = \mu + \phi_0 + \phi_1\, y_{t\text{-}1} + \ldots + \phi_2\, y_{t\text{-}p}\, \ldots + \theta_1\, e_{t\text{-}1} - \ldots - \theta_q\, e_{t\text{-}q} \tag{1}$$

In Equation 1, p represents the order of the autoregression, which includes the overall effect(s) of past values under consideration. The notation q, on the other hand, denotes the order of the moving average, constructing the error of ARIMA as a linear combination of the error values observed at the previous time points in the past (Meyler et al. [1998]; Fan [2019: 10-11]).

4.1.2. Random Walk

The general equation of Random Walk is:

$$\hat{y}_t = \epsilon_t + y_{t\text{-}1} \tag{2}$$

In Equation 2, the y_t and $y_{t\text{-}1}$ represent the observations of the time series and ϵ_t is the white noise with zero mean and constant variance [Fan 2019: 12].

4.1.3. Dynamic Factor Model

The Dynamic Factor Model (DFM) is expressed as:

$$X_t = \lambda(L) f_t + \epsilon_t \tag{3}$$

In Equation 3, notation X_t represents the vector of observed time series variables depending on a reduced number of latent factors f_t and an idiosyncratic component ϵ_t. The $\lambda(L)$ denotes the lag polynomial matrix, which represents the vector of dynamic factor loading (Stock and Watson [2016]; Fan [2019]).

4.1.4. Ridge Regression

Equation 4 depicts the residual sum of squares and the penalty term (λ) in a Ridge Regression:

$$\sum_{t=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{4}$$

The notation n represents the total number of observations included in the model, while p is the number of candidate predictors. The essential factor in this equation is the tuning parameter λ, which controls the relative impact of the regression coefficient estimates [James et al. 2013: 215]. When $\lambda = 0$, the penalty has no effect, and Ridge Regression produces estimates similar to OLS estimates. However, as $\lambda = \infty$, the impact of the shrinkage penalty increases, and the coefficient estimates approach zero [Tiffin 2016].

4.1.5. Least Absolute Shrinkage and Selection Operator (LASSO)

Similar to Ridge Regression, LASSO also includes a penalty term for its RSS (Equation 5).

$$\sum_{t=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{5}$$

In contrast with the Ridge Regression, which only shrinks all of its coefficients towards zero, LASSO forces its coefficients to be precisely equal to zero when the tuning parameter λ is adequately large [James et al. 2013]. Therefore, due to its substantial penalty, the main difference between LASSO and Ridge Regression is their ability to select variables and produce a parsimonious model with fewer predictors.

4.1.6. Elastic Net (ENET)

ENET is a regularization method that contains both properties of Ridge Regression and LASSO (See Equation 6).

$$\sum_{t=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} [(1 - \alpha)(\beta_j^2) + \alpha|\beta_j| \tag{6}$$

In particular, it utilizes the shrinkage properties of Ridge Regression and LASSO by selecting the best predictors to provide parsimonious models while still identifying groups of correlated predictors. The respective weights of the two penalties are determined through the additional tuning parameter α [Richardson et al. 2018].

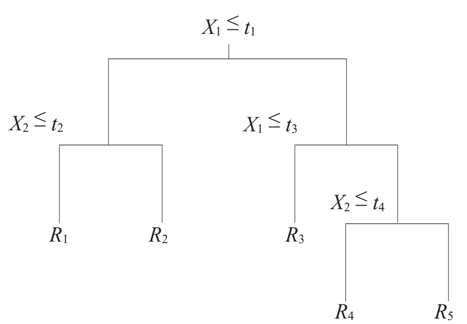
4.1.7. Random Forest (RF)

RF is a tree-based machine learning algorithm that uses combinations of multiple decision trees to formulate a comprehensive forecast.[32] It modifies the decision tree approach to minimize the overfitting problem and maximize the data's information content by using subsamples of observations and predictions (Tiffin [2016]; Bolhuis and Rayner [2020]). In particular, RF uses bootstrap aggregation (also known as bagging) in each decision tree using a random sample of observations in the training dataset. This procedure is repeated k number of times, and the results are averaged to reduce the overall variance without increasing the bias of the dataset. It also uses random sampling in each split to ensure that the multiple trees that go into the final collection are relatively diverse (Tiffin [2016]; Bolhuis and Rayner [2020]).

4.1.8. Gradient Boosted Trees (GBT)

GBT is a machine learning algorithm that formulates sequential decision trees rather than combinations to construct an aggregate forecast (Figure 1). This tree-based model does not involve the bootstrap sampling that RF conducts. Instead, GBT trains an initial decision tree based on the time-series data. It then uses the prediction errors from said decision tree to train a second decision tree. Next, the errors from the second decision tree are used to train the tree, and so on. After the final iteration, the algorithm uses the summation of these predictions to provide a final forecast (James et al. [2013]; Bolhuis and Rayner [2020]).

FIGURE 1. Decision tree growing process
Recursive binary splitting of two-dimensional feature space



Source: James et al. [2013]

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[32] Decision Tree is the fundamental structure of any tree-based machine learning method used for classification and regression problems (James et al. [2013]; Fan [2019]). This approach divides categorical (e.g., name, address) or continuous (e.g., level, growth rate) data into two classes in a systematic manner to reduce the prediction error of the target variable of interest. This procedure is repeated until the number of training samples at the branch exceeds the minimum node size. The algorithm, afterward, performs the estimation by using the mean or mode of training observation in that particular region [James et al. 2013].

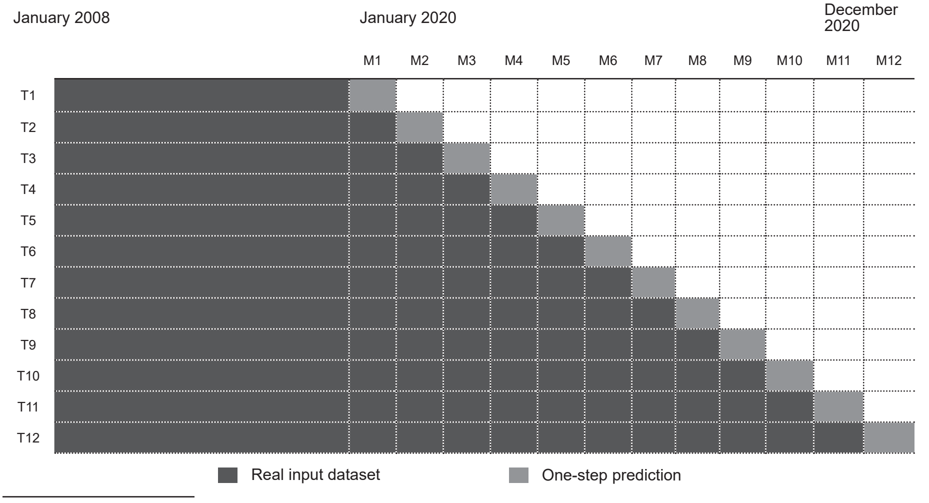
4.2. Nowcast evaluation methodology

In order to estimate domestic liquidity growth in the short run, this study evaluates the performance of time series models and machine learning algorithms based on their one-step-ahead (out-of-sample) nowcast. This approach is preferred over multi-step-ahead (out-of-sample) estimates because it fulfills the objective of providing an estimate for currently unavailable data that can be utilized for more timely prediction and policy analysis.

In addition, it is crucial to determine the consistency of simulated models. Therefore, the benchmark and machine learning models are trained over an expanding window to provide a series of one-step-ahead nowcasts.[33] The dataset covering 13 years from 2008 to 2020 is divided into training and test datasets to perform the said approach. The first training dataset covers the numerical figures of the target and input variables from January 2008 to December 2019. Meanwhile, its corresponding test dataset comprises the numerical statistics of target and input variables as of January 2020. This process is accomplished until the test dataset covers the numerical figures of the target and input variables as of December 2020 (Figure 2).

Under this approach, the accuracy of each time series and machine learning model is measured through their respective forecast errors, such as RMSE and MAE. The forecast errors of regularization and tree-based methods are then individually and collectively evaluated against benchmark (i.e., univariate, multivariate) models in order to determine whether the nowcast results obtained from the former are significantly superior to the latter methods or vice versa.

FIGURE 2. Expanding window process



[33] For conducting an expanding window (or recursive scheme) evaluation in this study, the dataset used for the first nowcast (i.e. January 2020) was based on January 2008 to December 2019. Likewise, the dataset used for the second nowcast (i.e., February 2020) is based on January 2008 to January 2020. This process is done until the last out-of-sample period (December 2020).

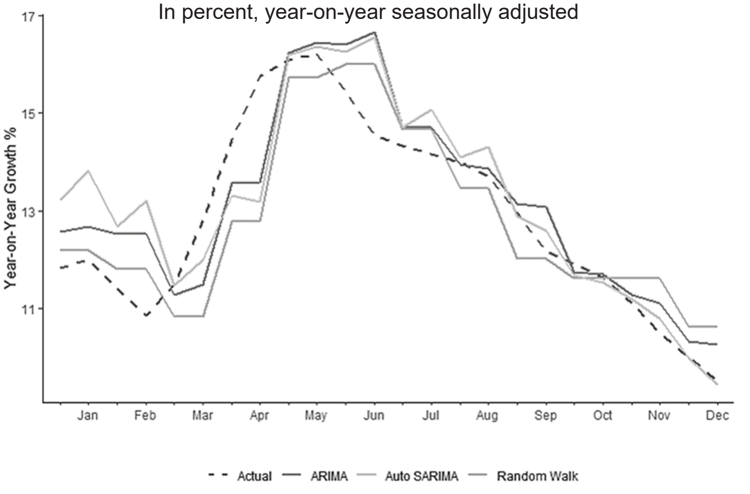
5. Results and analysis[34]

5.1. Univariate models

The results of ARIMA, Random Walk, and Seasonal ARIMA (SARIMA) indicate that their respective one-step-ahead (out-of-sample) nowcasts from January to December 2020 depict the overall trend of domestic liquidity growth in the Philippines (Figure 3).[35] Furthermore, the said univariate models provided reasonable estimates in the months wherein the growth of domestic liquidity (i.e., April, May) suddenly expanded due to the decrease of national government deposits to the central bank (e.g., central bank liabilities to central government).

FIGURE 3. Autoregressive model nowcasts vs. Actual M3 growth (January to December 2020)

In percent, year-on-year seasonally adjusted



However, by comparing their respective monthly forecast errors, it can be observed that SARIMA has provided the highest number of months with low RMSE and MAE (i.e., March, May, September, November, December) (Tables 3 and 4). This was followed by the results from Random Walk (i.e., January, February, June, July) and ARIMA (i.e., April, August, October), respectively.

The overall forecast errors of the three univariate models, on the other hand, gave different results. Based on their overall forecast errors, ARIMA provides relatively reasonable estimates with an RMSE of 0.917 and an MAE of 0.688.

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[34] All of the models used in this study are calibrated. Optimal lags for univariate models were based on the result of Partial Autocorrelation Function (PACF) and Akaike Information Criterion (AIC). DFM followed the calibration made by Mariano and Ozmucur [2020], which was centered through the optimal eigenvalues through factor analysis. Lastly, machine learning techniques were calibrated using cross-validation method (i.e., tenfold cross-validation, leave-one-out cross validation).

[35] The decision to consider three univariate models, such as ARIMA, Random Walk, and SARIMA are based on the conducted stationarity (i.e., Augmented Dickey-Fuller, Philips-Perron) tests and the result of lag selection based on their respective AIC and Bayesian Information Criterion (BIC). ARIMA has (4,1,1) parameters, Random Walk has (0,1,0) parameters, and SARIMA has (5,1,1)(1,0,1) parameters.

These are lower than the overall forecast errors of Random Walk (1.016 and 0.766) and SARIMA (1.066 and 0.739), respectively (Tables 3 and 4).

TABLE 3. RMSE of autoregressive models[36]

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.716	1.422	0.936	1.663	0.196	1.636	0.474	0.102	0.649	0.117	0.452	0.577	0.917
RWalk	0.288	0.722	1.470	2.415	0.434	1.095	0.425	0.403	0.669	0.199	0.880	0.895	1.016
SARIMA	1.622	1.879	0.556	1.986	0.134	1.535	0.702	0.428	0.299	0.174	0.222	0.057	1.066

TABLE 4. MAE of autoregressive models

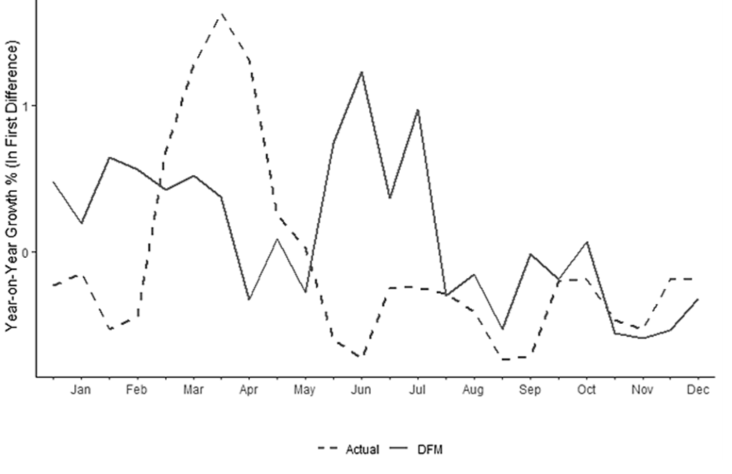
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.715	1.395	0.762	1.537	0.194	1.527	0.467	0.088	0.544	0.106	0.389	0.537	0.688
RWalk	0.273	0.669	1.319	2.327	0.428	0.996	0.416	0.380	0.543	0.149	0.825	0.862	0.766
SARIMA	1.609	1.801	0.405	1.854	0.134	1.411	0.650	0.355	0.244	0.162	0.194	0.050	0.739

5.2. Dynamic Factor Model[37,38]

In contrast to the three univariate models, DFM provides inconsistent estimates of the overall movement of domestic liquidity in the first semester of 2020. Notably, the monthly one-step-ahead (out-of-sample) nowcasts of DFM did not capture the sudden expansion of this monetary indicator (Figure 4).

FIGURE 4. DFM nowcasts vs. actual M3 growth (January to December 2020)

In percent difference, seasonally adjusted



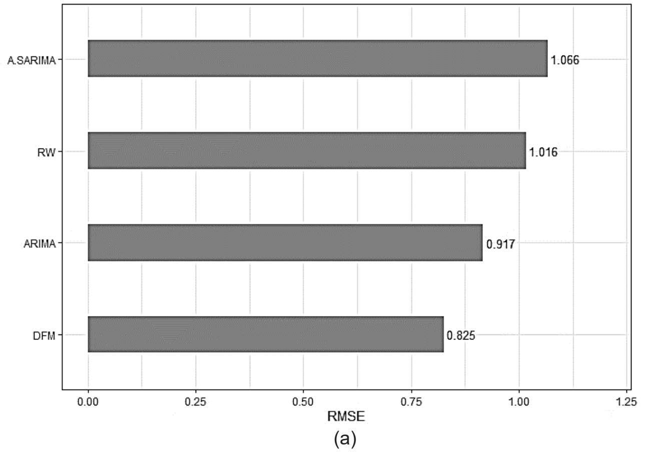
[36] M1 to M12 refers to the months included in the expanding window validation (e.g., January, February 2020).

[37] DFM was utilized as multivariate model because it reduces the dimension of the wide range of high-frequency monetary, financial, and external sector indicators as input variables used in this study.

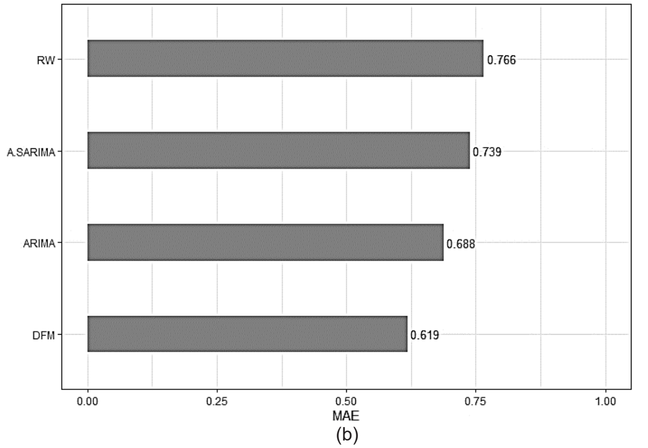
[38] Three factors were extracted from the initial 20 input variables using the method of maximum likelihood by performing factor analysis.

However, DFM provides more accurate results in the latter half of the year. It can be observed that the monthly forecast errors of the said model are relatively lower than those under ARIMA, Random Walk, and SARIMA, particularly from August to December 2020 (Tables 5 and 6). In addition, this particular outcome can similarly be observed in the overall forecast errors of DFM. The multivariate model only conveyed an overall RMSE and MAE of 0.825 and 0.619, respectively. These forecast errors are relatively lower than the ones displayed by the univariate models (Figure 5).

FIGURE 5. Overall (a) RMSE and (b) MAE of autoregressive models and DFM



(a)



(b)

TABLE 5. RMSE of DFM

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
DFM	0.557	1.093	0.565	1.458	0.247	1.678	0.965	0.184	0.513	0.182	0.078	0.267	0.825

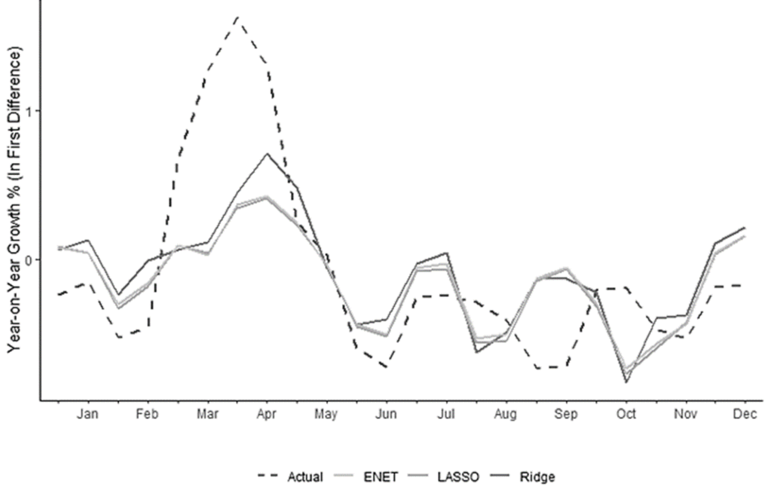
TABLE 6. MAE of DFM

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
DFM	0.526	1.091	0.509	1.446	0.237	1.649	0.918	0.138	0.452	0.136	0.077	0.246	0.619

5.3. Regularization methods[39]

The result showed that Ridge Regression, LASSO, and ENET could provide estimates with relatively higher precision than the benchmark models. In particular, the monthly nowcasts of these models have lower forecast errors than the individual estimates stipulated by ARIMA, Random Walk, SARIMA, and DFM (Tables 7 and 8), except for September and October 2020 (Figure 6). In addition, the regularization methods estimate domestic liquidity with low forecast errors in the months when it unexpectedly expands due to the increase in borrowings and deposits of the national government to the central bank from March to May 2020 (Tables 7 and 8).

FIGURE 6. Regularization method nowcasts vs. actual M3 growth (January to December 2020)
In percent difference, seasonally adjusted



A similar result was observed from the overall forecast errors when using the three regularization methods. In particular, the Ridge Regression, LASSO, and ENET showed lower overall RMSE and MAE than ARIMA (0.917 and 0.688), Random Walk (1.016 and 0.766), SARIMA (1.066 and 0.739), and DFM (0.825 and 0.619) (Figure 7).

[39] All regularization methods used in this study are tuned/calibrated using tenfold cross-validation method.

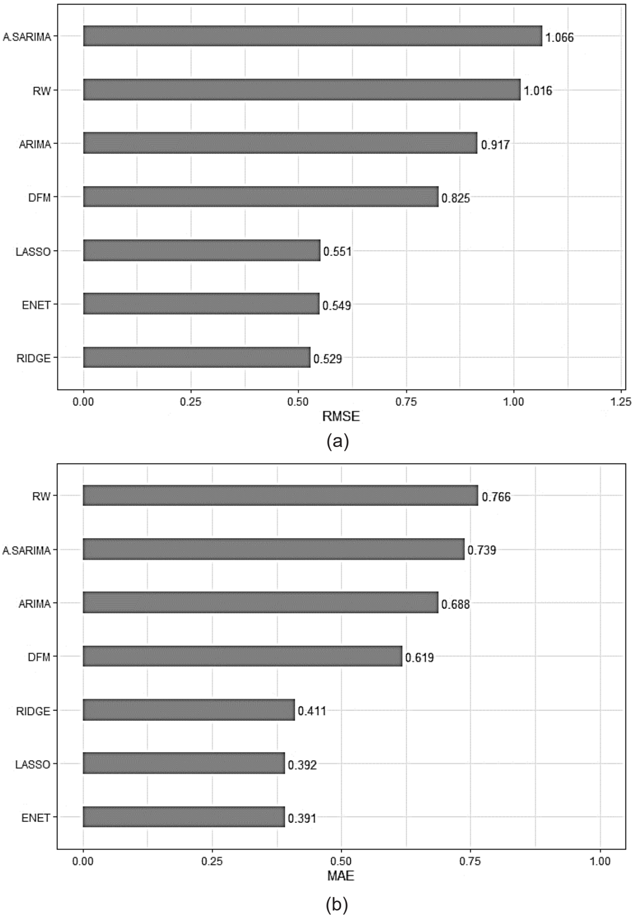
TABLE 7. RMSE of ridge regression, LASSO, and ENET

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
Ridge	0.292	0.372	0.928	1.163	0.173	0.258	0.261	0.248	0.596	0.449	0.123	0.349	0.529
LASSO	0.264	0.237	0.964	1.348	0.046	0.185	0.179	0.215	0.621	0.416	0.115	0.286	0.551
ENET	0.262	0.259	0.973	1.328	0.048	0.199	0.206	0.187	0.631	0.390	0.099	0.291	0.549

TABLE 8. MAE of ridge regression, LASSO, and ENET

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
Ridge	0.292	0.364	0.887	1.136	0.156	0.245	0.259	0.209	0.596	0.325	0.116	0.345	0.411
LASSO	0.257	0.234	0.909	1.340	0.040	0.182	0.179	0.202	0.620	0.345	0.114	0.281	0.392
ENET	0.255	0.257	0.916	1.321	0.036	0.196	0.206	0.171	0.631	0.318	0.099	0.286	0.391

FIGURE 7. Overall (a) RMSE and (b) MAE of benchmark models and regularization methods



(a)

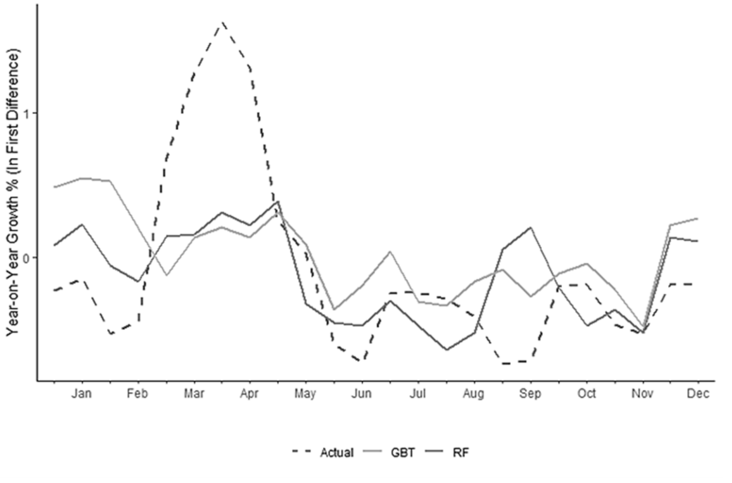
(b)

By comparing the three models under the regularization method, it can be observed that LASSO provided the highest number of months (i.e., five months) with relatively low forecast errors from January to December 2020 (Tables 7 and 8). On the other hand, in terms of their overall forecast errors, Ridge Regression and ENET registered low overall RMSE and MAE compared to LASSO, with 0.529 and 0.391, respectively (Figure 7).

5.4. Tree-based methods[40]

Similar to the results under regularization methods, utilizing RF and GBT as nowcasting models provide more consistent estimates with relatively higher precision than the benchmark models used in this study. The monthly forecast errors of the two machine learning models are significantly lower than those under ARIMA, RW, SARIMA, and DFM, except for the nowcast result under RF in September 2020 (Figure 8). Likewise, the results indicate that RF and GBT estimate domestic liquidity growth with low forecast error in the months wherein the growth of this monetary indicator suddenly expanded due to the increased borrowings and deposits of the national government (Tables 9 and 10).

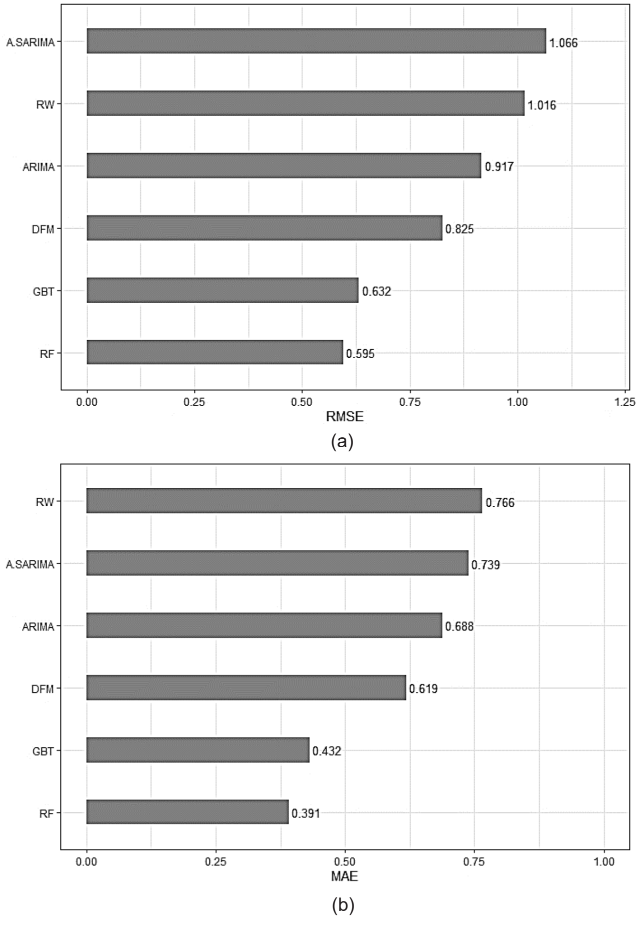
FIGURE 8. Tree-based method nowcasts vs. actual M3 growth (January to December 2020)
In percent difference, seasonally adjusted



Aside from their robust monthly estimates, the overall nowcasts of RF and GBT also registered lower forecast errors. The result reveals that RF only displayed an RMSE of 0.595 and MAE of 0.432, while GBT provided an RMSE of 0.632 and MAE of 0.469. These figures are significantly lower than the overall forecast errors registered by the univariate and multivariate models performed in this study (Figure 9).

[40] Nowcasts under RF are tuned/calibrated using out-of-bag (OOB) scores, while nowcast under GBT are tuned/calibrated using tenfold cross-validation.

FIGURE 9. Overall (a) RMSE and (b) MAE of benchmark models and tree-based methods



In addition, among the tree-based methods used in this study, it can also be established that RF provided the lowest forecast errors. Despite having an inaccurate estimate in September 2020, this model provided the highest number of months (i.e., eight months) with higher precision from January to December 2020. This includes nowcasts for January, February, March, April, June, July, November, and December 2020 (Tables 9 and 10).

TABLE 9. RMSE of RF and GBT

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
RF	0.346	0.389	0.879	1.455	0.265	0.208	0.167	0.265	0.855	0.203	0.077	0.307	0.595
GBT	0.180	0.686	0.986	1.536	0.060	0.495	0.305	0.241	0.636	0.248	0.201	0.216	0.632

TABLE 10. MAE of RF and GBT

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
RF	0.346	0.389	0.879	1.455	0.265	0.208	0.167	0.265	0.855	0.203	0.077	0.307	0.595
GBT	0.180	0.686	0.986	1.536	0.060	0.495	0.305	0.241	0.636	0.248	0.201	0.216	0.632

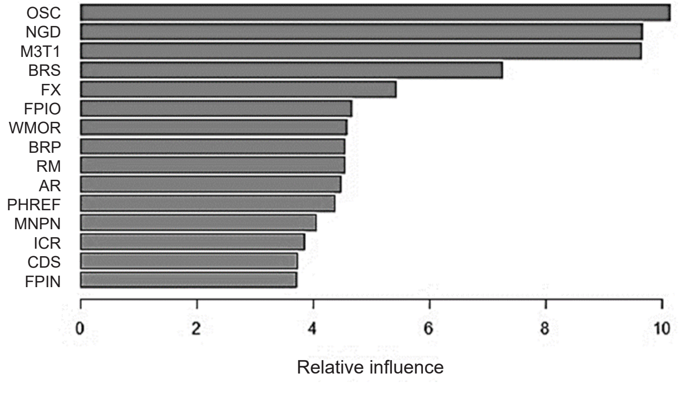
5.5. Variable importance

One of the main advantages of using machine learning algorithms in economic nowcasting is their capacity to identify a subset among selected input variables that better predicts the movement or growth of a particular macroeconomic indicator. In addition, numerous studies have established that these machine learning models can formulate quantitative models with accurate estimates despite using a limited number of indicators.[41] The machine learning algorithms that specifically have this ability are regularization and tree-based methods, such as LASSO, ENET, RF, and GBT.

5.5.1. Regularization methods

The nowcasts conducted by LASSO and ENET from January and December 2020 indicate that (1) foreign exchange rate (FOREX), (2) inflow of foreign portfolio investment (FPI), (3) London Interbank Offered Rates (LIBOR), (4) bank savings rate, (5) national government deposits to the central bank, and (6) liabilities of other sectors to the central bank are among the critical indicators that should be considered in estimating domestic liquidity growth in the Philippines. Mainly because among the 21 indicators used as input variables, these are the consistent determinants under LASSO and ENET that do not stipulate zero coefficients from January to December 2020 (Table 11).[42]

FIGURE 10. Variable importance plot via gradient boosted trees



[41] See the studies of Cepni et al. [2018], Richardson et al. [2018], Ferrara and Simoni [2019], and Tamara et al. [2020].

[42] BSP Discount Rate, Bank Savings Rate, and WMOR as important indicators were also identified (Annex F and G).

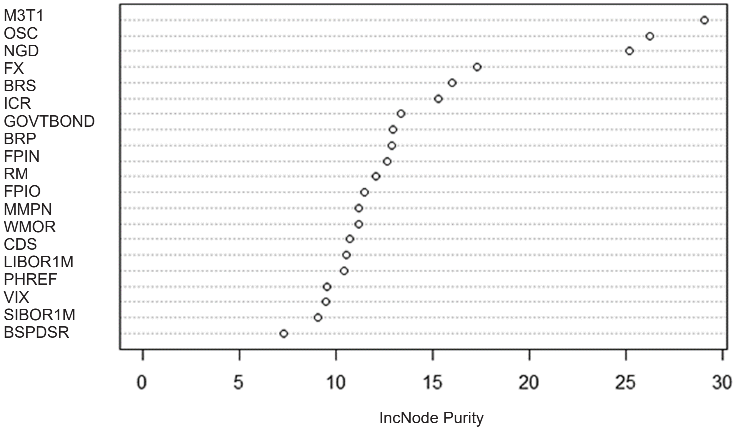
TABLE 11. Variable coefficients via LASSO and ENET (January to February 2020)

No.	Variable	LASSO (Jan. 2020)	LASSO (Feb. 2020)	ENET (Jan. 2020)	ENET (Feb. 2020)
-	Intercept	0.016	0.015	0.016	0.015
1	M3 Growth (T-1)	-	-	-	-
2	BSP Liabilities on National Government	-0.015	-0.015	-0.014	-0.014
3	BSP Claims on Other Sectors	0.235	0.235	0.216	0.216
4	Foreign Portfolio Investment (In)	-0.003	-0.004	-0.010	-0.010
5	Foreign Portfolio Investment (Out)	-	-	-	-
6	Available Reserves	-	-	-	-
7	Reserve Money	-	-	-	-
8	CBOE Volatility Index	-	-	-	-
9	Credit Default Swap	-	-	-	-
10	London Interbank Reference Rate	0.111	0.114	0.097	0.100
11	Singapore Interbank Reference Rate	-	-	-	-
12	Philippine Interbank Reference Rate	-	-	-	-
13	Philippine Government Bond Rate	-	-	-	-
14	BSP Discount Rate	-	-	-	-
15	Bank Savings Rate	-0.103	-0.110	-0.080	-0.087
16	Bank Prime Rate	-	-	-	-
17	Money Market Rate (Promissory Note)	-	-	-	-
18	Treasury Bill Rate	-	-	-	-
19	Interbank Call Rate	-	-	-	-
20	Philippine Peso per US Dollar (FOREX)	0.124	0.124	0.111	0.119
21	Weighted Monetary Operations Rate	-	-	-	-

5.5.2. Tree-based methods

The critical indicators identified under RF and GBT are similar to the input variables that LASSO and ENET provided. However, the main difference is that both of the tree-based methods used in this study have identified that lagged value (t–1) of the target variable, as an input variable, is also critical in estimating domestic liquidity growth in the Philippines. In particular, Figures 10 and 11 indicate that (1) domestic liquidity (t–1), (2) liabilities of other sectors to the central bank (OSC), and (3) national government deposits to the central bank (NGD) are by far the three most significant variables that should be considered in estimating the growth of domestic liquidity.

FIGURE 11. Node impurity via random forest



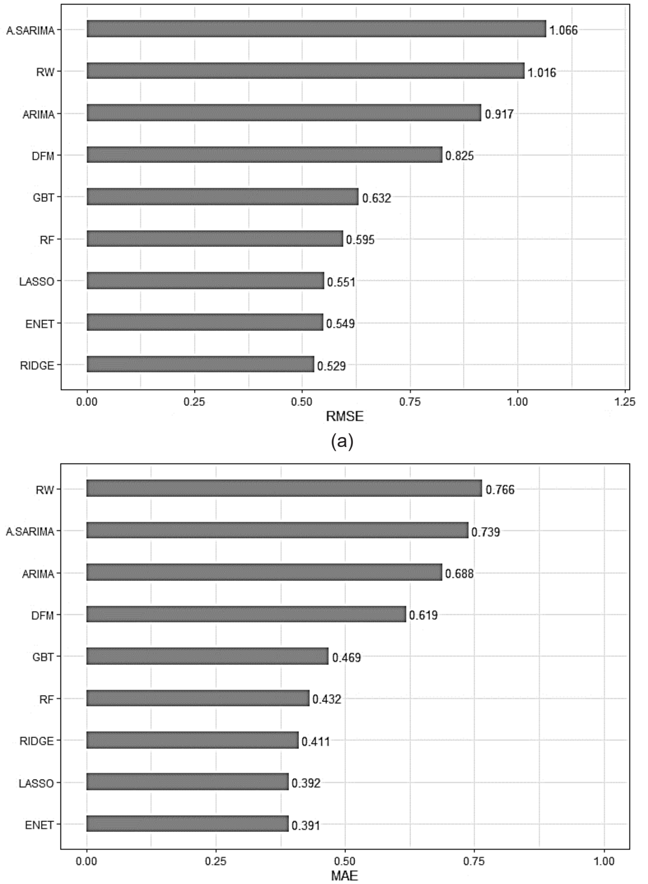
6. Conclusion

This study utilized different methods now popularly used in machine learning to support the BSP's current suite of macroeconomic models used to forecast and analyze domestic liquidity growth in the Philippines. In particular, regularization (i.e., Ridge Regression, LASSO, ENET) and tree-based (i.e., RF, GBT) methods are employed to estimate the year-on-year (Y-O-Y) growth of the said monetary indicator from January to December 2020. The following algorithms are then compared against traditional univariate (i.e., ARIMA, Random Walk, SARIMA) and multivariate (i.e., DFM) time series models. Hence, their respective one-step-ahead (out-of-sample) nowcasts under an expanding window process are evaluated based on monthly and overall RMSE and MAE.

The results indicate that machine learning algorithms provide relatively higher precision estimates than the traditional time series models due to their consistent monthly nowcasts with low forecast errors, especially in the months wherein domestic liquidity suddenly expanded (i.e., increased national government borrowings and deposits). In addition, based on their overall RMSE and MAE, it can be concluded that the two machine learning techniques could be considered as alternative models to estimate the domestic liquidity growth (Figure 12).

However, among these algorithms, LASSO and RF provided the highest number of months with low forecast errors from January to December 2020 (Figure 12). The Ridge Regression and ENET, on the other hand, registered the lowest overall RMSE and MAE with 0.529 and 0.391, respectively (Tables 12 and 13). These results suggest that nowcasting through regularization methods is the most suitable approach to nowcast domestic liquidity growth among the machine learning algorithms used in this study.

FIGURE 12. Overall forecast errors of benchmark and machine learning models



(a)

(b)

TABLE 12. RMSE of benchmark and machine learning models (summary)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.716	1.422	0.936	1.663	0.196	1.636	0.474	0.102	0.649	0.117	0.452	0.577	0.917
RWalk	0.288	0.722	1.470	2.451	0.434	1.095	0.425	0.403	0.669	0.199	0.880	0.895	1.016
SARIMA	1.622	1.879	0.556	1.986	0.134	1.535	0.702	0.428	0.299	0.174	0.222	0.057	1.066
DFM	0.557	1.093	0.565	1.458	0.247	1.678	0.965	0.184	0.513	0.182	0.078	0.267	0.825
Ridge	0.292	0.372	0.928	1.163	0.173	0.258	0.261	0.248	0.596	0.449	0.123	0.349	0.529
LASSO	0.264	0.237	0.964	1.348	0.046	0.185	0.179	0.215	0.621	0.416	0.115	0.286	0.551
ENET	0.262	0.259	0.973	1.328	0.048	0.199	0.206	0.187	0.631	0.390	0.099	0.291	0.549
RF	0.346	0.389	0.879	1.455	0.265	0.208	0.167	0.265	0.855	0.203	0.077	0.307	0.595
GBT	0.180	0.686	0.986	1.536	0.060	0.495	0.305	0.241	0.636	0.248	0.201	0.216	0.632

TABLE 13. MAE of benchmark and machine learning models (summary)

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	OVR.
ARIMA	0.715	1.395	0.762	1.537	0.194	1.527	0.467	0.088	0.544	0.106	0.389	0.537	0.688
RWalk	0.273	0.669	1.319	2.327	0.428	0.996	0.416	0.380	0.543	0.149	0.825	0.862	0.766
SARIMA	1.609	1.801	0.405	1.854	0.134	1.411	0.650	0.355	0.244	0.162	0.194	0.050	0.739
DFM	0.526	1.091	0.509	1.446	0.237	1.649	0.918	0.138	0.452	0.136	0.077	0.246	0.619
Ridge	0.292	0.364	0.887	1.136	0.156	0.245	0.259	0.209	0.596	0.325	0.116	0.345	0.411
LASSO	0.257	0.234	0.909	1.340	0.040	0.182	0.179	0.202	0.620	0.345	0.114	0.281	0.392
ENET	0.255	0.257	0.916	1.321	0.036	0.196	0.206	0.171	0.631	0.318	0.099	0.286	0.391
RF	0.345	0.377	0.830	1.454	0.242	0.201	0.140	0.235	0.852	0.147	0.058	0.307	0.432
GBT	0.179	0.684	0.972	1.530	0.060	0.490	0.243	0.201	0.636	0.218	0.200	0.215	0.469

Aside from their robust one-step-ahead (out-of-sample) estimates, machine learning algorithms also provide substantial advantages against traditional time series models. These models can identify indicators that could stipulate parsimonious nowcasting models with more accurate results. Hence, nowcasts based on LASSO, ENET, RF, and GBT indicate that (1) national government deposits, (2) BSP claims on other sectors, (3) FOREX, and (4) lagged values of domestic liquidity are among the indicators that could be useful in nowcasting the growth of domestic liquidity in the Philippines.

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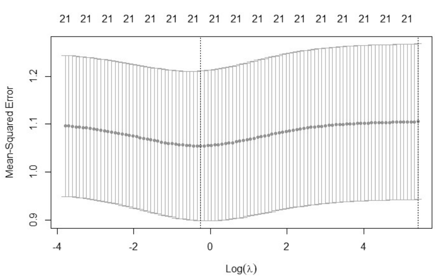
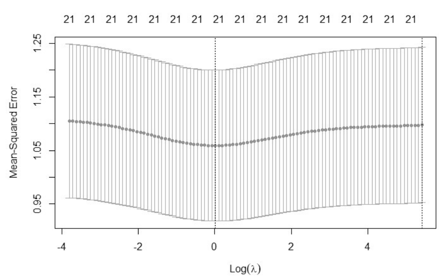
Annex

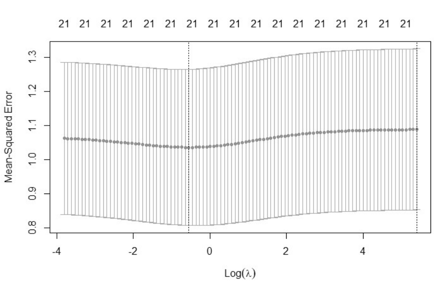
ANNEX A. Optimal shrinkage penalty via ridge regression



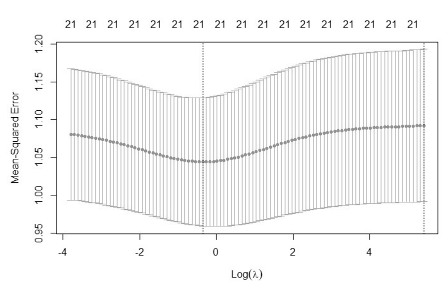
January 2020 – 0.772



February 2020 – 1.012

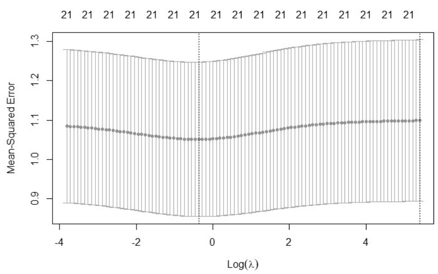


March 2020 – 0.577

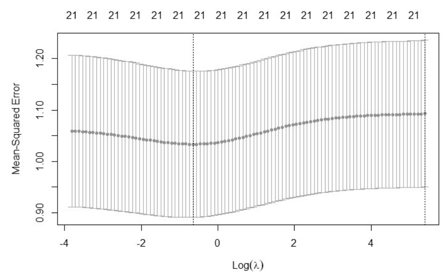


April 2020 – 0.700

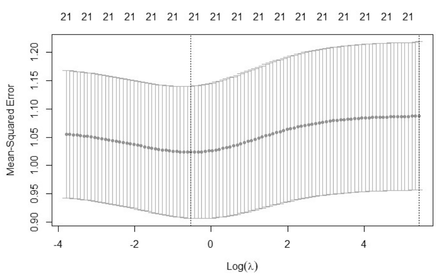
ANNEX A. Optimal shrinkage penalty via ridge regression (continued)



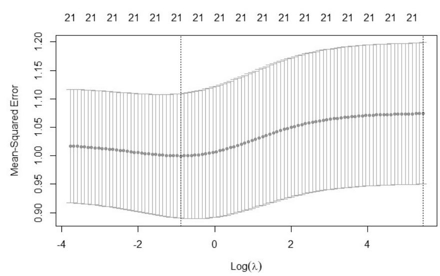
May 2020 – 0.691



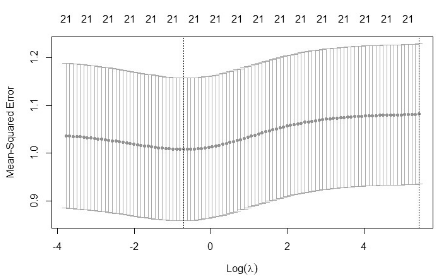
June 2020 – 0.523



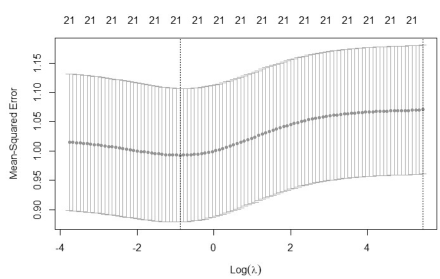
July 2020 – 0.589



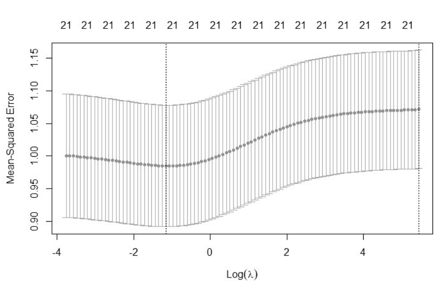
August 2020 – 0.491



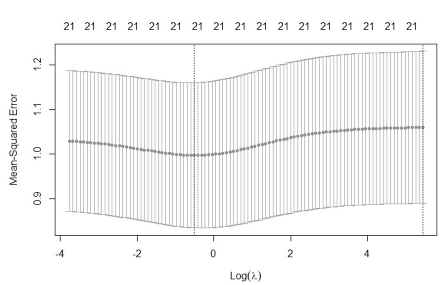
September 2020 – 0.411



October 2020 – 0.415

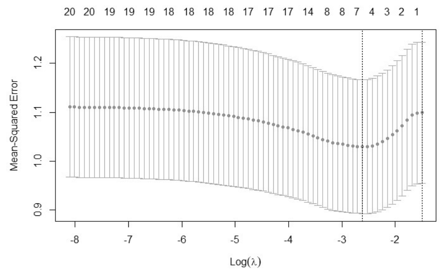


November 2020 – 0.313

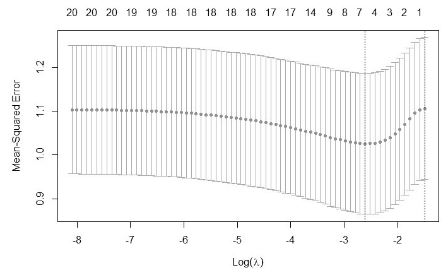


December 2020 – 0.600

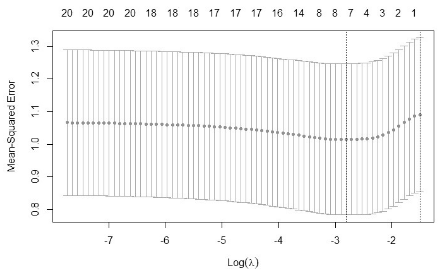
ANNEX B. Optimal shrinkage penalty via LASSO



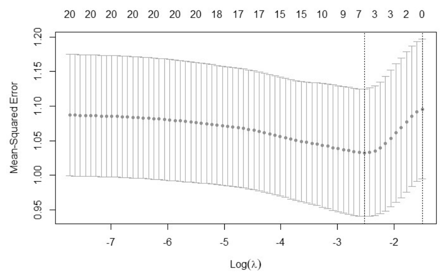
January 2020 – 0.737



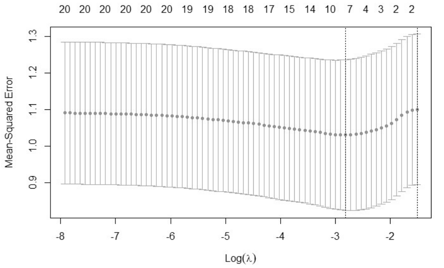
February 2020 – 0.073



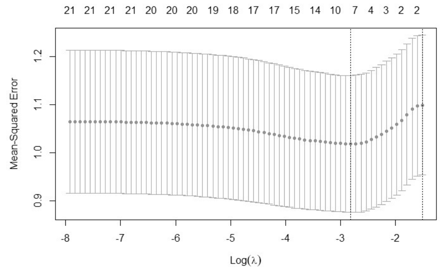
March 2020 – 0.060



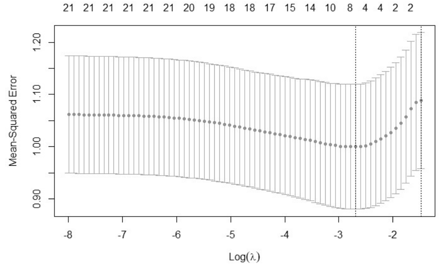
April 2020 – 0.080



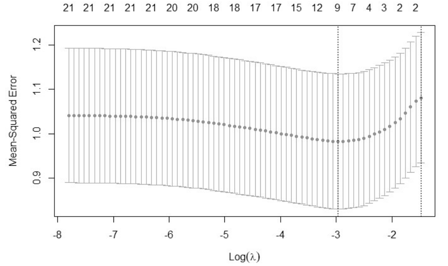
May 2020 – 0.060



June 2020 – 0.060

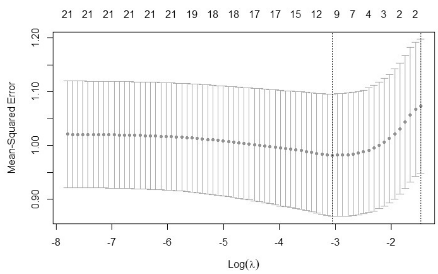


July 2020 – 0.068

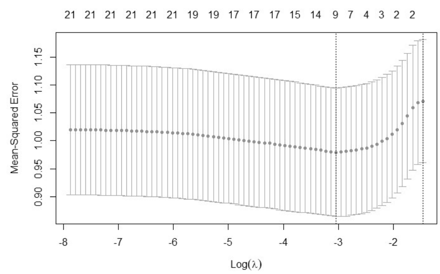


August 2020 – 0.051

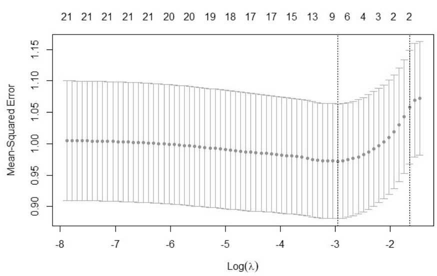
ANNEX B. Optimal shrinkage penalty via LASSO (continued)



September 2020 – 0.047



October 2020 – 0.048



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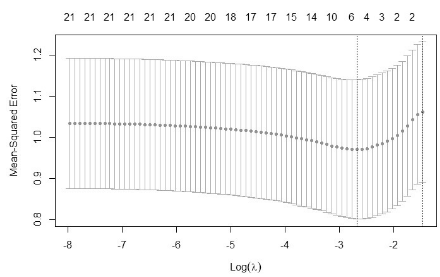
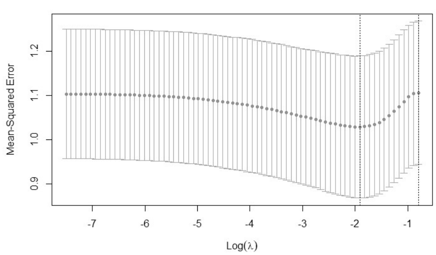
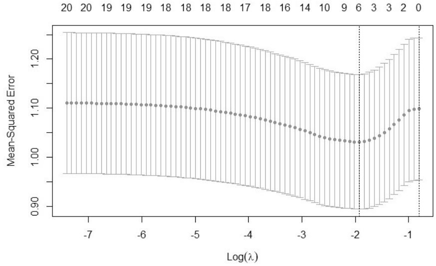


December 2020 – 0.069

ANNEX C. Optimal shrinkage penalty via ENET



January 2020 – 0.147



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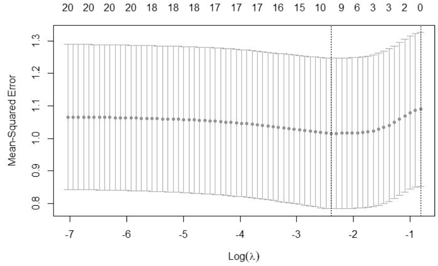

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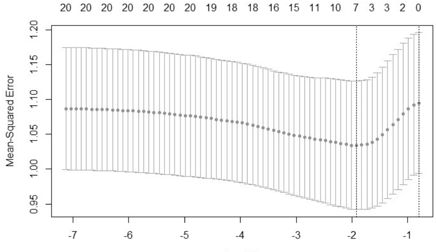
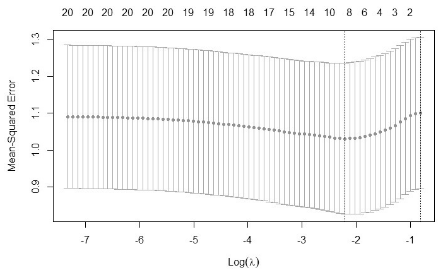
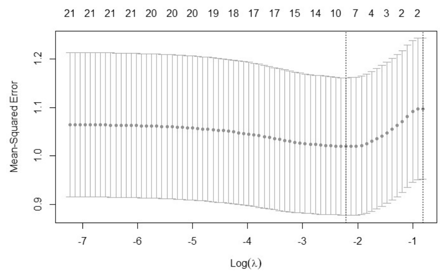


April 2020 – 0.147

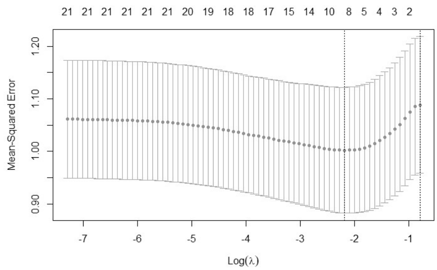
ANNEX C. Optimal shrinkage penalty via ENET (continued)



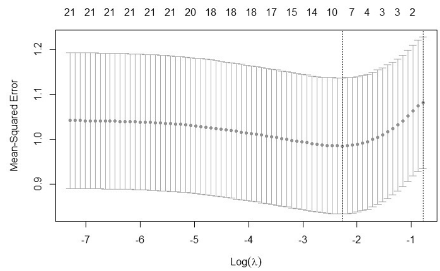
May 2020 – 0.110



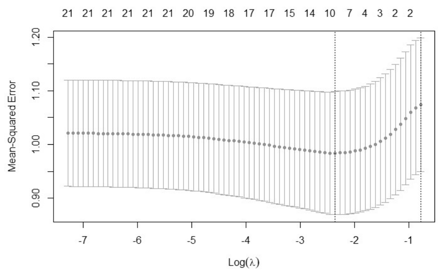
June 2020 – 0.110



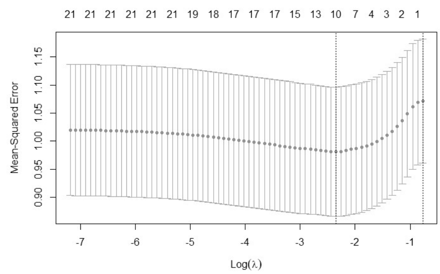
July 2020 – 0.112



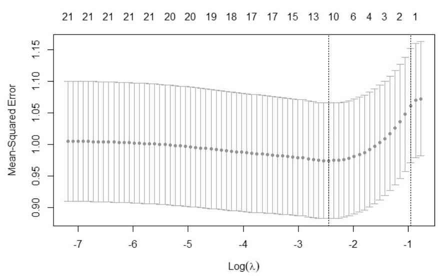
August 2020 – 0.103



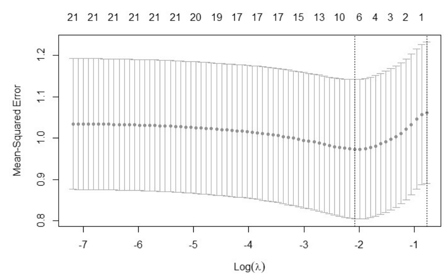
September 2020 – 0.095



October 2020 – 0.095

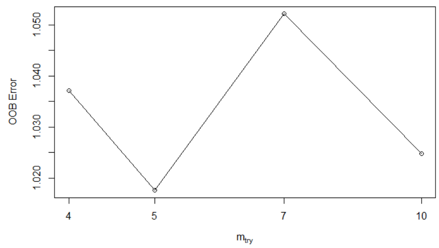


November 2020 – 0.087

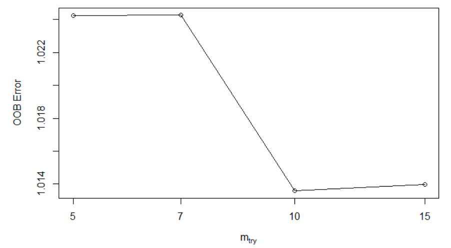


December 2020 – 0.126

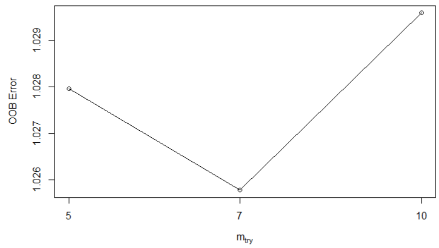
ANNEX D. OOB error of training datasets via random forest



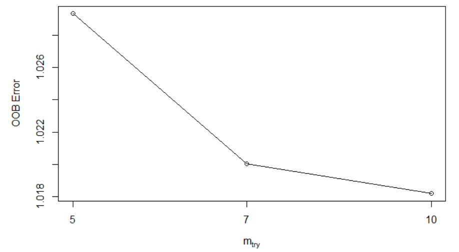
January 2020 – 5 Variables (1.018)



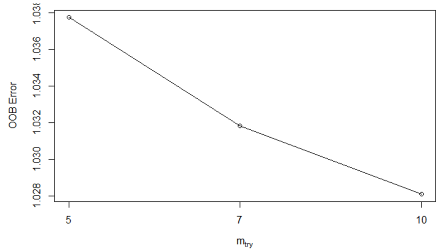
February 2020 – 10 Variables (1.014)



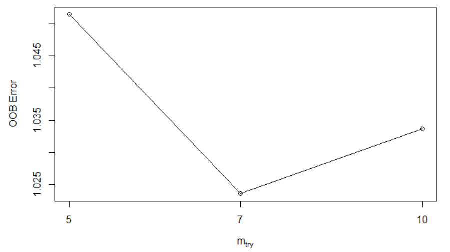
March 2020 – 7 Variables (1.026)



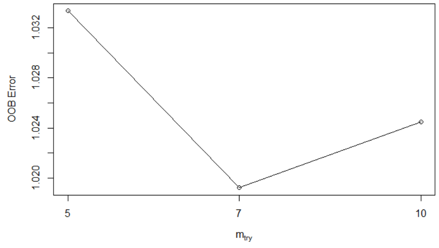
April 2020 – 10 Variables (1.018)



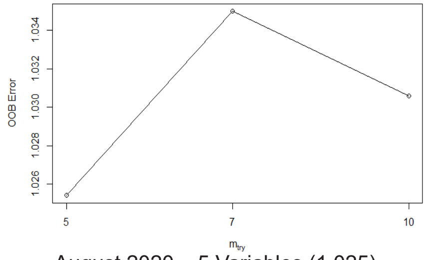
May 2020 – 10 Variables (1.028)



June 2020 – 7 Variables (1.024)

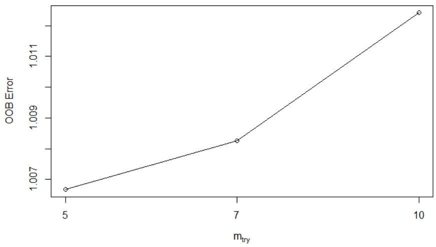


July 2020 – 7 Variables (1.019)

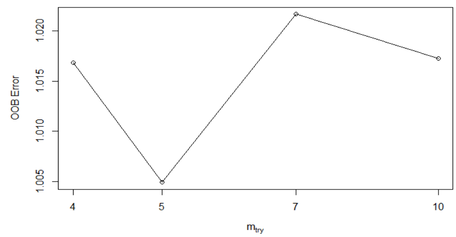


August 2020 – 5 Variables (1.025)

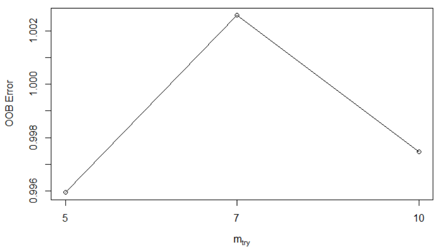
ANNEX D. OOB error of training datasets via random forest (continued)



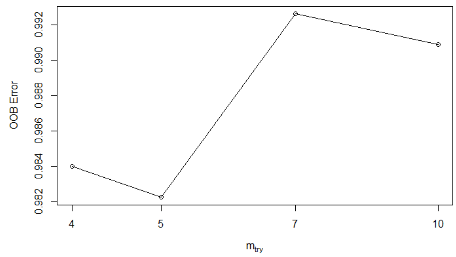
September 2020 – 5 Variables (1.007)



February 2020 – 10 Variables (1.014)

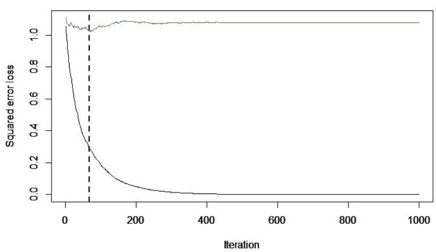


January 2020 – 5 Variables (1.018)

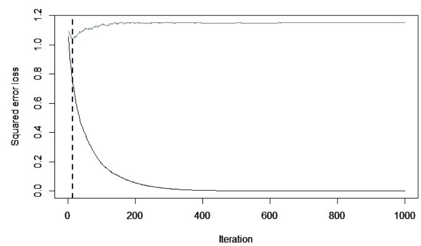


February 2020 – 10 Variables (1.014)

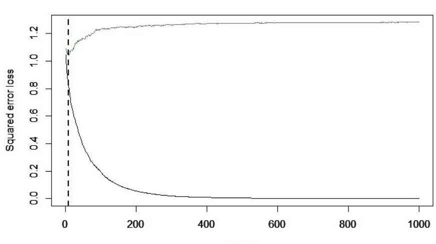
ANNEX E. Optimal number of trees via gradient boosted trees



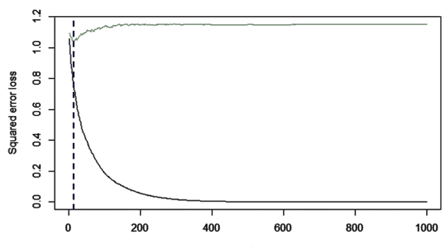
January 2020 – 67 Iterations



February 2020 – 15 Iterations

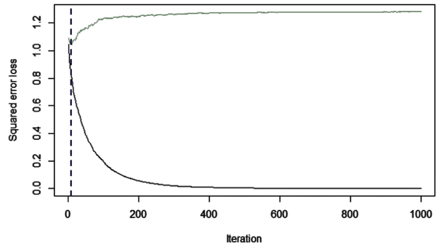


March 2020 – 8 Iterations

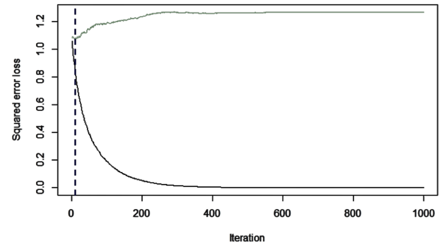


April 2020 – 10 Iterations

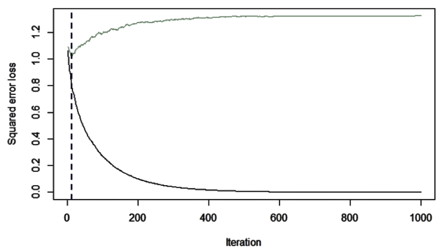
ANNEX E. Optimal number of trees via gradient boosted trees (continued)



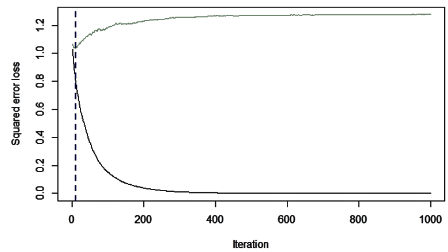
May 2020 – 2 Iterations



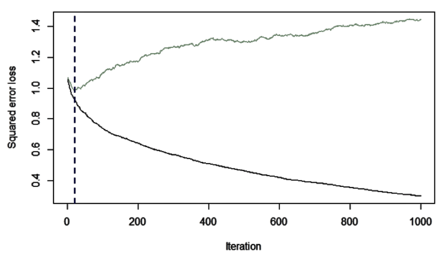
June 2020 – 4 Iterations



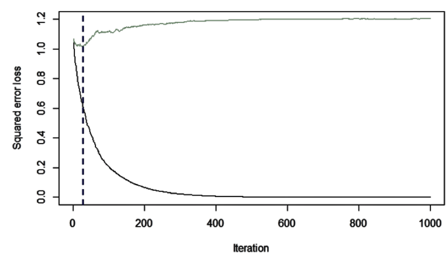
July 2020 – 13 Iterations



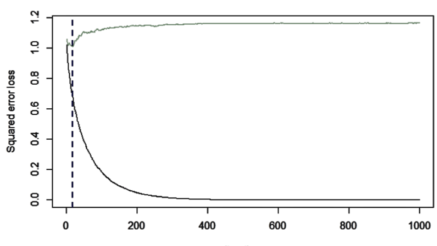
August 2020 – 10 Iterations



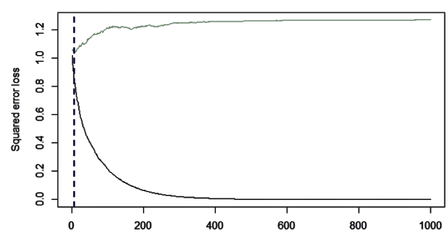
September 2020 – 22 Iterations



October 2020 – 28 Iterations



November 2020 – 17 Iterations



December 2020 – 7 Iterations

ANNEX F. Variable coefficients via LASSO (January to December 2020)

No.	Variable	1/2020	2/2020	3/2020	4/2020	5/2020	6/2020	7/2020	8/2020	9/2020	10/2020	11/2020	12/2020
-	Intercept	0.016	0.015	0.010	0.020	0.020	0.021	0.022	0.017	0.017	0.013	0.016	0.020
1	M3 Growth (T-1)	-	-	-	-	-	-	-	-	-	-	-	-
2	BSP Liabilities on NG	-0.015	-0.015	-0.017	-0.014	-0.017	-0.017	-0.016	-0.018	-0.018	-0.018	-0.017	-0.015
3	BSP Claims on Other Sectors	0.235	0.235	0.257	0.226	0.265	0.265	0.255	0.284	0.291	0.294	0.284	0.254
4	Foreign Portfolio Investment (In)	-0.003	-0.004	-0.042	-0.003	-0.050	-0.047	-0.018	-0.064	-0.070	-0.063	-0.026	-
5	Foreign Portfolio Investment (Out)	-	-	-	-	-	-	-	-	-	-	-	-
6	Available Reserves	-	-	-	-	-	-	-	-	-	-	-	-
7	Reserve Money	-	-	-	-	-	-	-	-	-	-	-	-
8	CBOE Volatility Index	-	-	-	-	-	-	-	-	-	-	-	-
9	Credit Default Swap	-	-	-	-	-	-	-	-	-	-	-	-
10	LIBOR	0.111	0.114	0.203	0.013	0.116	0.115	0.052	0.182	0.219	0.220	0.184	0.043
11	SIBOR	-	-	-	-	-	-	-	-	-0.013	-	-	-
12	PHIREF	-	-	-	-	-	-	-	-	-	-	-	-
13	Philippine Government Bond Rate	-	-	-	-	-	-	-	-	-	-	-	-
14	BSP Discount Rate	-	-	0.039	-	0.023	0.020	-	0.086	0.108	0.102	0.064	-
15	Bank Savings Rate	-0.103	-0.110	-0.396	-	-	-	-	-0.178	-0.243	-0.247	-0.157	-
16	Bank Prime Rate	-	-	-	-	-	-	-	-	-	-	-	-
17	Money Market Rate (Prom. Note)	-	-	-	-	-	-	-	-	-	-	-	-
18	Treasury Bill Rate	-	-	-	-	-	-	-	-	-	-	-	-
19	Interbank Call Rate	-	-	-	-	-0.062	-0.061	-0.036	-0.050	-0.049	-0.040	-0.038	-0.024
20	PHP per USD (FOREX)	0.124	0.124	0.149	0.106	0.134	0.133	0.121	0.155	0.160	0.158	0.147	0.110
21	WMOR	-	-	-	-0.052	-0.844	-0.817	-0.645	-0.935	-1.030	-1.019	-0.920	-0.557

ANNEX G. Variable coefficients via ENET (January to December 2020)

No.	Variable	1/2020	2/2020	3/2020	4/2020	5/2020	6/2020	7/2020	8/2020	9/2020	10/2020	11/2020	12/2020
-	Intercept	0.016	0.015	0.007	0.019	0.019	0.020	0.020	0.017	0.017	0.014	0.014	0.019
1	M3 Growth (T-1)	-	-	-	-	-	-	-	-	-	-	-	-
2	BSP Liabilities on NG	-0.014	-0.014	-0.017	-0.014	-0.016	-0.016	-0.016	-0.017	-0.017	-0.017	-0.017	-0.015
3	BSP Claims on Other Sectors	0.216	0.216	0.268	0.218	0.257	0.257	0.257	0.267	0.274	0.277	0.283	0.246
4	Foreign Portfolio Investment (In)	-0.010	-0.010	-0.086	-0.026	-0.068	-0.065	-0.053	-0.067	-0.072	-0.065	-0.056	-0.001
5	Foreign Portfolio Investment (Out)	-	-	-	-	-	-	-	-	-	-	-	-
6	Available Reserves	-	-	-	-	-	-	-	-	-	-	-	-
7	Reserve Money	-	-	-	-	-	-	-	-	-	-	-	-
8	CBOE Volatility Index	-	-	-	-	-	-	-	-	-	-	-	-
9	Credit Default Swap	-	-	-	-	-	-	-	-	-	-	-	-
10	LIBOR	0.097	0.100	0.301	0.054	0.142	0.141	0.127	0.161	0.201	0.199	0.249	0.074
11	SIBOR	-	-	-	-	-	-	-	-	-0.033	-0.007	-0.053	-
12	PHIREF	-	-	-	-	-	-	-	-	-	-	-	-
13	Philippine Government Bond Rate	-	-	-	-	-	-	-	-	-	-	-	-
14	BSP Discount Rate	-	-	0.142	-	0.053	0.050	0.041	0.074	0.094	0.089	0.115	-
15	Bank Savings Rate	-0.080	-0.087	-0.617	-	-0.079	-0.082	-0.065	-0.164	-0.229	-0.231	-0.309	-
16	Bank Prime Rate	-	-	-	-	-	-	-	-	-	-	-	-
17	Money Market Rate (Prom. Note)	-	-	-	-	-	-	-	-	-	-	-	-
18	Treasury Bill Rate	-	-	-	-	-	-	-	-	-	-	-	-
19	Interbank Call Rate	-	-	-0.015	-0.012	-0.0823	-0.081	-0.075	-0.070	-0.069	-0.061	-0.061	-0.056
20	PHP per USD (FOREX)	0.111	0.119	0.177	0.115	0.142	0.141	0.139	0.151	0.156	0.153	0.162	0.119
21	WMOR	-	-	-0.285	-0.151	-0.877	-0.851	-0.795	-0.847	-0.936	-0.929	-1.012	-0.590

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Does bank competition affect bank risk-taking differently?

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This paper examines the presence of two competing views—"competition-fragility" and "competition-stability"—in analyzing the impact of competition on bank stability. The approach is to first construct measures of bank competition from a unique dataset of balance sheet and income statements for 542 banks operating in the Philippines from March 2010 to December 2020. The paper then estimates the impact of these competition measures on solvency risk or the risk of being unable to absorb losses with the available capital across universal/commercial banks (U/KBs), thrift banks (TBs) and rural/cooperative banks (R/CBs) industries.

Using panel quantile regression, the results reveal that, at the industry level, bank competition reduces solvency risk and that it enhances bank stability. Looking at the risk distribution, the study shows the presence of the competition-fragility and competition-stability hypotheses holding simultaneously for U/KBs suggesting that the effect of competition depends crucially on the underlying individual bank risk. Importantly, the results highlight that the relationship between competition and bank risk is sensitive to other bank-specific characteristics and macro-financial factors related to extent of diversification strategy, cost-to-income ratio, deposit growth, capitalization, changes in the physical banking networks, and growth of real Gross Domestic Product.

JEL classification: D4, G21, L1
Keywords: Bank competition, cost efficiency, bank solvency risk, COVID-19 pandemic

1. Introduction

Since the 2000s, important reforms have greatly reshaped the structure of the global financial system. Some banks have become big and interconnected while some have become generally risk takers. Studies suggest that financial sector reforms promote bank competition in most advanced and emerging market economies. As such, discussions on bank competition have intensified in recent past years particularly in constructing different measures of bank competition and in explaining factors driving the monetary authorities' policy mandates. However, some studies also find that bank competition in many emerging countries have

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declined despite the implementation of financial sector reforms. The impact of the COVID-19 pandemic on bank operations has contributed to the decline in bank competition. These findings are particularly evident in diverse banking industries where smaller banks also offer great services.

Crucially, the array of empirical studies has highlighted the influence of bank competition on financial stability, credit growth, and the regulatory drivers of competition in banking markets [De-Ramon and Straughan 2020]. Many of these recent empirical studies use a measure of bank competition that is based on either market concentration in asset markets or market power and its impact on indicators of bank stability such as strength of bank capital, quality of loans, profitability such as net income, return on assets, or return on equity. Recent discussions on bank competition have focused on the implications of the entry of digital banks and the proliferation of big technologies which have been increasingly encroaching in the financial services industry. For instance, in the Philippines, the Bangko Sentral ng Pilipinas or BSP (the Philippine central bank) has already approved six digital bank license applications. The entry of digital banks is expected to enhance bank competition and reap its benefits in terms of lower interest rates for loan products, improved banking services, and greater innovation in banking products.

This study follows more closely the role of bank competition on banking stability. There is currently a debate in the banking literature regarding the effect of competition on the stability of banks. In the traditional "competition-fragility" view, Jimenez et al. [2013] explain that increased competition among banks could threaten the solvency of individual banks and endanger the stability of the banking system. This could erode the franchise value of a bank, that is the ongoing concern or market value of a bank beyond its book value. This in turn could encourage a bank to pursue riskier policies to maintain its profits. These riskier policies are expected to increase the probability of higher nonperforming loan ratios and lead to bank failures.

By contrast, the "competition-stability" view posits that a less intensive competition could result in higher interest rates on loans, which may in turn raise the credit risk of borrowers due to moral hazard issues. The increased default risk could potentially lead to more problem loans and greater bank instability. However, such a situation allows a bank to protect its franchise value by pursuing safer policies that contribute to the stability of individual banks and the entire banking system [Boyd and De Nicolo 2005].

Empirical studies observe that competition in the banking industry can improve allocative, productive, and dynamic efficiencies through innovation, with the ultimate benefit being stronger economic growth. These benefits compel central banks to provide a level playing field for banks by ensuring that policies are fair to both big and small banks. However, it is also the responsibility of central banks to ensure that individual banks and the banking system are stable.

This paper examines the relationship between bank competition and bank risk-taking following the global financial crisis using a single country setting. In this paper, I add to the literature on bank competition and stability by first constructing measures of market power to determine the extent of bank competition across the three banking groups in the Philippines using quarterly bank-level balance sheets and income statements of 542 Philippine banks from March 2010 to December 2020. To the best of my knowledge, this is the first time that an analysis on bank competition has used the source bank reports in the Philippines. The BSP requires banks to report their quarterly balance sheets and income statements to provide the BSP with a comprehensive view of the financial strength and soundness as well as potential financial risks and transmission channels emanating from counterparties of individual Philippine banks. The Philippine banking system is dominated by three banking groups—the universal and commercial bank (U/KB) industry is composed of 41 banks, the thrift bank (TB) industry of 55 banks and the rural and cooperative bank (R/CB) industry of 441 banks.

Four unique databases are constructed from March 2010 to December 2020 to help address the main objective of the study:

First, a quarterly database of Income Statements to determine details of profit and loss, including return on assets, return on equity of individual banks, cost-to-income ratio and extent of bank diversification.

Second, a quarterly database of bank-specific characteristics from the Financial Reporting Package such as asset size, loan portfolio, loan loss reserves, nonperforming loan (NPL) ratio, NPL coverage ratio, deposits, and investments.

Third, a quarterly database containing information on the BSP's overnight policy rate, peso-dollar rate, real Gross Domestic Product (GDP) growth, and inflation based on Consumer Price Index.

Finally, a quarterly database on changes in the physical banking networks such as the number of mergers, consolidations, acquisitions, new banks, closure of banks and number of banks with payment channels such as InstaPay and PESONet.

Then I estimate the impact of the different measures of bank competition on bank risk-taking activities focusing on the differences in responses among U/KBs, TBs and R/CBs using panel quantile regression. Following De-Ramon et al. [2020], I compile the Z-score to represent stand-alone bank risk for all the banking groups. Measures of bank competition are then regressed on the Z-scores to estimate the impact of these measures of competition on bank risk. The regression equation also underscores the importance of specific bank features such as the extent of diversification measures, asset quality, capital and liquidity ratios of individual banks, macro-financial indicators such as consumer price inflation, real GDP growth, policy interest rates as well changes in physical banking network brought about by merger, consolidation, entry of new banks, closure of banks and the rising digitalization in payment channels.

The results may be summarized as follows:

First, competition reduces bank risk taking activities at the industry level.

Second, looking at the risk distribution, the competition-fragility and competition-stability hypotheses are holding simultaneously for U/KB and R/CB industries. This finding implies that the impact of competition on bank risk depends crucially on the underlying individual bank risk.

Third, the relationship between competition and bank risk is sensitive to other bank-specific characteristics and macro-financial factors related to extent of diversification strategy, changes in the physical banking networks, funding source, capitalization, and growth of real GDP.

The rest of this paper is organized as follows. Section 2 briefly presents the empirical findings of the studies on bank competition and stability. Section 3 identifies the main factors driving the major changes in the Philippine financial system during the past decade. Section 4 discusses databases used and empirical methodology, while Section 5 highlights the main findings of the paper. Section 6 concludes.

2. Survey of empirical findings

Research on bank competition has received considerable attention in the literature in recent years. Studies focus on evaluating the influence of bank competition on bank risk and stability (e.g., Schaeck and Cihák [2014]; Dutta and Saha [2021]) and credit growth (e.g., Cetorelli and Strahan [2006]). Some studies delve on developing a better understanding of the underlying regulatory drivers of competition in banking markets (e.g., Casu and Girardone [2006]). This area includes research on how regulatory, structural and technological changes in banking markets affect competition and economic outcomes [De-Ramon and Straughan 2020]. This study follows more closely the strand of research on bank competition and its impact on bank risk and stability.

There is currently a debate in the banking literature regarding the effect of competition on the stability of banks. As mentioned earlier, Jimenez et al. [2013] explain that the traditional "competition-fragility" view sees increased competition among banks as threat to the solvency of individual banks and a hindrance to the stability of the banking system at a broader level. Such a competition could erode the franchise value of a bank—the ongoing concern or market value of a bank beyond its book value. This in turn encourages a bank to pursue riskier policies to maintain its profits. Examples of riskier policies are taking on more credit risk and lower quality in the loan portfolio, reducing capital levels, or both. These riskier policies are expected to increase the probability of higher nonperforming loan ratios and possibly more bank failures that could eventually lead to greater fragility and financial instability. Therefore, less concentrated banking systems are more prone to experience crises [Berger et al. 2009].

Boyd and De Nicolo [2005] initiate a contrary "competition-stability" view. Basically, the competition-stability hypothesis argues that more competitive banking systems result in financial stability. This view is mainly built on the "risk shifting paradigm" which states that increase in market power and the resulting higher loan rates have the potential to negatively affect the stability of banks due to moral hazard and adverse selection problems on the part of borrowers. This could potentially lead to more problem loans and greater bank instability. Under such a scenario, Boyd and De Nicolo [2005] argue that banks would take immediate actions to protect their franchise value by pursuing safer policies that contribute to the stability of the entire banking system.

Meanwhile, Bahadur and Sharma [2016] highlight that another evidence of the competition-stability view is related to the impact of "too-big-to-fail" policies in concentrated banking systems on risk taking incentives of banks. They explain that the presence of bigger banks constitutes a potential threat to the safety and soundness of the financial system because a failure of a large bank could potentially expose the financial system to systemic risk. Governments signal that they are willing to guarantee the survival of these banks to avoid a system-wide crisis. Such an implicit guarantee of government bailout provides an incentive for big banks to pursue excessive risk taking (Mishkin [1999]; Beck et al. [2006]). However, concerns about contagion and financial crisis resulting from the failure of these large banks make regulators even more vigilant in monitoring their performance and risk management practices so as not to let them fail in the event of solvency problems. Under such a scenario, banks maintain safe and sound policies for stability.

Martinez-Miera and Repullo [2010] show that a nonlinear relationship theoretically exists between bank competition and risk-taking in the loan market. They extend the Boyd and De Nicolo's [2005] model by allowing for imperfect correlation across individual firms' default probabilities. Their model also identifies a risk-shifting effect that accounts for fewer firm defaults when loan rates decrease in a more competitive banking environment. However, since imperfect correlation between firms is assumed, there is also a "margin" effect that reduces the interest payments from performing loans and bank revenues. These two effects work in opposite directions, so that the net effect on bank risk-taking and financial stability becomes unclear. In their model, the risk-shifting effect is shown to be dominated by the margin effect in competitive banking environments, such that increased competition amplifies risk of bank failure. In a more concentrated banking market, the model suggests that the risk-shifting effect dominates and thus bank failure risk declines with more intense competition.

The empirical studies point to mixed findings. Using a cross-country panel of banks, Beck et al. [2013] show that competition has a strong positive relationship with bank fragility for distressed banks. Schaeck and Cihák [2014] find evidence consistent with the competition-stability hypothesis, but this relationship is less (more) pronounced for European banks closer to (farther from) insolvency.

Using data on nonperforming loans for Euro area banks, Karadima and Louri [2019] observe that profit margins exert a positive impact on the change in nonperforming loans for firms in the medium and upper quantiles of their distribution, supporting the competition-stability view. Liu and Wilson [2013] reveal that Japanese banks farther from insolvency take on more risk in response to more intense competition, consistent with the competition-fragility hypothesis, while those closer to insolvency reduce risk, consistent with the competition-stability hypothesis. Jimenez et al. [2013] test the competing theories of bank competition and bank risk using data from the Spanish banking system. After controlling for macroeconomic conditions and bank characteristics, they find support for this nonlinear relationship using standard measures of market concentration in both the loan and deposit markets. When direct measures of market power are used, the empirical results are more supportive of the franchise value hypothesis, but only in the loan market. Drawn from 16 developing economies over the period 2000–2012, Kabir and Worthington [2017] find the competition–fragility hypothesis supported in both Islamic and conventional banks. They measure the lack of competition using the Lerner Index, and stability using Z-score, nonperforming loan ratio, and market-based measures, including Merton's distance to default. The findings also show the magnitude of the market power effect on stability to be greater for conventional banks than Islamic banks. Meanwhile, Bahadur and Sharma [2016] show a positive relationship between greater banking competition and financial stability in Nepal, supporting the "competition-stability" view. Competition in banking sector is found to result in decrease in credit risk and contribute to financial stability. In their study, the Herfindahl-Hirschman Index (HHI) and n-bank concentration ratios are used as measure of competition while Z-index and nonperforming loans ratio are used as proxies of financial stability. Using data from the UK and multiple measures of bank competition and risk, De-Ramon et al. [2020] document relationships similar to those reported in Liu and Wilson [2013], further supporting the idea that the link between bank competition and risk may vary depending on the underlying solvency risk of the firm.

Recently, Jaume et al. [2022] examined the relationship between bank competition and bank risk-taking not through the asset market but through the retail deposit market. Using Mexican banks and constructing Lerner Index in deposits, they show that banks that compete effectively in the deposit market through various nonprice strategies such as differences in services and advertising achieve more market power that ultimately leads to less risk-taking. In the paper, Jaume et al. [2022] pushed for such an approach called "vertical differentiation." It occurs when customers rank products from the best to the worst using an objective measurement such as quality.[1]

[1] By contrast, Jaume et al. [2022] explain that horizontal differentiation occurs when depositors choose between products based on personal preferences. In the paper, they apply the concepts of differentiation to depositors and differentiation among banks.

While empirical findings on the relationship between bank competition, bank efficiency, and bank risk-taking remain inconclusive, studies on how to measure bank competition using market concentration and market power continue to evolve. There are several approaches to measuring bank competition. These include decomposition of interest spreads, measures of bank concentration under the so-called "structure-conduct-performance" paradigm, regulatory indicators that measure the contestability of the banking sector, and direct measures of bank pricing behavior or market power based on the "new empirical industrial organization" literature.

An approach used by some studies to analyze bank competition is based on interest spread decomposition. But spreads are outcome measures of efficiency, and in addition to the competition environment, cross-country differences in spreads can reflect macroeconomic performance, the extent of taxation of financial intermediation, the quality of the contractual and judicial environment, and bank-specific factors such as scale and risk preferences. So, these effects need to be controlled for in the analysis of competition.

The "structure-conduct-performance" paradigm assumes that there is a stable, causal relationship between the structure of the banking industry, firm conduct, and performance. It suggests that fewer and larger firms are more likely to engage in anti-competitive behavior. In this framework, competition is negatively related to measures of concentration, such as the share of assets held by the top three or five largest banks.

According to this approach, banking concentration can be approximated by the concentration ratio—the share of assets held by the largest banks (typically three or five) in a given economy—or the HHI, the sum of the squared market share of each bank in the system. The HHI accounts for the market shares of all banks in the system and assigns a larger weight to the biggest banks. Instead, concentration ratios completely ignore the smaller banks in the system.

However, in many empirical studies, findings suggest that concentration measures are generally not good predictors of competition. The predictive accuracy of concentration measures on banking competition is challenged by the concept of market contestability. The behavior of banks in contestable markets is determined by threat of entry and exit. Banks are pressured to behave competitively in an industry with low entry restrictions on new banks and easy exit conditions for unprofitable institutions—even if the market is concentrated.

Majority of recent research on the subject has focused on direct measures of bank pricing behavior or market power based on the "new empirical industrial organization" (NEIO) literature. The aim of the NEIO measures is to assess the level of competition directly from the firms' conduct. These include the Panzar-Rosse-H-statistic, the Lerner Index, and the Boone Indicator. The H-statistic captures the elasticity of bank interest revenues to input prices. Another frequently used measure is based on markups in banking. The Lerner Index is defined as the difference between output prices and marginal costs (relative to prices). Higher values of the Lerner Index signal less bank competition. Finally, the Boone Indicator is a recent addition to this group of indices. It measures the effect of efficiency on bank performance in terms of profits. It is calculated as the elasticity of profits to marginal costs. The main assumption behind the Boone Indicator is that more efficient banks achieve higher profits. The more negative the Boone Indicator is, the higher the level of competition is in the market because the effect of reallocation is stronger.

Studies use an array of measures to indicate bank competition. This study follows De-Ramon and Straughan [2020] who both use four indicators that provide different perspectives on bank competition. The intention is to help understand the nature and extent of competition in a single country setting. De-Ramon and Straughan [2020] compare the measures of market power such as the Panzar-Rosse-H-statistic, the Lerner Index, and the Boone Indicator and market concentration at the industry level (the HHI) for the UK from 1989 to 2013. These comparisons allow them to identify periods when the signals from each indicator are yielding similar or contradictory inferences.

This paper is related to research on measures of bank competition and their impact on individual bank risk-taking using a single country setting. Bank competition in this study is defined as industry-wide competition. This research intends to shed light on the relationship between bank competition and bank solvency risk from the perspective of an emerging market economy, the Philippines. The focus on a single country in examining the relationship between various measures of competition and bank risk is expected to help ensure consistency in measures of the dependent and independent variables and to avoid having to control for potentially confounding factors that can influence the link [Beck et al. 2013]. The study also attempts to understand how bank efficiency [Dutta and Saha 2021] and central bank reforms and policies affecting competition are transmitted across banks [De-Ramon et al. 2020]. Indeed, the empirical evidence on this topic remains due.

There are broad similarities with De-Ramon and Straughan [2020], Dutta and Saha [2021], and Liu and Wilson [2013]. The study looks at the universe of 542 banks as of December 2020 located in the Philippines to examine measures of bank competition and how these influence bank risk using the Financial Reporting Package from March 2010 to December 2020. The study adds another dimension by providing initial insights on the impact of bank efficiency, changes in the physical banking network, and the COVID-19 pandemic on bank solvency risk.

The study shares the estimation approach used in De-Ramon and Straughan [2020]. The disaggregated data from the Financial Reporting Package (FRP) allows the study to employ a panel quantile regression. Moreover, due to the diverse nature of bank structures, the estimation approach is applied across the three banking groups—U/KB, TB, and R/CB groups.

3. "Forces of change" in the Philippine banking system during the past decade

The BSP continues to leverage on the structural changes, including the financial sector reforms it had started even before the global financial crisis, to promote a sound, stable and globally competitive financial system anchored on prudent risk management [Bayangos and Moreno 2021]. Major components of these reforms include a set of reforms in the foreign exchange regulatory framework starting in 2007, the formal shift in the monetary operations of the BSP to an interest rate corridor (IRC) system in June 2016, and the adoption of strategic financial sector reforms.[2] Eleven waves of foreign exchange liberalization reforms have been introduced since 2007. In November 2014, Republic Act (RA) No. 10641 was approved, providing the legal basis for BSP to regulate and supervise the entry and operation of foreign banks (FBs) in the country.

Moreover, RA No. 10574 was implemented to allow infusion of foreign equity in rural banks' capital. As of end-December 2021, there were 29 foreign banks that were authorized by the BSP to operate in the Philippines. Since the implementation of RA No. 10641 dated May 1994, the BSP has approved 12 FB applications (ten branches and 2 subsidiaries).[3] There are also four FBs which entered in the Philippines in the form of representative office. Most of the FBs and subsidiaries originated from the Asia-Pacific region (Taiwan and South Korea) or 73.3 percent of the total number of FBs.

In April 2020, the BSP eased the asset cover requirement on banks with expanded/foreign currency deposit units (E/FCDU) to provide these units with greater flexibility to manage their foreign currency exposures by allowing E/FCDU to offset any deficiency in the asset cover incurred on one or more days of the week with the excess cover that they may hold on other days of the same week and the immediately succeeding week.[4]

In 2020, the BSP approved the Digital Banking License Framework under the BSP Circular No. 1105, series of 2020 to support the expansion and use of digital financial services in the country. The framework forms part of the BSP's three-year digital payments transformation roadmap which aims to achieve a shift of at least 50 percent retail payment transactions to digital and 70 percent of adult Filipinos having and using a transaction account by 2023. A digital bank is a bank offering financial products and services that are processed end-to-end through a

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[2] The IRC is a system for guiding short-term market rates towards the BSP policy interest rate which is the overnight reverse repurchase (RRP) rate. The primary aim of the adoption of the IRC is to improve the transmission of monetary policy.

[3] In December 2019, the BSP approved an application to establish a rural bank with a purely digital platform and majority owned by a foreign non-bank financial institution (NBFI).

[4] The previous regulation required banks to maintain a 100 percent asset cover for their foreign currency liabilities in the E/FCDUs at all times to ensure they have sufficient foreign currency-denominated assets to service withdrawals of deposits and meet payments denominated in foreign currency. The BSP also approved the alignment of the licensing process for applications for E/FCDU authority with the risk-based licensing framework being implemented by the BSP.

digital platform and/or electronic channels with no physical branch/sub-branch or branch-lite unit offering financial products and services. The end-to-end processing of products and services distinguishes the operating model of digital banks vis-à-vis traditional banks that are in the process of digitally transforming their operations to improve efficiency and maintain competitiveness. As of December 2021, the BSP had granted six digital banking licenses to Overseas Filipino Bank, Tonik Digital Bank, UNObank, Union Digital Bank, GOtyme, and Maya Bank. The entry of digital banks is expected to enhance the competitive landscape in the Philippine financial sector by offering consumers with improved electronic banking services and customized financial solutions.[5]

The BSP also pushed for a broad set of strategic reforms in the financial system to better promote financial stability, preserve the institutional safety and soundness of individual banks, and protect the public. More capital-based measures and disclosure standards have been implemented since 2008 due in part to the implementation of the Basel III requirements. The BSP adopted the Basel III capital rules for U/KBs and their subsidiary banks on January 1, 2014. U/KBs are required to comply with the 10 percent total capital adequacy ratio (CAR),[6] the leverage ratio of 5 percent in July 2018 and the framework on the countercyclical capital buffer in December 2018. However, simpler standards are applied to TBs and R/CBs that are not subsidiaries of commercial banks. Finally, the BSP adopted the international framework for dealing with domestic systemically important banks (D-SIBs),[7] requiring staggered implementation of higher capital buffers starting in January 2017, and enhanced the framework in 2019. A D-SIB is required to maintain higher capital buffers to meet regulatory capital requirements that include a Higher Loss Absorbency (HLA) requirement.[8] The BSP classifies banks depending on the extent of their systemic importance using pre-defined indicators for market size, interconnectedness, substitutability and market reliance as a financial market infrastructure as well as complexity. Market size is based on a bank's total resources relative to the banking system.[9] As of December 2021, bank capital ratios were stable despite a pick-up in risk-weight assets and were well above the minimum thresholds set by BSP (10 percent) and the Bank for International Settlements (8 percent).

[5] In August 2021, the Monetary Board of the BSP approved the closure of application window for new digital banks, including converting banks, starting August 31, 2021 to allow the BSP to monitor the performance and impact of digital banks on the banking system and their contribution to the financial inclusion agenda.

[6] The BSP also adopted the 6.0 percent common equity Tier 1 (CET1), 7.5 percent Tier 1 and the capital conservation buffer (CCB) of 2.5 percent.

[7] D-SIBs are characterized as banks whose distress or disorderly failure would cause significant disruptions to the wider financial system and economy.

[8] This serves to strengthen a D-SIB's capacity to absorb losses thereby reducing its probability of distress or failure during periods of stress. D-SIBs must also meet higher supervisory expectations. In the annual submission of their internal capital adequacy assessment process (ICAAP) document, D-SIBs must have in place acceptable recovery plans to be carried out in the event of breaches in capital requirements. These requirements, in turn, will contribute to a safer and more resilient financial system.

[9] The D-SIBs framework is in line with the initiatives pursued under the Basel III reform agenda.

The BSP also introduced liquidity standards. The Liquidity Coverage Ratio (LCR) requires banks to maintain highly liquidity assets to ensure their ongoing ability to meet short-term obligations. As of end-December 2020, the banking system's LCR was way above the BSP's regulatory threshold of 100 percent [Bayangos and Moreno 2021]. Another liquidity standard is the Net Stable Funding Ratio (NSFR) that aims to promote resilience over a longer time horizon by creating incentives for banks to fund their activities with more stable sources of funding on an ongoing basis. The general objective is to support financial stability by ensuring that funding shocks do not significantly increase the probability of distress for individual banks, a potential source of systemic risk. In January 2019, stand-alone TBs, R/CBs and non-banks with quasi-banking functions (NBQBs) were required to adopt the minimum liquidity ratio (MLR). As a result, banks opted to increase their issuances of fixed-income securities, including bonds and long-term negotiable certificates of time deposits (LTNCTDs) to better manage their funding costs. The BSP also laid down the proactive financial surveillance and reporting towards a dynamic banking system such as in supervision of conglomerates, cross-border risks and vulnerabilities tools as well as enhanced reports.

Financial technology (fintech) has also developed rapidly in the Philippines in recent years. Technologies such as Artificial intelligence (AI), big data, cloud storage and blockchain have been driving the digital transformation of financial institutions. Majority of fintech players in the Philippines are in the business of payments and lending, while the rest are into e-wallets, remittance services, blockchain/cryptocurrencies, e-commerce, insurance, and even regulatory technology services, based on the Philippines Fintech Report 2020. The same report highlights that fintech companies are heavily engaged in lending and payments, electronic wallets and remittance services.

In many studies, there are claims that fintech has improved lending services to businesses as well as the self-employed. Empowered by digital technologies, financial institutions can digitalize the whole procedures of credit approval and risk control, which enables them to provide services more quickly, better target risks, and serve more people. There are also observations that fintech has fundamentally changed banking sector competition while significantly improving the services and efficiency of operations. More and more financial transactions are intertwined with customers' consumption, work, and life. With massive data on customers' behavior, platform companies can extrapolate the financial needs and financial situations of their customers. The rapid development of innovative online financial products has also accelerated diversion of bank deposits. In response to rapid changes, many big banks are investing heavily in fintech and its application. Mobile Internet, biometric identification, big data, artificial intelligence, and many other technologies can help banks expand service channels, reduce human labor, strengthen whole-process risk control, and lower compliance cost.

Fintech has also supported the Philippines' response to the COVID-19 pandemic. Following the demand for contactless financial services after the outbreak of the pandemic, fintech has enabled the shift from physical meeting to virtual communication, which has softened the negative impact of COVID-19 on businesses, as financial consumers are still able to enjoy undisrupted financial services. Banks have been more open to exploring the potentials of innovative solutions following the onset of the pandemic.[10] Some banks have embraced digital transformation as a strategic move to give them the edge over their competitors. In the case of U/KBs, many of them have already adopted programs on digitalization even prior to the pandemic. Some have carefully planned their digital transformation while other institutions simply put the idea on hold.

As shown in Table 1 below, U/KBs and subsidiary banks are ahead in the digital transformation process compared to stand-alone TBs and R/CBs. With the sudden shift in priorities following the outbreak of the pandemic, many banks plan to fast-track the adoption of newer technologies and re-assess the timeline of their digital transformation journey. For some TBs and R/CBs, operational changes brought about by the "new normal" have made them realize the importance of digital transformation and are incorporating the same in their business plans moving forward. In the short-term, banks intend to collaborate with fintech companies and participate in payment platforms such as InstaPay and PESONet.

TABLE 1. Current phase in digital transformation

Particulars	U/KBs*	Stand-alone TBs	Stand-alone R/CBs
Right on schedule	53%	20%	28%
Behind schedule	28%	30%	39%
Has not started yet but are planning their approach	19%	50%	33%

*Including subsidiary banks
Source: Based on BSP-supervised financial institutions' (BSFI) survey responses in 2020. Financial Supervision Sector-TRISD.

Since 2019, the BSP has been seeing a growing interest from fintechs that are looking to provide enhancements to the domestic payments' ecosystem, with an increasing number of applicants aspiring to obtain authority to operate as electronic money issuers and virtual asset service providers. Newcomers and established financial institutions alike have started considering the acquisition of a digital banking license following the recently established framework for digital banks. For instance, GCash, the most widely used fintech application, has partnered with a Malaysian foreign bank, CIMB. Another is Union Bank of the Philippines (UBP) which is pushing for more financial inclusion initiatives and the adoption

[10] BSP Financial Supervision Sector-TRISD Briefing Notes, September 2021.

of innovative services through its platforms in e-commerce, lending, payments, and recently in open finance. At the forefront of these innovative services is UBX, the fintech venture studio and fund spun out of the UBP. The UBX's i2i platform aims to grow its network of digitized rural banks to help achieve greater financial inclusion, especially among rural Filipinos. Launched in 2019, i2i is a Distributor Ledger Technology (DLT)-based platform that links rural banks to the country's mainstream financial network. To date, the network has 106 bank members, representing TBs and R/CBs, making up a total of 2,000 branches nationwide.[11] Moreover, UBX launched its open finance platform, Xpanse. Its main goal is to enable banks, fintechs and startups to build new financial solutions through APIs and customer-controlled data sharing across member institutions in the Philippines. Given a large number of smartphone users, the Philippines remains a key strategic area for fintechs to tap. Financial innovators can potentially thrive in the expanding market for digital finance services and secure a foothold in the Philippine financial system.

However, the ease and speed with which these companies could scale up their activities and expand into financial services may create significant concentration dynamics. This could eventually affect the adequate functioning of the financial system and may endanger market contestability and eventually increase operational vulnerabilities due to the excessive reliance of market players, including banks, on the services provided by big techs [Crisanto et al. 2021].

Another "force of change" has been the increasing digitalization in payment services. In November 2017, the BSP launched the Philippine Electronic Fund Transfer (EFT) System and Operations Network Automated Clearing House (PESONet), a batch EFT service which replaced the paper-based check system. Unlike a check, the PESONet allows the receipt of funds on the same banking day the sender initiates the payment within a certain cut-off time. In January 2022, the BSP and the Philippine Payments Management, Inc. (PPMI) launched the PESONet's Multiple Batch Settlement (MBS) facility to increase the frequency of PESONet settlements from once to twice a day. Settlements are done at 10 AM and 4 PM on weekdays.

Meanwhile, InstaPay, a real-time EFT facility that allows fund transfers at near-real time 24/7, went live in April 2018. Being a fast payment system, InstaPay addresses low value and urgent payment requirements. InstaPay caps each transaction at ₱50,000 (approximately USD 1,000). Hence, InstaPay enables the performance of person-to-person payments, domestic remittances, e-commerce transactions, bills payment and other immediate low value payments.

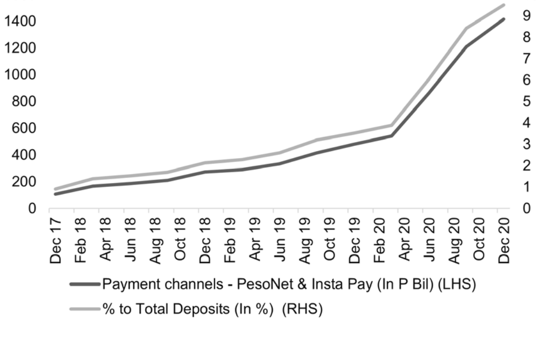
By using PESONet and InstaPay rails, the end-users can transfer funds from their own account to any transaction account of a BSP-supervised financial institution (BSFI) using any mobile device. This means that an end-user, which may be an

[11] Based on the Union Bank's Media Release, "Union Bank continues digitizing more rural banks", November 30, 2020.

individual or an institution, need only to maintain a single bank or electronic money account to be able to conveniently transact with other individuals or institutions whose accounts are maintained with other payment service providers. With such added efficiency and convenience, these interoperable digital payment solutions urge more end-users to use digital channels for making payments. This also encourages industry players to develop more innovative digital payment streams that can function through these rails, thereby promoting industry collaboration and healthy competition.

Since the launch of PESONet and Instapay, digital payments have exhibited sustained uptrend with broader adoption of digital payments following the outbreak of COVID-19 pandemic in March 2020. As of end-December 2020, the combined value of PESONet and InstaPay fund transfers reached ₱1.4 trillion. This is equivalent to 9.5 percent of the banking sector's total deposits. In terms of YoY growth, the combined value of InstaPay and PESONet grew by an annual average of 124.1 percent from December 2017 to December 2020 (Figure 1). These developments indicate the consumers' growing sentiment towards the use of digital payments due to social mobility restrictions following the outbreak of the pandemic. The number of participating institutions also rose to 82 BSFIs participating in PESONet and 54 in InstaPay as of 30 June 2021. TBs and R/CBs as well as non-bank electronic money issuers (EMIs) participate in these facilities, indicating a more diverse set of payment service providers.

FIGURE 1. Rising annualized value of combined InstaPay and PESONet transactions, December 2017 to December 2020



Source: BSP-DSA.

Banks are the more dominant players in PESONet since this digital payment rail is envisioned as the digital alternative that will eventually replace checks as a means of payment. Meanwhile, non-bank EMIs such as G-Xchange, Inc. (operator of GCash) and PayMaya exhibit stronger market position in InstaPay which facilitates smaller size immediate retail payments.

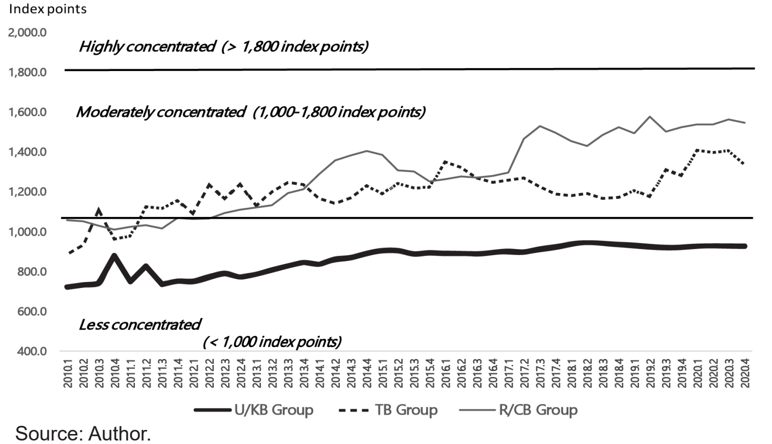
An expected strategy among BSFIs due to the adoption of financial reform initiatives are mergers and consolidation. Given the rapid pace of globalization and accelerating technological advancement, the BSP sees merger and consolidation as a means to create stronger and globally competitive banking institutions. Mergers and consolidation are expected to help merged/consolidated banks harness with greater efficiency their collective experience, expertise and technological know-how. It is implicit that parties to mergers and consolidation have a strategic vision to make their merged enterprise more competitive, since mergers and consolidation will allow them to complement each other in terms of the markets they serve and the products and services they offer, allowing them to focus on core competencies. From March 2010 to December 2020, there were 28 episodes of mergers, consolidations and conversions; majority of these involved U/KBs and thrift banks, U/KBs and R/CBs, and TBs and R/CBs.

To determine the effect of mergers and consolidations on market concentration, I construct an HHI[12] each for the three Philippine banking groups—U/KB, TB and R/CB industries—from March 2010 to December 2020. There are perceived shortcomings of the HHI as a measure of market concentration. However, I treat this measure as a first approximation of market concentration. Following Meyer [2018], the HHI has three key ranges and market classifications: less than 1,000 index points (less concentrated); 1,000-1,800 index points (moderately concentrated) and above 1,800 index points (highly concentrated). If the HHI value for a specific banking group exceeds 1,800, that group can be considered highly concentrated—that is, merger activity is severely limited. Figure 2 shows that the U/KB industry and R/CB industry are relatively far from being oligopolistic in terms of asset distribution. This means that there are numerous competitors with significant market shares. Figure 2 reveals that among the three groups, TB and R/CB industries, which both account for about 7.2 percent of the banking sector's total assets as of end-December 2020, are moderately concentrated, while the U/KB industry, which accounts for 92.8 percent of the sector's assets, is less concentrated.

The decline in the HHIs of TB and R/CB industries from 2015 to 2017 can be attributed to the larger banks being able to establish branches in markets that were previously only served by UKBs, while the gradual rise in HHI after 2008 may be the result of post-Global Financial Crisis consolidation. This implies that there may be limitations in mergers among TBs and R/CBs. This may also mean that an out-of-group bank merger is a reasonable strategy.

[12] The HHI is calculated by summing the square of the share of assets for each bank with the group total assets. For example, if there are five banks operating, each holding a 20 percent market share, the HHI will be 2,000. If the market has only one bank (a monopoly), the HHI will be 10,000.

FIGURE 2. Competitive structure of Philippine banking groups based on Herfindahl-Hirschman Index (HHI), March 2010 to December 2020



Source: Author.

I then compare the computed bank-level HHI with return on assets (ROA) over the same period. Figure 3 shows that the ROA has been generally increasing with the HHI, although there are R/CBs with negative ROAs. This may also be attributed to the higher degree of diversification among U/KBs. Table 2 shows that the range of diversification between interest and non-interest activities among U/KBs is higher than those of the TBs and R/CBs. Overall, the results show that banks are generally stable and that while recent big mergers and consolidation have increased market concentration, these are not enough to pose a threat to the overall competition levels since market shares remain relatively well dispersed among the remaining players. The results also confirm that the U/KB industry still has enough room for more mergers and consolidation without necessarily inhibiting efficient competition.

FIGURE 3. Bank-level market concentration and return on assets, March 2010 to December 2020

Source: Author.

TABLE 2. Indicator of diversification[1/] measures of Philippine banks, March 2010 to December 2020

Descriptive statistics	U/KBs	TB group	R/CB group
Mean	-2.06	-0.02	-0.62
Median	0.03	0.05	-0.57
Std. deviation	78.53	0.16	0.27
Coefficient of variation	-38.12	-10.47	-0.44
Number of banks	41	44	457

[1/]Based on Liang et al. (2020). Defined as:
Diversification Measure = 1-[(*Interest income/total operating income*)^2 + (*Non-interest Income/Total Operating Income*)^2]
Source: Author.

4. Data and empirical strategy

I compile three unique quarterly datasets on detailed balance sheets and income statements of 542 banks from the Financial Reporting Package (FRP)[13] covering March 2010 to December 2020. These supervisory datasets allow the study to pose a number of questions. Tables A1 to A4 in Annex A present the variables and variable names used in the study. The databases are briefly described here.

4.1. Bank-level balance sheet and income statements

All banks are required to prepare the FRP on solo[14] and consolidated basis.[15] In the dataset, there are 41 U/KBs (composed of 14 UKBs, four commercial banks or KBs, and 23 FBs[16]), 44 TBs and 457 R/CBs as of end-December 2020. To arrive at a balanced panel, I only include the surviving or the latest list of banks with minimum observation points of three years. To eliminate the effects of outliers, I winsorize all variables at the first and 99th percentiles.

The bank-specific data include quarter-end data on the size of a bank (relative to total bank assets), credit growth, liquid assets relative to total assets, capitalization relative to total assets, funding composition using outstanding deposits relative to total liabilities, profitability of banks using annualized

[13] The FRP is a set of financial statements for prudential reporting purposes composed of the Balance Sheet, Income Statement and Supporting Schedules. The FRP is primarily designed to align the BSP's reportorial requirements with the (a) provisions of the Philippine Financial Reporting Standards (PFRS)/Philippine Accounting Standards (PAS), and (b) Basel 2 Capital Adequacy Framework. It is also designed to meet the BSP's statistical requirements.

[14] Solo basis refers to the combined financial statements of the head office and branches/other offices.

[15] Consolidated basis refers to the combined financial statements of parent bank and subsidiaries consolidated on a line by line basis. Only banks with financial allied subsidiaries, excluding insurance subsidiaries are required to submit the report on consolidated basis.

[16] Three foreign banks which entered the industry in 2018 and two commercial banks are excluded due to data limitations.

net income or loss, net interest margin (NIM), total operating income, interest income, non-interest income, Return on Equity (ROE), ROA, and quality of bank loans using nonperforming loans ratio (NPL), nonperforming assets ratio (NPA), nonperforming loan coverage ratio, and loan loss reserves (LLR). Other quarterly bank accounts in the income statements of banks are also compiled such as cost-to-income ratio (a measure of bank efficiency), total expenses, input costs, total revenues, variable profits, and variable costs. In the study, I use financial reporting data on solo basis. I also include dummy variables for banks' business model or banking group.

4.2. Vector of controls

This dataset includes macro-financial indicators and the BSP policy actions. These indicators include real GDP growth, inflation, monetary policy rate or overnight policy rate, bank lending rate, deposit rate, outstanding bank loans, nominal peso-dollar rate, and real effective exchange rates.

4.3. Measures of bank risk and bank competition

This database contains specific measures on individual bank risk and bank competition. Competition in this study refers to banking markets or banking groups, not in a specific product. I construct individual competition measures for the three banking groups—U/KB, TB and R/CB. As discussed in the previous section, the three groups show different market concentration based on HHI.

Following De-Ramon et al. [2020], I estimate the Z-score to represent stand-alone bank risk for all the banking groups. The relationship between the individual Z-scores and measures of bank competition are then estimated to examine the impact of these measures of competition on bank risk.[17]

The Z-score is an accounting-based measure of risk calculated at the bank level as,

$$Z_{b,t} = (ROA_{b,t} + c_{b,t}) / \sigma ROA_{b,t} \,, \tag{1}$$

where $ROA_{b,t}$ refers to ROA of bank b at time t, $c_{b,t}$ is total capital to assets ratio of bank b at time t, and $\sigma ROA_{b,t}$ is the standard deviation of ROA of bank b at time t. Following episodes of mergers and consolidation, I use a four-quarter (one year) rolling window of ROA to calculate $\sigma ROA_{b,t}$.[18]

I construct three measures of market power to represent bank competition: Panzar-Rosse-H-statistic (H-statistic), the Lerner Index (LI) and Boone Indicator (BI).[19]

[17] See Boyd et al. [2006]; Schaeck and Cihák [2014].

[18] In the initial estimation, bank-level Return on Equity and NPL ratio are used. However, the results are not significant. In the future, forecasted bank-level ROA can be used. This is an area for future research.

[19] Following the other papers by De-Ramon et al. [2020], Meyer [2018], Anginer et al. [2014], and Berger et al. [2009], I also use the HHI to compute the market concentration for bank assets of U/KBs, TBs, and R/CBs. The HHI is calculated by summing the square of the share of assets for each bank with the banking

4.4. *Panzar-Rosse-H-statistic* (*H-statistic*)

The H-statistic infers the degree of competition among banks by capturing the elasticity of bank interest revenues to input prices, that is, how sensitive interest revenue is to changes in bank costs.[20] The H-statistic is calculated in two steps. First, running a panel regression with bank and time fixed effects of the logarithm of measures of banks' input prices on the logarithm of gross total revenues.[21] Second, adding the estimated coefficients for each input price. Input prices include the price of deposits (commonly measured as the ratio of interest expenses to total deposits), the price of personnel (as captured by the ratio of personnel expenses to assets), and the price of equipment and fixed capital (approximated by the ratio of other operating and administrative expenses to total assets)

Higher values of the H-statistic are associated with more competitive banking systems. Under a monopoly, an increase in input prices typically results in a rise in marginal costs, a fall in output, and a decline in revenues (assuming that the demand curve is downward sloping), leading to an H-statistic of less than or equal to 0. Under a perfect competition, an increase in input prices generally raises both marginal costs and total revenues by the same amount (assuming that the demand curve is perfectly elastic); hence, the H-statistic will be equal to one.

4.5. *Lerner Index* (*LI*)

The LI directly measures pricing power by calculating the price markup over marginal cost, that is, the extra cost of producing an additional unit of output. Following De-Ramon and Straughan [2020], the LI ($L_{b,t}$) is seen in Equation 2 as,

$$L_{b,t} = (A_{b,t} - MC_{b,t}) / A_{b,t} \, , \tag{2}$$

as the ratio of the difference in output price $A_{b,t}$ of bank b at time t and marginal cost of bank b at time t ($MC_{b,t}$) to output price ($A_{b,t}$). The output price is proxied by total assets and is calculated as the sum of interest and non-interest revenue

group's total assets. I recognize that the HHI is not a direct measure of bank competition, but I include this in this study to provide a comparison with previous studies and to help assess the robustness of results from previous studies.

[20] In the initial regression, I used the interest income to revenue ratio. However, the bank-level ratios are relatively small. There are also banks that registered losses from their interest-earning transactions. Hence, there are challenges in using the ratio in regressions. Defined as the sum of interest and non-interest income, operating income has a bigger scope and therefore higher than interest income.

[21] The results of panel regression with bank and time fixed effects from March 2010 to December 2020 are as follows:

	Log (total revenues)		
	U/KBs	TBs	R/CBs
Log(total input prices)	0.671	0.238	0.632

Source. Author.

per unit of total output.[22] The marginal cost ($MC_{b,t}$) is not directly observable. In this study, the LI is calculated in two steps. First, running a panel regression with bank and time fixed effects of the logarithm of total cost on the logarithm of total assets and banks' input prices (*ln W*) in Equation 3.[23] These input prices include bank personnel compensation, funding cost, and other operating costs. Second, adding the estimated coefficients for each input price in Equation 3. Equation 3 below approximates the ($MC_{b,t}$) as,

$$MC_{b,t} = \frac{TC_{b,t}}{A_{b,t}} \left[a_{1b,t} + a_{2b,t}\, lnA + \sum\nolimits_{b=1}^{3} a_{3t}\, lnW \right]. \tag{3}$$

The LI estimated for individual bank denotes its pricing power. Based on the theory, the LI can range between 0 and 1. An LI with a value approaching one indicates increasing level of market power or wider margins on the part of the bank and lower levels of competition.

4.6. Boone Indicator (BI)

The BI measures the effect of efficiency on bank performance in terms of profits. Following De-Ramon and Straughan [2020], it is calculated as the elasticity of variable profits to average variable costs. The BI in Equation 4 below is,

$$LogP_{b,t} = a + \beta_1 LogC_{b,t} + \beta_2 O_{b,t} + \mu_{b,t}\ , \tag{4}$$

where $LogP_{b,t}$ is the logarithm of variable profits for bank b at time t, $LogC_{b,t}$ is the logarithm of average variable costs, $O_{b,t}$ are other control variables which include macro-financial indicators and other specific characteristics of bank b, and $\mu_{b,t}$ is the error term. For consistency with the specifications of H-statistic and LI, the baseline BI calculation excludes the $O_{b,t}$. The BI is seen in β_1 which is estimated for bank b at time t. To estimate Equation 4, I calculate variable profits as the ratio of total revenue less variable costs (i.e., interest paid, personnel expenditure, other variable costs including occupancy of building) to total assets.[24]

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[22] The impact of competition based on differentiated products on risk can be explored. Also, by type of portfolio such as households, corporates. I take this as an area of future research.

[23] The results of panel regression with bank and time fixed effects from March 2010 to December 2020 are as follows:

	Log (total cost/total assets)		
	U/KBs	TBs	R/CBs
Log(total input prices)	0.030	0.109	0.211

Source. Author.

[24] Equation 4 is estimated by panel regression with bank and time fixed effects from March 2010 to December 2020. The results are as follows:

	Log (variable profit/total assets)		
	U/KBs	TBs	R/CBs
Log(total input prices)	0.010	0.098	0.110

Source. Author.

Average variable costs are measured as variable costs scaled by variable revenue derived directly from current activity (i.e., interest received, foreign exchange receipts, investment income, fees and other charges).

In the actual estimation, the computed BI is then regressed on the four-quarter rolling window of ROA and $O_{b,t}$. I use bank-level variables found in the literature in addition to variable profit and average variable cost as controls for macro-financial indicators and other bank-specific characteristics such as capitalization/total assets, outstanding deposits/total liabilities, and loan-to-asset ratio. As mentioned in the previous section, the main assumption behind the BI is that more efficient banks achieve higher profits. In practice, the BI is negative. The more negative the BI is, the higher the level of competition is in the market, because the effect of reallocation is stronger.

4.7. Measure of changes in the physical banking network

This database compiles the number of closed banks, entry of new banks (including entry of foreign and digital banks), mergers, consolidation, acquisition, and banks which applied for digital payment channels for banking services such as InstaPay and PESONet from March 2010 to December 2020. A dummy variable is assigned a value of 1 when a bank enters, merges, consolidates, and applies for digital payment services and 0 if otherwise. The measures are computed as the quarterly sum of banks to match the frequency of the dependent variables in the models. In the final regression results, only the measures on changes in physical banking network are significant.

Table 3 shows the descriptive statistics of the major variables used in the final estimation. The main variables of interest are the Z-scores and measures of market power—the H-statistics, BIs, and LIs—of U/KBs, TBs and R/CBs. The Z-score of U/KBs is the most volatile among these measures following the entry of new foreign banks and abrupt movements in their ROAs from March 2010 to December 2020. Among the bank-specific characteristics, the cost-to-income ratios (CI), a traditional measure of bank efficiency, of U/KBs and R/CBs are the more volatile indicators. I see large variations in the operating incomes of U/KBs and R/CBs particularly following the outbreak of the pandemic in March 2020.

TABLE 3. Summary of descriptive statistics of selected variables, March 2010 to December 2020

Variable name	Description	Mean	Median	Max.	Min.	Std. Dev.	10th percentile	90th percentile
Zscore_UKB	4-quarter moving average Z-score of universal and commercial Banks (U/KBs)	8.27	5.24	214.35	-9.12	10.98	0.49	17.74
Zscore_TB	4-quarter moving average Z-score of thrift banks (TBs)	10.92	8.94	29.17	3.78	8.12	4.22	26.29
Zscore_RCB	4-quarter moving average Z-score of rural and cooperative banks (R/CBs)	5.74	3.96	19.65	-2.10	5.72	0.06	13.59

TABLE 3. Summary of descriptive statistics of selected variables, March 2010 to December 2020 (continued)

Variable name	Description	Mean	Median	Max.	Min.	Std. Dev.	10th per-centile	90th per-centile
HSTAT_UKB	H-Statistic of UKBs	0.06	0.05	0.20	0.01	0.02	0.03	0.09
HSTAT_TB	H-Statistic of TBs	0.12	0.13	0.15	0.03	0.02	0.09	0.15
HSTAT_RB	H-Statistic of R/CBs	0.21	0.22	0.28	0.07	0.04	0.16	0.26
BI_UKB	Boone Indicator (BI) of U/KBs	0.11	0.06	4.32	-0.02	0.26	0.02	0.17
BI_TB	BI of TBs	0.48	0.45	0.79	0.33	0.13	0.31	0.79
BI_RCB	BI of R/CBs	0.86	0.79	1.41	0.44	0.21	0.62	1.25
LI_UKB	Lerner Index (LI) of U/KBs	-1.46	-0.37	1.40	-86.16	5.38	-3.15	0.37
LI_TB	LI of TBs	-2.98	-2.93	-1.71	-5.22	0.99	-6.20	-1.71
LI_RCB	LI of R/CBs	-6.39	-6.17	-4.12	-15.05	2.06	-8.97	-4.20
TLP_UKB	Total outstanding loans/total assets of U/KBs	0.46	0.50	0.98	0.00	0.23	0.05	0.70
TLP_TB	Total outstanding loans/total assets of TBs	0.79	0.79	0.81	0.74	0.02	0.77	0.81
TLP_RCB	Total outstanding loans/total assets of R/CBs	0.84	0.87	0.94	0.67	0.08	0.72	0.93
CAP_UKB	Total capitalization/total assets of U/KBs	0.20	0.14	0.99	0.04	0.17	0.09	0.50
CAP_TB	Total capitalization/total assets of TBs	2.68	2.78	3.37	1.58	0.56	1.88	3.58
CAP_RCB	Total Capitalization/total assets of R/CBs	0.15	0.14	0.24	0.11	0.04	0.12	0.23
CI_UKB	Cost-to-income ratio (CI) of UKBs	0.73	0.72	1.08	0.48	0.14	0.56	0.93
CI_TB	CI of TBs	0.61	0.60	0.67	0.50	0.04	0.57	0.66
CI_RCB	CI of R/CBs	0.91	0.77	1.86	0.56	0.33	0.60	1.43
DV_UKB	Diversification index (1-[(Interest Income/Total Operating Income)^2 + (Non-Interest Income/Total Operating Income)^2]	-0.09	0.02	0.47	-4.16	0.52	-0.76	0.57
DV_TB	DV of TBs	-0.01	0.05	0.17	-0.38	0.16	-0.22	0.19
DV_RCB	DV of R/CBs	-0.64	-0.60	-0.18	-1.24	0.27	-0.99	-0.28
RGDP	Real gross domestic product (GDP)	0.05	0.06	0.08	-0.17	0.05	0.03	0.08
INF	Inflation	0.95	0.94	1.07	0.85	0.06	0.86	1.01
POL	BSP policy rate	0.04	0.04	0.05	0.02	0.01	0.03	0.05
PES	Peso-dollar rate (average)	47.55	47.17	54.25	40.94	3.86	43.00	52.21

Source: Author.

4.8. Estimation method

To date, there is no generally accepted framework for analyzing the relationship between bank risk and competition. Moreover, the results are sensitive to the details of model specification, notably the choice of control or instrument variables. In this study, the parameters in the main model are estimated using balanced panel quantile regression. This is a more appropriate empirical methodology to estimate the influence of various measures of bank competition and other factors affecting bank risk at bank level. Specifically, the panel quantile regression encourages a finer view of the potential heterogeneous effects across the conditional risk distribution.

The study recognizes that competition may be endogenous if weaker, less-efficient institutions increase leverage and balance sheet size (potentially raising return on assets) to avoid insolvency in periods of instability. These actions can be misinterpreted as a sign of increased competition. I address this problem by using lags (*t-j*) in the competition measures and bank-specific characteristics [Liu and Wilson 2013]. The choice of lag length is supported by results of exogeneity tests that formally evaluate the null hypothesis that the specified endogenous regressor, i.e., competition in this case, can be treated as exogenous.

4.9. Robustness checks

Diagnostics tests are used to check the stability of indicators in the study, including measures of competition, bank risk, and bank-specific characteristics. I use alternative specifications of the parameters of the model. For bank risk, I use one-year (four quarters) and two-year (eight quarters) rolling average ROA. Bank-specific characteristics such as the NPL ratio, NPL coverage ratio, loan loss reserves, liquid assets to total assets ratio, outstanding deposits to outstanding total liabilities ratio are used as factors driving ROA.[25] I employ 1 percent, 5 percent, and 10 percent levels of significance.

4.10. Empirical analysis

Equation 5 denotes the baseline model of the impact of bank competition on bank risk. On the left-hand side, $R_{b,t}$ represents a measure of risk of bank *b* during quarter-end *t-j*. I use the Z-score based on four-quarter (one year) moving average of ROA (see Annex A, Tables A1 to A4). Following De-Ramon and Straughan [2020], I interpret the Z-score as a measure of how many standard deviations a bank is away from exhausting its capital base. A higher value indicates lower probability of insolvency and therefore lower bank risk. This also indicates higher overall bank stability.

On the right-hand side, $K_{b,t-j}$ refers to a measure of competition of bank *b* during quarter-end *t-j*. $V_{b,t-j}$ represents a vector of macro-financial indicators and other bank-specific characteristics. $\varepsilon_{b,t}$ is a random error that has a normal distribution. The main coefficient of interest in Equation 5 is that associated with competition, β_1.

$$R_{b,t} = a_b \,(\pm)\, \beta_1 K_{b,t-j} + \beta_2 V_{b,t-j} + \varepsilon_{b,t}\,. \tag{5}$$

[25] However, the estimations yielded insignificant coefficients and were dropped in the final regression.

I analyze the relationship between bank competition and bank-level risk using separate regressions for each measure of bank competition and for each banking group—U/KBs, TBs and R/CB.

Following De-Ramon et al. [2020], Equation 6 specifies the panel quantile regression.

$$Q_{\phi}(R_{b,t} \setminus K_{b,t\text{-}j}\,, V_{b,t\text{-}j}) = a_b\,(\pm)\,\beta_{1\phi} K_{b,t\text{-}j} + \beta_{2\phi}\, V_{b,t\text{-}j} + \varepsilon_{b,t}\;, \tag{6}$$

where the term $Q_{\phi}(R_{b,t} \setminus K_{b,t\text{-}j}, V_{b,t\text{-}j})$ on the left hand side of Equation 6 refers to the ϕ^{th} conditional quantile of bank risk given competition ($K_{b,t\text{-}j}$), bank-specific characteristics and macro-financial controls ($V_{b,t\text{-}j}$); $\beta_{1\phi}$ and $\beta_{2\phi}$ are vectors of parameters on competition and other bank-specific characteristics and macro-financial controls, respectively; and $\varepsilon_{b,t}$ is the residual. The term Q_{ϕ} denotes the difference with the standard least squares' estimator expressed in Equation 5, which provides information only about the effect of competition at the conditional mean of bank risk. The quantile regression produces multiple coefficient estimates for competition that are unique to each quantile of the conditional distribution of bank risk. This approach allows the study to examine whether the relationship between competition and bank-level risk differs across banks depending on each bank's underlying risk profile.

Testing for equality of the coefficient estimates at various quantiles requires estimation of the variance-covariance matrix.[26] The test statistic is computed by using the variance-covariance matrix of the coefficients of the system of quantile regressions. The null hypothesis is that the coefficient on competition at the $\phi_{1^{st}}$ quantile is statistically the same as the one in the $\phi_{2^{nd}}$ or that the quantiles are symmetric using the Wald test. The alternative hypothesis is where the coefficients are not equal. The intention of this test is to determine if the relationship between risk and competition varies across the conditional risk distribution. I also check if the model has no omitted variables and is correctly specified using the Ramsey RESET test. Finally, I ensure that the data used are normally distributed using the Jarque-Bera test.

The study implemented a number of tests to highlight the dynamics between bank competition and bank risk. The focus of the discussions is the dynamics between bank competition and measures of bank risk such as the H-statistic (Table A1), Lerner Index (Table A2) and Boone Indicator (Table A4). These are posed as questions listed below.

First, does competition reduce bank risk? I find that the H-statistic, Lerner Index and Boone Indicator covary and correlate with bank risk (Z-score) across the three banking groups at 1 percent, 5 percent and 10 percent levels of significance from March 2010 to December 2020. I also observe that these measures Granger cause the Z-score at 1 percent and 5 percent levels of significance during the

[26] The covariance matrix is derived by using Huber sandwich technique.

same period. The test is on the overall significance of β_1 in Equations 5 and 6. As implied in the previous section, β_1 in Equations 5 and 6 will have a different interpretation for the Boone Indicator and the Lerner Index. A positive coefficient of β_1 suggests that more competition is associated with higher risk (lower Z-scores), consistent with the competition-fragility hypothesis, while finding a negative coefficient implies that more competition is related with lower risk and supports the competition-stability hypothesis.

For H-statistic, a positive β_1 suggests that as competition increases, profitability and capitalization rise, bank risk declines and bank stability improves. This supports the risk-shifting paradigm and competition-stability hypothesis. A negative β_1 indicates that as competition intensifies, profitability and capitalization decrease, bank risk increases, and bank stability weakens. This supports the competition-fragility hypothesis.

I assume that the overall significance of β_1 depends on bank-specific characteristics and macroeconomic variables. I include other key attributes of banking performance following the specifications in Liu and Wilson [2013]. All these bank-specific characteristics and macro-financial variables have bilateral Granger causality with bank risk from March 2010 to December 2020.

Bank efficiency in this study refers to operational cost-to-income (CI) ratio.[27] It is defined as the ratio of annualized non-interest expenses (net of impairment losses) to annualized total operating income,[28] I expect the CI ratio to be negatively related to bank risk as less efficient banks are likely to take on greater risk to generate returns and to improve their financial performance [Boyd et al. 2006]. In the dataset, the CI ratios of U/KB, TB and R/CB groups are relatively high at more than 60 percent. Among the groups, the TB industry has the lowest average CI ratio at 62.2 percent from March 2010 to December 2020, followed by the U/KB industry at 65.5 percent and the R/CB industry at 76.1 percent.

Moreover, the ratio of outstanding total bank loans to total assets (total loan portfolio or TLP) could be positively related to bank risk, since greater loan exposure may mean higher probability of a default risk. If TLP is low, however, profits (which could act as the buffer to default risk) may be reduced. I also assume that the size of a bank, measured by the logarithm of total assets, is negatively related to bank risk. The idea is that the benefits of economies of scale and market power may allow large banks to remain more stable than their smaller counterparts. However, it may be assumed that larger banks are prepared to accept more risk particularly when their capital buffers are healthy.

Finally, the degree of diversification may also affect the dynamics between competition and bank risk. Using risk distribution among banks in 48 countries

[27] Dutta and Saha [2021] suggest that bank efficiency could be measured by either efficiency index of net interest margin, working capital ratio, asset turnover ratio, and operating efficiency ratio constructed by Principal Components Analysis (PCA).

[28] Based on the Report on the Philippine Financial System, Second Semester 2020, BSP.

from 1998 to 2018, Liang et al. [2020] find that higher diversification in bank portfolio reduces stand-alone bank risk but not the systemic risk as diversification tends to expose banks to a common risk in terms of activities and portfolio. Following Liang et al. [2020], I construct a bank-level diversification index (DV)[29] across the three banking groups.

To capture the effects of macro-financial shocks on bank risk, I include Inflation (INF) and real GDP growth (RGDP) in the baseline model. Inflation is calculated as the percentage change in consumer price index (CPI). Inflation has been used in previous studies of banking performance to account for macroeconomic shocks, which have been found to affect the financial system and the real economy. Specifically, higher inflation can distort decision-making, exacerbate information asymmetry and introduce price volatility. Consequently, a positive relationship between inflation and bank risk is expected. RGDP growth is included to capture movements in the business cycle. A significant strand of recent literature emphasizes the procyclical nature of the banking business, enhanced by a tendency of financial institutions to lend excessively during economic upturns, and to adopt cautious lending standards during downturns. Such lending patterns are likely to have implications for bank risk over the business cycle.

Meanwhile, I capture the initial impact of pandemic on bank risk by assigning a dummy variable for the pandemic period from March 2020 to December 2020.

I use the components of the Z-score in Equation 1 to shed light on the impact of competition on bank risk. These include the impact on profitability ($ROA_{b,t}$), bank capitalization ($c_{b,t}$) and volatility of bank profits ($\sigma ROA_{b,t}$). I also control for changes in physical banking network (DCHANGE). I expect a positive relationship between Z-score (lower bank risk) and DCHANGE.

To the best of my knowledge this is the first attempt to construct indicators of market concentration and market power using detailed bank-level balance sheet data and income statements from source reports in the Philippines.

Second, does the relationship between changes in competition and bank risk differ across banks? The main motivation behind this question is to capture the impact of changes in competition on bank risk distribution. I expect the association between measures of competition and bank risk to vary across banks given that the banks in the dataset have different ownership structures, serve different geographical areas (National Capital Region and in areas outside the National Capital Region), have different access to external finance, and are subject to proportionality in regulation.[30]

[29] Based on Liang et al. [2020], Diversification Measure = 1-[(Interest Income/Total Operating Income)^2 + (Non-Interest Income/Total Operating Income)^2].

[30] Rostoy [2018] defines proportionality in banking regulations as the application of simplified prudential requirements for small, non-complex institutions with simpler business models.

In addition, the relationship between competition and risk may differ depending on the initial risk level of banks [Liu and Wilson 2013]. High-risk banks (lower Z-score) may tend to avoid taking on more risk in order to protect their franchise values (which tend to decline) when competition increases. Low-risk banks (higher Z-score), by contrast, when faced with more intense competition, may tend to take on riskier projects in order to gain or protect market share and increase profitability. However, in empirical studies, the exact nature and impact of such interaction remains inconclusive. The test is on the overall significance of the measures of bank competition on the distribution of bank risk (Tables A2 to A4 in Annex A) based on the interpretation of β_1 in Equation 6. I use the results from the panel quantile regression.

5. Results

Table 4 below provides the summary of detailed results (Tables A1, A2 and A4 in Annex A) of the baseline model. Following the diagnostics and robustness checks, the results are consistent with the results of the previous studies (De-Ramon et al. [2020]; Liu and Mathison [2013]).

TABLE 4. Summary of the impact of measures of competition on bank risk, March 2010 to December 2020

	Bank competition measures		
	H-Stat	Boone	Lerner
Banking group	Coef.[1]	Coef.[1]	Coef.[1]
U/KB	0.118**	-0.539**	-0.028*
TB	-0.162*	-0.031*	0.019**
R/CB	0.127***	-0.045***	0.456 **

[1] The symbols *, **, and *** represent significance of regression coefficients at 10 percent, 5 percent and 1 percent levels of significance, respectively.
Source: Author.

First, competition reduces bank risk taking activities at industry level. Table 4 shows that across the three banking groups, the Boone Indicator significantly reduces bank-level solvency risk. Specifically for the U/KB industry, the impact of Boone Indicator on bank risk is higher than the Lerner Index and the H-statistic suggesting that bank efficiency in terms of profits is a significant driver of competition. This result is in line with the findings in previous studies by De-Ramon et al. [2020]. This is also consistent with the competition-stability hypothesis. However, the H-statistic (except the TB industry) and Lerner Index (except for U/KB) show a positive impact on bank risk that is consistent with competition-fragility hypothesis. This result may mean that banks are competing for quality of products and that there is a high degree of collusion among banks [Tabak et al. 2013]. I take this as an area of future research.

Looking at the coefficients of the H-statistic, Boone Indicator and Lerner Index, Table 4 shows that bank competition eases bank risk taking activities at the industry level. Among the banking groups, the U/KB group shows the highest impact on bank risk. This also implies that the banking sector continues to have adequate capitalization. Based on latest available data, total capitalization as a share of total assets stood at 12.5 percent as of end-June 2021, with the R/CB industry recording the highest ratio at 18.9 percent.[31]

Contrary to the previous findings by Liang et al. [2020], I find a negative impact of the diversification index (DV) on bank risk across banking groups (Tables A1, A2 and A4 in Annex A). This means that the banking groups are not that well-diversified and that their portfolio strategy may need to be enhanced. When looking at the DV by banking group, the R/CB is the least diversified as its portfolio is largely skewed to interest income. However, in terms of the average net interest margin (NIM)[32] from March 2010 to December 2020, the R/CB industry's average NIM was higher at 12.5 percent compared to the TB industry at 9.1 percent and to the U/KB industry at 3.1 percent.

In the initial regressions, the NPL ratio, Return on Equity (ROE), Inflation and peso-dollar rate were included. However, these were consequently excluded from the final regression as the coefficients turned out to be insignificant. I checked the robustness of the coefficients for the Boone Indicator and Lerner Index across all quantiles. All coefficient estimates are statistically distinct using the Wald F-test. This finding indicates that the relationships are heterogeneous across the quantiles. This result is also consistent with a two-year rolling average of ROA.

Second, competition affects individual bank risk-taking differently. In Tables A1, A2 and A4, I find mixed relationships between competition and Z-score when looking at the conditional risk distributions within the three banking groups using panel quantile regression from March 2010 to December 2020. In the case of the U/KB industry, the negative relationship (competition-stability hypothesis) between the Boone Indicator and Z-score is significant only for U/KBs in the 40th to the 70th percentile or for those banks in the middle of risk distribution (low-medium Z-score) (Table A3, Figure A1). Majority of U/KBs in these distributions are large domestic U/KBs and foreign banks. In the case of the Lerner Index and Z-score, the negative relationship between the two variables is more dispersed and is significant only for U/KBs in the 50th and 60th percentiles (Table A4, Figure A2). These banks are in the middle of risk distribution (medium Z-score). Large U/KBs universal and new foreign banks dominate these quantiles. These findings imply that the impact of competition on bank risk depends ultimately on the underlying individual bank risks.

[31] The corresponding ratios for the U/KB and TB industries are 12.5 percent and 13.9 percent. Data are based on the Balance Sheet of the Philippine Banking System as of August 9, 2021 in the BSP website.

[32] Defined as the ratio of net interest income to average earning assets. Based on Report on the Philippine Financial System (Second Semester of 2020) in the BSP website.

However, I estimate a mixed relationship between competition and bank risk within the risk distributions in TB and R/CB industries. Using the Boone Indicator, the negative association is consistent and significant across the quantiles in the TB and R/CB industries at 1 percent level of significance. Looking at the Lerner Index in Table A4, I estimate a positive and significant impact on Z-score in TB and R/CB industries. This relationship is consistent and significant within the TB industry. In the case of the R/CB industry, the positive impact of Lerner Index on the Z-score is seen in all risk distributions, except in the 40th percentile when the relationship between the two switches to negative. Together, these findings imply that the relationship between competition and risk can potentially be countervailing within banking groups [De-Ramon et al. 2020].

These results are consistent with Liu and Wilson [2013] who both find that the strength of the relationship between competition and risk of Japanese commercial and cooperative banks varies across initial levels of risk. They find that competition reduces risk at the weakest banks in Japan, while at the same time it increases risk at healthier banks. These contrasting results for the different quantiles are consistent with both the competition-fragility and competition-stability hypotheses holding simultaneously for individual banks in the Philippines. This also suggests that competitive opportunities remain for smaller U/KBs and to a limited extent the R/CBs.

I also show that the relationship between competition and risk is sensitive to other bank-specific characteristics related to deposit growth, capitalization (Liu and Wilson [2013]; Schaeck and Cihák [2014]), cost-to-income ratio, diversification index, and macro-financial factors that could potentially have further influences. For instance, across estimations, bank-level Z-scores increase (risk decreases) as real GDP growth rises.

Third, changes in physical banking network (DCHANGE) lead to lower bank risk for large banks but not so for smaller banks. Results in Table A3 show that *DCHANGE* when interacted with Lerner Index has a negative and significant influence on the U/KBs' Z-score. This means that *DCHANGE* leads to lower risk. To some extent, this finding is consistent with observations by Altunbas and Marques [2008] and Sharma [2020] that merger has tangible benefits in areas such as profitability driven by diversification and utilization of economies of scale, technical progress (particularly in communication technology), deregulation, globalization and the resulting competition for banks. In the database, I account for 28 mergers and consolidations across the U/KB, TB and R/CB industries from March 2010 to December 2020.[33]

By contrast, the interaction between DCHANGE and bank risk (Boone Indicator) is negative and significant for TBs and R/CBs. This means that the objectives of merger, acquisition, and consolidation may not necessarily be favorable as discussed in Rezitis [2008].[34]

[33] The main reference is Factbook: The Philippine Banking System: 2010-2020, a BSP publication.

[34] Using a Generalized Malmquist productivity index on five merged banks in Greece, Rezitis [2008] concludes that banks that participated in merging activity experienced a decline in technical efficiency and in total factor productivity.

6. Conclusion

This paper contributes to the debate regarding the impact of competition on the stability of banks by examining the "competition-fragility" and "competition-stability" views. Three measures of market concentration and market power are constructed from a unique dataset of balance sheet and income statements for 542 banks operating in the Philippines from March 2010 to December 2020. These measures include the H-Statistic, Lerner Index and the Boone Indicator. The impact of these measures on bank solvency risk is then estimated across the U/KB, TB, and R/CB industries using panel quantile regression.

Following the diagnostics and robustness checks, the paper finds that, at the industry level, bank competition significantly reduces bank-level solvency risk. Looking at the risk distribution, the results show the competition-fragility and competition-stability hypotheses holding simultaneously for U/KBs. These findings imply that the impact of competition on bank risk depends crucially on the underlying individual bank risk. The results also mean that competitive opportunities remain for smaller U/KBs.

The study argues that the relationship between competition and risk is sensitive to other bank-specific characteristics and macroeconomic factors related to extent of diversification strategy, cost-to-income ratio, deposit growth, capitalization and real GDP growth. Importantly, the findings show the significant impact of changes in the physical banking network on bank risk for U/KBs, but negative for TBs and R/CBs.

From the technical standpoint, the results of the study may be extended to examine the impact of bank competition on economic growth in the long run and on monetary policy transmission mechanism. Empirical findings on the existing theoretical frameworks on bank competition and economic growth remain inconclusive. This study shows a significant and positive influence of real GDP growth on bank solvency risk. It will be interesting to analyze the impact of bank competition and bank stability on economic growth.

The results of the paper imply that the analysis of bank competition does not only depend on market size. It is equally relevant to include measures of market power. This could be relevant in the analysis of capital charge for operational risks that is dependent on banks' gross income. It could be expanded to include variable profits consistent with the Boone Indicator or marginal cost like the Lerner Index. Operational risk is defined in the capital framework as the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events. Philippine banks are using the Basic Indicator Approach (BIA) in computing the operational risk capital charge for regulatory capital purposes. Under the BIA, the aggregate gross income of a bank is subject to a 15 percent operational risk capital charge.

Different measures of competition may be useful in the determination of D-SIBs. As I have mentioned in Section 2, the BSP classifies banks depending on the extent of their systemic importance using pre-defined indicators for market size, interconnectedness, substitutability, and market reliance as a financial market infrastructure as well as complexity. Market size is based on a bank's total resources relative to the banking system. The market size of a bank may consider measures of market power such as the H-statistic, Lerner Index and the Boone Indicator.

The results suggest that supervisory, regulatory, and competition authorities would benefit significantly from regularly assessing the combined effect of competition and innovation on financial stability. This assessment would also probably include other considerations, such as efficiency gains derived from financial innovation or competition especially when the services include a financial technology company. This may involve coordination among several institutions. For instance, micro and macro prudential supervisors and other institutions in charge of financial stability may need to coordinate and regularly exchange data with competition authorities. A first step in this direction could be the development of measures of bank competition that can be integrated in the financial stability framework of these institutions.

Importantly, a reliable, timely, complete, and readily accessible database are crucial for efficient and effective risk identification and assessment in financial sector supervision and enforcement. Such a database is particularly important for financial supervisors who are facing fast innovation and a regulatory perimeter that is getting bigger because of the growing digital financial services and the entry of digital banks. What kind of data to collect, how frequently, in what format, through what means are important questions, along with what aspects to improve upon. It may be useful and relevant to re-assess the approach to data collection, with the goal of further strengthening supervision while fostering digital transformation.

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Annex

TABLE A1. Bank competition and bank risk using H-Statistic, March 2010 to December 2020

Independent variables	Dependent variable (I) UKB/KB Group Z-Score (ZSCORE)		Dependent variable (II) Thrift Bank Group Z-Score (ZSCORE)		Dependent variable (III) Rural/Coop Bank Group Z-Score (ZSCORE)	
	Coef.	Standard error	Coef.	Standard error	Coef.	Standard error
H-statistic	-0.118	0.259	-0.162	(0.017)***	0.127	(0.075)***
Significant percentile	Not significant in all percentiles		All percentiles		All percentiles	
Bank-specific characteristics						
DEP (-1) (Ratio of deposits/total liabilities)	0.872	(0.275)***	0.179	(0.046)***	-	-
TLP (-1)	-	-	0.226	(0.029)***	0.562	(0.830)***

TABLE A1. Bank competition and bank risk using H-Statistic, March 2010-December 2020 (continued)

Independent variables	Dependent variable (I) UKB/KB Group Z-Score (ZSCORE)		Dependent variable (II) Thrift Bank Group Z-Score (ZSCORE)		Dependent variable (III) Rural/Coop Bank Group Z-Score (ZSCORE)	
	Coef.	Standard error	Coef.	Standard error	Coef.	Standard error
LIQ (-1) (Ratio of liquid assets/deposits)	-	-	-	-	-	-
CI (-1) (Cost-to-income ratio)	-0.008	(0.004)**	-0.179	(0.021)***	-0157	(0.003)***
DV (-1) (Diversification index)	-0.145	(0.132)*	-	-	-0.397	(0.082)***
CAP (-1) (Ratio of total capitalization to total assets)	0.265	0.364***	-0.132	(0.095)***	-0.157	(0.682)**
Macro and other indicators						
RGDP (Real GDP growth)	0.036	(0.172)*	0.202	(0.062)***	0.956	(0.324)***
POL (BSP policy rate)	-	-	-	-	-	-
DCHANGE (Dummy for changes in banking structure)	0.049	(0.033)*	0.042	(0.201)*	-0.060	(0.002)***
DCHANGE*HSTA (Interaction term)	-0.564	0.118	0.169	(0.035)**	-0.045	(0.003)**
DCOV (Dummy for pandemic)	-0.109	0.274	0.054	0.012	0.154	(0.124)***
Diagnostics						
Adjusted R^2	*0.501*		*0.868*		*0.621*	
Sample period	*2010Q1-2020Q4*		*2010Q1-2020Q4*		*2010Q1-2020Q4*	
Banks	*41*		*44*		*457*	
No of bank observations	*1,365*		*1,044*		*14,167*	
Stability test 1	*0.000*		*0.078*		*0.023*	
Residual test 2	*0.123*		*0.167*		*0.176*	
Symmetric quantiles test 3	*0.201*		*0.111*		*0.211*	
Standard error of regression	*0.008*		*0.000*		*0.000*	

Notes: Robust standard errors are reported in brackets. The symbols *, **, and *** represent significance levels of 10 percent, 5 percent, and 1 percent respectively.
[1] Reports *p*-values for the null hypothesis that the model has no omitted variables and is correctly specified using Ramsey RESET test.
[2] Reports *p*-values for the null hypothesis that the data is normally distributed using Jarque-Bera test.
[3] Reports *p*-values for the null hypothesis that the quantiles are symmetric using Wald test.
Source: Author.

TABLE A2. Bank competition and bank risk using Boone Indicator, March 2010 to December 2020

Independent variables	Dependent variable (I) UKB/KB Group Z-Score (ZSCORE)		Dependent variable (II) Thrift Bank Group Z-Score (ZSCORE)		Dependent variable (III) Rural/Coop Bank Group Z-Score (ZSCORE)	
	Coef.	Standard error	Coef.	Standard error	Coef.	Standard error
Boone	-0.539	(0.254)**	-0.031	(0.935)**	-0.045	(0.143)**
Significant quintile	0.4, 0.5, 06, and 0.7 quintiles		All quintiles		All quintiles	
Bank-specific characteristics						
DEP (-1) (Ratio of deposits/total liabilities)	0.172	(0.103)*	-	-	-	-
TLP (-1)	-	-	-	-	-	-
LIQ (-1) (Ratio of liquid assets/ deposits)	-	-	-	-	-	-
CI (-1) (Cost-to-income ratio)	-	-	-0.517	(0.195)**	-0.193	(0.005)**
DV (-1) (Diversification index)	-0.039	(0.849)***	-0.127	(0.263)**	-0.112	(0.297)
CAP (-1) (Ratio of total capitalization to total assets)	-0.863	(0.233)***	-0.155	(0.624)***	-0.567	(0.117)**
NPLR (Nonperforming loan ratio)	-0.027	0.026	-	-	-	-
Macro and other indicators						
RGDP (Real GDP growth)	0.049	(0.098)*	0.110	(0.226)***	0.020	(0.115)**
POL (BSP policy rate)	0.027	(0.022)				
DCHANGE (Dummy for changes in banking structure)	-0.084	(0.063)*	0.179	(0.342)**	0.377	(0.009)**
DCHANGE*HSTA (Interaction term)	0.162	(0.089)***	-0.178	(0.503)**	-0.507	(0.013)
DCOV (Dummy for pandemic)	-0.100	0.121	-0.095	0.181	0.787	(0.198)**
Diagnostics						
Adjusted R^2	*0.308*		*0.6552*		*0.574*	
Sample period	*2010Q1-2020Q4*		*2010Q1-2020Q4*		*2010Q1-2020Q4*	
Banks	*41*		*44*		*457*	
No of bank observations	*1,227*		*968*		*15,081*	
Stability test[1]	*0.052*		*0.095*		*0.000*	
Residual test[2]	*0.210*		*0.201*		*0.178*	
Symmetric quantiles test[3]	*0.100*		*0.189*		*0.142*	
Standard error of regression	*0.096*		*0.043*		*0.021*	

Notes: Robust standard errors are reported in brackets. The symbols *, **, and *** represent significance levels of 10 percent, 5 percent, and 1 percent respectively.

[1] Reports *p*-values for the null hypothesis that the model has no omitted variables and is correctly specified using Ramsey RESET test.

[2] Reports *p*-values for the null hypothesis that the data is normally distributed using Jarque-Bera test.

[3] Reports *p*-values for the null hypothesis that the quantiles are symmetric using Wald test.

Source: Author.

TABLE A3. Bank competition, bank efficiency, and bank risk using Boone Indicator, March 2010 to December 2020

Independent variables	Dependent variable (I) UKB/KB Group Z-Score (ZSCORE)		Dependent variable (II) Thrift Bank Group Z-Score (ZSCORE)		Dependent variable (III) Rural/Coop Bank Group Z-Score (ZSCORE)	
	Coef.	Standard error	Coef.	Standard error	Coef.	Standard error
Boone	-0.323	(0.032)*	-0.031	(0.935)**	-0.042	(0.002)*
Boone^2[a]	Linear	Linear	0.002	(0.001)**	-	-
Significant quintile	0.2, 0.7, 08, and 0.9 quintiles		All quintiles		All quintiles	
Bank-specific characteristics						
DEP (-1) (Ratio of deposits/total liabilities)	-	-	-	-	-	-
TLP (-1)	-	-	-	-	0.152	(0.022)**
LIQ (-1) (Ratio of liquid assets/ deposits)	-	-	-	-	-0.051	(-0.011)**
CI (-1) (Cost-to-income ratio)	-0.685	(0.351)***	-0.136	(0.023)***	-0.245	(0.024)**
Boone (-1) * CI (-1) (Interaction term)	-0.575	0.685	-0.495	(0.151)*	-0.024	(0.023)*
DV (-1) (Diversification index)	-	-	-0.043	(0.077)**	0.059	(0.032)*
CAP (-1) (Ratio of total capitalization to total assets)	-0.354	(0.036)***	-0.088	(0.009)***	-0.411	(0.037)**
NPLR (Nonperforming loan ratio)	-0.027	0.026	-0.062	0.010	-0.047	(0.002)**
Macro and other indicators						
RGDP (Real GDP growth)	0.039	(0.016)***	0.161	(0.013)***	0.064	(0.019)**
POL (BSP policy rate)	-	-	-0.199	(0.034)***	-	-
DCHANGE (Dummy for changes in banking structure)	0.014	0.033	0.018	(0.034)**	0.069	(0.001)*
DCOV (Dummy for pandemic)	-0.055	(0.023)*	-0.102	(0.056)*	-0.017	(0.007)**
Diagnostics						
Adjusted R^2	*0.502*		*0.683*		*0.723*	
Sample period	*2010Q1-2020Q4*		*2010Q1-2020Q4*		*2010Q1-2020Q4*	
Banks	*41*		*44*		*457*	
No of bank observations	*1,227*		*968*		*15,081*	
Stability test[1]	*0.011*		*0.026*		*0.001*	
Residual test[2]	*0.198*		*0.278*		*0.199*	
Symmetric quantiles test[3]	*0.101*		*0.201*		*0.156*	
Standard error of regression	*0.008*		*0.056*		*0.041*	

Notes: Robust standard errors are reported in brackets. The symbols *, **, and *** represent significance levels of 10 percent, 5 percent, and 1 percent respectively.
[1] Reports *p*-values for the null hypothesis that the model has no omitted variables and is correctly specified using Ramsey RESET test.
[2] Reports *p*-values for the null hypothesis that the data is normally distributed using Jarque-Bera test.
[3] Reports *p*-values for the null hypothesis that the quantiles are symmetric using Wald test.
Source: Author.

TABLE A4. Bank competition and bank risk using Lerner Index, March 2010 to December 2020

Independent variables	Dependent variable (I) UKB/KB Group Z-Score (ZSCORE)		Dependent variable (II) Thrift Bank Group Z-Score (ZSCORE)		Dependent variable (III) Rural/Coop Bank Group Z-Score (ZSCORE)	
	Coef.	Standard error	Coef.	Standard error	Coef.	Standard error
Lerner	-0.028	(0.014)**	0.019	(0.244)*	0.456	(0.013)***
Significant quintile	0.5 and 0.6 quintiles		All quintiles		All quintiles except 0.40 quintile	
Bank-specific characteristics						
DEP (-1) (Ratio of deposits/total liabilities)	-	-	-	-	-	(0.142)***
TLP (-1)	-	-	0.127	(0.877)*	-	-
CI (-1) (Cost-to-income ratio)	-0.449	(0.292)**	-0.150	(0.387)*	-0.185	(0.083)***
DV (-1) (Diversification index)	-0.021	(0.399)*	-0.095	(0.174)**	-0.011	(0.046)***
CAP (-1) (Ratio of total capitalization to total assets)	-0.361	(0.114)***	-0.266	(0.167)**	-0.031	(0.236)**
Macro and other indicators						
RGDP (Real GDP growth)	0.761	(2.517)*	0.117	(0.133)**	0.010	(0.159)**
POL (BSP policy rate)	0.016	(1.053)	-	-	-	-
DCHANGE (Dummy for changes in banking structure)	-0.072	(0.037)*	0.125	(0.020)**	-0.177	(0.005)***
DCHANGE*Lerner (Interaction term)	-0.009	(0.004)**	0.128	(0.004)*	0.029	(0.011)**
DCOV (Dummy for pandemic)	-0.198	0.236	-0.042	(0.254)**	0.090	(0.026)***
Diagnostics						
Adjusted R^2	*0.5*		*0.797*		*0.574*	
Sample period	*2010Q1-2020Q4*		*2010Q1-2020Q4*		*2010Q1-2020Q4*	
Banks	*41*		*44*		*457*	
No of bank observations	*1,804*		*998*		*15,081*	
Stability test[1]	*0.068*		*0.000*		*0.000*	
Residual test[2]	*0.120*		*0.211*		*0.231*	
Symmetric quantiles test[3]						
Standard error of regression	*0.083*		*0.003*		*0.051*	

Notes: Robust standard errors are reported in brackets. The symbols *, **, and *** represent significance levels of 10 percent, 5 percent, and 1 percent respectively.
[1] Reports *p*-values for the null hypothesis that the model has no omitted variables and is correctly specified using Ramsey RESET test.
[2] Reports *p*-values for the null hypothesis that the data is normally distributed using Jarque-Bera test.
[3] Reports *p*-values for the null hypothesis that the quantiles are symmetric using Wald test.
Source: Author.

FIGURE 1A. Bank competition and bank risk among universal and commercial banks using Boone Indicator, March 2010 to December 2020

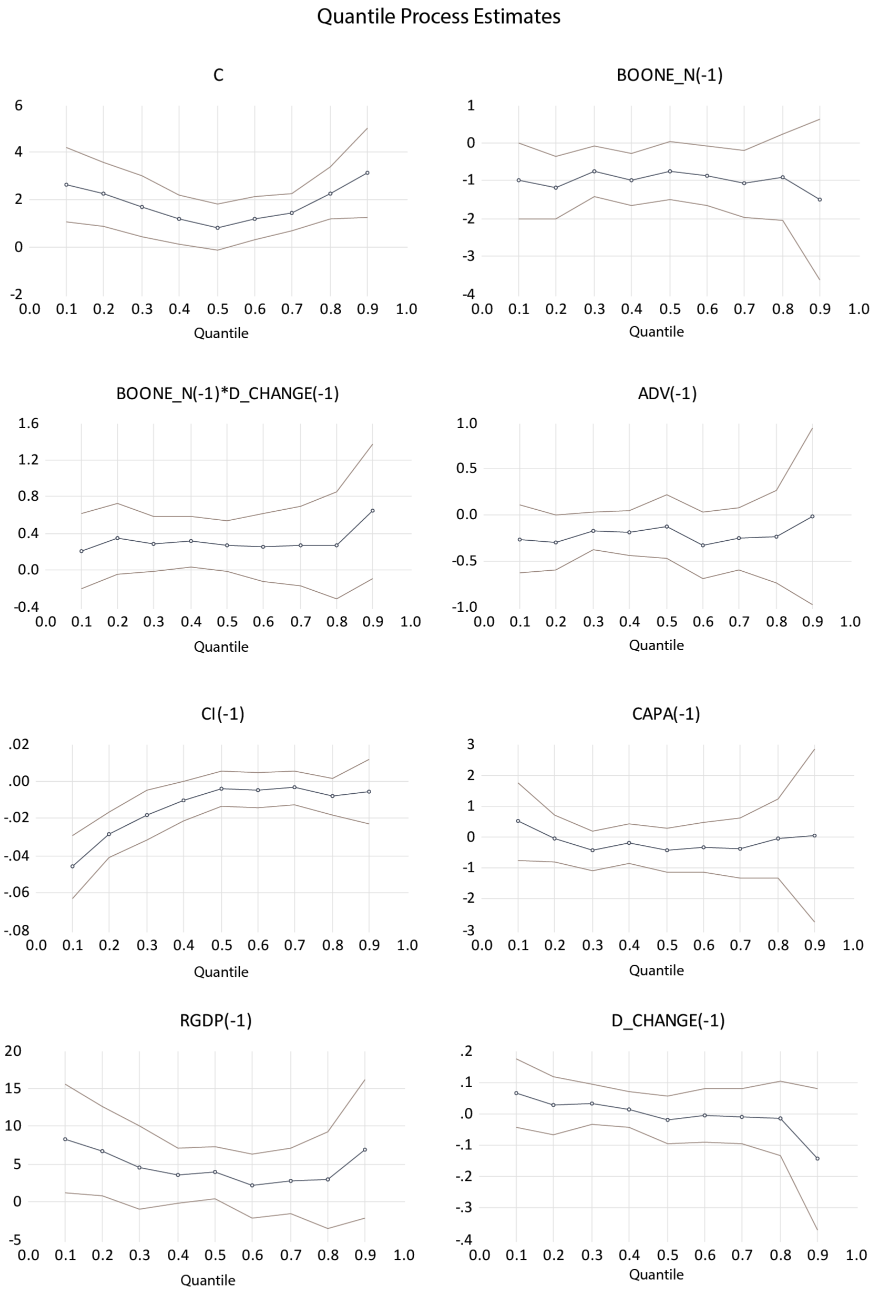


FIGURE 1A. Bank competition and bank risk among universal and commercial banks using Boone Indicator, March 2010 to December 2020 (continued)

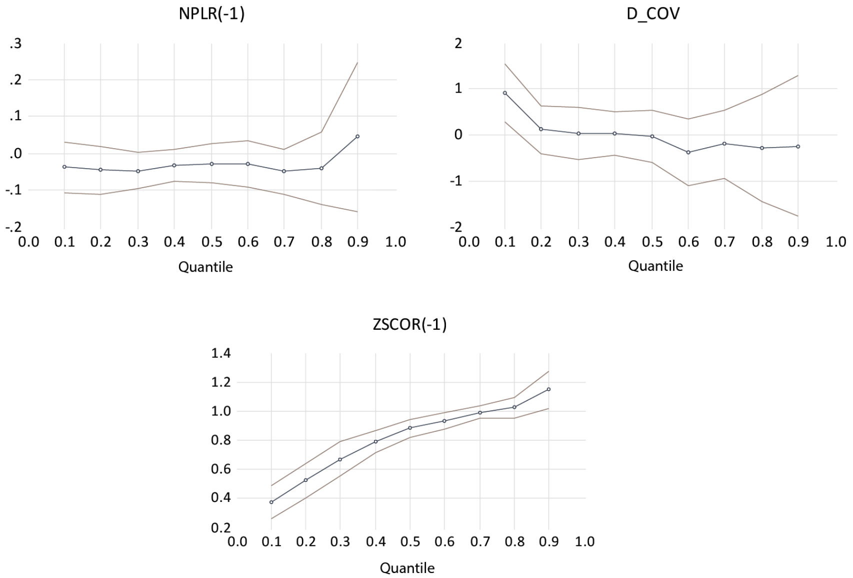


FIGURE 1B. Bank competition and bank risk among universal and commercial banks using Lerner Index, March 2010 to December 2020

Quantile Process Estimates

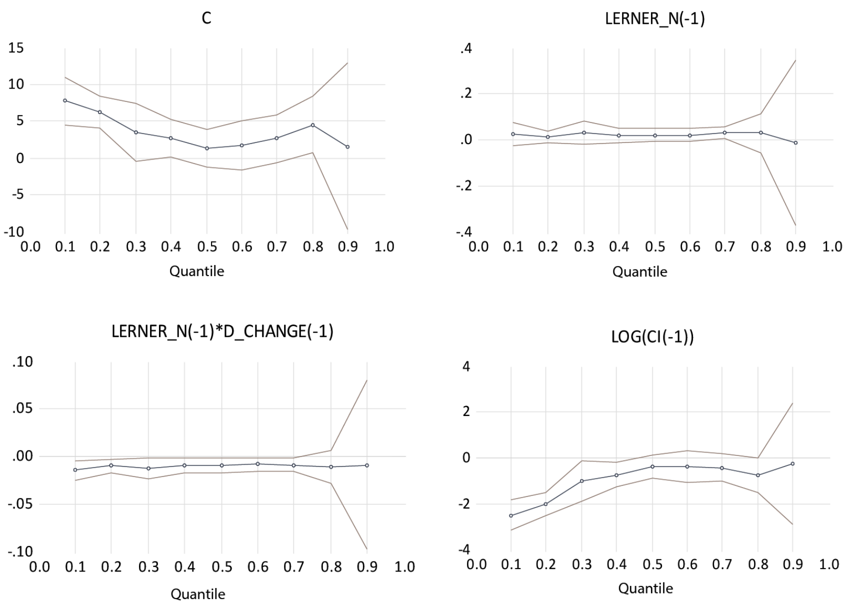
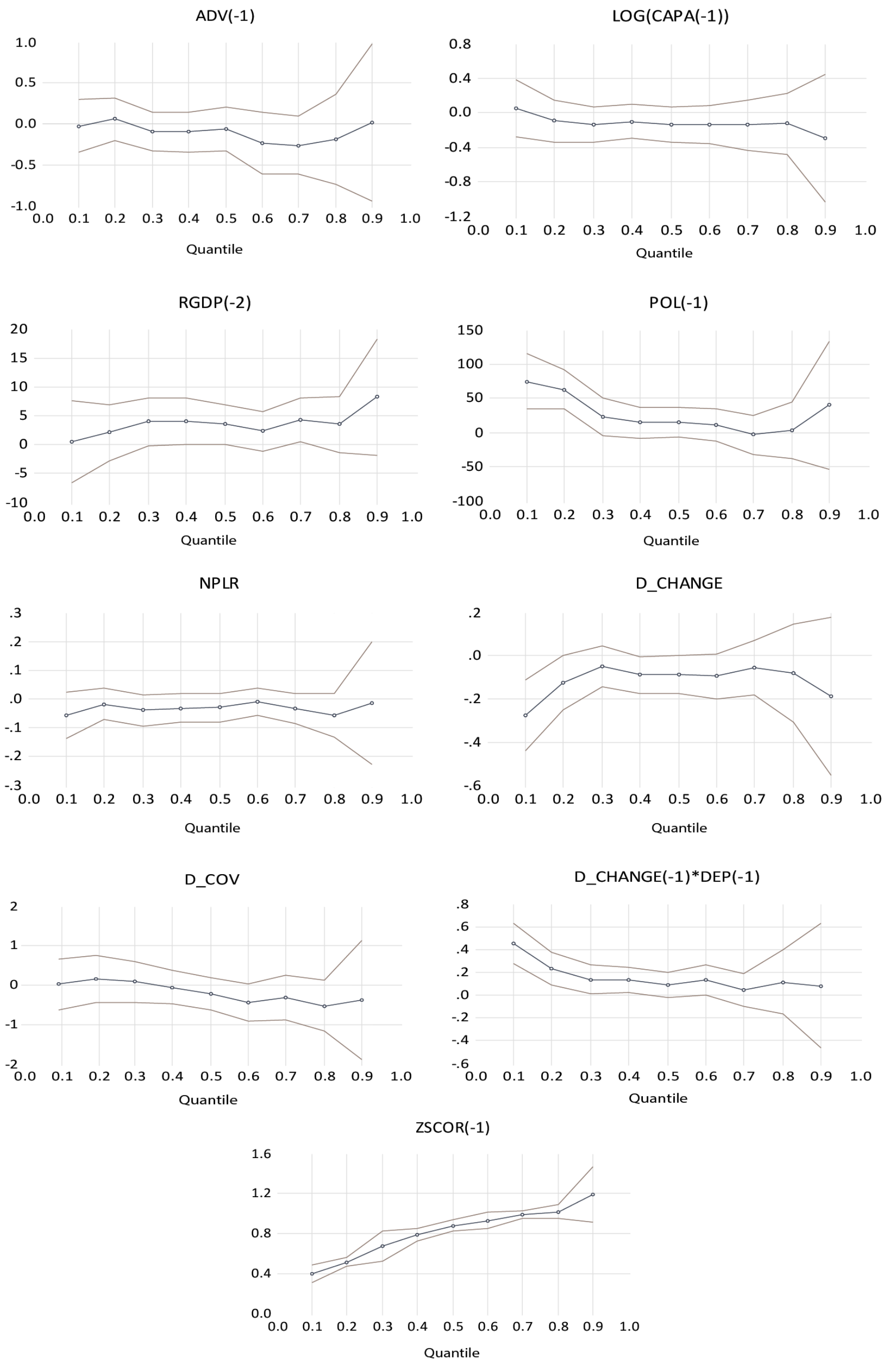


FIGURE 1B. Bank competition and bank risk among universal and commercial banks using Lerner Index, March 2010 to December 2020 (continued)



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Insights on inflation expectations in the Philippines from a household survey

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The study contributes to the literature on expectations by providing insights on household expectations from an emerging market and inflation targeting country like the Philippines. Using the results of the Consumer Expectations Survey (CES), a quarterly household survey conducted by the Bangko Sentral ng Pilipinas (BSP), the study is the first to look at the characteristics and determinants of household inflation expectations in the Philippines at a granular level. Results show that survey-based household expectations in the country are not rational. Filipino households exhibit an upward bias in their forecast of future inflation and they tend to rely more on information about past inflation to form their expectations. Nonetheless, in recent years, households have started to incorporate information about future outcomes in their inflation expectations process. To determine the factors that drive household expectations in the Philippines, aggregated (i.e., time series) and disaggregated (i.e., pooled data) data from CES quarterly survey rounds between 2010 and 2020 are used on a standard inflation expectations model. Empirical results point to a significant effect of income conditions, perceptions on economic and financial conditions, the inflation target, and demographic factors (e.g., educational attainment, marital status) on the formation of household expectations in the Philippines. Based on the findings and observations, the study draws insights for central bank communication strategy, particularly in influencing household expectations.

JEL classification: D10, D84, E31, E58
Keywords: central banks, expectations, households, household survey, inflation expectations, inflation dynamics

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** The views expressed in this paper are those of the authors and do not necessarily reflect those of Bangko Sentral ng Pilipinas. Any errors and omissions are solely of the authors.

"…*We need to know more about the manner in which inflation expectations are formed and how monetary policy influences them*" [Yellen 2016].

1. Introduction

Central banks have long recognized the crucial role of inflation expectations in the conduct of monetary policy. Well-anchored inflation expectations allow central banks to achieve price stability and reduce volatilities of key economic variables like interest rates, wages, and output. During the 2009 Global Financial Crisis (GFC), the significance of the expectations transmission channel became acutely evident when central banks shifted to using unconventional monetary policy tools. With interest rates at the zero-lower bound (ZLB), central banks resorted to the use of quantitative easing policies and forward guidance on the future path of interest rates to affect economic outcomes. Extensive discussions were also made on alternative monetary policy actions such as raising the inflation target and adopting nominal gross domestic product (GDP) or price level targets, with the view to influencing the inflation expectations of economic agents. Expectations of higher future inflation will lower households' and firms' perception of current real interest rates. This, in turn, would encourage households to increase current spending. Anticipation of higher inflation can lead firms to raise their prices and workers to bargain for higher wages.

Several measures of inflation expectations are currently in use in central banks. These are commonly based on two sources of information. Market-based inflation expectations (e.g., yield curve, term structure of interest rates) are derived from information on expected inflation based on the prices of assets in the financial market. Meanwhile, survey-based inflation expectations are generated from the responses of professional forecasters, businesses, households, and consumers on questions regarding predicted future inflation.

Survey-based measures have increasingly been used in exploring the different aspects of the expectations formation process of economic agents (e.g., professional forecasters, firms, households). These measures are observed to capture important economic information, including the public's understanding of monetary policy (Berge [2017]; Clark and Davig [2011]; Kiley [2009]). Some studies (e.g., Faust and Wright [2013]; Gil-Alana et al. [2012]; Ang et al. [2007]) have shown that survey-based measures of inflation expectations have better predictive power on future inflation developments than standard time series models. Thus, an expanding literature on inflation dynamics uses survey-based expectations to estimate the New Keynesian Phillips curve (NKPC) (e.g., Fuhrer [2012]; Koop and Onorante [2012]; Zhang et al. [2009]; Gerberding [2001]; Fuhrer and Moore [1995]). However, these studies offer contradicting conclusions regarding these expectations measures (Fuhrer [2012]). Roberts [1995, 1998] estimated the NKPC for the US using survey measures of inflation expectations from the Michigan and Livingston surveys as proxy for inflation expectations.

His model managed to track and explain the behavior of US inflation in the 1990s. Meanwhile, Adam and Padula [2011] use inflation forecasts from the Survey of Professional Forecasters (SPF) and concluded that survey expectations are an important determinant of inflation for UK data. By contrast, Rudebusch [2002] estimates the hybrid NKPC for the US using data from the Michigan survey and observed a relatively small coefficient on the expectations term. His finding is echoed by Nunes [2010] who finds little empirical role for survey expectations.

While expectations measures from surveys can provide economic information, they do not strictly adhere to rationality conditions. They have been found to deviate from rational expectations in a systematic and quantitatively significant way, including forecast-error predictability and bias (Coibion et al. [2018]; Nunes [2010]; Capistran and Timmerman [2009]; Caroll [2003]; Mehra [2002]; Thomas [1999]; Batchelor and Dua [1989]; Perasan [1987]). Rational expectations hypothesis holds that market agents form expectations on an economic variable using all available information, including past values of the variable and current information on its future values. It is a central economic theory which has been used as the main approach in incorporating expectations in macroeconomic modelling. Deviations from this assumption imply that economic agents make systematic errors in forming their expectations [Muth 1961]. For policymakers and authorities, such deviations present a challenge when trying to influence the behavior of economic agents to achieve a given objective (e.g., price stability).

In this paper, we test for the rationality of micro-level, survey-based expectations in the Philippines using the Consumer Expectations Survey (CES), a quarterly household survey conducted by the Bangko Sentral ng Pilipinas (BSP). Results of tests of rationality on expectations reveal whether or not economic agents have inherent biases (i.e., in addition to noisy signals and passing uncertainties) (Thomas [1999]; Kean and Runkle [1990]; Gramlich [1983]). Moreover, these tests indicate if economic agents use all available and relevant information to them (i.e., efficient). Tests of rationality are useful in understanding how economic agents use available information to form their expectations. They are also useful in informing policy. For example, if economic agents display some bias in their expectations, decision makers can properly calibrate their analysis and policy prescriptions to take this into account. This, in turn, could make policy more effective.

Our test results signify that survey-based household expectations in the Philippines are outperformed by naïve forecasts which are based on lagged values of actual inflation. This indicates that households rely more on past information about actual inflation than on future information about inflation in making their forecast. However, we observe that the forecast accuracy of household inflation expectations has improved in recent years. Nonetheless, there is little evidence that these survey-based expectations are characterized by rationality (i.e., unbiased and efficient). Results suggest that Filipino households do not utilize all available information and they tend to put more weight on information about the past to form their expectations of future outcomes. Moreover, expectations are not fully, but only partly, driven by fundamentals. Thus, realized inflation is not necessarily a result of self-fulfilling variations in expectations [Rafiq 2013].

Tests of rationality offer insights on how households use and process information to form their inflation expectations. However, these do not tell the specific information and factors that underpin the expectations formation process of households. Understanding the underlying process of how households form their inflation expectations is crucial as these could affect their economic decisions such as consumption, savings, and investment (Armantier et al. [2015]; Bernanke [2007]). From a macro perspective, central banks' commitment to low and stable inflation, which is generally associated with the adoption of the inflation targeting framework, is observed to have led to better monetary policy and, consequently, to the firmer anchoring of inflation expectations (Mishkin [2007]; Gurkaynak et al. [2007]; Levin et al. [2004]). Meanwhile, at a micro level, factors including age, gender, income, and educational status have been found to be important characteristics in forming expectations. Households that are better educated and with higher incomes tend to have lower inflation forecast relative to those that are younger, less educated, and with lower incomes (Blanchflower and MacCoille [2009]; Armantier et al. [2015]; Pfajfar and Santoro [2008]). Moreover, perceptions about current inflation as well as the frequency and size of goods price changes matter for inflation expectations [D'Acunto et al. 2019].

Using the BSP CES micro-level data, we explore the factors that drive household expectations in the Philippines. Our regression results point to the significant effect of income conditions, perceptions on economic and financial conditions, and the inflation target on the formation of household expectations in the country. Moreover, we use a more disaggregated data (i.e., pooled CES survey data) to further examine the factors that could affect household expectations. The empirical results yield similar observations on the effect of household income conditions and perceptions about economic and financial conditions on expectations. In addition, we find that demographic factors (e.g., educational attainment, marital status, gender) also affect the formation of household expectations.

Our study contributes to the literature on expectations by providing insights on household expectations from an emerging market and inflation targeting country like the Philippines. The study is the first to look at the characteristics and determinants of household inflation expectations in the Philippines at the granular level. The inferences and observations offer clear distinctions on how demographics and perceptions affect the formation of household expectations. These are useful for studying inflation dynamics as well as in designing an effective central bank communication strategy to manage expectations.

The paper is organized as follows. Section 2 evaluates the rationality of household expectations in the Philippines. It also presents some of the key characteristics and properties of survey-based expectations in the country. Section 3 looks at the expectations formation process of Filipino households and determines the factors that affect it. Section 4 discusses the observed decline in inflation expectations in the Philippines. Section 5 presents the policy implications on central bank communication. The last section concludes.

2. Survey-based expectations in the Philippines: forecast accuracy and rationality

We first provide a short description of the BSP CES, the main source of data for this study. Next, we explore the characteristics and properties of survey-based expectations in the Philippines. We then evaluate whether or not expectations based on the CES have forecast bias and if they exhibit rationality.

2.1. Data

In 2002, the Philippines adopted inflation targeting as its framework for monetary policy. The shift led to the greater significance of the expectations channel in the transmission of monetary policy in the country. This increased the importance of monitoring inflation expectations to ensure that they are aligned with the central bank's policy objectives as well as to inform monetary policy formulation. Hence, the BSP initiated and institutionalized the conduct of expectations surveys for firms, consumers, households as well as professional forecasters.

For this study, we use the results of the CES, a quarterly survey of a random sample of about 5,000 households in the Philippines, to analyze expectations in the country.[1,2] The CES, together with the BSP Business Expectations Survey (BES),[3] is a tool that the BSP uses to gather information to gauge the sentiment of consumers, households, and businesses. The survey was first officially conducted in the 4th quarter of 2004. It initially included a sample of households in the National Capital Region (NCR). Eventually, the survey was expanded to cover the entire Philippines starting in the first quarter of 2007.[4]

The CES results provide advanced information on the consumption spending and buying intentions of households as well as potential changes in family incomes and financial conditions. It gives monetary authorities some leading indications of household sentiments for the current quarter, for the next quarter, and for the

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[1] The CES adopts the sampling design of the Labor Force Survey (LFS) of the Philippine Statistics Authority (PSA). The CES samples are drawn from the PSA Master Sample for household surveys, which is considered as a representative sample of households nationwide. The CES sample households are generated using a stratified multi-stage probability sampling scheme.

[2] Central banks that conduct surveys on the inflation expectations of consumers include the Bank of England, Bank of Canada, European Central Bank, Federal Reserve of New York, Bank of Japan, Bank Indonesia, and the Reserve Bank of India.

[3] The BES gathers information from entrepreneurs about business conditions in their own companies. It also collects information about entrepreneurs' views on the general business situation in their own industry and on the national economy. Additionally, the BES presents the perception of different groups on current and near-term business conditions, including levels of production and economic activity and factors that could influence the movement of key economic variables such as GDP, interest rate, peso/dollar exchange rate, and inflation rate.

[4] From an initial sample survey of 3,039 households in NCR, the quarterly CES currently covers about 5,000 sample households equally allocated at about 2,500 households for each geographical area (i.e., NCR and areas outside NCR).

next 12 months on selected economic indicators, including inflation. For instance, the CES asks households their expected inflation for the next 12 months. In Q1 2021, the CES started asking households their expected inflation for both the current quarter and the next quarter. In this paper, we focus on inflation expectations for the next 12 months (i.e., long-run inflation expectations) given that it has a longer series.

Since Q2 2014, the CES has been reporting two series that try to capture households' expectations of price changes for the next 12 months. These are (i) inflation rate aggregated from the individual inflation rate of major consumer price index (CPI) items[5] (i.e., inflation rate CPI items); and (ii) inflation rate as a point forecast (i.e., inflation rate point forecast). For the inflation rate (CPI items), households are asked about their expectations of what would happen to the prices of goods and services in the next 12 months.[6] Meanwhile, for the inflation rate (point forecast), households are asked the question about their expected inflation rate for the next 12 months. A comparison of the two series shows that over the period Q2 2014 to Q2 2021, average inflation rate (CPI items) is higher than average inflation rate (point forecast) by 0.6 percent (i.e., in terms of the rate and the trend). Nonetheless, correlation results indicate a significant positive association between the two series at 64.0 percent. The inflation rate (CPI items) has a longer series than the inflation rate (point forecast). Thus, for the purposes of this paper, we use the inflation (CPI items) as our measure for household inflation expectations.

2.2. Initial observations

Figure 1 plots the quarterly year-on-year percent change in CPI (i.e., inflation rate) together with quarterly survey-based household inflation expectations over the period 2010 to 2020. It also shows the upper- and lower-bounds of the National Government's (NG's) inflation target for the same period. The chart yields some general observations. First, Filipino households tend to overpredict future inflation. On average, the difference between inflation expectations and actual inflation is 2.7 percentage points. Interestingly, households underpredicted inflation in 2018, a year when inflation was above the BSP's inflation target. A possible explanation for this is that supply shocks in 2018 were unexpected which made them difficult to predict. The World Bank and International Monetary Fund (IMF) forecasts as well as oil futures contracts likewise failed to significantly foresee the steep rise in oil prices in 2018. However, the gap between actual inflation and expected inflation has narrowed in recent years.

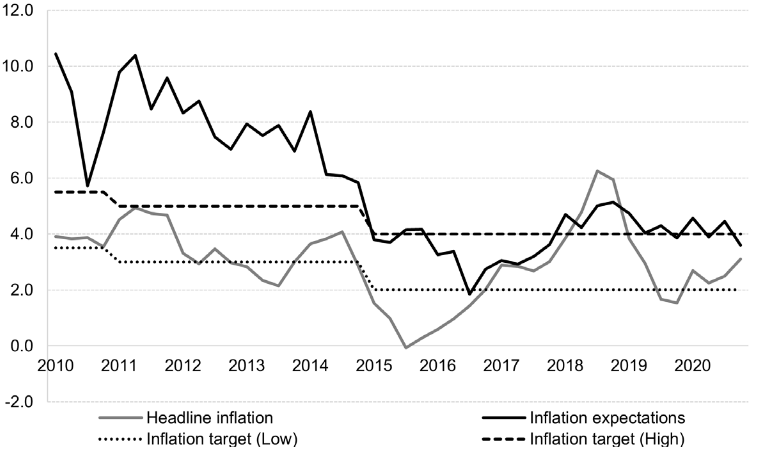
[5] The inflation rate (CPI items) is computed by multiplying the percentage of households that answered that prices will increase (decrease) with the average rate of price increase (decrease). The resulting difference between the two sets of household responses (i.e., price increase and decrease) is combined with the associated CPI weights of the different commodities.

[6] The CES questionnaire covers the major CPI commodity items. Since 2016, survey respondents have been asked about their expected inflation for 21 CPI commodity items in the next 12 months. These items account for 93.9 percent of the country's CPI basket.

Second, there is a noticeable lowering of expected inflation by households starting in the latter quarters of 2014. The dispersion of inflation forecasts has declined over time which may have contributed to lower expectations. This could have been partly due to the general decline in trend inflation (Figure 2). In 2015 and 2016, domestic inflation settled at 0.7 percent and 1.3 percent, respectively, which were substantially below the 2.0 percent lower-bound of the inflation target for those years. Factors that contributed to the disinflationary pressure were China's economic slowdown, the drop in international oil prices, and the general decline in food prices.[7] Subsequently, inflation would rise sharply to 5.2 percent in 2018 on the back of high food and energy prices. This figure was above the inflation target for 2018 and highest over the previous nine years.

Third, household expectations of inflation started to move closer to the NG's target range for inflation in recent years. Correlation results show that there is a positive and significant relationship between the BSP's inflation target and households' expected inflation (Table 1). This suggests that households have started to include the inflation target in their information set when forming expectations about future inflation.

FIGURE 1. Inflation, inflation expectations, and inflation target
(in percent; year-on-year)

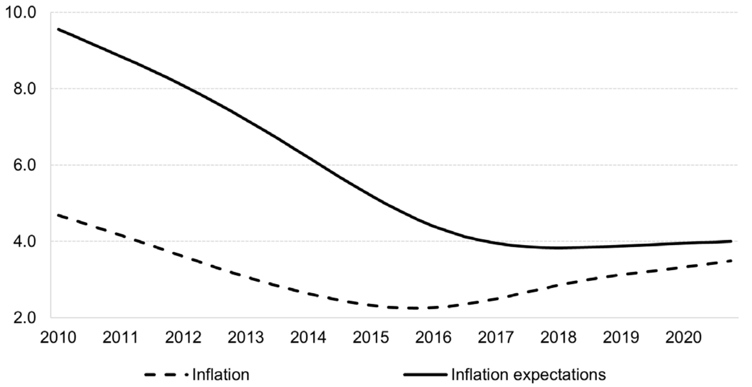


Source: Philippine Statistics Authority (PSA).

[7] In 2015, China's economy expanded at an average rate of 6.9 percent, its slowest growth in 25 years. Fears of an overheating economy, stock market meltdown, and possibility of a hard landing dominated the landscape for the Chinese economy in 2015. Moreover, international oil prices substantially declined between 2014 and 2016 owing to a supply glut.

FIGURE 2. Trend [a/]: inflation and inflation expectations

(in percent)



Note: [a/] Trend is generated using the HP filter.
Source: Philippine Statistics Authority (PSA).

TABLE 1. Descriptive statistics

	Inflation (in percent)			Household expected inflation (in percent)		
	Q1 2010–Q4 2020	**Q1 2010–Q4 2014**	**Q1 2015–Q4 2020**	**Q1 2010–Q4 2020**	**Q1 2010–Q4 2014**	**Q1 2015–Q4 2020**
Mean	3.1	3.6	2.7	5.6	8.0	3.9
Median	3.0	3.6	2.7	4.7	7.9	3.9
Maximum	10.4	4.9	6.3	6.3	10.4	5.1
Minimum	1.8	2.2	-0.1	-0.1	5.7	1.8
Std. Dev.	2.3	0.8	1.6	1.4	1.4	0.8
Correlation with inflation	1.0	1.0	1.0	0.44	0.42	0.46
Correlation with inflation target[1/]	0.32	0.14	0.18	0.87	0.08	0.60

Note: [1/] Using the midpoint of the inflation target range.
Source: Authors' calculations.

2.3. Testing for forecast accuracy and rationality

In Figure 1, we observe that households' prediction of future inflation is often higher than actual inflation. We formally test the forecast accuracy of households' expectations and assess their performance against a naïve model. Moreover, we assess whether or not household expectations in the Philippines are rational by testing for unbiasedness and efficiency (i.e., using all available information).

2.3.1. Forecast accuracy

To determine forecast accuracy, we use the mean error (ME), mean absolute error (MAE), and the root mean square error (RMSE). The mean error is the average magnitude of forecast error (e_t) over the n periods being forecasted. It is considered as a basic measure of forecasting bias. The forecast error (e_t) is defined as forecast (i.e., expected) inflation rate minus the actual inflation rate that subsequently occurred. Thus, a positive mean error signifies that households, on average, overpredict inflation. Conversely, a negative mean error indicates that households, on average, underpredict inflation. Meanwhile, the MAE measures the accuracy of forecasts. An alternative measure of accuracy is the RMSE. It is derived by summing the squares of each of the errors, divided by the number of forecast periods, and taking the square root of the resulting quotient. Relative to the MAE, the RMSE amplifies the effect of large forecast errors.

We calculate the ME, MAE and RMSE using standard equations, as follows:

$$ME = \tfrac{1}{n}\sum\nolimits^{n}_{i=1} e_t$$

$$MAE = \tfrac{1}{n}\sum\nolimits^{n}_{i=1} |e_t|$$

$$RMSE = \left[\tfrac{1}{n}\sum_{i=1}^{n} |e^2_i|\right]^{½} \tag{1}$$

Survey-based inflation expectations vis-à-vis naïve forecast

While these metrics provide numerical evaluation of forecast accuracy, they are difficult to assess without a baseline comparison. Thus, we compare them to a naïve forecast to better gauge the forecast accuracy of household inflation expectations. The naïve forecast is defined as the average rate of inflation during the past two quarters.[8] It is therefore a purely backward-looking process (i.e., adaptive expectations).[9] The household is assumed to know the average rate of previous inflation at the time that the forecast is made. If survey-based household expectations do not outperform the naïve forecasts, this implies that households fail to consider relevant information on future inflation other than that contained in previous rate of actual inflation [Thomas 1999].

Table 2 presents the forecasting statistics for the survey-based inflation expectations and the naïve forecasts. Based on the forecast evaluation metrics, the

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[8] The use of the average rate of inflation over the past two quarters is based on regression results of an augmented Phillips curve equation which shows that lagged inflation of up to two quarters significantly affects current inflation.

[9] This is based on the adaptive expectations hypothesis which posits that people form their expectations about future outcomes based on historical information (Fisher [1911]; Cagan [1956]). Thus, inflation expectations have been modeled adaptively (i.e., using distributed lags of actual inflation) in the analysis of the expectations-augmented Phillips curve [Friedman 1968].

survey-based inflation expectations are unable to outperform the naïve forecast.[10] This signifies that Filipino households heavily rely on information about past inflation to form expectations of future inflation. In Figure 1, we observe actual inflation and inflation expectations exhibit a more rapid decline starting in 2015. Hence, we split our sample period to account for this observation and see how the survey-based forecast and naïve forecast performed between periods. From Table 2, we note the marked improvement of the forecasting performance of survey-based inflation expectations between the Q1 2010–Q4 2014 period and the Q1 2015–Q4 2020 period. This suggests that Filipino households are incorporating more information about future economic outcomes in their expectations in recent years.

TABLE 2. Inflation forecasting performance[2/]

Forecast	Q1 2010–Q4 2020			Q1 2010–Q4 2014			Q1 2015–Q4 2020		
	Mean Error	Mean Absolute Error	Root Mean Square Error	Mean Error	Mean Absolute Error	Root Mean Square Error	Mean Error	Mean Absolute Error	Root Mean Square Error
Survey-based inflation expectations (CES)	2.722	2.841	3.393	4.396	4.396	14.472	1.328	1.544	1.911
Naïve forecast	0.026	1.123	1.391	-0.049	0.773	0.904	0.089	1.415	1.692

Note: [2/] Based on authors' calculations.

2.3.2. Rationality: unbiasedness and efficiency

For inflation expectations to be considered rational, they must be unbiased and efficient (Thomas [1999]; Mehra [2002]). Expectations are unbiased if economic agents, on average, can forecast inflation correctly. Meanwhile, expectations are efficient if economic agents use all relevant information with the marginal benefit of gathering and processing the information exceeding the associated marginal cost [Thomas 1999].[11]

a. Test for unbiasedness

We test for bias using the following regression equation:

$$\pi_t = \alpha + \beta\pi^e_t + \varepsilon_t \tag{2}$$

where π_t is actual inflation, π^e_t is expected inflation with a forecast horizon of h periods (i.e., expectations of inflation formed at period $t-h$; $h=12$ months), and ε_t is a random residual. The existence of bias is determined by testing the joint null

[10] Our analysis provides a simple comparison of the predictive accuracy of two competing forecasting procedures. However, we would like to note that there are statistical tests (e.g., Diebold-Mariano test) that can be used for a more formal significance tests of equal predictive accuracy.

[11] Rational expectations requires that the forecast error be distributed independently of the expected value [Muth 1961].

hypothesis that $\alpha = 0$ and $\beta = 1$. Forecasts are considered unbiased if the joint null hypothesis cannot be rejected.

We use the quarterly (year-on-year) inflation rate and quarterly results of the BSP CES for households' expected inflation. Table 3 presents the results of the test of for unbiasedness of survey forecasts for inflation.

TABLE 3. Test for unbiasedness, Q1 2010–Q4 2020

	α	β	*F*-stat for Ho	No. of obs
Inflation expectations	1.57 (0.762)	0.26 (0.094)	7.87*** [0.007]	44

*** Significant at 0.01 level.
Note: Figures in parentheses are standard errors while figure in bracket is *p*-value. Equation was estimated using OLS. Hypothesis test was based on Newey-West HAC covariance matrix of residuals.

Table 3 shows that the null hypothesis is rejected at 1 percent confidence level. This indicates the presence of a forecast bias in the expectations results of the BSP CES.[12] The BIS [2016] reported a similar finding when they assessed survey-based expectations from the Philippines. Moreover, the result of the test for unbiasedness is in line with the calculated mean errors of household inflation expectations from Table 2. The survey-based inflation forecasts were shown to have a positive forecast bias.

Average (or median) survey-based expectations are observed to be a biased estimate of actual inflation (e.g., Thomas [1999]; Mehra [2002]; Carroll [2003]; Capistran and Timmerman [2009]; Nunes [2010]; Coibion [2018]). In the case of households, they often exhibit forecast bias because inflation may not always be part of their core information sets. Thus, households' beliefs about inflation may not be properly formed when they are asked about their expectations. There is also a lack of incentive for households to make an exhaustive assessment of the information available to them to come up with the best possible prediction of future inflation. Moreover, households know that there is no penalty in case their expectations turn out to be inaccurate. Thus, they may become indifferent and give biased responses to survey questions. However, the presence of an aggregate bias does not necessarily preclude the possibility that households are giving what they perceive as an accurate assessment of future inflation on which they base their economic decisions [Armantier et al. 2015]. Also, households may not be able to consider the structural changes or regime shifts happening in the economy. This could result in systematic errors in their forecasts over certain periods, even if they are fully rational [Thomas 1999].

[12] Results from the test for unbiasedness could suggest a weak form of rationality. Lovell [1986] distinguishes between a weak form rationality and strong form rationality. He described the weak rationality condition as "sufficient" expectations which requires the forecast error to be uncorrelated to historical information on previous values of the variable being forecast. Meanwhile, the strong rationality condition needs to be satisfied to attain full rationality. This entails that any other variables known to the forecaster must also be uncorrelated with the forecast error.

b. Test for efficiency[13]

Efficiency tests are done to reveal whether or not households use readily available information to improve expectations accuracy. To do this, we test the hypothesis that $\alpha_0 = 0$, $\alpha_1 = 1$, and $\alpha_2 = 0$ in the following equation [Keane and Runkle 1990]:

$$\pi_{t+h} = \alpha_0 + \alpha_{1t}\pi^e_{i,t+h} + \alpha_2 X_{i,t} + \varepsilon^i_{t,1}, \qquad (3)$$
$$E(\varepsilon^i_{t,i} \,|\, I_{i,t}) = 0$$

where π_{t+h} is actual inflation in period $t + h$ (i.e., h = 12 months); while $\pi^e_{t,}$ is household i's expected inflation with a forecast horizon of h periods (i.e., expectations of inflation formed at period t). The set of other variables affecting actual inflation is represented by $X_{i,t}$.

Testing the hypothesis on expectations by applying CES data to run a regression analysis of Equation 3, we cannot conclusively say that households efficiently use information in formulating their expectations. In Table 4, the null hypothesis that the constant term is zero is rejected. Furthermore, the coefficient of households' expected inflation does not indicate a one-to-one ($\alpha_1 = 1$) relationship with actual inflation. Overall, aggregate information from survey data does not provide evidence that Filipino households form their expectations using all available information. Thus, households' inflation forecast does not sufficiently predict actual inflation, even after considering other factors such as time variables (i.e., year and survey quarter), lagged inflation, and expectations error. The two variables on expected income are derived from the CES questions on perceived income conditions of households (i.e., expected income in the current quarter and expected income in the next 12 months, respectively). These variables refer to survey questions relating to (i) the current level of the household's income (relative to 12 months ago) and (ii) expectations about the household's income in the next 12 months, respectively.

TABLE 4. Tests of efficiency in the formulation of household expectations using aggregated time series CES data, Q1 2010 to Q4 2020

Dependent variable: π_{t+h} (i.e., actual inflation 12 months from t). Column headings refer to different specifications of Equation 3

	1		2		3		4	
	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error
Constant	2.353	0.620	239.19	305.9	917.17*	246.10	37.905*	11.270
Lagged inflation (1st lag)	0.912*	0.287	0.887*	0.295	-0.102	0.276	0.808*	0.258
Expected inflation at t	-0.718*	0.291	-0.760*	0.301	0.500	0.299	-0.411	0.277
Expectations error (1st lag)	0.733*	0.299	0.643**	0.329	-0.197	0.273	0.628*	0.268

[13] An efficiency test determines whether no readily available information could have improved forecast accuracy.

TABLE 4. Tests of efficiency in the formulation of household expectations using aggregated time series CES data, Q1 2010 to Q4 2020 (continued)

	1		2		3		4	
	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error
Survey quarter			-0.022	0.209	-0.077	0.150		
Year			-0.117	0.151	-0.415*	0.119		
Expected income (current quarter)					-32.020*	6.902		
Expected income (12 months ahead)					-8.166	5.662	-19.338*	6.120
N	39		39		39		39	
Adjusted R-squared	0.163		0.129		0.589		0.334	
F-statistic (p-value)	3.47 (0.026)		2.13 (0.087)		8.78 (0.000)		5.77 (0.001)	
Root mean squared error (RMSE)	1.33		1.36		0.93		0.93	

Note: ** and * indicate significance at 0.05 and 0.10 percent levels.

We apply a similar empirical exercise of testing the hypothesis to a pooled CES data. This gives us a more disaggregated view of the data and allows us to include more factors in the equation.

Table 5 also rejects the null hypothesis that the α_2 coefficients are zero. In particular, there appears to be a relationship between inflation and other variables such as lagged inflation and perceived income conditions, i.e., “Expected income (current quarter)” and “Expected income (12 months ahead).” This result suggests that there are many other factors that affect overall inflation performance which are not necessarily captured or reflected in households’ expectations. As such, the assumption of rationality of expectations in terms of the availability and use of relevant information in forming expectations is not evident in the survey data.

The coefficients of the year and quarter variables indicate that temporal and timing conditions are important exogenous factors affecting inflation. Expectations results could therefore be dependent on the period when the survey was conducted. This could imply that households do not renew their information set every period.[14] Moreover, the negative coefficient of the year variable reflects the decline of households’ expectations in recent years which coincided with the general downtrend in inflation over the same period (Figure 1 and Table 1). These developments could, in part, be attributed to the successful adoption of inflation targeting in the country and the resulting deceleration of inflation and “disinflation of expectations” in the country.

[14] Ueno [2014] argues that although households may not be renewing their expectations periodically, it is more frequent than what is assumed in the literature. In addition, expectations are updated more often during periods of shocks and volatilities.

Past expectations error (i.e., difference between expected inflation minus actual inflation in the previous period) tend to have a significant coefficient, indicating that α_2, the coefficient associated with variables other than expected inflation, is nonzero. Thus, it may be concluded that the formulation of households' expectations does not appear to be sufficiently explained by future outcomes. Expected inflation therefore does not pass the efficiency criteria. Households do not use all available information in forming their expectations. Actual inflation is affected by factors that could or could not be correlated with or predicted by their own inflation expectations.

Several authors (e.g., Mankiw and Reis [2002]; Sims [2006]; Mackowiak and Wiederholt [2009]; Capistran and Timmermann [2009]) have recognized that agents, like households, may not be using all available information when making economic decisions. The reason for this is the presence of information asymmetries and rigidities. Information could be "sticky" such that agents do not frequently update their information sets. On the other hand, when they do, agents tend to adhere to the assumption of rational expectations [Mankiw and Reis 2002]. Another possible explanation is that of rational inattention among economic agents. Rational inattention assumes that agents face constraints in processing information. They either receive noisy signals (i.e., agents observe the true values but with some error) [Woodford 2002] or they rationally choose the information that they would pay attention to subject to some information constraints (Sims [2006]; Mackowiak and Wiederholt [2009]).

TABLE 5. Tests of efficiency in the formulation of household expectations using pooled CES data Q1 2010 to Q4 2020

Dependent variable: π_{t+h} (i.e., actual inflation 12 months from t). Column headings refer to different specifications of Equation 3

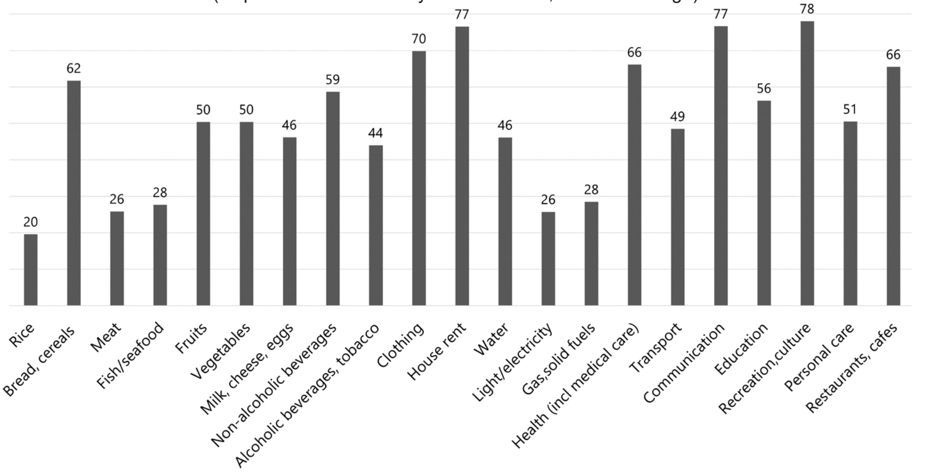
	1		2		3	
	Coeff.	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**
Constant	2.296*	0.008	86.894*	2.115	115.560*	2.233
Lagged inflation (1st lag)	0.930*	0.004	0.921*	0.004	0.939*	0.004
Expected inflation at *t*	-0.730*	0.004	-0.739*	0.004	-0.759*	0.004
Expectations error (1st lag)	0.736	0.004	0.740*	0.004	0.760*	0.004
Survey quarter			0.022*	0.002	0.025*	0.002
Year			-0.042*	0.001	-0.056*	0.001
Gross family income					0.036	0.001
Expected income (current quarter)					-0.037	0.004
Expected income (12 months ahead)					-0.070	0.006
N	215,006		215,006		214,999	
Adjusted R-squared	0.238		0.244		0.250	
F-statistic (p-value)	22400 (0.000)		13900 (0.000)		8950 (0.000)	
Root mean squared error (RMSE)	1.26		1.25		1.25	

Note: ** and * indicate significance at 0.05 and 0.10 percent levels.

We assess the degree to which Filipino households are either rationally attentive or inattentive to information about price changes in major CPI commodity groups. Annex 1 presents the composition of the Philippine CPI basket and their corresponding weights. Using the results of the CES, we examine their response and nonresponse rates to survey questions on price expectations for these commodity groups. We observe that Filipino households are more perceptive to price movements of basic commodities like food items (i.e., rice, meat, fish and milk), gasoline and fuel, utilities (i.e., electricity, water), transport, and alcoholic beverages (Figure 3). This finding is unsurprising given that households consume more of these commodities relative to other goods. Thus, they see the prices of these commodities more frequently. Filipino households are less attentive to developments in house rents and in the costs of communication, recreation, and clothing. These observations suggest that developments in the prices of different commodities have varying effects on the household expectations of inflation. Georganas et al. [2014] show laboratory evidence that, when forming expectations, consumers put more weight on price changes that they are exposed to more frequently.

FIGURE 3. Consumer Expectations Survey: Nonresponse per commodity group Q1 2010–Q4 2020

(as percent of total surveyed households; median average)



Note: Nonresponse rates are obtained by calculating both the number of respondents who did not answer and the number of those who provided answer to the question "What do you think would happen to the prices of the following goods and services in the next 12 months?" where the goods and services are as indicated in the horizontal axis of the figure. The nonresponse rates shown in the figure are the median (between Q1 2010 to Q4 2020) percentage shares of the number of respondents who did not provide answers to the total number of respondents for each survey period.

Source: BSP Consumer Expectations Survey, various quarters, authors' calculations.

3. Drivers of household inflation expectations

The growing literature on household expectations has tried to determine how these expectations are formed. Understanding the process that underpins how households form their expectations is crucial as these could affect their consumption, savings, and investment decisions. For central banks, these economic decisions and actions of households have important implications for the transmission of monetary policy to the real economy.

To identify the factors that drive household expectations in the Philippines, we conduct regression analyses based on the following specification:

$$\pi^{e}_{t,th} = \alpha + \beta_1 \cdot \pi_{t\text{-}1} + \beta_i \cdot X_t + \varepsilon_t \tag{4}$$

where: π^{e}_{t} is expected inflation with a forecast horizon of h periods (i.e., expectations of inflation formed at period t; h = 12 months) and $\pi_{t\text{-}1}$ is lagged inflation. X_t is a set of the other factors that could affect inflation expectations, including general macroeconomic conditions (e.g., unemployment, interest rate and exchange rate), demographic variables, and households' perception of their future income and financial condition as well as general economic conditions. We also include the BSP's inflation target which is denoted as the mid-point in the NG's inflation target range.

We estimate Equation 4 using aggregated (i.e., time series) and disaggregated (i.e., pooled data) data per CES quarterly survey round. Table 6 shows that, in aggregated terms, demographic variables such as age and sex do not appear to offer significant contribution to expectations formation. Meanwhile, gross family income appears to be significant for a given specification (i.e., specification 1) but not in the other equations. Gross family income refers to the household's gross monthly income which includes income from domestic employment and remittances from family members.

The inflation target is observed to be significant only for the third and fourth specifications. This could indicate that households are partly anchored to the monetary policy objectives of price stability and they find monetary policy to be credible. Moreover, this could suggest that households are incorporating authorities' inflation outlook in their assessment of future inflation.

Compared to the result obtained for gross family income, household's perception of their own future income conditions for the current quarter and in the next 12 months appears to be significant in the formation of their expectations about prices of goods and services. In aggregate terms, households appear to implicitly recognize the role of current market conditions (e.g., supply factors, public policies and external developments such as in the global oil markets) on prices when forming their expectations.

Moreover, household perceptions about future economic and financial conditions could potentially affect price conditions and, thus, their own expectations about inflation. Household's expected financial conditions for the current quarter and in the next 12 months in Table 6 refer to the household's assessment of their current financial situation relative to 12 months ago (i.e., same, better, or worse) and expectations about their financial situation in the next 12 months (i.e., same, better, or worse), respectively. Variables for the household's expected economic conditions for the current quarter and in the next 12 months refer to household's perception about the country's current economic condition relative to 12 months ago (i.e., same, better, or worse) and expectations about the country's economic condition in the next 12 months (i.e., same, better, or worse).

To gain deeper micro perspective on household expectations, we use disaggregated data (i.e., pooled CES data) on Equation 4. Some of the results we generated are aligned with our findings using aggregated CES data (Table 7). Households' perceptions about the current and future performance of some macro variables appear to affect how their expectations are formed.[15] A specific result from Table 7 is the consistency of the inflation expectations with the Phillips curve prediction that higher unemployment is associated with declining inflation expectations. The coefficient of unemployment is negative and significant. Moreover, regressions on the drivers of inflation expectations also indicate the significant reaction of inflation expectations on perceived future setting of monetary policy. Perception of higher interest rates over time tends to decrease inflation expectations over the same period of time.

The results of the pooled CES data point to demographic factors like educational status, marital status, and gender as significantly affecting expectations. The estimates in Table 7 show that households with members that have attained a higher level of education tend to have lower inflation expectations. This is consistent with the findings in other studies that people with better access to information or more developed information-processing skills, such as those with more education, tend to have lower and more accurate and lower inflation expectations [Brischetto and de Brouwer 1999]. Households that are better educated are assumed to be more financially literate and more aware of economic conditions relative to households with lower educational attainment [Blanchflower and MacCoille 2009]. Survey respondents that are single are more likely to have higher inflation expectations than those who are married. A possible reason for this is the differences in the consumption patterns and choices of single and married individuals. On one hand, the consumption baskets of married individuals, on average, tend to have more basic commodities in them, especially, if there are children in the household. Moreover, married individuals are more inclined to follow a household budget and, thus, they are more conscious of the prices of the goods and services that they purchase. On the other hand, single individuals, on average, have the propensity to purchase more of the non-basic, more expensive consumption goods and services (e.g., luxury items).

[15] Households' perceptions about future unemployment, interest rates and exchange rates pertain to their expectations on whether or not these variables will increase or decrease in the current quarter (relative to 12 months ago) and whether or not these variables will increase or decrease in the next 12 months.

TABLE 6. Regression of aggregated CES results and perceptions on economic conditions

Dependent variable: π^e_t (expectations of inflation formed at period t-h with h = 12 months). Column headings refer to different specifications of Equation 4.

	1		2		3		4		5	
	Coeff.	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**
Constant	0.309*	45.170	2.377	1.471	61.692*	10.183	37.476*	5.567	14.607*	2.353
Lagged inflation	0.626*	0.338	0.338*	0.200	0.290*	0.159	0.261	0.173	0.504*	0.156
Past error (1st lag)			0.078	0.188	0.317*	0.141	0.237	0.146	0.418*	0.159
Age	0.536	0.505								
Sex	19.239	19.420								
Marital status	-20.346*	2.660								
Educational attainment	-0.924	4.244								
Gross family income	0.562*	0.260	-0.035	0.159	-0.090	0.111	-0.034	0.106	-0.033	0.114
Inflation target			-0.238	0.748	1.179*	0.649	1.883*	0.673	-0.269	0.648
Expected own income condition (current quarter)					-23.615*	5.929				
Expected own income condition (12 months ahead)					-9.201	6.203				
Expected financial condition (current quarter)							-19.414*	4.773		
Expected financial condition (12 months ahead)							0.148	5.072		
Expected economic condition (current quarter)									-2.070	1.621
Expected economic condition (12 months ahead)									-5.019*	1.904
N	42		39		39		39		39	
F-statistic (p-value)	20.420 (0.000)		0.93 (0.000)		7.48 (0.000)		8.80 (0.000)		6.93 (0.000)	
Adjusted R-squared			0.008		0.506		0.552		0.484	

Note: Initial set of regressions indicate that outlook for macroeconomic variables such as unemployment, interest rate and exchange rate did not seem to be significant factors in the formation of household expectations. ** and * indicate significance at 0.05 and 0.10 percent levels.

TABLE 7. Drivers of household expectations using pooled CES data Q1 2010 to Q4 2020

Dependent variable: π^e_t (expectations of inflation formed at period t-h with h = 12 months). Column headings refer to different specifications of Equation 4.

	1		2		3		4		5	
	Coeff.	**Std.error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**	**Coeff.**	**Std. error**
Constant	69.758*	1.108	87.908*	1.183	86.583*	1.183	81.683*	1.185	81.741*	1.200
Lagged inflation	0.836*	0.001	0.835*	0.001	0.834*	0.001	0.834*	0.001	0.835*	0.000
Expectations error (1st Lag)	0.991*	0.000	0.990*	0.000	0.990*	0.000	0.990*	0.000	0.990*	0.000
Survey quarter	-0.012*	0.001	-0.012*	0.001	-0.012*	0.001	-0.011*		-0.011*	0.000
Year	-0.034*	0.001	-0.043*	0.001	-0.043*	0.001	-0.040*		-0.040*	0.000
Age	0.0004*	0.000	0.0002*	0.000	0.000	0.000				
Sex	0.004*	0.003					-0.014*	0.003		
Marital status	-0.020*	0.002							-0.016	0.000
Educational attainment	-0.004*	0.001								
Gross family income			0.016*	0.000	0.017*	0.000	0.016*	0.000	0.016*	0.000
Expected own income condition (current quarter)			0.028*	0.002						
Expected own income condition (12 months ahead)			0.020*	0.003						
Expected financial condition (current quarter)					0.038*	0.002				
Expected financial condition (12 months ahead)					0.045*	0.003				
Expected economic condition (current quarter)							0.070*	0.002		
Expected economic condition (12 months ahead)							0.075*	0.002		
Expected unemployment condition (12 months ahead)									-0.050*	0.000
Expected interest rate (12 months ahead)									-0.035*	0.000
Expected exchange rate (12 months ahead)									0.0127*	0.000
N	230,851		230,844		230,851		230,855		230,856	
F-statistic (*p*-value)	2750000		2770000		2770000		2800000		2460000	
Error variance estimate	0.54		1.81		0.54		0.53		0.53	
Root mean square error (RMSE)	0.74		0.73		0.73		0.73		0.73	

Note: ** and * indicate significance at 0.05 and 0.10 percent levels.

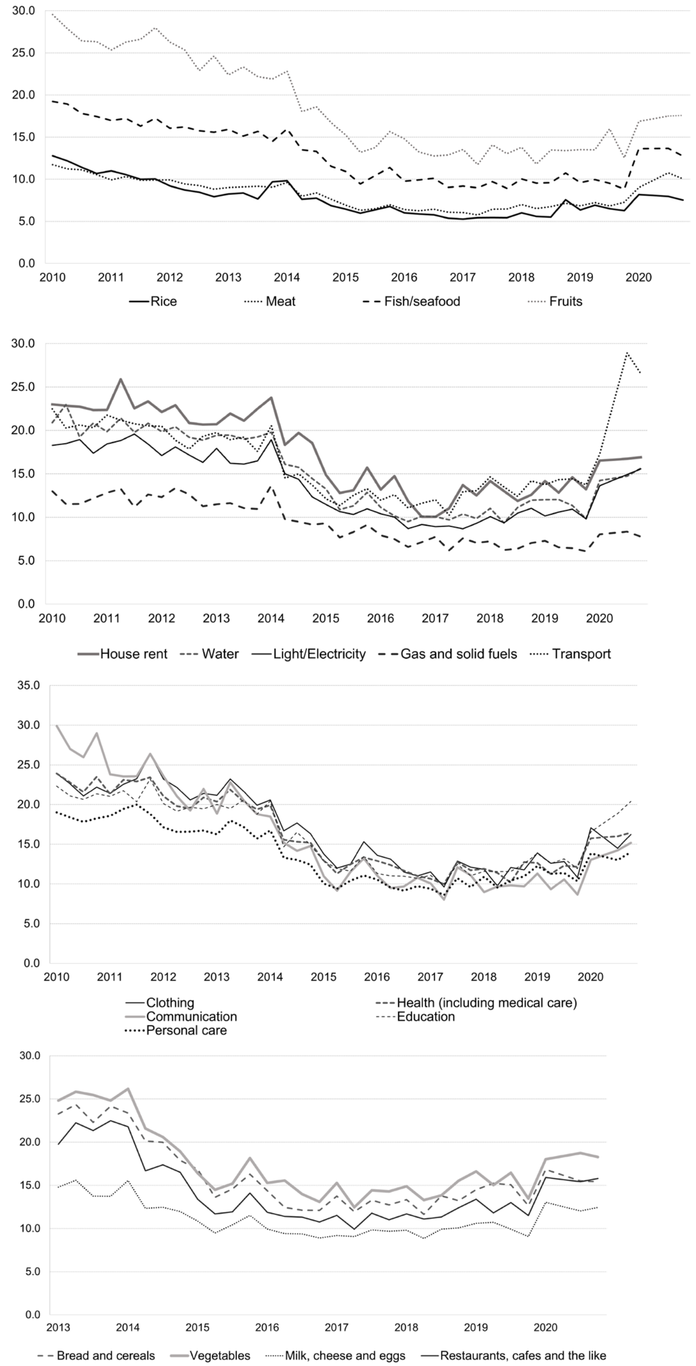
Depending on the other factors that are considered in the regressions, women have lower inflation forecasts compared to men (i.e., fourth column regression results in Table 7). Women are often the ones who handle household needs and purchases. Thus, they are more exposed to the changes in the prices of goods and services than men.

4. Decline in inflation expectations

Households' expected inflation has declined perceptibly starting in 2015. Together with better monetary policy, globalization factors such as increased trade flows, wider use of supply chains to optimize production costs, greater role of emerging markets and their impact on commodities, and lessened bargaining power of workers have also played significant roles in inflation developments in recent decades [Forbes 2019]. These developments resulted in more favorable price conditions which, in turn, led to the decline in inflation expectations. Average inflation forecast fell to 3.9 percent in the Q1 2015 to Q4 2020 period from 8.0 percent in the Q1 2010 and Q4 2014 period. This was largely ascribed to the low and stable inflation that prevailed during the pre-pandemic period (i.e., 2010–2019). Figure 4 presents the mean inflation forecasts for the different CPI commodity groups. Price expectations for these commodities show declining trends, except for a perceptible uptick in 2020, a year marked by the COVID-19 pandemic. However, the rate of decrease in expectations varied across commodities. Fruits, vegetables, bread and cereals, and fish and seafood showed larger declines relative to other commodities as did light/electricity, water, and transport (Figure 4). Figure 3 indicates that Filipino households tend to be more attentive to price developments in certain commodities like food, energy, and utilities compared to other commodities. This could in part explain the differences in the rate of decline in expectations for the various commodities. Moreover, Basilio and Cacnio [2020] observe that, over the past two decades, there was a decline in the frequency of commodity price changes and a lengthening of the duration between price adjustments in the country. Such developments signify lower price volatilities which could have contributed to lower inflation and inflation expectations.

The decline in long-run inflation expectations has also been linked to reduced uncertainty of consumer and households about future inflation [Binder and Verbrugge 2016]. Binder and Verbrugge [2016] attributed lower inflation uncertainty to improvements in macroeconomic conditions and to the adoption of an inflation target. Uncertainty measures point to a countercyclical relationship between uncertainty and economic conditions. Strong economic performance is associated with lower uncertainty. We note that these arguments are in keeping with the empirical results presented in Section 3. Households' perceptions of their future income and financial conditions and economic outcomes affect their expectations of future inflation.

FIGURE 4. Mean inflation forecast of CPI commodity groups (in percent)



Source. BSP Consumer Expectations Survey (CES), various quarters and years.

The inflation target was similarly observed to affect households' inflation expectations. Announcement of an explicit inflation target from a central bank contributes to the stronger anchoring of inflation expectations to the target which reduces uncertainty about future inflation. In the post-GFC period, the Philippines experienced strong economic growth which was broad-based and more resilient to shocks. Aggregate demand expanded but inflation remained low and stable. These developments, in turn, contributed to lower inflation expectations.

5. Expectations and their implications central bank communication

Central bank communication is crucial in managing expectations. The observations and findings from this study provide insights for central bank communication, particularly in influencing household expectations.

Since the 1990s, central banks have increasingly become more open and transparent in discussing their objectives, policy decisions, and actions. Central banks have designed and implemented communication strategies aimed at providing market participants and the general public a view of what they are doing and what they are trying to achieve for the economy. Clear communication is seen as helping reduce financial and economic volatilities resulting from central bank decisions as well as expanding the tool set of monetary policy [Blinder et al. 2008]. For example, statements regarding the expected path of future short-term interest rates can affect long-term interest rates, thereby influencing current economic conditions even without any change in policy [Coibion et al. 2020].

Central bank communication has often been more focused on influencing the expectations of financial market participants and professional forecasters. The reason for this is that financial markets' perception of the future path of monetary policy could affect long-term interest rates. Subsequently, interest rate movements will have an impact of the economic decisions of households and firms [Coibion et al. 2020]. Nonetheless, theory suggests that household and firm decisions are based on their perceived real interest rate, which depends on both nominal interest rates and their expectations of future inflation. Thus, inflation expectations of households should matter when they make decisions about consumption, savings, and investments and for firms in their price- and wage-setting decisions. This argument has been supported by empirical evidence on the significant effect of inflation expectations on the economic decisions of households and firms (e.g., Coibion et al. [2019]; Duca et al. [2018]; D'Acunto et al. [2016]; Malmendier and Nagel [2016]; Armantier et al. [2015]).

However, while professional forecasters and financial market agents are known to monitor macroeconomic conditions more closely and are able to respond to shocks more swiftly, households seem to be less attuned to economic developments, including price changes [De Fiore et al. 2021]. Moreover, some studies have shown that economic agents in low inflation countries tend to pay less attention and be less informed about price developments compared to those who are in high inflation economies (Coibion and Gorodnichenko [2015]; Cavallo et al. [2017]; Franche and Lluberas [2017]). The seeming lack of attention of households to market developments poses a challenge for central bank communication strategies that try to influence the inflation expectations of these economic agents.

Should central banks then give up on trying to influence the expectations of households through communication policies? Some recent studies show that, even if households do not give much attention to inflation developments and monetary policy, when they are provided with explicit information about these, their inflation expectations respond quite strongly (Coibion et al. [2020]; Armantier et al. [2012]). This implies that communication policies could still effectively affect the inflation expectations of households. Furthermore, it has been observed that communication that focuses on the inflation expectations of households leads to larger changes in perceived real interest rates, and consequently, results in more substantial effects on economic activity.

Based on the insights and results from this study, we highlight four key points for central bank communication strategy in influencing household inflation expectations.

First, households are different from professional forecasters and financial market participants when forming expectations. Professional forecasters have access to a wider set of information and they are more adept at using these to make predictions about future economic outcomes. Households are not as sophisticated and they may face information constraints. Thus, central banks may consider a communication strategy that takes these differences into consideration. Communication that targets households should be direct, clear, concise and easier to understand (i.e., less use of technical words and jargon). However, some caution needs to be taken if this kind of a communication strategy is adopted. It should not appear that the central bank is providing different messages. The key message should be the same for all economic agents. Communication that targets households could be layered to provide more simplified explanations and discussions.

Second, households have become more forward-looking in their assessment of current inflation and therefore they adjust their expectations more to new information. Also, households are observed to put more attention to price developments in certain commodities (e.g., rice, meat, gasoline, utilities) relative to others (e.g., house rents, communication, recreation). Monetary authorities could therefore emphasize different information in their communication depending on how they want to influence expectations. Additionally, households are generally observed to retain information for a short period of time (i.e., six months) and they do not renew their information sets periodically. Thus, information such as the price developments in specific commodities could only have transitory effects on expectations. If the central bank wants the effects to be longer, it should ensure that the information or message, for example, on inflation developments or on the inflation target is communicated repeatedly.

Third, less uncertainty about future economic outcomes leads to lower expected inflation. A related finding is that household expectations are affected by their perceptions about economic and financial conditions. If they are more certain about where economic and financial conditions will be, households will have lower inflation expectations. Thus, clear communication could lead to greater certainty about current developments and on the outlook for the economy, including price developments. This becomes even more important during periods of high volatility and uncertainty. Periods of greater uncertainty may require more intensive policy communication initiatives in order to offset the potential impact of uncertainty on expectations and inflation.

Fourth, economic and learning programs for households could contribute to lower household inflation expectations. An empirical finding of this paper is that better educated households have lower inflation expectations. This is because these households are assumed to be more financially literate and are able to understand better existing economic conditions. Thus, they can form more informed expectations of future outcomes on which they base their current economic decisions. Economic and financial learning programs are a means to provide information and educate households about the various factors that they should consider when they make their decisions about consumption, savings, and investments. Policymakers can explore the use of digital platforms for learning and communication. These platforms, such as social media applications and internet websites, present opportunities for reaching a wider audience.

Greater openness and transparency of monetary policy is foreseen to further increase in the future but it will vary across central banks [Blinder 2018]. This entails better and more effective communication strategies by central banks to attain their policy objectives and to manage expectations.

6. Conclusion

In this study, we use the results of the CES, a quarterly survey of households that the BSP conducts, to evaluate whether or not survey-based subjective expectations in the Philippines deviate from rational expectations and to determine the factors that drive household expectations in the country. Based on the tests that we conducted, we find that expectation results from the CES are outperformed by naïve forecasts (which are based on lagged values of actual inflation). This indicates that households fail to consider relevant information on future inflation other than that contained in previous rate of actual inflation. However, we observe that the forecast accuracy of household inflation expectations has improved in recent years. Nonetheless, there is little evidence that expectations from the CES are characterized by rationality (i.e., unbiased and efficient). Results denote that households do not utilize all available information and that they rely more on information about past inflation to form expectations of future inflation. Expectations are not fully, but only partly, driven by fundamentals.

Nonetheless, we note that in recent years, households seem to incorporate more information about future outcomes in their expectation formation process. Households are also more attentive to price movements of basic commodities like food items (i.e., rice, meat, fish and milk), gasoline and fuel, utilities (i.e., electricity, water), transport, and alcoholic beverages and less on price changes in house rents and in the costs of communication, recreation, and clothing. These observations signify that developments in the prices of different commodities have varying effects on households' expectations of inflation.

Using aggregated and disaggregated CES data, we explore the factors that drive household expectations in the country. Our regression results point to the potential significant effect of income conditions, perceptions on economic and financial conditions and the inflation target on the formation of household expectations in the Philippines. Moreover, we find that demographic factors (e.g., educational attainment, marital status, gender) also affect household expectations.

Our observations and findings help derive some insights for central bank communication strategy, particularly in influencing household expectations. We highlight four key points. First, households are different from professional forecasters and financial market participants when forming their expectations. Thus, central banks should consider communication strategies that take these differences into consideration. Second, households have become more forward-looking in their assessment of current inflation and therefore they adjust their expectations more to new information. Also, households are observed to put more attention to price developments in certain commodities (e.g., rice, meat, gasoline, utilities) relative to others (e.g., house rents, communication, recreation). Central banks could therefore emphasize different information in their communication depending on how they want to influence expectations. Third, less uncertainty about future economic outcomes leads to lower expected inflation. Clear communication could lead to greater certainty about current developments and on the outlook for the economy, including price developments. Thus, periods of greater uncertainty may require a more intensive policy communication initiatives to offset the possible impact of uncertainty on expectations and inflation. Fourth, economic and learning programs could contribute to lower household inflation expectations.

Expectations are an important channel in the transmission mechanism of monetary policy. Well-anchored inflation expectations allow central banks to achieve price stability and lessen the volatilities and gyrations in the economy. Thus, understanding how expectations are formed by economic agents such as households is important for monetary policy decisions and actions. As household expectations become more forward-looking, households' perceptions about future inflation and their planned consumption decisions can potentially provide an additional means by which stabilization policies can be made effective. This study contributes to efforts to gain insights into the expectations process. The findings offer some possible benchmarks or points of comparison for observing household expectations in an emerging market economy that is under inflation targeting like the Philippines.

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Annex

ANNEX 1. Weights by commodity group for Consumer Price Index (CPI), 2012-based

Commodity groups	Weights
1. Food and non-alcoholic beverages	39.34
Food, of which:	35.46
Rice	9.59
Bread and cereals (except rice)	3.86
Meat	6.25
Fish and seafood	5.74
Fruits	1.40
Vegetables	2.60
Milk, cheese, and eggs	3.08
Non-alcoholic beverages	2.88
2. Alcoholic beverages, tobacco, etc.	1.58
3. Clothing and footwear	2.93
4. Housing, water, electricity, gas and other fuels, of which:	22.04
House rent	12.88
Water	1.17
Light/electricity	4.80
Gas and solid fuels	2.63
5. Furnishings, household equipment and routine maintenance of the house	2.95
6. Health	3.89
7. Transport	8.06
8. Communication	2.93
9. Recreation and culture	1.41
10. Education	3.28
11. Restaurant, miscellaneous goods, and services	8.05
ALL ITEMS	**100.0**

Source: PSA

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Heterogenous impact of monetary policy on the Philippine rural banking system

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This paper shows the differential impact of monetary policy on the lending behavior of rural banks, with the bank lending channel being operational in small rural banks. While big rural banks are able to protect their lending portfolio from contractionary monetary policy by the size of their balance sheet, small rural banks with less diversified funding portfolio cannot. Moreover, highly capitalized rural banks are more inclined to protect their capital than expand their lending portfolio, following monetary tightening and higher capital requirement. The insignificance of gross domestic product (GDP) growth may reflect weakness in effective loan demand and lack of diversification that could have also impinged on the earning capacity of rural banks, as supported by initial estimates on the drivers of rural bank profitability. The finding on heterogeneous effects of monetary policy on rural banks has a secondary implication of lending credence to the principle of proportionality embodied in the BSP's bank regulatory framework.

JEL classification: B23, C55, E52, E58
Keywords: rural bank, bank lending channel, monetary policy

1. Introduction

The creation of the Philippine rural banking system through Republic Act 720 or the Rural Bank Act 1952 was a step towards fulfilling the vision of social and financial inclusion of small farm households in the post-war era. It has been recognized as an important mechanism for enabling economic and social integration of small farm households.

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The network of rural banks in the Philippines has similarities with the community banking industry in the US and the *Sparkassen* in Germany. Corner [2010] observes that the emergence of thousands of community banks in the US is a legacy from an era when competition was curtailed. He notes that much of the community banks' cost and revenue advantages have been significantly diminished in an environment of heightened competition and financial technological advancement. Perhaps, the same can be said for the Philippine rural banks that have to carve out a niche market for their products and services as they face stronger competition with significantly bigger and more technologically agile universal and commercial banks.

Rural finance research in the Philippines typically ranges from farm-level assessment of credit efficiency to the broader question of rural financial market efficiency (Geron et al. [2016], Llanto [2005]). In all of these, the rural banking system, by virtue of its mandate, plays an important function in credit intermediation. Over time, the general views on the role of rural banks have significantly changed from a credit conduit to farmers to a more dynamic, profit-maximizing producer of financial services (Von Pischke [1978] as cited by Tolentino [1987]). At the same time, the policy and regulatory environment within which small, rural banks operate has non-neutral effects on the profit maximization objective of banks.

The significance of the bank-lending channel is premised on the extent of bank-dependent borrowers and the quantitative impact of monetary policy on the supply of bank loans. In jurisdictions with limited alternative sources of financing other than bank credit, this channel is likely to be more important. Whether as wholesaler or retailer of credit, rural banks play an important role in credit facilitation. Familiarity with local cultural norms works to their advantage because monitoring and compliance with know-your-customer (KYC) protocols for small depositors/borrowers may be relatively easier. This, however, does not discount the possibility that KYC requirements are shunned because of difficulties of small depositors and borrowers in complying with documentary requirements. However, the effect of market imperfections on rural banks' ability to generate marginal sources of financing may be more evident in the loan supply portfolio of smaller banks.

By far, there are very few studies that examine the rural banking system in the Philippines, more so on strength or even the presence or absence of bank lending channel due to the relative smallness of the asset size and deposit base of rural banks. This is the gap in the literature that our research intends to fill. It is equally important to understand the transmission of monetary policy through the lending behavior of rural banks since they cater to smaller borrowers in underserved areas. At the same time, rural banks are particularly niche players in countryside lending. In some areas, a rural bank, regardless of the asset size or loan portfolio, is the sole provider of financial services.

The study seeks to empirically determine if bank lending channel operates in the least studied class of banks in the Philippines, i.e., rural banks. Specifically, the study examines if monetary policy adjustments have a differential impact on rural banks' loan supply based on their balance sheet-specific characteristics such as size, liquidity and capitalization. In this way, the study also analyzes whether these rural banks' balance sheet indicators absorb or amplify the effects of monetary policy adjustments.

The paper is outlined as follows: Section 2 reviews the theoretical and empirical underpinnings of the bank lending channel of monetary policy and provides some perspectives from the literature on the Philippine banking system. Section 3 presents the data and profile of the rural banks under study. Section 4 elaborates on the model specification, methodology used in this study, and the robustness of the model. Section 5 provides an analysis of the results. Section 6 concludes.

2. Review of related literature

The credit market creates value through the activities generated from the use of loans [Swinnen and Gow 1997]. At the same time, the credit market is characterized by asymmetric information and incentive compatibility problems. Lenders earn from financial intermediation by mobilizing short-term and demandable deposit liabilities to fund longer-term financing requirements of borrowers. To attenuate information asymmetry, lenders screen borrowers, stipulate terms of the loan contract, and monitor payment streams to ensure repayment and full recovery of capital throughout the life of the contract. An external finance premium is charged on the loan to cover the monitoring costs and uncertainty arising from the risk profile of the borrowers.

Expected profits of banks depend not only on interest income but also on the probability of default. On one hand, higher rates lead to higher expected returns for banks. On the other hand, higher rates also affect the riskiness of the total loan portfolio and hence, the probability of default. Since banks cannot distinguish good borrowers from bad borrowers, they may also resort to credit rationing, which could adversely affect credit-worthy but riskier entrepreneurial borrowers with relatively smaller business scale. Borrowers, in need of funds, enter into loan covenant defined by lenders' standards. They could default in payment, not necessarily because of bad intentions but due to inadequate returns that impair their capacity to repay the loan [Stiglitz and Weiss 1981].

2.1. The bank lending channel revisited

The policy actions of the central bank impact the lending operations of financial institutions like banks. The traditional view of the bank lending channel of monetary policy works through the effect of monetary policy on reservable deposits that could expand or contract the supply of bank loans and consequently, affect the real spending of borrowers. Two conditions must be satisfied for the bank lending channel to hold: first, the banks cannot fully insulate their loan portfolio from monetary policy actions by central banks and second, borrowers cannot protect their spending from the changes in loan availability [Oliner and Rudebusch 1995], or more commonly referred to as the broad credit channel.

Other than the impact of monetary policy on reservable deposits, Disyatat [2010] posits a bank lending channel that works primarily through the impact of monetary policy on banks' balance sheet strength and risk perception. Banks, in general, have access to other funding sources like commercial paper and borrowings. As such, bank characteristics like size, liquidity, and capitalization could help shield their lending portfolio from monetary policy action by the central bank.

Many of the studies that utilize bank-level data looked into the lending behavior of commercial banks in response to monetary policy. Kashyap and Stein [1995] as well as Kishan and Opiela [2000] utilized US bank-level data and found evidence of bank lending channel by looking into cross-sectional differences in the responses to monetary policy shocks by different classes of banks. Lui [2012] used bank size and loans and concluded that monetary policy in Australia has distributional effects on bank loans, depending on asset size and industry. Worms [2001] did the same for Germany and found that lower ratio of short-term interbank deposits-to-total assets leads to stronger reaction of lending to contractionary monetary policy. Others looked into distance effect using gravity model of bank lending. Gudmundsdottir et al. [2017] found that negative relationship between lending and distance in the European Union, which they largely ascribed to information costs, combined with other factors such as capital requirements, local competition, and cross-border trade, imply constraints to full European financial integration. Carling and Lundberg [2005], on the other hand, found no evidence of geographical credit rationing in Sweden in the face of restrictive monetary policy.

The preponderance of studies that examine the nexus between commercial bank lending behavior and monetary policy may have been partly motivated by relatively easier access to data. The same can be said for the Philippines where there are a few studies on the bank lending channel, ranging from the assessment of the quantitative importance of capital adequacy of banks in channel at a macroeconomic level to the use of universal and commercial bank-level data.

Bayangos [2010], using a macroeconomic model, found that the aggregate measure of capital adequacy of commercial and universal banks is an important factor in banks' ability to sustain their lending activities after monetary policy adjustment. Aban [2012; 2013], using asset size data of commercial and universal banks, found that loan growth from smaller banks is sensitive to movements in monetary policy. Glindro et al. [2016] expanded the set of universal and commercial bank characteristics to include asset size, capitalization, and liquidity in understanding the bank lending channel of monetary policy in the Philippines. The study found that capital-to-asset ratio is the most statistically significant bank-specific indicator that helps shield universal and commercial banks' loan portfolio from the impact of contractionary monetary policy. Moreover, a significantly negative interaction term was obtained only after controlling for interbank deposits, possibly indicating higher risk aversion and greater concern for preserving capital and meeting liquidity requirements in times of contractionary monetary policy.

Meanwhile, Austria and Bondoc [2018] and Armas [2021] find very little or weak evidence of bank lending channel in the Philippines using a larger sample size of banks and longer period. Austria and Bondoc [2018] highlighted that their results could be due to loan portfolio rebalancing where banks do not reduce their lending but rather reallocate their loan provision to different economic sectors (e.g., drop in consumer loans but an increase in industrial loans). Similarly, Armas [2021] showed that the bank lending channel of monetary policy in the Philippines is quite weak as highly liquid banks tend to react more to monetary tightening than less liquid banks. More liquid banks would rather hold their stock of liquid assets as buffers against crises than sustain or expand their lending activity amid monetary tightening. Banks are also risk-sensitive in their lending behavior as the increase in the cost of borrowing following tighter monetary policy could increase the likelihood of loan default.

Unlike universal and commercial banks that have a large and more diverse corporate client base and wider access to alternative funding sources, the asset-liability profile of rural banks is simpler. Notwithstanding the relative smallness of the collective asset base of rural banks compared to bigger and highly diversified universal and commercial banks, there is also huge variation across the spectrum of rural banks, ranging from stand-alone rural banks to those with extensive branch networks. Thus, even within their ranks, the impact of central bank policy actions on their lending behavior would differ.

2.2. Perspectives from the literature on Philippine rural banking system

There are fewer studies on the Philippine rural banking system. The study by Aragon et al. [2011] analyzed lending behavior of rural banks under capital regulation with prompt corrective action (PCA). The study found that the effectiveness of the combined capital regulations and PCA diminishes in the case of undercapitalized banks. A capital shock in the presence of more risk-sensitive capital reduces loans for undercapitalized banks, contributing to a credit crunch in the rural area. Mendoza and Rivera [2017], on the other hand, looked at the determinants of bank profitability. They found that credit risk, measured by the loan loss reserves-to-total loan portfolio, better explains the profitability of rural banks than capital adequacy requirement.

Meslier-Crouzille et al. [2012] studied the contribution of rural banks to regional economic development for the period 1993–2005. They generally found no clear evidence of a banking-led economic development for the Philippines. However, when they specifically accounted for the presence of rural banks, their estimates showed positive impact on the economic development of intermediate and less developed regions, with a stronger impact for intermediate regions. Their findings lend credence to the important function of rural banks in fostering regional economic development.

For a central bank like the Bangko Sentral ng Pilipinas (BSP) that is responsible for both monetary policy and regulatory supervision of the banking system, understanding the lending response of banks to its policy actions is vital. Over time, significant macroeconomic and regulatory developments may have either supported or constrained rural banks from fulfilling their mandate to be agents of rural growth through credit facilitation. The encompassing reforms in the regulatory milieu such as the introduction of Basel regulatory standards, the Consolidation Program for Rural Banks (CPRB), the establishment of microfinance business offices, and branch lite concept in banking, among others, may have spawned differential effects of monetary policy on the credit intermediation function of rural banks. Given that banking supervision is about safeguarding prudential soundness, the BSP follows the principle of proportionality, in which supervisory practices are adapted to the risk profile, business model and size of the bank.[1]

Overall, the empirical evidence on the existence of bank lending channel across different jurisdictions underlines the significance of bank-specific characteristics in determining the existence and relative strength of the bank lending channel.

3. Data

The study uses comprehensive quarterly dataset balance sheet indicators of rural banks in the Philippines, which are sourced from the Department of Supervisory Analytics-Financial Supervision Sector of the BSP. The dataset has an unbalanced panel data structure due to closures, mergers of some banks, upgrading of some rural banks into thrift banks, and establishment of new rural banks over time.

The dataset includes accounts of 609 head offices of rural banks. This is in view of the consolidated approach to supervisory examination of rural banks that encompasses the bank's branch network. The period covered by the study spans 40 quarters, i.e., 2010Q1–2018Q2, for which risk-weighted capital adequacy

[1] The goal of prudential regulation is to internalize the externalities from the distress or failure of individual banks and the banking system. Since externalities depend on the risk profile of each bank, proportionality is defined as setting prudential standards that are tailored to the bank's risk profile, business model, cross-border activity, and systemic importance (Basel Committee on Banking Supervision [2019]; Hakkarainen [2019]).

ratio (CAR) is available. The dataset covers 16,606 observations for balance sheet indicators and 16,588 observations for profitability indicators, which include income statement indicators such as return on assets (ROA) and net interest margin (NIM).[2]

The variables used for the empirical estimation of the bank lending channel have been log transformed since the base form, in level, tends to increase or grow exponentially as in the case of stock variables like balance sheet indicators. The selection of most of the variables used in this paper was largely based on widely-referenced bank lending literature (Kashyap and Stein [1995], Zulkhibri [2013], Ananchotikul and Seneviratne [2015], and Ehrmann et al. [2001]). Table 1 describes the variables in the dataset used for the empirical estimation of the bank lending channel.

TABLE 1. Description of variables

Variables		Definition	Reference
response variable	Total loan portfolio	Sum of (i) loans to BSP, (ii) loans to other banks, (iii) loans and receivables-others, and, (iv) loans and receivables arising from repurchase agreements/certificate of assignment/participation with recourse/securities lending and borrowing transactions, net of amortization.	Bangko Sentral ng Pilipinas (BSP)
monetary policy indicator	Overnight reverse repurchase rate	Borrowing rate of the Bangko Sentral ng Pilipinas' (central bank of the Philippines). It is the central bank's main monetary policy tool in absorbing excess liquidity from the banking system.	BSP
bank-specific variables	Total assets	Sum of total assets, net of due to head office/branches/ agencies and non-performing assets cover.	BSP
	Liquid assets	Sum of cash and cash items, due from banks, and financial assets (net of amortisation, accumulated market gains/losses, allowance for credit losses excluding equity investment in subsidiaries/associates/joint ventures).	BSP
	Size	Measured as log of total assets of bank *i* at time *t*.	BSP
	Liquidity	Liquid asset ratio, i.e., liquid assets divided by total assets of bank *i* at time *t*.*	
	Capitalization	Capital adequacy ratio, i.e., ratio of qualified capital to risk-weighted assets of bank *i* at time *t*.	
control variables	Real GDP	GDP at constant prices (2000-based).	Philippine Statistics Authority (PSA)
	Consumer Price Index (CPI)	CPI measured using 2006 prices as the base year.	BSP

* Another definition of liquidity used in bank examination is liquid assets-to-total liabilities.

It is difficult to isolate the monetary policy-induced loan supply effects using macro data since there are two confounding channels—the money demand channel works though deposit liabilities while the bank lending channel operates through the asset side. In a nutshell, when a central bank undertakes monetary policy (MP)

[2] Annex 1 provides the complete list of indicators used for the profitability regression.

tightening, it drains deposits from the system through the conduct of open market operations whereby bonds are swapped with reserve deposits (liability side). This means lesser money available for lending by banks, which implies a shift in the banks' loan schedule. The study by Kashyap and Stein [1995][3] made reference to the work of Bernanke and Blinder [1992] that empirically shows the negative relationship between monetary policy and bank lending using aggregate data. Kashyap and Stein [1995] noted that there are alternative interpretations, which Bernanke and Blinder [1992] recognized. One plausible interpretation is that MP-induced hike in interest rates does not only raise the cost of borrowing but also erodes the value of collateral of firms (particularly small firms), both of which affect firms' demand for credit.

In view of this identification problem with aggregate data, bank-specific balance sheet information would help to clearly distill the loan supply effects of monetary policy. Hence, this study applies panel econometric techniques on bank-level data to determine bank-specific balance sheet information that affects credit intermediation function of banks.

The bank indicators used in the study specifically pertain to size, liquidity, and capitalization. Larger asset size may indicate more diverse sources of funds and bigger client base, thus, helping banks accommodate contractionary monetary policy. Capitalization, which is measured as total qualifying capital relative to risk-weighted assets, provides funding flexibility and accords lower external finance premium. While it represents a cost to the bank, it also signals the adequacy of standby capital to cover losses to avert insolvency risk. Lastly, the liquidity position of the bank lends additional cushion to insulate rural banks' lending portfolio in the face of contractionary monetary policy. The specification also controls for macroeconomic factors that influence loan demand, i.e., GDP growth and inflation.

However, higher capitalization and higher liquid assets could also imply limited funding sources and higher risk aversion of rural banks, which could eventually constrain their lending to the public, especially during periods of financial stress. When they fall of short of the regulatory minimum, banks would be subjected to more intense supervisory actions. These would include prohibition or limits on the distribution of net profits. There may be times that they may be required to allocate a portion or all of net profits to prop up capital until the minimum requirements are fulfilled. With equity being more expensive than debt, additional capital is seen to reduce the ability to expand lending activities.

3.1. Profile of the financial condition of the rural banking system

On average, rural banks maintain capital adequacy ratio (CAR) in excess of the 10 percent prudential limit set by the BSP. Liquid assets account for an average of 32.5 percent of total assets. The average total loan portfolio-to-asset ratio is 56 percent while the deposit-to-asset ratio is 69 percent (see Table 2).

[3] Kashyap and Stein [1995] extensively discussed the identification problem with aggregate data.

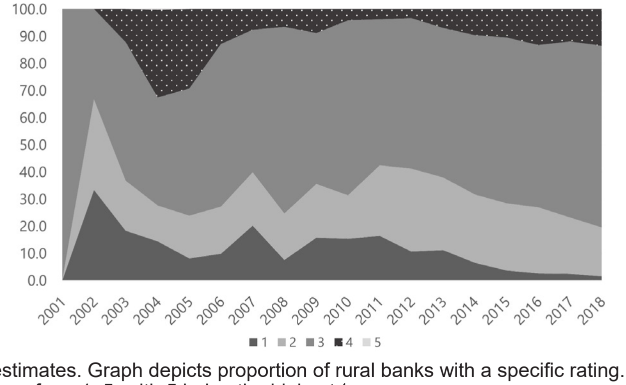
TABLE 2. Selected performance indicators

Variables	(1) Number of observations	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max
Total assets (log)	16606	11.84	1.22	4.11	17.23
Liquid assets (log)	16598	10.51	1.41	2.92	16.36
Total Loan Portfolio (log)	16592	11.19	1.28	2.26	16.93
Capital Adequacy Ratio (log)	16045	2.99	0.57	-3.14	6.36
Total loan-to-total asset ratio	16591	56.37	20.44	3.17	235.50
Liquid asset-to-total asset ratio	16597	32.52	18.54	0.12	93.37
Deposit-to-asset ratio	16595	69.18	17.58	0.28	256.88

Note: Authors' estimates based on quarterly data from 2010Q1 to 2018Q2
Source of basic data: Department of Supervisory Analytics, Financial Supervision Sector, Bangko Sentral ng Pilipinas.

Based on confidential reports of examination for the period 2001–2018 that employs CAMELS rating system, there has been a notable decline in the number of rural banks with critically deficient rating that requires strong remedial measures (Figure 1). Annex 2 shows that the largest decline in the number of rural banks with critically deficient rating has been observed for liquidity (L) and sensitivity to market risks (S). It must be noted that smaller rural banks have low exposure to market risks such as repricing risk since their activities are limited to deposit taking and lending, with mostly fixed rates to maturity. However, asset quality (A), management (M), and earning capacity (E) are still largely constrained, with a larger proportion having less satisfactory rating and below. This is possibly symptomatic of high-risk aversion and lack of diversification among rural banks.

FIGURE 1. Overall CAMELS rating of rural banks, 2001-2018



Note. Authors' estimates. Graph depicts proportion of rural banks with a specific rating. BSP CAMELS rating scale ranges from 1–5, with 5 being the highest.[4]
Source of basic data: BSP's Department of Supervisory Analytics, Financial Supervision Sector.

[4] The rating scale is defined as follows: 1 – critically-deficient and inadequate risk management practices; 2 – serious financial and management deficiencies that warrant close supervision; 3 – some degree of supervisory concern but the magnitude of deficiencies will not cause any component to be rated more severely than 2; 4 – fundamentally sound with none of the component ratings falling below 3; 5 – sound in every respect with component ratings between 4 and 5 (BSP-Financial Supervision Sector).

4. Empirical methodology

The empirical analysis follows the influential works of Gambacorta [2005], Kashyap and Stein [2000], Zulkhibri [2013], and Ananchotikul and Seneviratne [2015]. The baseline specification of the paper is as follows:[5]

$$\Delta L_{it} = \alpha \Delta L_{it\text{-}1} + \sum_{j=0}^{1} \beta_j \,\Delta MP_{t\text{-}j} + \sum_{k=1}^{3} \omega_k \, X_{i,t\text{-}1} + \sum_{k=1}^{3} \tau_k \, X_{i,t\text{-}1} * \Delta MP_{t\text{-}1} \qquad (1)$$
$$+ \theta \Delta Y_t + \delta \Delta P_t + \Delta \vartheta_i + \Delta \mu_{it}$$

The first difference operator is given by Δ; i=1,2,…N and t=1,2,…T, N is the total number of banks while T is the number of time series observations. The response variable is the change in the logarithm of total loan portfolio of bank i in period t (ΔL_{it}). Among the regressors, MP is the monetary policy indicator used in this paper to test for the contemporaneous (at t=0) and delayed (at t=1) effects of policy rate shocks on bank loans. This is measured by the overnight reverse repurchase rate (RRP), which is the monetary policy rate of the BSP. The vector X_{it} represents the three bank-specific characteristics (k): (i) size, (ii) liquidity, and (iii) capitalization. The interaction term between the monetary policy indicator and bank-specific factors (MP*X) captures the bank lending channel of monetary policy where the impact of monetary policy adjustment differs with bank-specific features.

The model also includes real GDP (Y) and consumer price index (P) to control for the demand-side impact on loans as well as to capture the cyclical movements in the economy [Hernando and Martínez-Pagés 2003]. These control variables for the demand aspect of loans are independent of bank-specific features and are dependent on macroeconomic factors only.

The total error term, e_{it}, is categorised into: (i) ϑ_i which captures the unobserved bank-specific fixed effects; and (ii) μ_{it} which are the observation specific errors (time varying unobservables). Both ϑ_i and μ_{it} follow an independent, identical distribution (IID), with zero mean and constant variance ~$IID\,(0,\sigma^2)$.

4.1. Accounting for bank-specific characteristics

To assess the impact of each bank-specific characteristic on rural banks' loan supply growth, the following models, with simplified notations, are estimated independently:

$$\Delta L_{it} = \alpha_1 \Delta L_{it\text{-}1} + \sum_{j=0}^{1} \beta_{1j} \,\Delta MP_{t\text{-}j} + \varphi Size_{it\text{-}1} + \emptyset \Delta MP_{t\text{-}1} * Size_{it\text{-}1} \qquad (2)$$
$$+ \theta_1 \Delta Y_t + \delta_1 \Delta P_t + \Delta \vartheta_i + \Delta \mu_{it}$$

[5] This full model specification is the difference Generalized Method of Moments (GMM) transformation (as shown by the first difference operator).

$$\Delta L_{it} = \alpha_2 \Delta L_{it\text{-}1} + \sum_{j=0}^{1} \beta_{2j}\, \Delta MP_{t\text{-}j} + \eta Liquidity_{it\text{-}1} + \psi \Delta MP_{t\text{-}1} * Lqd_{it\text{-}1} \quad (3)$$
$$+ \theta_2 \Delta Y_t + \delta_2 \Delta P_t + \Delta \vartheta_i + \Delta \mu_{it}$$

$$\Delta L_{it} = \alpha_3 \Delta L_{it\text{-}1} + \sum_{j=0}^{1} \beta_{3j}\, \Delta MP_{t\text{-}j} + \lambda Capital_{it\text{-}1} + \rho \Delta MP_{t\text{-}1} * Cap_{it\text{-}1} \quad (4)$$
$$+ \theta_3 \Delta Y_t + \delta_3 \Delta P_t + \Delta \vartheta_i + \Delta \mu_{it}$$

If any of the parameters $\emptyset$, ψ, and ρ are negative, it can be concluded that the bank lending channel (BLC) of monetary policy is functioning in the country through the rural banks. If the same parameters are positive, it can be concluded that bank-specific characteristics help shield rural bank lending from the contractionary effect of monetary policy.

The above equations (2 to 4) are also estimated to test for the following alternative hypotheses:

a. larger banks are less vulnerable to changes in policy interest rate vis-à-vis smaller banks.
b. more liquid banks react less to monetary tightening than less liquid banks.
c. adequately capitalized banks are less sensitive to monetary policy shocks than less-capitalized banks.

4.2. Estimation method

In estimating the model, this study accounts for the persistence of bank loans by employing a linear dynamic panel Generalized Method of Moments (GMM) technique.[6] Hence, the lagged dependent variable is included as one of the regressors. The GMM technique, which was initially proposed by Arellano and Bond [1991], Arellano and Bover [1995], and later extended by Blundell and Bond [1998], was chosen due to some econometric and specification problems that can potentially arise from the untransformed version of model Equation 5, as shown below:

$$L_{it} = \alpha L_{it\text{-}1} + \sum_{j=0}^{1} \beta_j\, \Delta MP_{t\text{-}j} + \sum_{k=1}^{3} \omega_k\, X_{i,t\text{-}1} + \sum_{k=1}^{3} \tau_k\, X_{i,t\text{-}1} * MP_{t\text{-}1} \quad (5)$$
$$+ \theta Y_t + \delta P_t + \vartheta_i + e_{it}$$

Estimating Equation 5 instead of the baseline model given by Equation 1 will result in biased and inconsistent coefficient estimates due to problem of reverse causality or simultaneity bias.[7] This is because bank-specific determinants are not

[6] The panel regression is undertaken using Stata 16.
[7] Reverse causality or simultaneity occurs when changes in the explanatory variables cause the variations in dependent variable and vice-versa.

strictly exogenous and are likely to be correlated with the composite error process given by $\vartheta_i + \mu_{it}$. Moreover, the inclusion of lagged dependent variables ($L_{it\text{-}1}$) as one of the regressors in Equation 5 gives rise to Nickell bias [Nickell 1981]. This bias arises in Equation 5 since the lagged value of loans is correlated with $e_{it\text{-}1}$, which is a function of the unobserved bank-specific fixed effects, ϑ_i. Thus, the "*resulting correlation creates a large-sample bias in the estimate of the coefficient of the lagged dependent variable, and which is not mitigated by increasing the number of N*" [Baum 2006: 236]. If the regressors are correlated with the lagged dependent variable, their coefficients will be biased as well. This bias arises even if the error process is identically independently distributed (IID). While getting the first difference of the untransformed version of the model removes the constant term and individual effects, there is still correlation between the lagged dependent variable and the disturbance process.

In order to address the aforementioned econometric issues, the dynamic panel GMM will be used. The estimation procedure uses "internal" instruments, i.e., lagged differences of endogenous variables in the model to solve the endogeneity problem associated with the endogenous regressors. These instruments must be strongly correlated with the endogenous variables but uncorrelated with the error term, hence, exogenous. The exogeneity condition will be examined using the Hansen test for a two-step difference GMM, given its known property of generating consistent coefficient estimates and robust standard errors [Roodman 2006, 2009]. Moreover, the Hansen test ensures that the number of internal instruments used in the regression is limited by using one to four lags only.[8] To detect whether or not there is autocorrelation, second order autocorrelation test, AR (2), is also carried out.

4.3. Robustness of the model

There are two types of difference-GMM technique that are used as the yardsticks for assessing robustness of estimates in this study. These are (i) standard difference-GMM and the (ii) difference-GMM with orthogonal deviations. The latter, proposed by Arellano and Bover [1995], is a type of GMM procedure that preserves the sample size especially with strong unbalanced panel data structure because it subtracts the past observation from the average of all *available* observations [Roodman 2006]. As a reiteration, interaction terms between the monetary policy indicator represented by the RRP and bank-specific characteristics are included in testing the existence of bank lending channel in the Philippine rural banking system.

To account for possible differential impact of monetary policy across the spectrum of rural banks, rural banks are categorized into several quantiles based on asset size, liquidity, and capitalization, for which separate regressions were undertaken. The categorization is structured such that the bottom 25 percentiles

[8] Referred to as collapsing the instruments.

of the distribution constitute the "small, less liquid and less capitalized" rural banks while "big, highly liquid and well-capitalized" rural banks comprise those that fall in the upper 75 percentiles of the distribution [Zulkhibri 2013]. For each bank-specific regression, a dummy variable is created, which assumes a value of 0 is classified as small and 1 if classified as big.

5. Empirical results

The baseline model of this paper, as specified in Equation 1 under Section 4, is tested first for robustness by estimating it using the dynamic data panel (DPD) models. Based on the estimates, the orthogonal deviation difference-GMM model is selected as the best DPD technique (See Annex 3).

5.1. Baseline model

The estimation results affirm the appropriateness of GMM as shown by the statistical significance of the lagged dependent variable. The results of the baseline model indicate presence of bank lending channel in the Philippine rural banking system, with asset size providing a cushion against contractionary monetary policy (Equation 1). The results, however, may be skewed by the big rural banks. Thus, different regressions that separate each of the bank characteristics were conducted.

5.2. Alternative specifications

Unlike the baseline specification, asset size becomes insignificant and the interaction term between monetary policy rate and asset size turns out to be negative and statistically insignificant (Table 3). Partial elasticities show that the delayed effect of monetary policy (ΔMP_{t-1}) causes the growth of loan supply to react positively while the contemporaneous impact of policy rate (ΔMP_t) affects growth negatively, albeit statistically insignificant (Equation 2). Consistent with theory and most of the empirical studies, the availability of more liquid assets leads to higher growth in rural banks' loan supply (Equation 3). Quite interesting is the significant and negative interaction term between liquid asset ratio and monetary policy. This may signify that rural banks prefer to preserve their liquid assets more than their lending portfolio in the presence of contractionary monetary policy. In all specifications, demand condition, as proxied by GDP growth, is not a significant factor in determining loan supply growth. This could also broadly suggest insufficient effective demand that may also be a limiting factor.[9]

[9] In a separate regression, non-performing asset as proxy for demand condition was insignificant. Nonetheless, the main narrative of the results remains. The signs and size of the estimated coefficients did not materially change.

TABLE 3. Results of baseline model and bank indicator regressions

Dependent variable: first difference log of total loan portfolio				
	ALL (Eq. 1)	**SIZE (Eq. 2)**	**LIQUIDITY (Eq. 3)**	**CAPITAL (Eq. 4)**
ΔL_{it-1}	-3.26***	-1.73***	0.08**	-0.60*
	(1.85)	(0.98)	(0.04)	(0.14)
ΔMP_t	1.01	1.33	0.40	0.22
	(0.85)	(0.88)	(0.43)	(0.42)
ΔMP_{t-1}	-21.39	2.34	6.93*	2.67
	(18.82)	(16.03)	(3.42)	(6.19)
Impact of bank-specific characteristics				
$Size_{it-1}$	0.65	2.43		
	(2.08)	(2.00)		
$Liquidity_{it-1}$	-2.16		2.96**	
	(3.75)		(1.48)	
$Capital_{it-1}$	1.82			1.23
	(3.54)			(2.81)
Existence of bank lending channel of monetary policy				
$\Delta MP_{t-1}*Size_{it-1}$	2.07**	-0.30		
	(0.98)	(1.30)		
$\Delta MP_{t-1}*Lqd_{it-1}$	0.46		-2.25*	
	(2.13)		(0.97)	
$\Delta MP_{t-1}*Cap_{it-1}$	-2.01			-1.02
	(2.41)			(2.00)
Control variables				
ΔY_t	-0.02	-0.13	-0.15	0.11
	(0.34)	(0.30)	(0.28)	(0.36)
ΔP_t	0.88	-1.31	-0.96	0.09
	(1.13)	(1.20)	(0.83)	(0.80)
No. of IV	23	12	13	13
Hansen *p*-value	0.92	0.42	0.16	0.65
AR (2) *p*-value	0.35	0.50	0.16	0.00
No. of banks	609	609	609	609
No. of observations	14,640	14,999	14,999	14,640

Note: Robust standard errors in parentheses; ***, **, * denote significance at the 10 percent, 5 percent and 1 percent level, respectively. The Hansen and AR (2) tests show that the instruments are valid and there is no autocorrelation, respectively (*p*-value is greater than 0.10, 0.05, and 0.01).

5.3. Differential impact of monetary policy

To account for potential differential impact of monetary policy, rural banks are categorized into "*small, less liquid, and less-capitalized*" and "*big, highly liquid, and well capitalized*" rural banks, as shown in Table 4. The categorization of the banks was based on Zulkhibri [2013], and is intended to draw further insights on the heterogeneous lending responses of banks to monetary policy shock.

Banks are categorized as $small_{it}$ or big_{it} if bank i's total assets at time t falls at the bottom or upper 25 percentiles of the distribution, respectively. Less and high liquid banks are classified as $less\ liquid_{it}$ or $highly\ liquid_{it}$ if bank i's ratio of liquid assets to total assets is at the bottom or upper 25 percentiles of the distribution, respectively. Banks are either less-capitalized or well-capitalized if bank i's ratio of capital and reserves to total assets falls at the bottom or upper 25 percentiles of the distribution, respectively.

Table 5 summarizes the results of tests on the differential impact of monetary policy. Whereas monetary policy rate is insignificant on its own in the baseline specification (Equation 1), the new results (eq 1.a) show that a one percentage point increase in lagged monetary policy rate (ΔMP_{t-1}) leads to a reduction in rural bank lending growth by 0.71 ppt. This result is consistent with the standard impact of monetary tightening on bank lending.

Moreover, the regression that has only asset size as bank characteristic shows that lending of rural banks with smaller asset base is adversely affected during periods of contractionary monetary policy whereas higher asset base of larger banks enables them to insulate their bank lending activity from the impact of contractionary monetary policy (eq. 2a). This is not surprising since smaller rural banks also presumably face tougher competition from branch network and branch-lite operations of bigger universal and commercial banks as well as from government lending programs.

TABLE 4. Bank-specific characteristic by category (*in logs*)[10]

Percentiles	Size		Liquidity		Capitalization	
	small	large	less liquid	highly-liquid	poorly capitalized	well-capitalized
1%	9.26		0.91		1.39	
5%	9.91		1.91		2.18	
10%	10.35		2.33		2.36	
25%	11.03		2.85		2.65	
50%	11.79		3.40		2.96	
75%		12.60		3.82		3.34
90%		13.35		4.08		3.72
95%		13.89		4.20		3.93
99%		15.04		4.34		4.31

Note. Authors' estimates.

Meanwhile, the interaction between policy rate and capital ($\Delta MP_{t-1} * HCAP$) reveals that highly capitalized banks are more inclined to protect their capital than their lending portfolio in the face of contractionary monetary policy and higher capital requirement (eq. 4a). This may possibly indicate that regulatory compliance and its concomitant reputational effect may be a factor.

[10] Interpretation: The 25th percentile of rural banks has an asset size equivalent to 11.03 in logs.

Similar to findings in Equations 1 to 4, demand condition, as proxied by GDP growth, is of the wrong sign and not a significant factor in determining loan supply growth.

The preceding findings may also be ascribed to the limited sources of funds, which could also affect the profitability and ability of rural banks to intermediate credit whenever there is a contractionary monetary policy alongside risk-focused regulatory requirements. Thus, a separate robustness test on rural bank profitability was also undertaken. With available data on ROA for earlier periods, regressions corresponding to the global financial crisis (GFC) and pre-GFC periods were also estimated.[11]

TABLE 5. Differential impact of monetary policy

Dependent variable: first difference log of total loan portfolio

	ALL (Eq. 1)	SIZE (Eq. 2)	LIQUIDITY (Eq. 3)	CAPITAL (Eq. 4)
ΔL_{it-1}	0.14** (0.07)	0.13* (0.04)	0.20** (0.11)	0.18** (0.10)
ΔMP_t	0.43 (0.28)	0.84* (0.24)	15.09 (12.91)	0.19 (0.53)
ΔMP_{t-1}	-0.71* (0.33)*	-1.08* (0.26)	-15.37 (12.69)	-0.30 (0.58)
Impact of bank-specific characteristics				
$Size_{it-1}$	-0.12 (0.08)	-0.10* (0.04)		
$Liquidity_{it-1}$	0.05*** (0.03)		0.01 (0.05)	
$Capital_{it-1}$	-0.01 (0.03)			0.88 (0.81)
Existence of bank lending channel of monetary policy				
ΔMP_{t-1}*SMALL	-0.83* (0.18)	-0.75* (0.17)		
ΔMP_{t-1}*LARGE	1.21* (0.21)	0.94* (0.17)		
ΔMP_{t-1}*LLIQUID	0.38* (0.15)		0.35 (0.44)	
ΔMP_{t-1}*HLIQUID	-0.05 (0.22)		2.10 (1.50)	
ΔMP_{t-1}*LCAP	0.16 (0.17)			1.08 (0.71)
ΔMP_{t-1}*HCAP	-0.06 (0.24)			-1.14** (0.63)

[11] Refer to Annex 1 for the indicators used in the profitability regression. The indicator return on asset (ROA) from income statement of rural banks is available over a longer period, i.e., 2001–2018. However, comparable dataset for balance sheet indicator "CAR" used in the bank lending regression is not available for earlier periods.

TABLE 5. Differential impact of monetary policy (continued)

	ALL (Eq. 1)	SIZE (Eq. 2)	LIQUIDITY (Eq. 3)	CAPITAL (Eq. 4)
Control variables				
ΔY_t	-0.13 (0.14)	-0.243*** (0.15)	-4.10 (3.61)	-0.05 (0.37)
ΔP_t	0.36 (0.40)	0.12 (0.33)	7.73 (6.20)	0.99 (0.84)
No. of IV	31	21	13	18
Hansen *p*-value	0.33	0.17	0.36	0.15
AR (2) *p*-value	0.93	0.22	0.29	0.21
No. of banks	609	609	609	609
No. of observations	14,640	14,999	14,999	14,640

Note. Robust standard errors in parentheses; ***, **, * denote significance at the 10 percent, 5 percent and 1 percent level, respectively. The Hansen and AR (2) tests show that the instruments are valid and there is no autocorrelation, respectively (*p*-value is greater than 0.10, 0.05, and 0.01).

For the comparable estimation period i.e., 2010–2018Q2, capital to risk-weighted assets (CAR) and liquid asset-to-total assets are the key drivers of profitability, whereby higher CAR enhances profitability while higher liquid asset-to-total assets leads to lower profitability (Table 6). This is in stark contrast to the pre-GFC period wherein asset size, credit risk, and inflation were the principal determinants of profitability. During the GFC, however, both credit risk and liquidity risk had a dampening effect on profitability, possibly reflecting propensity to maximize cost efficiency by reducing expenditures on credit investigation of borrowers though possibly leading to higher credit exposures in the future (the "skimping" hypothesis by Berger and de Young [1997]).

TABLE 6. Drivers of profitability

Variables	Dependent variable: Return on Assets (ΔROA_{it})		
	Pre-GFC (2001Q4-2007Q2)	GFC (2007Q3-2009Q4)	Post-GFC (2010Q1-2018Q2)
$\Delta ROA_{it\text{-}1}$	0.21* (0.03)	-0.31** (0.15)	0.06** (0.02)
Bank-specific variables			
$\Delta Bank\ Size_{it}$	0.54* (0.21)	0.17 (0.24)	-0.30 (0.28)
ΔCAR_{it}[12]		-0.50 (0.41)	1.63** (0.76)

[12] For the periods covering Q4 2001 to Q2 2007, the variable "CAR" was dropped in the regression due to data unavailability.

TABLE 6. Drivers of profitability (continued)

Variables	Dependent variable: Return on Assets (ΔROA_{it})		
	Pre-GFC (2001Q4-2007Q2)	**GFC (2007Q3-2009Q4)**	**Post-GFC (2010Q1-2018Q2)**
$\Delta Funding\ Risk_{it}$	0.70	-0.13	-0.73
	(0.48)	(0.66)	(1.14)
$\Delta Credit\ Risk_{it}$	0.50**	-0.93***	0.26
	(0.23)	(0.52)	(1.91)
$\Delta Liquidity\ Risk_{it}$	-0.13	-0.60**	-1.46**
	(0.11)	(0.27)	(0.84)
Macroeconomic determinants			
ΔY_t	-0.26	-0.25	0.05
	(0.38)	(0.33)	(0.38)
ΔP_t	-4.04*	1.73	-0.28
	(0.93)	(1.34)	(1.96)
ΔR_t	-0.02	-0.07	0.13
	(0.03)	(0.05)	(0.12)
No. of IV	18	23	24
Hansen *p*-value	0.28	0.75	0.15
AR (2) *p*-value	0.22	0.27	0.95
No. of banks	742	584	589
No. of observations	8,693	2,418	7,415

Note. Robust standard errors in parentheses; ***, **, * denote significance at the 10 percent, 5 percent and 1 percent level, respectively. The Hansen and AR (2) tests show that the instruments are valid and there is no autocorrelation, respectively (*p*-value is greater than 0.10, 0.05, and 0.01).

6. Conclusion

The empirical analysis has shown that bank lending channel, in general, operates in the Philippine rural banking system through rural banks' asset size. The heterogenous effects of monetary policy are more evident in the lending behavior of smaller rural banks. While big rural banks are able to protect their lending portfolio from contractionary monetary policy by the strength (size) of their balance sheet, small rural banks with less diversified funding portfolio cannot. Moreover, highly capitalized banks are more inclined to protect their capital than their lending portfolio with contractionary monetary policy and higher capital requirement, possibly indicating that regulatory compliance and its concomitant reputational effect may be a factor. The finding on heterogeneous effects of monetary policy on rural banks has a secondary implication of lending credence to the principle of proportionality embodied in the BSP's bank regulatory framework.

The weakness in effective and productive loan demand may reflect lack of diversification that could have also impinged on the earning capacity of rural banks, as supported by initial estimates on the drivers of rural bank profitability. An interesting area for future study is one which would account for region-specific characteristics that may influence the lending behavior of rural banks.

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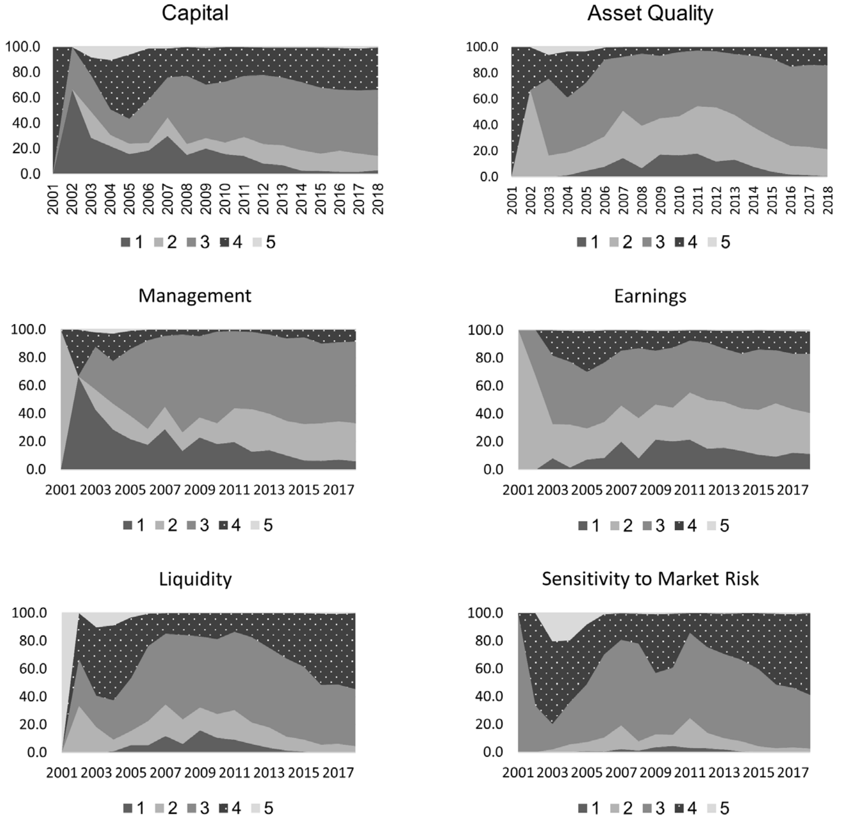
Annex

ANNEX 1. Indicators in the profitability regression

Variables		Definition	Expected Sign	Reference
Dependent variable	Return on Assets (ROA)	Computed as net profit of bank *i* at time *t* divided by total assets of bank *i* at time *t*.		Al-Homaidi et al. [2018]
Bank-specific variables	Bank size (BS)	Bank size is measured as the log of total assets of bank *i* at time *t*.[13]	±	Adusei [2015]
	Capital Adequacy Ratio (CAR)	Refers to the ratio of total qualifying capital to total risk weighted assets.	+	BSP
	Credit Risk (CR)	Computed as log of total loan portfolio of bank *i* at time *t* divided by the log of total assets of bank *i* at time *t*.[14]	+	Adusei [2015]
	Liquidity Risk (LR)	Calculated as log of liquid assets of bank *i* at time *t* divided by log of total assets of bank *i* at time *t*.[15]	-	
	Funding Risk (FR Z-score)	Computed as deposit liabilities-to-assets ratio of bank *i* at time *t* plus equity-to-assets ratio of bank *i* at time *t* divided by the standard deviation of deposit liabilities-to-assets ratio of bank *i* at time *t*. $Funding\ Risk\ (Z - score)_{it} = \left[\frac{\left(\frac{Deposits}{Assets}\right)_{it} + \left(\frac{Equity}{Assets}\right)_{it}}{\sigma\left(\frac{Deposits}{Assets}\right)_{it}}\right]$ The funding risk z-score measures the extent to which a bank needs to recapitalize based on the extent of the needed reduction in the volatility of the bank's deposit liabilities (i.e., customer deposits). Thus, the stability of the bank's funding source is reflected in a higher z-score of a bank.	+	
	Real GDP growth (Y)	The estimates for the constant price of GDP are obtained by expressing the values in terms of a base period (i.e., 2000).	±	Philippine Statistics Authority (PSA)
Macro-economic variables	CPI inflation (P)	CPI is measured using 2006 prices as the base year.	+	BSP
	Bank average lending interest rate (R)	Reflects the annual percentage equivalent of all commercial banks' actual interest income on their peso-denominated loans to the total outstanding levels of their peso-denominated loans, bills discounted, mortgage contract receivables and restructured loans.	+	

[13] Total assets (ta) refers to the sum of total assets, net of due to head office/branches/agencies and non-performing assets cover.
[14] Total loan portfolio (tlp) refers to the sum of (i) loans to BSP, (ii) loans to other banks, (iii) loans and receivables-others, and, (iv) loans and receivables arising from repurchase agreements/certificate of assignment/participation with recourse/securities lending and borrowing transactions, net of amortization.
[15] Liquid assets (la) are the sum of cash and cash items, due from banks, and financial assets (net of amortization, accumulated market gains/losses, allowance for credit losses excluding equity investment in subsidiaries/associates/joint ventures).

ANNEX 2. Evolution of CAMELS component ratings of rural banks



Note: Rating scale ranges from 1–5, with 5 being the highest.
Source of basic data: BSP's Department of Supervisory Analytics, Financial Supervision Sector.

ANNEX 3. Dynamic panel data model selection

The table below shows the estimates for Equation 1 under the two types of DPD models, namely, standard diff-GMM and orthogonal diff-GMM.

	Dependent variable: Total Loan Portfolio (ΔL_{it-1})	
	diff GMM orthogonal	**diff GMM standard**
ΔL_{it-1}	-3.26*** (1.85)	-2.21 (1.60)
ΔMP_t	1.01 (0.85)	0.97 (0.60)
ΔMP_{t-1}	-21.39 (18.82)	-5.34 (33.90)

ANNEX 3. Dynamic panel data model selection (continued)

	Dependent variable: Total Loan Portfolio (ΔL_{it-1})	
	diff GMM orthogonal	**diff GMM standard**
Impact of bank-specific characteristics		
$Size_{it-1}$	0.65 (2.08)	1.69 (3.17)
$Liquidity_{it-1}$	-2.16 (3.75)	-0.05 (5.55)
$Capital_{it-1}$	1.82 (3.54)	-3.14 (5.71)
Existence of bank lending channel of monetary policy		
$\Delta MP_{t-1}*Size_{it-1}$	2.07** (0.98)	0.34 (2.20)
$\Delta MP_{t-1}*Lqd_{it-1}$	0.46 (2.13)	-1.28 (3.57)
$\Delta MP_{t-1}*Cap_{it-1}$	-2.01 (2.41)	1.45 (4.29)
Control variables		
ΔY_t	-0.02 (0.34)	-0.31 (0.36)
ΔP_t	0.88 (1.13)	-0.17 (1.78)
No. of IV	23	23
Hansen *p*-value	0.92	0.60
AR (2) *p*-value	0.35	0.89
No. of banks	609	609
No. of observations	14,640	14,110

Note: Robust standard errors in parentheses; ***, **,* denote significance at the 10 percent, 5 percent and 1 percent level, respectively. The Hansen and AB autocorrelation tests show that the instruments are valid and there is no autocorrelation, respectively (*p*-value is greater than 0.10, 0.05, and 0.01).

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How do exchange rates affect the Big One? An empirical analysis of the effect of exchange rates on RCEP exports using the gravity model

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The often disparate and conflicting effects of exchange rate on bilateral exports reported by previous literature necessitate a further study of the relationship between monetary and trade variables. This study contributes to the stream of literature by analyzing monetary variables such as exchange rate volatility, exchange rate misalignment, exchange rate regimes, and real effective exchange rates with bilateral aggregate exports through a sample of 15 nations comprising the Regional Comprehensive Economic Partnership (RCEP) region for the years 1996 to 2017 using Ordinary Least Squares and Poisson Pseudo-Maximum Likelihood panel fixed effects regression. Results indicate that a country's real effective exchange rate ratio and the exchange rate volatility for countries under a floating exchange rate regime reduce aggregate exports.

JEL classification: E52, F31, F15
Keywords: exchange rates, volatility, gravity model

1. Introduction

International trade plays an important role in a country's development. World trade accounted for around 60 percent of the global economy or more than one half of the Gross Domestic Product (GDP) in 2019, indicating a rapid increase of trade activities for goods and services across the globe (Figure 1). As the world tries to recover from the pandemic and shift to the new normal, international trade will continue to play a strong role in the economy and a country's growth. This growing share of trade in world GDP can be attributed to developments in trade policy such as the establishment of the World Trade Organization (WTO) in 1994, establishment of preferential trade agreements (PTAs) among countries and free trade agreements (FTAs).

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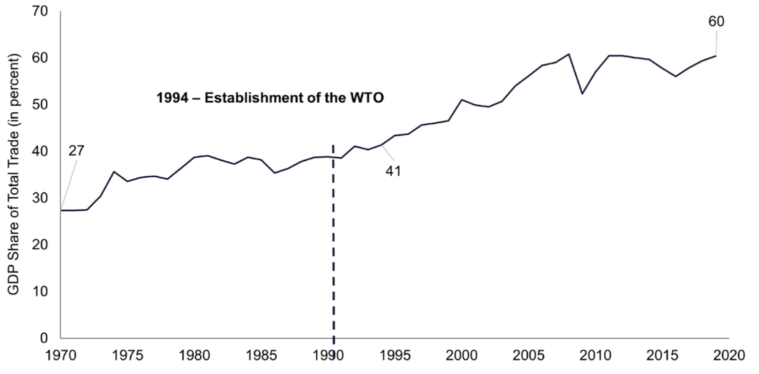
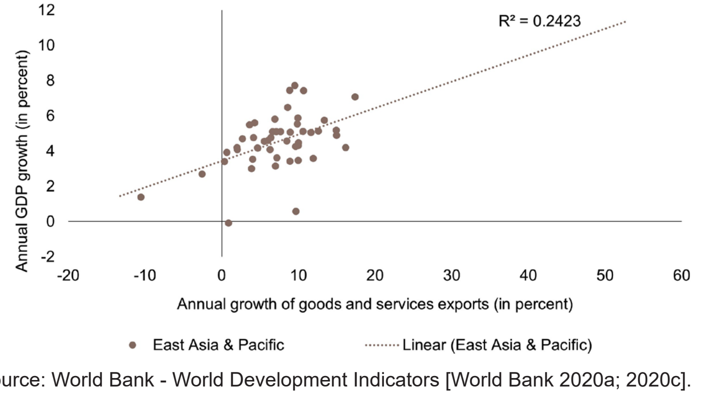
FIGURE 1. Percentage share of total trade in GDP (world aggregate; 1970-2019)



Source: World Bank - World Development Indicators [World Bank 2020e].

Given this relationship, several studies have theorized and observed how trade contributes to economic development such as Andersen and Babula [2008] and Keho [2017]. Both studies have observed that there is a strong complementary relationship between a country's total trade and capital formation and economic growth. Increase of trade through exports has allowed domestic businesses and firms to expand their respective markets. Tan et al. [2019] also explained that exports are considered an important engine of growth and development as it enables the exporting country to benefit from technological spillovers, increased specialization, and positive externalities. This is especially evident in countries in the East Asia and Pacific region where there is a positive relationship between exports and GDP growth (Figure 2).

FIGURE 2. Annual growth of exports and GDP (East Asia and Pacific Region; 1970-2019)



Source: World Bank - World Development Indicators [World Bank 2020a; 2020c].

An important factor that affects the level of trade of countries is the exchange rate. This is because the market prices of traded goods and services are governed by a country's prevailing exchange rate. Given this, the exchange rate is one of the most important price indicators in an open economy.

For example, the price a domestic exporter gets paid for its exports is relative to the exchange rate between the domestic currency and the foreign buyer's currency. If the current exchange rate is 1:1, then a unit of domestic currency is equal to a unit of a foreign currency. If 100 units of the exported good is worth one unit of the domestic currency, then the foreign buyer spends one unit of the foreign currency to purchase 100 units of the exported good. However, if the new exchange rate becomes 1:2, then a unit of the domestic currency is now equal to two units of the foreign currency.

The domestic currency appreciates because it can purchase more of the foreign currency. The foreign buyer can now only purchase half or 50 units of the exported good due to the domestic currency appreciating. This demonstrates how currency appreciation (depreciation) makes exports more expensive (cheaper).

Pomfret and Pontines [2013] point out that exchange rate policy can be considered a substitute for trade policy. A change in exchange rates is equivalent to a combination of changes in import taxes and export subsidies. In simpler terms, changes in exchange rates are tantamount to changes in trade transaction costs and risks that can affect the volume of exports for a country.

The relevance of exchange rate policies demonstrates the importance of identifying the significant exchange rate factors and policies that affect a country's level of exports. Following Pomfret and Pontines [2013], exchange rate policies should be included in the arsenal of government trade instruments typically confined to WTO membership, PTA membership, tariff rates, quota restrictions, non-tariff measures (NTMs), and the like. The proliferation of preferential and regional trade agreements in recent decades underscores the importance of studying how exchange rate variables influence the trade dynamics specific to regional economic partnerships.

This issue is especially relevant in the case of the states under the Regional Comprehensive Economic Partnership (RCEP) where international production networks proliferate and governments in the region are perceived to influence their domestic currencies in order to drive their strategic plans. Examining the role of exchange rate policies would be relevant in assessing their effectiveness in inducing trade and growth in the region.

The RCEP region is composed of the following countries: Australia, Brunei Darussalam, Cambodia, People's Republic of China, Indonesia, Japan, Lao People's Democratic Republic, Malaysia, Myanmar, New Zealand, Philippines, Singapore, Republic of Korea, Thailand, and Vietnam. This aggrupation is based on the RCEP, a trading agreement signed last November 15, 2020. As of 2020, RCEP parties contributed 30 percent of the world's GDP [World Bank 2022b], 29 percent of the world's population [World Bank 2022c], and 26 percent of the world's total exports [World Bank 2022a]. This makes the region the largest free trade deal in the world at the present time making it "The Big One."

This paper attempts to determine the relevant exchange rate variables, such as exchange rate volatility, misalignment, real effective exchange rates, and a floating exchange rate regime, that affect the level of RCEP exports through an augmented gravity model estimation. It is highly important to determine the effects of the said variables given that the actual effect of exchange rates on trade is still an open and controversial question due to the mixed theories and empirical results obtained by multiple studies [Nicita 2013]. Moreover, being the largest trading bloc in the world, it is important to determine what direction and by what magnitude exchange rate variables affect exports within the region.

2. Exchange rates and international trade

The following exchange rate variables to be discussed have been theorized and observed to affect the level of trade between countries in past empirical studies. This paper will incorporate the variables in the model along with some recommendations to properly determine the effect of exchange rates on trade in the RCEP region. Table 1 summarizes the different empirical studies found regarding the effect of exchange rates on trade.

2.1. Real Effective Exchange Rates (REER)

The REER is defined as the measure of the real value of a country's currency against a basket of currencies of its trading partners, where an increase in the REER of a country implies currency appreciation [Darvas 2012]. Currency appreciation occurs when less of the domestic currency is needed to purchase a unit of a foreign currency. Benkovskis and Wörz [2013] explained that an increase in REER would generally reduce export competitiveness. Exports from the country whose currency has appreciated would cost more, making exports from other competing countries relatively cheaper. An empirical study by Tan et al. [2019] observed that an increase in REER significantly reduces exports.

2.2. Exchange rate misalignment

Exchange rate misalignment is defined as the difference between the observed exchange rate and an estimated equilibrium exchange rate [Nicita 2013]. This paper follows the approach of Rodrik [2008] wherein a higher level of misalignment yields an undervaluation of the domestic currency. More units of the domestic currency needed to purchase a unit of a foreign currency indicates currency undervaluation. An undervalued currency is expected to make exports competitive since it makes domestic exports cheaper for other countries to purchase, hence increasing export volume.

An empirical study by Nicita [2013] observed that exchange rate misalignment significantly affects trade. However, a recent study by Nasir and Jackson [2019] cautioned that misalignment is not the sole responsible factor in causing trade imbalances. Other factors such as exchange rate volatility should be analyzed in line with misalignment to determine its effect on trade.

2.3. Exchange rate volatility

Exchange rate volatility measures the level of fluctuations a country's exchange rate undergoes over a period of time. Nicita [2013] argued that volatility reduces trade due to the presence of risks and transaction costs these fluctuations cause. However, the significant effects of a lower level of exchange rate volatility are indirect and "originate from long-term exchange rate commitments such as currency unions and pegged exchange rates rather than short-term exchange rate fluctuation" [Nicita 2013].

Similar to the recommendation by Nasir and Jackson [2019] on exchange rate misalignment, Clark et al. [2004] pointed out that the effects of exchange rate volatility on trade should be interacted with monetary policies such as currency unions and exchange rate regimes. This suggests, in theory, that monetary policies and exchange rate policies have to be analyzed jointly rather than individually. Separately, these policies may not significantly affect trade; however, evaluating these policies as a set or through interactions can better demonstrate their effect on trade.

Bahmani-Oskooee and Hegerty [2009] explained that exchange rate volatility can either be trade creating or trade reducing. It can increase trade if exporters and importers decide to increase their trade volumes in order to attain certain levels of income. Trade increases as exporters and importers increase the number of units purchased or sold in order to make up for the possible effects of exchange rate volatility, such as a decrease in the per-unit value of a good. Senadza and Diaba [2018] also posited that exchange rate volatility can increase trade as it encourages producers to increase production in an attempt to evade severe decreases in income.

De Grauwe [2005] also explains that exchange rate volatility allows firms to increase prices not just to compensate the risk of fluctuating rates but also as an opportunity for financial gain. With the expected profit of firms likely to increase given price increases due to higher exchange rate volatility, it is possible that production and exports will increase.

On the other hand, exchange rate volatility can also reduce the levels of trade if risk-averse buyers and sellers foresee losses due to fluctuations in the exchange rate. This leads buyers and sellers not to partake in any deal to trade [Bahmani-Oskooee and Hegerty 2009]. Naseem et al. [2009] further explains that volatility becomes a barrier for trade due to the uncertainties it brings about.

TABLE 1. Summary of previous empirical studies on exchange rates and international trade

Paper	Methodology	Country	Period	Dependent Variable	Independent Variables	Controls	Findings
Banik and Roy [2020]	OLS, Fixed-Effects, and Random-Effects model for panel data	SAARC[1] countries	2005-2018	Bilateral Exports	Real Exchange rate volatility	Level of Output, Level of Income, Distance, Common Language, Common Border	Exchange rate volatility significantly reduces bilateral exports
Clark et al. [2004]	Country-pair time fixed-effects model for panel data	178 countries	1975-2000	Bilateral trade	Real exchange rate volatility, Currency union	GDP product, GDP per capita Product, Distance, Common language, Common border, Landlocked countries, Island countries, Country area product, Common colonizer, Colonial links, FTA membership, WTO membership	Real exchange rate volatility significantly reduces bilateral trade.
Chi and Cheng [2016]	Autoregressive Distributed Lag (ARDL)	Australia	2000-2013 (quarterly)	Volume of Bilateral Exports	Exchange rate volatility	GDP, Bilateral exchange rate	Exchange rate volatility significantly affects the volume of bilateral exports in the long run for majority of trading partners. However, the effect varies per country-pair.
Hayakawa and Kimura [2009]	OLS and exporter-year, importer-year fixed effects model for panel data	Eight countries[2]	1992-2005	Real bilateral exports	Real exchange rate volatility, Unanticipated volatility, Exporter's risk index, Importer's risk index, Tariffs	Exporter GDP, Importer GDP, Distance, Common border, Colonial links, Common colony, Common language, Regional dummy variable	Exporter's risk index and Importer's risk index significantly increase real bilateral exports; Real exchange rate volatility, Unanticipated volatility and tariffs on real exports significantly reduce real bilateral exports.
Hondroyiannis et al. [2008]	OLS, random-effects, fixed-effects, General Method of Moments, random coefficient estimation	12 countries[3]	1977-2003 [4]	World exports	Real exchange rate volatility	Exporter GDP, Relative prices of exporting country, real export earnings of exporting country	No statistically significant long-run relationship between Exchange Rate Volatility and Total Bilateral Trade.

[1] Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri-Lanka.
[2] China, Hong Kong, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, and Thailand.
[3] Canada, France, Germany, Italy, Japan, United Kingdom, United States, Switzerland, Norway, Ireland, Spain, and Netherlands.
[4] Quarterly data used.

TABLE 1. Summary of previous empirical studies on exchange rates and international trade (continued)

Paper	Methodology	Country	Period	Dependent Variable	Independent Variables	Controls	Findings
Klein and Shambaugh [2006]	Country-pair time fixed-effects model and instrumental variable regression for panel data	181 countries	1973-1999	Bilateral trade	Currency union, Exchange rate volatility, Direct peg, Indirect peg	GDP product, GDP per capita product, Distance, Country area product, Common land border, Common language, Colonial relationship, Landlocked country, Island, Common colonizer, FTA	Direct peg, Indirect peg and Currency union significantly increase bilateral trade; Exchange rate volatility significantly reduce bilateral trade.
Nicita [2013]	Country-pair time fixed-effects model for panel data	100 countries	2000-2009	Bilateral exports	Exchange rate misalignment, Exchange rate volatility, Tariff Trade Restrictiveness Index (TTRI)	Exporter GDP, Importer GDP, Distance, Common border, Colonial links, Common language	Exchange rate misalignment, Exchange rate volatility and TTRI significantly reduce total bilateral exports.
Njoroge [2020]	OLS-Pooled, Fixed-effects, and Random Effects model for panel data	COMESA countries[5]	1997-2019	Bilateral exports	Exchange rate volatility	GDP Product, Distance, Common Language, Common Border, Population	Exchange rate volatility significantly reduces exports.
Pomfret and Pontines [2013]	Country-pair time fixed- and random-effects models for panel data	16 countries[6]	1990-2010	Average bilateral trade	Rate of exchange rate depreciation, Exchange rate volatility, RTA*Rate of exchange rate depreciation, RTA*Exchange rate volatility	GDP product, GDP per capita product, Distance, Country Area Product, Common Land Border, Common Language, RTA	Rate of exchange rate depreciation and RTA*Rate of exchange rate depreciation significantly increase average bilateral trade; Exchange rate volatility and RTA*Exchange rate volatility significantly reduce average bilateral trade.

[5] Burundi, Comoros, Congo, Dem Rep., Djibouti, Egypt, Eritrea, Ethiopia, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, Seychelles, Sudan, Swaziland, Uganda, Zambia, and Zimbabwe.

[6] Brunei Darussalam, Cambodia, Hong Kong, China, Indonesia, Japan, Republic of Korea, Lao PDR, Macau, Malaysia, Mongolia, Myanmar, Philippines, Singapore, Thailand, and Vietnam.

TABLE 1. Summary of previous empirical studies on exchange rates and international trade (continued)

Paper	Methodology	Country	Period	Dependent Variable	Independent Variables	Controls	Findings
Prajakschitt [2015]	Fixed-effects model for panel data	China and ASEAN 6 countries[7]	2001-2013	Bilateral Imports	Exchange rate volatility	GDP product, Distance, China (Dummy)	No significant relationship between exchange rate and imports.
Santana-Gallego and Pérez-Rodríguez [2019]	High-Dimensional Fixed Effects and PPML model for panel data	191 countries	1970-2016	Bilateral exports	Exchange rate regimes, Presence of crises	RTA	Direct pegs and indirect pegs significantly increase exports
Satawatananon [2014]	Autoregressive Distributed Lag (ARDL)	Thailand and USA	1971-2012	Bilateral exports and imports[8]	Real exchange rate, Real exchange rate volatility	Exporter GDP	Real exchange rate positively affect trade in the short-run for the clothing sector. Real exchange rate volatility reduces trade in the short-run for the textile sector. No significant effect on the clothing and textile sector in the long-run.
Senadza and Diaba [2017]	Autoregressive Distributed Lag (ARDL) [Pooled-Mean Group] model for panel data	11 countries[9]	1993-2014	Real exports	Exchange rate volatility	Nominal exchange rate, GDP of exporter country, Inflation rate of exporter country, Real FDI	Exchange rate volatility significantly reduce real exports in the short-run; Exchange rate volatility significantly increase real exports in the long-run.
Tan et al. [2019]	Country-time fixed effects model for panel data	Eight countries[10]	1995-2011	Real gross exports	Lag of REER, Lag of REER Volatility, Lag of FVA share on gross exports, Lag of FVA share*Lag of REER, Lag of FVA share*Lag of REER volatility	GDP product, Real FDI stock	Lag of FVA share*Lag of REER and Lag of FVA share*Lag of REER volatility significantly increase real gross exports; REER volatility and Share of FVA in gross exports significantly reduce real gross exports.

7 Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam.
8 All Harmonised Product (HS) codes were used. Regressions were performed per products code and using the aggregate.
9 Ghana, Gambia, Kenya, Madagascar, Mauritius, Mozambique, Nigeria, Sierra Leone, Tanzania, Uganda, and Zambia.
10 Brunei Darussalam, Cambodia, Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam.

TABLE 1. Summary of previous empirical studies on exchange rates and international trade (continued)

Paper	Methodology	Country	Period	Dependent Variable	Independent Variables	Controls	Findings
Tarasenko [2021]	Fixed-effects model for panel data	72 countries	2004-2018	Bilateral Exports of different products	Real exchange rate volatility	Real GDP, Average Exchange Rate	Exchange rate volatility significantly reduces exports of manufactured goods, and machinery and transport equipment and significantly increases imports of fuels, textiles, chemicals, and manufactured goods.
Tenreyro [2007]	IV-PPML for panel data	87 countries	1970-1997	Bilateral Trade	Exchange rate volatility	Exporter GDP, Importer GDP, Distance, Common border, Common language, Colonial links, FTA	No statistically significant long-run relationship between Exchange Rate Volatility and Total Bilateral Trade.
Vo et al [2019]	Dynamic Ordinary Least Squares (DOLS) regression for panel data	Vietnam	2000-2015	Bilateral exports[11]	Real exchange rate volatility	Real exchange rate, Importer GDP	For textile and clothing sector, real exchange rate volatility is not significant for ASEAN partner countries and all sample partner countries.
Wong and Chong [2016]	Country-pair time fixed-effects model and instrumental variable regression for panel data	186 countries	1974-2009	Real bilateral trade	Currency union, Direct peg, Indirect peg, Inflation targeting, Exchange rate volatility, Inflation rate	GDP product, Free Trade Agreement (FTA)	Currency union, Direct peg and Inflation targeting significantly increase real bilateral trade; Indirect peg, Exchange rate volatility and Inflation rate significantly reduce real bilateral trade.

[11] Ten sectors were analyzed individually: (1) food products, beverages and tobacco, (2) textiles, wearing apparel, leather and related products, (3) wood and products of wood and cork, (4) paper and printing, (5) chemicals, rubber, plastics and fuel products, (6) non-metallic mineral products, (7) basic metals and fabricated metal products, (8) machinery and equipment, (9) transport equipment, and (10) furniture and other manufacturing.

Côté [1994] and McKenzie [1999] both discuss that the presence of exchange rate volatility forces firms to incur additional costs to mitigate risks on the exchange rate. This additional cost would be shouldered by the firm and will affect the cost of production. The additional cost reduces the quantity of exports supplied by the firm compared to the quantity exported without the additional cost. Due to this, exports are reduced because of exchange rate volatility.

Moreover, Dell'Ariccia [1998] argues that the additional costs can also take the form of transaction costs between trading partners shouldered by both trading parties. This, in turn, can lead to a decline in trading activity since costs increased, possibly forcing firms to redistribute production to local markets or other international markets to avoid the cost.

Clark et al. [2004] argued that although exchange rate volatility poses risks and additional costs for trading countries, the increase in instruments of financial hedging have lessened the risks of exchange rate fluctuations. The increase in these instruments is indicative of the growth of different financial instruments across the globe. Thus, it was posited that exchange rate volatility significantly but weakly reduces trade.

Given this, exchange rate volatility theoretically affects exports due to its effect on additional costs. As stated above, there are numerous studies explaining how exchange rate volatility affects exports. However, views regarding the effect of exchange rate volatility on trade are mixed.

Previous empirical studies analyzing the effects of exchange rate volatility on trade have reported mixed results as well. The empirical study of Hayakawa and Kimura [2009] observed that exchange rate volatility significantly reduces a country's bilateral exports. Additionally, Hayakawa and Kimura [2009] used a smaller sample size of eight countries all within the Asia-Pacific region. Hayakawa and Kimura [2009] analyzed the effects of unanticipated volatility, exporter's risk index, importer's risk index and tariffs on top of exchange rate volatility on exports. Exchange rate volatility was found to significantly reduce exports for the smaller sample size.

This is similar to more recent findings from Njoroge [2020] who saw a significant reducing effect of exchange rate volatility on exports for trade in the Common Market for Eastern and Southern Africa regional bloc and Banik and Roy [2020] who observed the same effect for countries belonging to the South Asian Association for Regional Cooperation bloc.

Other empirical studies, on the other hand, report opposite findings. Hondroyiannis et al. [2008] used a sample of 12 countries mostly located in North America and Europe with quarterly data from years 1977 to 2003. The estimates showed that there is no significant long-run relationship between exchange rate volatility and world exports. This conforms to Tenreyro's [2007] study on a sample of 87 countries located across different regions, where ten countries in the RCEP region are included, ranging from years 1970 to 1997 (28 years).

Tenreyro's results showed that there is no statistically significant relationship between exchange rate volatility and bilateral trade.

These observations were also affirmed recently by Prajakschitt [2015] and Vo et al. [2019]. Prajakschitt [2015] observed that there is no significant relationship between exchange rate volatility and imports after using a fixed-effects model for panel data on China and six Association of Southeast Asian Nations (ASEAN) member states. The results of Vo et al. [2019] also demonstrated that there is no significant effect of exchange rate volatility on textile and clothing exports for trade between Vietnam and 26 partner countries through a Dynamic Ordinary Least Squares model.

Other empirical studies, however, observed mixed results such as Senadza and Diaba [2018]. A sample of 11 Sub-Saharan African countries for the years 1993 to 2014 (22 years) was evaluated using an autoregressive distributed lag-pooled mean group model method. Their study reported that exchange rate volatility significantly reduces exports in the short run. However, exchange rate volatility significantly increases exports in the long run. Senadza and Diaba [2018] pointed out that the changing effect of exchange rate volatility on exports in the short run and long run reflect the vagueness of theoretical outcomes under the general equilibrium models.

Similarly, Satawatananon [2014], Chi and Cheng [2016], and Tarasenko [2021] observed mixed results in their respective models. Satawatananon [2014] observed a negative effect between exchange rate volatility and exports in the short run but no significant effect in the long run for trade between Thailand and the United States of America (USA). Chi and Cheng [2016] found that there is a significant relationship between exchange rate volatility and exports in majority of Australia's trading partners. However, the effect varies per country-pair. The recent study of Tarasenko [2021] also observed that exchange rate volatility's effect on exports varies depending on the commodity exported from Russia to its trading partners.

According to Clark et al. [2004], the mixed results from empirical studies regarding exchange rate variables such as volatility and trade suggest that the effect of the said variables may possibly be an empirical issue or dependent on the sample being analyzed. This could be the reason why the different empirical studies presented earlier vary in results. Moreover, this necessitates the need to determine what effect is dominant in the world's largest trading bloc—the RCEP.

2.4. Exchange rate regimes

Exchange rate regimes refer to the system that the country's monetary authority uses to determine the exchange rate of its currency against foreign currencies [International Monetary Fund 2006]. There are three general classifications for exchange rate regimes: direct peg; indirect peg; and floating. A direct peg is a system wherein the exchange rate is fixed against the value of another currency.

An indirect peg is similar to a direct peg, but monetary authorities can induce small adjustments on the exchange rate based on different factors.

A floating regime is a system where the exchange rate is completely market-determined or when the monetary authority tries to influence the rate without a particular path. It has been theorized that direct pegs are expected to generate currency stability and foster bilateral trade with other fixed currencies [Klein and Shambaugh 2006]. This has been empirically observed by Wong and Chong [2016] in their model; countries that have a fixed peg regime significantly increase trade. However, no previous literature was found incorporating floating regimes.

Klein and Shambaugh [2006] observed that pegging to a foreign currency such as the United States Dollar (USD) fosters bilateral trade with the USA and all other countries that peg to the USD. Moreover, a currency peg is expected to generate macroeconomic stability as it reduces a country's exchange rate volatility.

A more recent study by Santana-Gallego and Pérez-Rodríguez [2019] similarly observed that countries that peg their currency to the USD or to a currency union experience greater trade flows. Moreover, indirect pegs were also found to be significantly trade increasing with its magnitude dependent on the anchor currency.

However, there is not enough evidence to suggest that floating exchange rate regimes are ultimately trade reducing in theory. It is still possible to be trade creating given the currency stabilizing mechanisms present in a floating exchange rate regime.

2.5. Exchange rates in the RCEP region

It is important to analyze the effects of exchange rate volatility and the rest of the variables on trade within the RCEP region. Following findings from Tan et al. [2019], competitive devalued exchange rates[12] are crucial to promote exports. This makes managing volatility an important priority for all countries in the RCEP region. Given that ten out of 15 countries in the RCEP region are ASEAN member states, analyzing the effects of exchange rate volatility, paired with monetary variables, on exports is of great importance. The lack of consensus on the relationship between exchange rate volatility and trade calls for an empirical evaluation of exchange rate volatility on an aggregate level, and to determine whether trade creating or trade reducing effects dominate the region.

[12] There are some cases where devalued exchange rates do not work in promoting trade such as in Pakistan [McCartney 2015]. In this case, the devaluation of the currency was not competitive compared to that of other countries.

3. Methodology and data

3.1. The gravity model and PPML estimation

The gravity model has been regarded as the "workhorse of the applied international trade literature" and has generated "some of the clearest and most robust findings in empirical economics" [Shepherd 2016]. Tinbergen [1962] presented the fundamental form of the trade flow equation as seen below:

$$E_{ij} = \alpha_0 \, Y_i^{\alpha_1} \, Y_j^{\alpha_2} \, D_{ij}^{\alpha_3} \tag{1}$$

where E_{ij} represents the exports of country i to country j, Y_i represents the Gross National Product (GNP) of country i, Y_j represents the GNP of country j, and D_{ij} represents the transportation costs assumed to correspond with the geographical distance between country i and country j. This model exhibits that distance acts as a determinant of export levels [Tinbergen 1962].

Anderson [1979] provided a theoretical explanation for the gravity equation concerned with the trade of commodities. Since then, the gravity model has been widely utilized in the study of international trade and has been enhanced to acclimate the other definitions for "distance."

This study uses an augmented gravity model to determine the effect of exchange rates on a country's exports. Additional variables such as exchange rate variables and control variables to proxy for trade costs were added to the model. The gravity model has been augmented to incorporate monetary variables as seen below:

$$\begin{aligned} \ln(Exports)_{ij,t} = \alpha_0 + \beta_1 \ln(GDP_{i,t} * GDP_{j,t}) + \beta_2 \ln(dist)_{ij} + \beta_3 contig_{ij} + \\ \beta_4 comlang\_off_{ij} + \beta_5 comcol_{ij} + \beta_6 \ln(REER)_{ij,t} + \beta_7 Misalign_{ij,t} + \\ \beta_8 Float_{ij,t} * \ln(Volatility)_{ij,t} + \beta_9 cty_{ij,t} + \varepsilon_{ij,t} \end{aligned} \tag{2}$$

where *Exports* represents aggregate exports of country i to country j at time t, α is the constant term, $GDP_{i,t}$ and $GDP_{j,t}$ represent the nominal GDP of the exporting and importing country, respectively, *distance* represents the geographical distance between each country-pair, *contig* is a dummy variable equal to one if the country-pair share a common land border and zero otherwise, *comlang_off* is a dummy variable equal to one if the country-pair share a common official language and zero otherwise, *comcol* is a dummy variable equal to one if the country-pair was previously under the same colonizer and zero otherwise, *REER* represents the bilateral real effective exchange rate between country-pairs, *Misalign* represents the bilateral exchange rate misalignment between country-pairs, *Float* is a dummy variable equal to one if the country-pair observes a floating exchange rate regime and zero otherwise, *Volatility* is the bilateral exchange rate volatility between country-pairs, *cty* are a set of proxy variables for time-varying outward and inward multilateral resistance terms, and ε represents the error term.

The inclusion of multilateral resistance terms in the gravity model came from Anderson and Van Wincoop [2003]. These terms capture how exports between two countries depend on trade costs across all possible export markets. Moreover, it captures how imports between two countries depend on trade across all possible suppliers. These terms remove several violations regarding the standard economic theory.

Aside from an Ordinary Least Squares (OLS) estimation, a Poisson Pseudo-Maximum Likelihood (PPML) estimator is utilized. The PPML estimator was developed by Santos Silva and Tenreyro [2006] in order to deal with the problem of possible bias in the estimates. Shepherd [2016], Yotov et al. [2016], Gauto [2012], and Siliverstovs and Schumacher [2008] explain how the PPML estimator is regarded as the "workhorse gravity estimator." First, the PPML estimator is consistent even with fixed effects estimation. Similar to that of OLS, fixed effects estimation through PPML can be done by using dummy variables. This demonstrates that multilateral resistance variables can be proxied in the PPML estimator through exporter and importer dummy variables.

Second, the PPML estimator accommodates observations that contain zero values of trade. OLS models tend to drop observations with zero values of trade due to the natural logarithm of zero being undefined. Including observations with zero values of trade removes the possible sample selection bias OLS models can possibly generate.

Third, the interpretation of coefficients regressed using the PPML estimator follows that of the OLS. Shepherd [2016] explains that the dependent variable, such as trade values, must be in levels rather than in logarithms. For example, instead of taking the natural logarithm of exports, exports must be reported in millions or thousands of dollars. On the other hand, independent variables can still be presented in logarithms.

Coefficients of the PPML estimator can still be interpreted as simple elasticities, even though the dependent variable is not specified in logarithmic form (Shepherd [2016]; Santos Silva and Tenreyro [2006]). For all these reasons, it is recommended to base the results of this study on the PPML estimator. For robustness purposes, both the OLS and PPML regression results are reported in the succeeding part of this study.

The augmented PPML econometric model can be seen below:

$$\begin{aligned}\left(\frac{Exports}{1{,}000{,}000}\right)_{ij,t} = {} & \exp[\beta_1 \ln(GDPi_{,t} * GDPj_{,t}) + \beta_2 \ln(dist)_{ij} + \beta_3 contig_{ij} + \\ & \beta_4 comlangoff_{ij} + \beta_5 comcol_{ij} + \beta_6 \ln(REER)_{ij,t} + \beta_7 Misalign_{ij,t} + \\ & \beta_8 Float_{ij,t} * \ln(Volatility)_{ij,t} + \beta_9 cty_{ij,t}] + \varepsilon_{ij,t} \qquad (3)\end{aligned}$$

Note that the variables included in the augmented gravity model have unique observations for each country-pair, such that no value of a variable is constant for a specific reporting country over different country-pairs. According to

Shepherd [2016], variables to be integrated in a fixed effects gravity model must vary bilaterally. This is because variables that do not vary bilaterally would be perfectly collinear with fixed effects and would be absorbed by the fixed effects.

This is the reason why the GDP product variable was used instead of the standard where individual GDPs of the reporting and partner countries are included. The GDP product variable has similarly been used by other studies incorporating the gravity model such as Clark et al. [2004], Klein and Shambaugh [2006], Pomfret and Pontines [2013], and Wong and Chong [2016] for the same reasons.

3.2. Classification and data

This paper covers observations from 15 countries comprising the RCEP region from 1996 to 2017 from various sources listed in Table 2.

TABLE 2. Definition and sources of empirical variables used

Variable	Description	Period	Source
$Export_{ij,t}$	Total exports of country *i* to country *j* in current USD at time *t*	1996-2017	United Nations Comtrade [2020]
$GDP_{i,t}$	Gross Domestic Product of country *i* at time *t*, in current USD	1996-2017	World Bank [2020b]
$GDP_{j,t}$	Gross Domestic Product of country *j* at time *t*, in current USD	1996-2017	World Bank [2020b]
$Distance_{ij}$	Geographical distance between country *i* and country *j*	N/A	Mayer and Zignago [2011]
$Contiguity_{ij}$	Dummy variable, equals 1 if countries *i* and *j* share a common land border	N/A	Mayer and Zignago [2011]
$Common\ Colony_{ij}$	Dummy variable, equals 1 if countries *i* and *j* were both under the same colonial power	N/A	Mayer and Zignago [2011]
$REER_{i,t}$	Annual Real Effective Exchange Rate index of country *i* weighted for 171 partner countries at time *t*	1996-2017	Bruegel [2020]
$REER_{j,t}$	Annual Real Effective Exchange Rate index of country *j* weighted for 171 partner countries	1996-2017	Bruegel [2020]
$REER_{ij,t}$	Annual Ratio of Real Effective Exchange Rate index of countries *i* and *j* weighted for 171 partner countries, respectively at time *t*	1996-2017	Author's Computation
$XRAT_{i,t}$	Nominal year average exchange rate of country *i* to a unit of USD at time *t*	1996-2017	Feenstra et al. [2015]
$PPP_{i,t}$	Purchasing Power Parity/Price Level for household consumption of country *i* at time *t*	1996-2017	Feenstra et al. [2015]

TABLE 2. Definition and sources of empirical variables used (continued)

Variable	Description	Period	Source
Real GDP$_{i,t}$	Per capita Gross Domestic Product of country *i* at time *t*, in 2010 USD	1996-2017	World Bank [2020d]
Misalign$_{i,t}$	Difference between actual "real" exchange rate and estimated equilibrium "real" exchange rate of country *i* at time *t*	1996-2017	Author's computation
ER$_{i,m}$	Nominal month average exchange rate of country *i* to a unit of USD at month *m*	1996-2017	International Monetary Fund [2020]
ER$_{j,m}$	Nominal month average exchange rate of country *j* to a unit of USD at month *m*	1996-2017	International Monetary Fund [2020]
Float$_{ij,t}$	Dummy variable, equals 1 if countries *i* and *j* observe a floating exchange rate regime relationship (*de-facto* classification) at time *t*	1996-2017	Harms and Knaze [2018]

Due to incomplete data availability from the data sources presented in the table, several observations are automatically dropped during the regression. Table 3 demonstrates the number of observations missing per variable included in the regression model.

TABLE 3.Tally of missing observations in the augmented model dataset

Variable	Number of missing observations	Percentage of missing observations
ln of Nominal GDP product	112	2.42
ln of Exchange Rate Volatility	8	0.17
ln of REER Ratio	616	13.33
Exports	584	12.64
ln of Exports	584	12.64
Float peg (dummy)	264	5.71
Float peg (dummy) * ln of Exchange Rate Volatility	272	5.89

The percentages of missing observations in the dataset are less than that of the missing observations from various empirical studies discussed earlier. Previous empirical studies discussed reported varying percentages of missing observations ranging from 12.52 percent to 61.27 percent.[13] The use of the PPML

[13] Hayakawa and Kimura [2009] reported 12.52 percent missing observations in the model that included 60 countries and 13.45 percent missing observations in the model that included eight Asian countries. Pomfret and Pontines [2013] reported 23.11 percent missing observations. Klein and Shambaugh [2006] reported 27.5 percent missing observations. Nicita [2013] reported 34.58 percent missing observations in the model that did not include exchange rate volatility and 61.27 percent missing observations in the full model that included exchange rate volatility.

estimator compensates for the missing observations in the dataset. According to Kareem et al. [2016] and Martin [2020], PPML estimates report lower biases in the presence of missing or zero trade values. Therefore, the PPML estimates aid the dataset's missing observations compared to the OLS estimator.

3.3. Computation of specific variables

3.3.1. Bilateral real effective exchange rates

The bilateral REER between country-pairs was computed similar to that of Nho and Hương [2015]. It is the ratio between the REER index of the exporting country and the importing country. The equation below demonstrates the computation similar to Nho and Hương [2015] where $REER_{i,t}$ is the REER of country i at year t and $REER_{j,t}$ is the REER of country j at year t.

$$REER_{ij,t} = \frac{REER_{i,t}}{REER_{j,t}} \tag{4}$$

3.3.2. Bilateral exchange rate misalignment

The bilateral exchange rate misalignment between country-pairs was computed using a four-step process similar to that of Rodrik [2008] and Nicita [2013]. First, a hypothetical "real" exchange rate (RER) was obtained from deflating a country's nominal exchange rate to the USD (XRAT) using a country's purchasing power parity conversion (PPP) factor as seen below.

$$\ln RER_{i,t} = \ln\left(\frac{XRAT_{i,t}}{PPP_{i,t}}\right) \tag{5}$$

This hypothetical "real" exchange rate must not be confused with the REER. An increase in the value of the hypothetical "real" exchange rate indicates that the domestic currency depreciated, while an increase in the REER index indicates a domestic currency appreciation.

Second, given that non-tradable goods are cheaper in poorer countries,[14] the hypothetical "real" exchange rate must be adjusted through the Balassa-Samuelson effect. The Balassa-Samuelson effect posits that there is a tendency for consumer prices to be higher in developed countries than developing countries [Rodrik 2008]. This was computed by regressing the hypothetical "real" exchange rate with the real GDP per capita of a country with time fixed effects.

$$\ln RER_{i,t} = \alpha + \beta \ln RGDPPC + \phi_t + \varepsilon_{i,t} \tag{6}$$

[14] Example of non-tradable goods are electricity, water supply and local transportation [Jenkins et al. 2011]. It is evident that these goods are cheaper in poorer countries. For example, the taxi flat rate (in USD) in the Philippines is cheaper compared to Singapore (0.83 USD vs. 2.40 USD).

where RER represents the hypothetical "real" exchange rate of country i at time t, α is the constant term, $RGDPPC$ represents the real GDP per capita, ϕ represents time fixed effects, and ε represents the error term.

Third, the level of exchange rate misalignment was computed by taking the difference between the actual hypothetical "real" exchange rate and the estimated/fitted equilibrium "real" exchange rate adjusted for the Balassa-Samuelson effect.

$$Misalign_{i,t} = \ln RER_{i,t} - \ln \widehat{RER}_{i,t} \tag{7}$$

Lastly, the bilateral exchange rate misalignment per country pair was obtained through the sum of exchange rate misalignment between the two countries.

$$Misalign_{ij,t} = Misalign_{i,t} + Misalign_{j,t} \tag{8}$$

Following Rodrik [2008], a positive level of misalignment demonstrates an undervalued currency compared to its equilibrium exchange rate. Therefore, an increase in the level of misalignment between countries indicate a weaker currency.

3.3.3. Bilateral exchange rate volatility

The bilateral exchange rate volatility is computed similar to that of Nicita [2013].

$$ER_{ij,t} = ER_{i,t} - ER_{j,t} \tag{9}$$

$$Volatility_{ij,t} = std.dev[ER_{ij,m} - ER_{ij,m\text{-}1}] \tag{10}$$

where $ER_{i,t}$ represents the nominal exchange rate of country i to a USD at time t, $ER_{ij,t}$ represents the difference between the nominal exchange rate of country i and country j, $ER_{ij,m}$ represents the difference between the monthly average of the nominal exchange rate of both countries at month m, and *Volatility* represents the standard deviation of the exchange rates for a given year t. The difference between both countries was adapted by Nicita [2013] to highlight the presence of hard peg exchange rate regimes where $ER_{ij,t}$ and $Volatility_{ij,t}$ are both equal to zero.

4. Results and discussion

4.1. Baseline model results

Estimation results for the baseline gravity models are reported in Table 4. Gravity model specifications are estimated as follows: Column 1 presents estimates using the OLS estimator; and Column 2 presents the estimates using the PPML estimator. The dependent variable for OLS estimates is the natural logarithm of exports while the dependent variable for PPML estimates is in levels (exports in millions).

TABLE 4. Baseline model regression results

Method Dependent Variable	[1] OLS In of Exports	[2] PPML Exports[m]
In of Nominal GDP Product	**1.213*** **	**0.840*** **
	(0.0672)	(0.0458)
In of Distance	**-0.993*** **	**-0.565*** **
	(0.140)	(0.0445)
Constant Term	-37.81***	-33.63***
	(3.869)	(2.770)
Observations	3,994	3,994
R-squared	0.887	0.949
Country pair FE	**Yes**	**Yes**

[m] Exports in millions

Both estimates of the baseline model utilize 3,994 observations and demonstrate an *R*-squared statistic of 0.89 for the OLS estimator and 0.95 for the PPML estimator. Both estimation methods yield high *R*-squared statistics demonstrating high levels of goodness-of-fit. Moreover, both the natural logarithm of the Nominal GDP product and the natural logarithm of distance between countries are significant at the 1 percent level for both the OLS and PPML estimator.

For the OLS estimates of the baseline model, a 1 percent increase in the GDP product of trading countries significantly increases a country's exports by 1.21 percent, ceteris paribus. Moreover, a 1 percent increase in the distance between trading countries significantly decreases a country's exports by 0.99 percent, ceteris paribus. For the PPML estimates of the baseline model, a 1 percent increase in the GDP product of trading countries significantly increases a country's exports by 0.84 percent, ceteris paribus. Also, a 1 percent increase in the distance between trading countries significantly decreases a country's exports by 0.57 percent, ceteris paribus. The results of the baseline model are consistent with the hypothesized signs of the variables.

4.2. Augmented model results

The augmented gravity model includes variables such as contiguity, common language, common colonizer, REER ratio, exchange rate misalignment, and the interaction variable between a floating exchange rate regime and exchange rate volatility. Both estimates of the augmented model utilize 3,563 country-pair observations ranging from years 1996 to 2017. The OLS panel fixed effects estimator reports an *R*-squared statistic of 0.91. On the other hand, the PPML panel fixed effects estimator reports an *R*-squared value of 0.95.

Both estimation methods demonstrate high levels of goodness-of-fit and provide good promise in analyzing the value of exports between country-pairs.

Furthermore, the improved *R*-squared statistic for the PPML regressions may indicate that PPML estimator is a more suitable method to estimate the effect of certain policies on trade through an augmented gravity model [Shepherd 2016].

The OLS panel fixed effects estimator reported six significant coefficients. All six coefficients are significant at the 1 percent level. On the other hand, the PPML fixed effects estimator reported four significant coefficients. Three coefficients are significant at the 1 percent level while one coefficient is significant at the 5 percent level (Table 5).

TABLE 5. Augmented model regression results

Method Dependent Variable	[1] OLS ln of Exports	[2] PPML Exports[m]
ln of Nominal GDP product	**1.192***** (0.0512)	**0.840***** (0.0388)
ln of Distance	**-0.564***** (0.148)	**-0.501***** (0.0704)
Contiguity (dummy)	**0.989***** (0.333)	0.0786 (0.122)
Common Official Language (dummy)	-0.213 (0.223)	0.0478 (0.135)
Common Colony (dummy)	**1.148***** (0.438)	0.293 (0.211)
ln of REER Ratio	-0.239 (0.446)	**-0.606**** (0.302)
Exchange Rate Misalignment	**-0.196***** (0.0582)	-0.0302 (0.0401)
Float peg (dummy) * ln of Exchange Rate Volatility	**-0.0909***** (0.0312)	**-0.0585**** (0.0242)
Constant Term	-38.64*** (3.089)	-33.02*** (2.334)
Observations	3,563	3,563
R-squared	0.905	0.952
Country pair FE	**Yes**	**Yes**

[m] Exports in millions

It can also be observed that the values of the coefficients reported from the PPML estimator are less than that of the OLS estimator. However, as stated in the early sections of this study, the PPML estimated coefficients will be analyzed to determine the significance and impact of the independent variables on the dependent variable.

From the PPML estimation, the natural logarithm of a country-pair's nominal GDP product significantly increases a country's exports. On the other hand, the natural logarithm of the distance between country-pairs, the REER ratio between country-pairs, and the natural logarithm of exchange rate volatility for country-pairs under a floating peg exchange rate regime significantly decrease a country's exports.

Among the three key variables of the study, two are significant. The natural logarithm of the REER ratio between country-pairs along with the interaction variable between floating exchange rate regimes and the natural logarithm of exchange rate volatility are both significant at the 5 percent level. A 1 percent increase in the REER ratio between country-pairs leads to a 0.61 percent reduction of the reporting country's exports, ceteris paribus. The negative effects of REER on exports are consistent with the results obtained by Tan et al. [2019].

The significant export reducing effects of REER and exchange rate volatility, as highlighted by the interaction term, are in line with the preliminary findings of previous studies. However, previous studies observed that the export reducing effects of REER and exchange rate volatility are offset and disappear when interacted with the concept of Foreign Value-Added (FVA). The relationship between exchange rates and the concept of FVA as discussed by Tan et al. [2019] is significant in the Asian region.

Although this is not similar to the empirical result of this study, it is worth noting that this highlights that the mixed empirical results observed regarding exchange rate volatility on trade is an empirical issue [Clark et al. 2004]. It is possible that the trade reducing effects of exchange rate variables such as volatility and REER disappear given the presence of FVA share in goods traded.

Note that for REER ratio to increase, the reporting country must have a higher REER index than its partner country. This result is in line with the hypothesized sign of the REER ratio's coefficient. As a country increases its REER index, its exports become less competitive since exports become more expensive compared to other countries.

A one percent increase in the exchange rate volatility of country-pairs under a floating peg exchange rate regime leads to a 0.06 percent decrease in a reporting country's exports, ceteris paribus. This result is also consistent with the hypothesized sign of the interaction variable's coefficient. The higher the exchange rate volatility for the specified countries, the higher the risk it is to trade. This risk can be present in many forms such as unexpected changes in the transaction costs of trade and the like. These risks ultimately make a country's exports less competitive compared to other countries that exhibit a less volatile currency.

Clark et al. [2004] pointed out that the effects of exchange rate volatility on trade needs to be interacted with monetary policies such as currency unions and exchange rate regimes. This suggests, in theory, that monetary policies and exchange rate policies have to be analyzed together rather than separately. Evaluating the effects of exchange rate volatility without considering the presence of other monetary variables can yield insignificant results. Hence, empirically, an interaction variable between exchange rate volatility and floating exchange rate regimes was utilized.

4.3. Alternative models for robustness

4.3.1. Alternative model incorporating FTA membership

With numerous bilateral and multilateral FTAs ratified within the sample period the paper covers, significant trade agreements such as the ASEAN-People's Republic of China Comprehensive Economic Cooperation Agreement signed in 2004, ASEAN-Korea Agreement on Trade completed in 2006, Comprehensive Economic Partnership between ASEAN and Japan signed in 2008, and the ASEAN-Australia-New Zealand Free Trade Area signed in 2009 may have influenced the level of exports within the RCEP region.

To account for this, an additional dummy variable indicating the presence of an FTA between country-pairs was included in the regression model. The variable is equal to one if an FTA is present between the country-pair, and zero otherwise. Data regarding FTAs were obtained from the Asian Development Bank's Asia Regional Integration Center Database [2022].

TABLE 6. Alternative regression model results
(LN of exchange rate volatility and float peg dummy variables included)

Method Dependent Variable	[1] OLS ln of Exports	[2] PPML Exports[m]	[3] OLS ln of Exports	[4] PPML Exports[m]
ln of Nominal GDP product	**1.192***** (0.0512)	**0.840***** (0.0388)	**1.200***** (0.0579)	**0.823***** (0.0396)
ln of Distance	**-0.564***** (0.148)	**-0.501***** (0.0704)	**-0.563***** (0.148)	**-0.494***** (0.0698)
Contiguity (dummy)	**0.989***** (0.333)	0.0786 (0.122)	**0.988***** (0.333)	0.109 (0.124)
Common Official Language (dummy)	-0.213 (0.223)	0.0478 (0.135)	-0.214 (0.222)	0.0806 (0.128)
Common Colony (dummy)	**1.148***** (0.438)	0.293 (0.211)	**1.149***** (0.438)	0.270 (0.203)
ln of REER Ratio	-0.239 (0.446)	**-0.606**** (0.302)	-0.107 (0.522)	**-0.789*** (0.429)
Exchange Rate misalignment	**-0.196***** (0.0582)	-0.0302 (0.0401)	**-0.181***** (0.0507)	-0.0594 (0.0373)
Float peg (dummy) * ln of Exchange Rate Volatility	**-0.0909***** (0.0312)	**-0.0585**** (0.0242)	**-0.0910***** (0.0312)	**-0.0548**** (0.0237)
FTA (dummy)			0.0211 (0.130)	-0.146 (0.100)
Constant Term	-38.64*** (3.089)	-33.02*** (2.334)	-39.21*** (3.522)	-31.79*** (2.378)
Observations	3,563	3,563	3,563	3,563
R-squared	0.905	0.952	0.905	0.956
Country pair FE	**Yes**	**Yes**	**Yes**	**Yes**

[m] Exports in millions

Results indicate that the previously significant key variables retain their significance (Table 6). The natural logarithm of the REER ratio is significant at the 10 percent level, wherein a one percent increase in the REER ratio leads to a 0.79 percent decrease in the reporting country's exports. Moreover, the interaction variable between floating exchange rate regimes and the natural logarithm of exchange rate volatility is significant at the 5 percent level. A one percent increase in the variable leads to a 0.05 percent decrease in the reporting country's exports.

4.3.2. Alternative model for interaction term

An alternative regression model was also estimated where exchange rate volatility and floating exchange rate regimes were regressed separately with the interaction term. Results indicate that only the interaction variable is significant (Table 7). This affirms the suggestion of Clark et al. [2004] both theoretically and empirically that volatility needs to be interacted with other monetary policy variables to determine its true effect on trade.

This result provides new insight regarding countries with floating exchange rate regimes. Countries under a floating exchange rate regime are affected by the trade reducing impact of exchange rate volatility. However, the same cannot be said for countries under a direct peg or indirect peg exchange rate regime. The observed negative effects of exchange rate volatility on exports are consistent with those of Clark et al. [2004], Hayakawa and Kimura [2009], Klein and Shambaugh [2006], Nicita [2013], Pomfret and Pontines [2013], Njoroge [2020], and Banik and Roy [2020].

Furthermore, this also reinforces the suggestion from Clark et al. [2004] about estimating multiple monetary policy and exchange rate policy variables. The exchange rate misalignment variable is also aligned with the hypothesized sign of the misalignment variable's coefficient, albeit insignificant.

TABLE 7. Alternative regression model results (LN of exchange rate volatility and float peg dummy variables included)

Method Dependent Variable	[1] OLS ln of Exports	[2] PPML Exports^m	[3] OLS ln of Exports	[4] PPML Exports^m
ln of Nominal GDP product	**1.020***** (0.0517)	**0.753***** (0.0433)	**0.959***** (0.0555)	**0.730***** (0.0479)
ln of Distance	**-0.576***** (0.147)	**-0.501***** (0.0722)	**-0.575***** (0.147)	**-0.494***** (0.0712)
Contiguity (dummy)	**1.070***** (0.348)	0.0754 (0.123)	**1.069***** (0.349)	0.104 (0.122)
Common Official Language (dummy)	-0.253 (0.222)	0.0405 (0.144)	-0.254 (0.222)	0.0676 (0.143)
Common Colony (dummy)	**0.926*** (0.478)	0.293 (0.222)	**0.927*** (0.478)	0.266 (0.207)
ln of REER Ratio	0.277 (0.433)	-0.175 (0.391)	**1.368***** (0.405)	0.453 (0.313)

TABLE 7. Alternative regression model results (continued)

Method Dependent Variable	[1] OLS ln of Exports	[2] PPML Exports^m	[3] OLS ln of Exports	[4] PPML Exports^m
Exchange Rate misalignment	0.196***	0.102***	0.0627	0.0352
	(0.0407)	(0.0346)	(0.0384)	(0.0240)
Float peg (dummy)	-0.0263	-0.0451	-0.0220	-0.106
	(0.224)	(0.133)	(0.214)	(0.135)
ln of Exchange Rate Volatility	-0.0477	-0.00117	-0.0476	-0.00242
	(0.0346)	(0.0339)	(0.0346)	(0.0315)
Float peg (dummy) * ln of Exchange Rate Volatility	**-0.0727****	**-0.0573****	**-0.0729****	**-0.0517****
	(0.0324)	(0.0267)	(0.0324)	(0.0258)
FTA (dummy)			0.0165	-0.162
			(0.117)	(0.101)
Constant Term	-28.66***	-28.26***	-25.47***	-26.94***
	(3.015)	(2.504)	(3.378)	(2.860)
Observations	3,563	3,563	3,563	3,563
R-squared	0.905	0.952	0.905	0.957
Country pair FE	**Yes**	**Yes**	**Yes**	**Yes**

^m Exports in millions

4.3.3. Alternative model controlling for volatility during the Asian Financial Crisis

Data regarding exports and exchange rate volatility demonstrate extreme spikes during years 1997 to 1999 due to the Asian Financial Crisis. Studies similarly indicate that the Asian Financial Crisis is the single most important event in the region where volatility soared to extreme levels.

Garnaut [1998] reported that negative growth in East Asian trade was observed during the crisis. Moreover, Rana [1998] observed how the yearly change of nominal exchange rates for the region drastically dropped and weakened during the crisis. For example, Rana's [1998] computations indicate that for years 1976-1996 the average yearly nominal exchange rate changes were at around 2.43 percent. However, during the crisis, the average yearly nominal exchange rate changes were at around 35.35 percent. This clearly indicates a high level of exchange rate volatility given that Rana [1998] compared the change in the region to that of the United Kingdom which reported a 0.2 percent nominal exchange rate change during the crisis.

Due to this, it is also important to determine if data from the Asian Financial Crisis affects the significance of exchange rate volatility in the model. An augmented model was estimated removing observations before and during the crisis: years 1996 to 1999. Alternatively, an augmented model was also estimated including a dummy variable equal to one for observations during the Asian Financial Crisis (1997 to 1999), zero otherwise (Table 8).

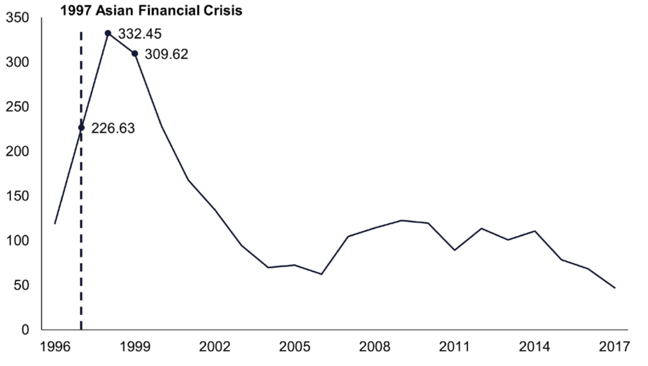
TABLE 8. Alternative aggregate regression model results (years 1996-1999 dropped, AFC dummy variable included)

Method Dependent Variable	[1] OLS ln of Exports	[2] PPML Exports[m]	[3] OLS ln of Exports	[4] PPML Exports[m]	[5] OLS ln of Exports	[6] PPML Exports[m]	[7] OLS ln of Exports	[8] PPML Exports[m]
ln of Nominal GDP product	**1.153***** (0.0488)	**0.796***** (0.0358)	**1.094***** (0.0445)	**0.797***** (0.0324)	**1.112***** (0.0640)	**0.758***** (0.0388)	**1.189***** (0.0513)	**0.834***** (0.0395)
ln of Distance	**-0.541***** (0.149)	**-0.499***** (0.0703)	**-0.542***** (0.148)	**-0.488***** (0.0704)	**-0.564***** (0.148)	**-0.501***** (0.0704)	**-0.563***** (0.148)	**-0.494***** (0.0698)
Contiguity (dummy)	**1.110***** (0.346)	0.0967 (0.122)	**1.110***** (0.347)	0.131 (0.125)	**0.989***** (0.333)	0.0786 (0.122)	**0.988***** (0.333)	0.109 (0.124)
Common Official Language (dummy)	-0.243 (0.233)	0.0472 (0.136)	-0.243 (0.233)	0.0860 (0.129)	-0.213 (0.223)	0.0478 (0.135)	-0.214 (0.222)	0.0806 (0.128)
Common Colony (dummy)	**1.107**** (0.445)	0.260 (0.213)	**1.106**** (0.446)	0.232 (0.204)	**1.148***** (0.438)	0.293 (0.211)	**1.149***** (0.438)	0.270 (0.203)
ln of REER Ratio	-0.212 (0.529)	-0.387 (0.290)	**-2.120***** (0.590)	**-1.264***** (0.480)	**4.164***** (0.648)	**1.493***** (0.434)	-0.325 (0.460)	**-0.564*** (0.337)
Exchange Rate misalignment	**-0.201***** (0.0559)	-0.0384 (0.0457)	**-0.390***** (0.0913)	**-0.110*** (0.0639)	**-0.165***** (0.0400)	-0.0444 (0.0277)	**-0.203***** (0.0588)	-0.0368 (0.0405)
Float peg (dummy) * ln of Exchange Rate Volatility	**-0.0866***** (0.0330)	**-0.0583**** (0.0245)	**-0.0866***** (0.0330)	**-0.0544**** (0.0239)	**-0.0909***** (0.0312)	**-0.0585**** (0.0242)	**-0.0910***** (0.0312)	**-0.0548**** (0.0237)
FTA (dummy)			-0.0160 (0.131)	-0.165 (0.104)			0.0211 (0.130)	-0.146 (0.100)
AFC (dummy)					0.372 (0.424)	0.0741 (0.541)	-0.209 (0.483)	-0.0878 (0.421)
Constant Term	-36.99*** (2.952)	-30.89*** (2.248)	-32.24*** (2.645)	-30.10*** (1.920)	-35.29*** (3.649)	-29.04*** (2.363)	-38.46*** (3.096)	-32.57*** (2.360)
Observations	3,096	3,096	3,096	3,096	3,563	3,563	3,563	3,563
R-squared	0.906	0.952	0.906	0.957	0.905	0.952	0.905	0.956
Country pair FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

[m] Exports in millions

Results indicate that the interaction of the natural logarithm of exchange rate volatility with a floating exchange rate regime continues to be significant. This demonstrates that the interaction term is still a significant determinant of exports regardless of an economic crisis occurring in the region.

FIGURE 3. RCEP Exchange rate volatility (three-year moving average; 1996-2017)



Source: Author's computation from International Monetary Fund [2020].

5. Summary and conclusion

This study analyzes the effects of REER, exchange rate volatility, exchange rate misalignment, and a floating exchange rate regime on aggregate exports within the RCEP region for the years 1996 to 2017 (22 years). Through an augmented gravity model approach, this study contributes to the literature exploring the effects of exchange rate volatility on exports by including more exchange rate variables in the model and by employing interactions between exchange rate variables and monetary policy instruments.

Common gravity variables such as the economic size and geographic distance are found to be significant in affecting the aggregate exports of a country in the RCEP region. The GDP product significantly increases exports while the distance between countries significantly reduces aggregate exports. However, other common gravity variables such as contiguity, common colony, and common language were not significant in affecting aggregate exports in the region. These results are interpreted as indicative of high economic integration brought by previously established PTAs in the region. Shared languages, a common colonizer, and the presence of a common border in the region are no longer a significant advantage to exports.

Key estimations performed in this study show that a country's REER ratio significantly reduces its aggregate exports and provides evidence of the aggregate export reducing effects of an appreciating currency relative to the country's trading partners. The results also provide empirical support to the use of interaction terms, as demonstrated by the derived negative effect of exchange rate volatility for countries under a floating exchange rate regime. Finally, the significant but minimal effect of exchange rate volatility estimated in the model is consistent with previous literature.

With this, exchange rates do affect the Big One as they play a hand in determining the level of exports traded within the region. This study also provides strong evidence of the significance of including monetary policy in the empirical analysis of trade policies such as economic integration initiatives. The particular case of the newly formalized RCEP agreement has the potential to re-energize trade in the region post-COVID, and to further prepare ASEAN for its venture towards more sophisticated FTAs in the future. As pointed out in this study, a country's monetary policy decisions and regimes play a vital role in estimating gains from trade out of these partnerships.

For future work, this study recommends expanding the augmented gravity model to include more monetary policy variables such as existence of currency unions and inflation targeting policies. However, these variables can only be considered if more countries are included in the sample data. Because no country in the RCEP region practices the use of currency unions, this variable cannot be analyzed in this paper due to lacks in the variation of the observations. This recommendation thus entails expanding the scope to a global dataset.

The dataset can also be expanded to evaluate a country's world export level on an aggregate and/or sectoral level. Expanding the dataset this way can explore the offsetting effect of FVA on significant export reducing variables such as REER and exchange rate volatility. Structural break dummy variables can also be explored to account for shocks in volatility levels caused by the Asian Financial Crisis.

It is also recommended to analyze the effects of the key variables in this study on other significant and dynamic sectors in the region such as rice and electronic products. The effects of exchange rate fluctuations vary for each product and conducting sectoral level analyses allow for a more nuanced study not afforded in aggregate-level analysis. Results of sectoral level studies can also allow researchers to compare the different levels of significance and magnitude of several key variables per sector or product. Thus, working on other disaggregated data makes the gravity model more efficient in analyzing the effects of independent variables on a country's exports.

Lastly, it is also recommended to re-estimate the model when trade data after the signing of the RCEP are available. This would help determine whether the RCEP, as an FTA, has significantly improved bilateral trade both inside and outside of the region. Although several studies have modelled the theoretical trade creating effects of RCEP, a complementary empirical estimation is needed to provide evidence on RCEP's trade creating effects.

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The long and the short of it: revisiting the effects of microfinance-oriented banks on household welfare in the Philippines

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Although evidence on the impact of microfinance is continuously accumulating, little is known about how long-term presence of microfinance institutions affects household welfare. This study addresses the issue by evaluating a household-level panel data and a unique event in the Philippines when the microfinance industry was mainstreamed and commercialized in the banking sector with microfinance-oriented banks (MOBs), which began to open in 2004. We find that the positive effects of longer MOB presence on entrepreneurial income and activities diminish or even regress over time. Moreover, no significant impacts are noted on real expenditures. Heterogeneity analysis further reveals that no immediate or incremental effects were observed on real expenditures of poor families and the immediate positive effect on entrepreneurial income and activities did not accrue in the long run. Lastly, no significant long-term impacts are noted on real expenditures as well as likelihood of and income from entrepreneurial and wage and salary activities of non-poor families from MOB presence. We, however, argue that MOB presence may reduce vulnerability as it affords households to be entrepreneurs.

JEL classification: G21, G23, G28
Keywords: microfinance, sample selection bias, household welfare, difference-in-differences, inverse probability weighting, Philippines

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*** The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not represent the views of the National Graduate Institute for Policy Studies (GRIPS), Bangko Sentral ng Pilipinas, and their affiliated organizations, or those of the President of GRIPS or the government they represent.

1. Introduction

Microfinance has been positioned as an important financial instrument for poverty alleviation and socioeconomic development. Its proliferation is fueled by the belief that simply "lending to the poor" will indeed improve their economic (e.g., wealth and income) and social (e.g., education and health status) welfare (Buera et al. [2012]; Coleman [2006]). Many empirical studies have been conducted to understand these impacts of microfinance on income, employment, consumption, asset accumulation, and profits (Angelucci et al. [2015]; Attanasio et al. [2015]; Augsburg et al. [2012]; Kaboski and Townsend [2012]; Karlan and Zinman [2011]; Morduch [1998]; Pitt and Khandker [1998]). However, they are mostly concerned with the short-term effects, and very few studies evaluate medium- and long-term effects, perhaps due to the difficulty of obtaining data with longer time interval between pre- and post-intervention surveys—approximately three years or longer.

To the best of our knowledge, only two studies exist that explicitly investigate the differential impacts of microcredit in terms of duration, and the results are mixed. Using data from Bangladesh, Islam [2011] finds that gains from microcredit programs vary with the length of participation and the benefits are larger for those participating in the program longer. He also finds that benefits may continue even after the participant leaves the program, but their magnitude diminishes. On the other hand, Banerjee et al. [2015a], in their study on a group lending microcredit program in Hyderabad, India, find no significant short- or long-term impact on non-durable consumption, education, or health after the introduction of microfinance.

Our study aims to complement the limited literature by evaluating whether—and to what extent—the impact of microfinance varies with the length of presence. We expand the scope of the existing studies in two important respects. First, as will be explained in more detail below, we will not only quantify the impact of *long-term* presence of microfinance institution but also differentiate said impact according to *immediate*, *incremental*, and *total* (or *net*) effects. It is important to understand these dynamics because microfinance institutions established in an area for more than a year may have positive *immediate* effects on households living in it but will have negative *incremental* effects several years after. Second, the study further investigates heterogeneous effects with respect to socio-economic classes, that is, whether the impact of microfinance presence differs by poverty level. The study's approach is closest to that of Islam [2011], but his study does not differentiate the effects in terms of poverty level.

We rely on a case from the Philippines where the microfinance industry has been growing on a commercial (i.e., for-profit lenders and extending individual liability credit) basis. The Bangko Sentral ng Pilipinas (BSP), or Central Bank of the Philippines, partially lifted the moratorium on the establishment of new banks in 2001, as long as the new bank is to be microfinance-oriented. We scrutinize this event as a quasi-experiment with nationally representative panel data from 2003, 2006, and 2009 taken from the Family Income and Expenditure Survey (FIES) conducted by the Philippine Statistics Authority (PSA). The study's analyses are limited to assessing the effect of microfinance-oriented banks (MOBs) presence in a locality as there are no available panel datasets on actual products and services availed of by clients of microfinance institutions at the time of study. Furthermore, only microfinance-oriented branches of thrift banks (TBs) and rural banks (RBs) as well as banks that have a business name that describe their business activities as microfinance were included in the sample.

Given the dataset, we consider 2003 as the *pre-intervention* period when there were absolutely no MOBs established in a municipality and 2006 and 2009 as the *post-intervention* periods when MOBs had been established. We then define those households living in a municipality with an MOB both in 2006 and 2009 as the treatment group or *continuing households*. The control group or *never households* are those households who reside in municipalities with no MOBs.

Along with these household categories, we further identify the *immediate*, *incremental*, and *total* (or *net*) effects of longer MOB presence in municipalities. Effects derived from *continuing* households in 2006 are considered as *immediate* because microfinance banks were established only after 2004 while those in 2009 represent *incremental* effects (i.e., effects that are added to the initial, immediate effects). The combined estimates for 2006 and 2009 of *continuing* households represent the *total* (or *net*) impact of microfinance presence through MOBs.

To obtain deeper insights into heterogeneity, we further disentangle these impacts depending on poverty level of the recipient as microfinance programs typically target poor individuals and also because much of the literature predicts that the impacts of microfinancing may differ depending on the economic class of the recipients (Attanasio et al. [2015]; Banerjee et al. [2015b]; Banerjee and Mullainathan [2010]; Crèpon et al. [2015]; Dichter and Harper [2007]; Hulme and Mosley [1996]; Khandker [1998]; Kondo et al. [2008]; Tarozzi et al. [2015]).

Primary outcomes of interest are the probability of and income from wage work and self-employment as well as real expenditures[1] (i.e., food, medical care, alcoholic beverage and tobacco, and education) because microfinance providers target micro-entrepreneurs and the widely used proxies for poverty are income and consumption.

The main challenge in using observational panel data is the endogeneity problem associated with self-selection as well as sample attrition. To address these concerns, we employ a difference-in-differences (DID) household fixed effects (FE) technique combined with inverse-probability-weighted (IPW). The DID-FE addresses the non-random selection of municipalities and households based on their observable attributes as well as time-invariant unobservable attributes (e.g., inherent ability, industriousness, or geographical landscape of the municipality,

[1] Consumption and expenditures are used interchangeably in this study.

including climate and susceptibility to natural disaster) that may affect a household's decision to avail itself of microfinance and MOB's choice of location. Meanwhile, the IPW accounts for the sample selection associated with households dropping out of the survey. Finally, we employ the methodology developed by Oster [2019] and Altonji et al. [2005] to check the robustness of treatment effects from the IPW DID-FE model against unobserved confounders.

Results indicate that MOBs' presence provides households with an opportunity to be an entrepreneur, but there is no evidence that real consumption increased. Moreover, the effects on self-employment regress when the presence of MOB in a municipality is long-term. We also find no significant effect on real expenditures of poor households, but entrepreneurial activities increased albeit temporarily, relative to non-poor families. These relatively benign results should be interpreted with caution. Our study focused on MOBs presence due to absence of readily available information about the locations of non-government organizations (NGOs) that can cater to microfinance clients. The presence of microfinance NGOs could amplify or reduce impacts.

The rest of this paper is organized as follows. Section 2 offers a brief background on MOBs in the Philippines and the study's data. Section 3 outlines estimation strategy. The results are reported in Section 4. Section 5 performs test on omitted variables. Lastly, Section 6 concludes the paper and Section 7 provides policy insights.

2. Data and context

2.1. Establishment of MOBs

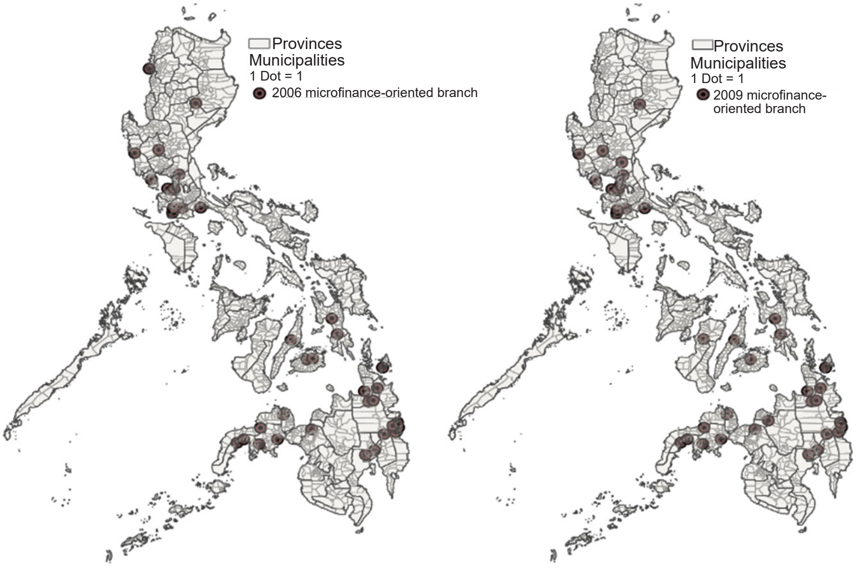
We use a unique event in the Philippines—when the BSP in 2001 and 2005 issued Circular Nos. 273 and 505, respectively—to evaluate the impact of longer MOB presence in municipalities on household welfare. BSP Circular No. 273, dated February 27, 2001, partly lifted the moratorium on the establishment of new banks, allowing new banks that are microfinance oriented to locate in places not fully served by existing rural banks or MOBs. On one hand, BSP Circular No. 505, dated December 22, 2005, allowed qualified MOBs and branches of regular banks to establish branches anywhere in the Philippines. Since then, MOBs have been established to provide financial services that cater primarily to the credit needs of the basic[2] and/or disadvantaged sectors for their microenterprises and small businesses. This event is unique in that commercial banks ventured into microfinance and opened MOBs in the country. This also formalized mandated

[2] The Social Reform and Poverty Alleviation Act of 1997 (or Republic Act No. 8425) defined basic sectors as farmer-peasants; artisanal fisherfolk; workers in the formal and informal sectors; migrant workers; indigenous peoples and cultural communities; women; differently-abled persons; senior citizens; victims of calamities and disasters; youth and students; children; and urban poor.

loans to basic sectors primarily for their microenterprises and small businesses to enable them to raise their income and improve their living standards [BSP 2001].

In most municipalities, banks started establishing MOBs only in 2004 [BSP 2005].[3] Most of these branches can be found in the capital or in cities and first-class municipalities[4] of the three geographic island groups (i.e., Luzon, Visayas, and Mindanao) of the country (Figure 1).

FIGURE 1. Geographical distribution of microfinance-oriented banks in the Philippines



Source: Bangko Sentral ng Pilipinas; data plotted by the authors.

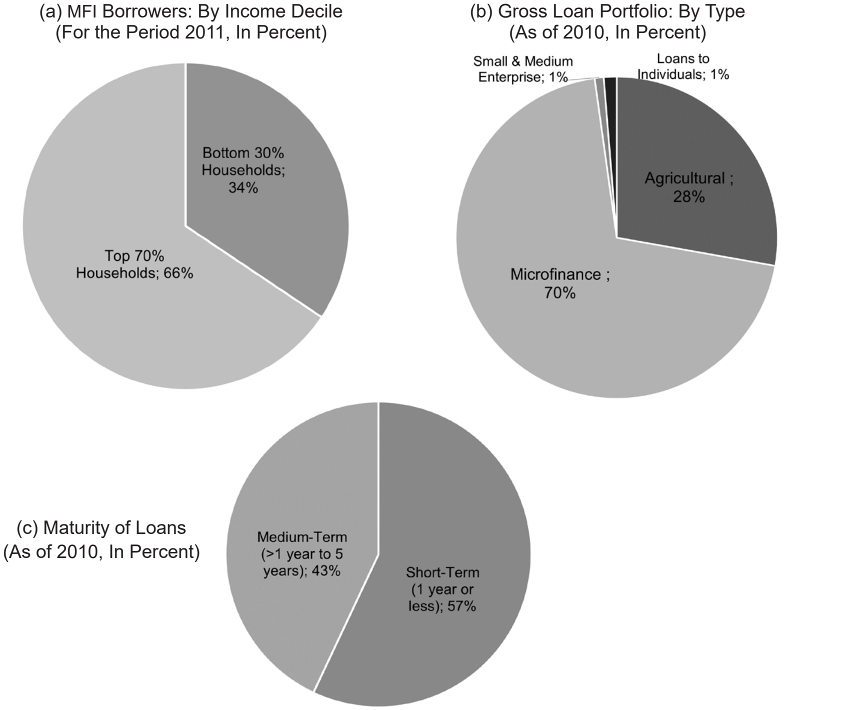
In Figure 2, we present client and loan portfolio of MOBs to determine if there are any systematic patterns of client self-selection and MOB location. Most microfinance programs claim that their primary goal is to alleviate rural poverty by delivering credit and other financial services to poor households. Such selective targeting may be useful to increase the efficacy but would threaten the identification strategy when we simply compare households with or without access to microfinance through MOBs. This issue will be revisited later (Section 3: Estimation Strategy).

[3] The MOB established beginning 2004 are newly created microfinance-oriented banks and are not a conversion of a regular bank.

[4] Based on the Department of Finance (DOF) Order No. 23-08 dated July 29, 2008, this class of municipalities has the highest average annual income at ₱45 million (USD 0.88 million) or more but less than ₱55 million (USD 1.08 million). The peso-dollar rate used is the period average for 2003, 2006, and 2009 posted by the BSP on its website.

Statistics in Figure 2 confirm that the clients served by MOBs are from low-income households. Their loan portfolio is comprised of agricultural, microfinance[5], small and medium enterprise, and individual loans, which typically have short-term (up to 365 days) maturity.

FIGURE 2. Client and loan portfolio of microfinance-oriented banks in the Philippines



Notes: The earliest statistics on microfinance-oriented banks consolidated by the BSP was in 2010 while the APIS prior to 2011 do not have information on household borrowing from microfinance institutions.
Source: Annual Poverty Indicator Survey (APIS) - Philippine Statistics Authority, and Bangko Sentral ng Pilipinas.

2.2. Data

The primary data source is the FIES for the year 2003, 2006, and 2009 collected by the PSA. The FIES is a nationwide household survey conducted every three years that provides information on households' level of consumption by items of expenditure as well as sources of income in cash and in kind. It also includes statistics on family size; occupation, age, and level of education of the household head; and other housing characteristics.

[5] The types of loan are agriculture, education, housing, health, microbusiness, capital/start-up capital, multipurpose, salary, life insurance, hospitalization, pension, motorcycle, and so on. Based on BSP Circular No. 694 dated October 14, 2010, microenterprise loans refer to small and short-term loans granted to the basic sectors, on the basis of the borrowers' cash flow, for their microenterprises and small businesses. The principal amount of a microenterprise loan can be generally pegged at ₱150,000 or USD 3,325.23. The foreign exchange rate used is the average for 2010 at ₱45.11, posted by the BSP on its website.

The surveys for 2003, 2006, and 2009 comprised 42,094, 38,483, and 38,400 households, respectively, covering all 17 administrative regions in the country. The administrative regions were also the survey's primary sampling unit (PSU). It used two-stage sampling with stratification at the PSU level. In the first stage, random samples of enumeration areas (EAs) or *barangays* were selected within sampled PSUs (or each region) with probability proportional to EA size (i.e., total number of households); in the second stage, random samples of households were selected within sampled EAs.

However, only 6,529 households or approximately 16 percent of the original sample are used in this study to construct a balanced panel dataset for the period 2003, 2006, and 2009. Possible reasons for the small proportion of households that remained in the surveys are that some households felt that the nature of the data being collected is sensitive, some relocated between data collection times, or data collection procedures are aversive or costly to the household being surveyed.

We also use statistics on the number of banks and MOBs in the municipalities compiled by the BSP for the periods 2003, 2006 and 2009. In the dataset, it is observed that in most municipalities, it was only in 2004 that banks started to set up MOBs. As stated earlier, the BSP partially lifted the moratorium on the establishment of new banks in 2001, which paved way for MOBs to be set up in municipalities. There were 24 municipalities that had MOBs in 2004. Of these, 21 had only one MOB established in the area, two municipalities had two MOBs each, and one municipality had three MOBs. Two municipalities out of the 24 had no other access to formal financial institutions but MOBs.

The opening of MOBs in 2004 allows us to identify the treatment and control groups in terms of time (i.e., *pre-intervention* and *post-intervention* periods) and units (i.e., *continuing* and *never households*). The *pre-intervention* period is set at 2003 when there were absolutely no MOB established yet in municipalities, while 2006 and 2009 are considered as *post-intervention* periods as MOBs had been established in municipalities by then.

Based on the status of MOBs in each municipality, we classify households into a control group or *never households* residing in municipalities with no MOB in *pre-* and *post-intervention* periods. Those households that resided in municipalities with MOBs in 2003 are excluded from the sample.[6] The treatment group or *continuing households* are those that lived in municipalities with MOBs both in 2006 and 2009. Of the 6,529 households surveyed, 36.33 percent (2,372 households) were classified as *continuing households*.

[6] There are only five RBs (i.e., Rural Bank of Dulag Inc. only has one microfinance (MF) branch; Banco ng Masa (an MF-oriented RB); CARD Bank (an MFRB); Vision Bank Inc. (an MFRB); and Xavier Tibod Bank (an MFRB); and one thrift bank (i.e., Opportunity Microfinance Bank) situated in 13 municipalities in 2003.

2.2.1. Descriptive statistics

Table 1 provides descriptive statistics on household and municipality attributes across the three waves of the survey to show a snapshot of the circumstances *before* (2003) and *after* (2006 and 2009) the issuance of BSP Circular Nos. 273 and 505. In the first survey (2003), households and municipalities had no MOBs established. In the second (2006) and third (2009) surveys, MOBs could be seen in some municipalities. The proportion of self-employed is statistically larger in pre-MOB presence period. There is no statistically significant difference in the share of wage workers between pre- and post-MOB presence periods. Meanwhile, the average income from wage work and entrepreneurial activities is higher in post-MOB bank presence period. It is also evident that spending on medical care is higher during post-MOB presence period while expenditure on food and alcoholic beverage and tobacco is lower. Lastly, no statistically significant difference between pre- and post-MOB presence periods is noted in education expenditure.

For household attributes, proportion of males, age of the household head, household's assets, and households that own a house are statistically higher while family size is lower after the establishment of MOBs. Education level of the household head is not statistically different between pre- and post-MOB presence periods. Lastly, the number of poor households and bank[7] density in the municipalities are higher post-MOB presence while population is not statistically different between pre- and post-MOB presence periods.

3. Estimation strategy

To identify the impact of MOB presence on various household activities and welfare, we employ an IPW DID-FE model to address the endogeneity problem associated with self-selection as well as sample attrition, which are common to any observational data where treatment status may not be randomized. The decision of MOBs on where to establish their branches is never entirely random. Some MOBs choose to situate themselves in less poor municipalities and where there is better complementary infrastructure to guarantee loan repayment or profitability. In fact, in the data analysis section, we discussed that most MOBs are situated in the capital or in cities and first-class municipalities (Figure 1).

[7] Banks comprise of head offices, branches, extension offices, and other banking offices.

TABLE 1. Summary statistics

	Pre-MOB Presence		Post-MOB Presence				Difference (Pre-MOB vs Post-MOB) *t*-statistics
	2003		2006		2009		
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome Variables							
Employment Status							
Employed	0.36	0.48	0.34	0.48	0.36	0.48	1.52
Self-employed	0.50	0.50	0.50	0.50	0.46	0.50	2.90***
Household Income							
Wage and Salaries	56,369.59 (USD1,039.97)	94,018.38	63,205.71 (USD1,231.74)	111,780.3	75,177.68 (USD1,578.13)	118,238.00	-8.33***
Entrepreneurial Activities	35,246.49 (USD650.26)	70,653.33	42,228.30 (USD822.93)	89,198.04	42,228.30 (USD886.46)	48,297.92	-7.81***
Real Household Expenditures (2012=100)							
Food	828.43	517.22	799.922	514.13	780.75	458.45	4.95***
Medical Care	34.16	117.09	50.55	237.09	59.25	289.97	-7.59***
Alcoholic Beverage & Tobacco	33.28	41.43	30.26	40.58	30.13	36.72	5.02***
Education	77.15	230.67	83.28	250.88	76.31	213.59	-0.75
Household Attributes							
Household Head Sex (1=male; 0=female)	0.85	0.35	0.83	0.37	0.81	0.40	-6.15***
Household Head Age	47.50	13.83	50.01	13.48	52.18	13.38	-17.29***
Household Head Education	7.58	16.89	7.76	17.15	7.98	17.44	-1.11

TABLE 1. Summary statistics (continued)

	Pre-MOB Presence		Post-MOB Presence				Difference (Pre-MOB vs Post-MOB) *t*-statistics
	2003		2006		2009		
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Family Size	5.07	2.15	5.01	2.20	4.86	2.19	4.21***
Amount of financial assets owned	5,148.51 (USD94.99)	33,505.34	6,619.99 (USD129.01)	74,965.86	8,479.13 (USD177.99)	61,808.68	-3.29***
House and/or land ownership (1=yes; 0=no)	0.74	0.44	0.78	0.41	0.77	0.42	-4.75***
Municipality Attributes							
Population	190,209.10	390,665.60	193,823.10	398,088.20	197,505.70	405,651.90	-0.91
Number of poor families	55,856.50	41,826.13	63,818.40	46,868.97	66,878.94	45,808.56	-14.43***
No. of banks	143.03	195.50	151.09	203.91	164.24	213.68	-4.83***
Observation				6,529			

Notes: MOB = microfinance-oriented banks. The numbers in the table are rounded-off to the nearest two decimal places. Financial assets owned comprised of dividends and investments, interest from bank deposits and loans to other households, amount deposited in banks/investments, and profits from sale of stocks and real property. Employed refers to those working for private household, private establishment, and government while self-employment comprised of self-employed without any employee and employer in own family-operated farm or business. Banks comprised of head offices, branches, extension offices, and other banking offices. The peso-dollar exchange rate used for the pre-MOB presence is the average for 2003 at ₱54.20 and for the post-MOB presence is the average for 2006 at ₱51.31 and in 2009 at ₱47.64, posted by the BSP in its website.

This could be a result of the BSP allowing establishment of MOBs only in places not fully served by existing rural banks or other MOBs. Nevertheless, some MOBs are also established in places that are unserved or underserved by financial institutions. The dataset indicates that third, fourth, and fifth-class municipalities or relatively poor municipalities[8] also have MOBs.[9]

In addition, the choice of whether a household avails itself of microfinance products and services is not determined by chance. Households living in municipalities where MOBs are present may share similar socio-economic and cultural backgrounds (e.g., religion, ethnicity, or income source) but have different levels of enterprising capacity leading to different probabilities of their decision to access microcredit. The selection bias arises because these unobservable characteristics may also affect outcomes of interest such as employment, income, and consumption. For example, households who are risk-takers (an attribute that is difficult to measure, if not impossible) have a higher tendency to self-select into microfinance borrowing, but such households are also expected to have higher income and expenditures even without microfinance.

The IPW DID-FE model addresses the selection bias on the following aspects. First, the DID-FE addresses the non-random selection of municipalities and households on the basis of their observable attributes as well as time-invariant unobservable attributes (e.g., inherent ability, industriousness, or geographical landscape of the municipality, including climate and susceptibility to natural disaster) that may affect households' decision to obtain microfinance and MOBs' choice of location.

Although we control selection on observable and time-invariant unobservable attributes in DID-FE, there may be other factors that still confound the estimates. We combine DID-FE with IPW to address the remaining concerns on sample selection associated with households dropping out of the survey, which are typically observed in longitudinal observational data. Finally, we employ the methodology developed by Oster [2019] and Altonji et al. [2005] to determine whether there are still unobserved confounders in the IPW DID-FE.

3.1. DID-FE model

We use the event when the BSP partially lifted the moratorium on the establishment of new banks in 2001 to evaluate the impact of MOB presence in municipalities. This regulatory policy led to the opening of MOBs in 2004. We also limit our analysis to microfinance-oriented branches and banks that have a business name that describe their business activities as microfinance.

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8 Third-class municipalities are defined as those earning an average annual income of ₱35 million (USD 0.69 million) or more but less than ₱45 million (USD 0.88 million), fourth-class municipalities are those earning an average annual income of ₱25 million (USD 0.49 million) or more but less than ₱35 million (USD 0.69 million), and fifth-class municipalities are those that have obtained an average annual income of ₱15 million (USD 0.29 million) or more but less than ₱25 million (USD 0.49 million).

9 For example, there are MOBs established in Buug, Zamboanga Sibugay; Santa Josefa, Agusan Del Sur (3rd class municipalities); Dapa, Surigao Del Norte; Danao, Bohol; Madrid, Surigao Del Sur; Calamba, Misamis Occidental, Braulio Dujali, Davao Del Norte (4th class municipalities); and Santa Teresita, Batangas (5th class municipality).

With this event, we can estimate the following household FE in a DID regression, which compares households with and without MOBs in 2003 (*pre-intervention*) and in 2006 and 2009 (*post-intervention*):

$$y_{imt} = \beta_i + \delta_1 \, (TREAT_{im} \, X \, POST_t) + \delta_2 \, (TREAT_{im} \, X \, POST_t \, X \, dum09) + \gamma_t + \pi^* \, X'_{imt} + \rho^* \, Z'_{imt} + \varepsilon_{imt} \quad (1)$$

where y_{imt} is the measure of activities and welfare for household i residing in municipality m at time t, including: 1) real[10] household expenditure on food, medical care, alcoholic beverage and tobacco, and education; 2) household head is employed or self-employed; and 3) income from wage and salary or entrepreneurial activities. Real expenditures and income are transformed to inverse hyperbolic sine (or arcsinh)[11] to retain zero values because some households do not spend on certain goods and services or may not be earning momentarily. We are interested in evaluating the employment status of the household head as microfinance programs are intended to enhance self-employment activities. We use income and consumption as they are common indicators of poverty or wellbeing.

$TREAT_{im}$ is our treatment variable for continuing households, which equals 1 for households i living in municipalities m that had at least one MOB and 0 otherwise. *Never households* are the control group that includes households living in municipalities that do not have MOBs. $POST_t$ is a dummy that equals 1 for years 2006 and 2009 (*post-intervention*) and 0 for year 2003 (*pre-intervention*). *dum*09 is a dummy that equals 1 for observation year 2009.

There are several potential threats to the validity of the DID-FE model. First, the location of MOBs is not random over municipalities and time as described earlier. Note that the BSP only restricted the establishment in areas not fully served by rural banks or MOBs, so we would expect that their establishment may depend on some pre-existing characteristics of their potential clients and municipality. In Table 2, we compare the baseline characteristics in 2003 of *continuing* households and the municipality that they reside in to *never households*. *Continuing households* are more likely to be headed by older adults and the proportion of male or self-employed household head is lower compared to *never households*. In terms of municipality attributes, *continuing households* reside in municipalities that have large number of poor families and banks. To deal with this non-random selection of households and MOBs, we included a set of household attributes X'_i and municipal characteristics Z'_m. Household characteristics include sex, age, age squared, and education level of the household head, family size, and ownership of house and/or lot and financial assets.[12] The municipality controls are population, number of banks, and poor households that have influence on MOB's choice of location. These observed controls comprised demand-side factors for the reason they are

[10] The amount of expenditure is deflated by consumer price index with base year of 2012.

[11] The inverse hyperbolic sine transformation can be expressed as $arcsinh(x)=log(\sqrt{(X^2+1)}+x)$. Bellemaret and Wichman [2020] explain that applied econometricians frequently transform a variable to an arcsinh because it "approximates the natural logarithm of a variable and allows retaining zero-valued observations."

[12] Financial assets owned comprised dividends and investments, interest from bank deposits and loans to other households, amount deposited in banks/investments, and profits from sale of stocks and real property.

exogenous—determined prior to the policy intervention. Supply-side factors are not considered because they are endogenous as they are mostly driven by household's choice of lender (i.e., outcome variable that also indicates level of competition and concentration in the credit market) and risk/return profile of the borrower.

TABLE 2. Pre-MOB presence comparison of household and municipality attributes

	Never Households (1)	Continuing Households (2)	Difference (3)
Outcome Variables			
Employment Status			
Employed	0.35	0.37	-0.03
Self-employed	0.53	0.47	0.05***
Household Income			
Wage and Salaries	55,135.34	59,214.45	-4,079.11
Entrepreneurial Activities	36,781.61	34,339.37	2,442.24
Real Household Expenditures (2012=100)			
Food	827.64	836.97	-9.33
Medical Care	33.90	35.51	-1.61
Alcoholic Beverage & Tobacco	32.82	33.15	-0.33
Education	78.03	78.31	-0.28
Household Attributes			
Household Head Sex (1=male; 0=female)	0.86	0.84	0.02*
Household Head Age	46.97	48.19	-1.22***
Household Head Education	7.53	7.514	0.02
Family Size	5.10	50.38	0.59
Amount of financial assets owned	4,731.58	5,934.36	-1,202.77
House and/or land ownership (1=yes; 0=no)	0.75	0.76	-0.01
Municipality Attributes			
Population	217,966.9	151,005.8	66,961.17
Number of poor families	45,816.10	68,679.18	-22,863.08***
No. of banks	123.71	177.05	-53.34*

Notes: MOB = microfinance-oriented banks. Column (1) reports group mean for each variable of those households that live in a municipality without MOBs (or "never households") while those with MOBs both in 2006 and 2009 (or "continuing") are reported in Column (2). The results of the *t*-test for differences in the means with standard errors clustered at the municipal level of these households are presented in Column (3). The Philippines has four levels of administrative divisions—regions, provinces, cities and municipalities, and barangays—the highest level is regions and lowest is barangays. The numbers in the table are rounded-off to the nearest two decimal places. Household income and financial assets owned are in Philippine peso. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

Additionally, we included household fixed effects β_i to effectively account for the time-invariant unobserved household attributes. For example, entrepreneurial ability and risk preference may greatly influence a household's decision to access microfinance products and services. According to Berg et al. [2013], less risk averse, and highly skilled households are more likely to engage in productive activities such as non-farm enterprises, and households with higher entrepreneurial ability are more likely to borrow. As such, households that are risk-takers with better entrepreneurial skills are more likely to avail themselves of microfinance through MOBs. We cluster the standard errors at the municipality-year level to allow for an arbitrary covariance structure within municipality across time as the error term ε_{imt} might be correlated across households within a municipality at a specific time period.

The identification strategy is based on the common trends assumption. Note that the dataset has just one pre-MOB period in 2003, which prevents the testing (indirectly) of the parallel trends assumption using multiple pre-intervention periods. To mitigate the concern, we control for time trend γ_t that captures temporal changes in the outcome variables that are common to all households, which reduces estimation bias, if any, originating from violation of the common trends.

The coefficient δ_1 is the estimated *immediate* causal effect of MOB presence for *continuing* households and δ_2 captures *incremental* effect. The sum of $\delta_1$and δ_2 pertains to *total* (or *net*) treatment effect. That is, if MOB presence has a true lasting positive effect on continuing households, then we should find statistically significant total (or net) positive impact of δ_1 and δ_2 as well as the corresponding F-statistic. But if we observe a statistically insignificant F-statistic, then positive effects of MOB presence do not accrue in the long run. These coefficients underscore the sensitivity of the impact with respect to the length of MOB presence, which can be very valuable in designing effective microfinance programs, products, and services.

We also determine the heterogeneous effects depending on the poverty level of the household. It is important to disentangle these effects as much of the literature predicts that the impacts of microfinancing may be influenced by economic class of the recipients and also because microfinance programs typically target poor individuals.

3.2. IPW DID-FE model

To obtain internally valid estimates, sample selection bias, arising out of the possibility of non-random dropping out of households from the survey across treatment and control groups, is another concern that needs to be addressed. In the data subsection of the paper, we discussed that the household panel dataset approximately represents 16 percent of the original sample in 2003, 2006, and 2009. It is important to account for those who drop out of the survey, especially if attrition is non-random so that the remaining sample can be representative of the original population [Barry 2005].

We checked if there are any systematic differences in the pre-intervention (2003) demographic and other socioeconomic characteristics of households that remained in the follow-up surveys in 2006 and 2009 and were, thus, used as our study sample (*stayers*) and those who did not (*attritors*). Table 3 indicates that there are significant differences in the outcome variables and attributes between attritors and stayers—except in spending on alcoholic beverage and tobacco and education as well as in income from entrepreneurial activities. We also analyzed the probability of stayers regressed on treatment dummy as well as a range of household and municipality attributes. Table 4 shows that the coefficient of the treatment dummy is never statistically significant. However, a test of joint significance shows that the covariates are jointly correlated with stayer status.

TABLE 3. Stayers versus attritors

		Stayers group			Stayers - Attritors	
	Obs	**Obs**	**Mean**	**Standard Deviation**	**Difference**	***p*-value**
Outcome Variables						
Real Household Expenditures (2012=100)						
Food	42,094	6,529	828.53	517.29	-11.84*	0.09
Medical	42,094	6,529	34.16	117.09	-3.91**	0.03
Alcoholic Beverage & Tobacco	42,094	6,529	33.27	41.43	0.41	0.47
Education	42,094	6,529	77.11	230.66	-0.94	0.77
Employment Status						
Employed	42,094	6,529	0.36	0.48	-0.04***	0.00
Self-employed	42,094	6,529	0.50	0.50	0.04***	0.00
Household Income						
Wage and Salaries	42,094	6,529	56,372.69	94,018.08	-4,205.26***	0.00
Entrepreneurial Activities	42,094	6,529	35,259.15	70,661.03	32.14	0.99
Household Attributes						
Household Head Sex (1=male; 0=female)	42,094	6,529	0.85	0.00	0.02***	0.00
Household Head Age	42,094	6,529	47.51	13.83	1.46***	0.00
Household Head Education	42,094	6,529	7.58	16.89	-1.03***	0.00
Family Size	42,094	6,529	5.07	2.15	0.28***	0.00
Financial assets owned	42,094	6,529	5,148.51	33,505.34	-2,178.34***	0.01
House and/or land ownership (1=yes, 0=no)	42,094	6,529	0.74	0.44	0.06***	0.00

Notes: Data source is 2003 FIES. Sample includes all households surveyed in 2003. The numbers in the table are rounded-off to the nearest two decimal places. Household income and expenditures as well as financial assets owned are in Philippine peso. Stayers are the households that were surveyed in 2006 and 2009. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

TABLE 4. Probability of household staying until 2009 FIES

	Dependent Variable: HH stayers between 2003 and 2009				
	(1)	(2)	(3)	(4)	(5)
MOB presence	0.060	0.072	0.078	0.082	0.075
	(0.232)	(0.238)	(0.235)	(0.232)	(0.244)
Household attributes	No	Yes	Yes	Yes	Yes
Household expenditures	No	No	Yes	Yes	Yes
Employment status	No	No	No	Yes	Yes
No. of banks	No	No	No	No	Yes
Observations	42,094	42,094	42,094	42,094	42,094
F-stat (test of joint significance) - including treatment		39.86	44.80	65.02	71.49
Prob>*F*		0.00	0.00	0.00	0.00
F-stat (test of joint significance) - excluding treatment		25.00	29.59	31.54	38.19
Prob>*F*		0.00	0.00	0.00	0.00

Notes: HH = Household. Data source is 2003 FIES. Sample includes all households surveyed in 2003. The numbers in the table are rounded-off to the nearest two or three decimal places. Coefficients and standard errors (in parentheses) clustered at the municipal level are from a probit regression where the dependent variable is an indicator of whether the household stayed or not. The standard errors are also corrected by propensity score-matched. Household attributes are sex, age and education of the household head, financial assets owned, and house ownership. Household expenditures comprise food, medical care, alcoholic beverage & tobacco, and education. Employment status refers to wage worker or self-employed. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

To deal with this potential sample selection bias, we take the DID-FE model a step further by combining it with IPW as outlined by Hirano et al. [2003]. The weights are estimated by fitting a logistic model of the probability of the stayer household, which is defined as:

$$Prob(STAYERS_i = 1) = \frac{exp(\delta X_i)}{1 + exp(\delta X_i)} \tag{2}$$

where i indexes households. The variable $STAYERS_i$ is a dummy equaling 1 for household i that is successfully interviewed until the 2006 and 2009 surveys and 0 otherwise. X_i is a vector of household characteristics such as household head's age, sex, and education level, as well as family size and house ownership from 2003 FIES that includes households who dropped out of the survey (see Annex Table A1 for the results).

We then check whether the weighting by the inverse propensity score creates an appropriate control group. The means of the observable baseline characteristics are balanced after weighting by the inverse propensity scores. Results in Annex Table A2 suggest that there is no significant difference in the means of the baseline characteristics between stayers and attritors once the means are weighted using the inverse propensity scores. We also perform a balancing check within the stayer sample, between never households (control group) and the continuing households (treatment group). The results of the exercise in Annex Table A3 indicate that there is no significant difference in the means of the baseline characteristics between households that live in a municipality with MOB and those that did not.

3.3. Selection on unobservable attributes

While we controlled for selection bias on the basis of observable attributes, time-invariant unobservable attributes, and households dropping out of the survey, there may be unobservable factors like time-variant attributes (e.g., dynamic learning effects and productivity of households and municipalities) that can still confound the estimates. To address this concern of endogeneity associated with self-selection because of time-variant unobserved factors, we employ the methodology developed by Oster [2019] and Altonji et al. [2005]. Oster's restricted estimator is used which assumes: 1) equal selection ($\tilde{\delta}$=1) or that the unobservable and observables are equally related to the treatment and 2) the relative contributions of each observed controls to the treatment must be the same as their contribution to the outcome variable. Given this, we can calculate an approximation of the bias-adjusted treatment effect with:

$$\beta^{*\prime} = \tilde{\beta} - [\dot{\beta} - \tilde{\beta}]\ \frac{Rmax - \tilde{R}}{\tilde{R} - \dot{R}} \tag{3}$$

where $\dot{\beta}$ is the coefficient resulting from the short regression of outcome variable on treatment and the R-squared from that regression as $\dot{R}$. $\tilde{\beta}$ is the coefficient from the intermediate regression of outcome variable on treatment and observed controls and the R-squared as $\tilde{R}$. Finally, $Rmax$ is the hypothetical R-squared from a regression of outcome variable on treatment, observed controls and not observed. In this study, $R_{max} = min\{1.3\tilde{R},1\}$. Oster [2019] explains that "$1.3\tilde{R}$ is a cut-off value derived from a sample of 76 results from randomized 27 articles from top journals which allow at least 90.0 percent of the results would remain robust against unobservable selection bias".

We then estimate a set of bounds for β based on Oster's restricted estimator to conduct the robustness test. One bound is $\tilde{\beta}$ (corresponding to those in IPW DID-FE with all observable controls included); the other bound is a restricted bias-adjusted coefficient $\beta^{*\prime}$, which is the value of β when $R^2 = R_{max} = min\{1.3\tilde{R},1\}$ and $\tilde{\delta} = 1$. With these two bounding assumptions, we can define a bounding set as [$\tilde{\beta}, \beta^{*\prime}$ ($min\{1.3\tilde{R},1\}$)]. If this set excludes 0, the results from the controlled regression can be considered robust to omitted variable bias. Additionally, when the bounding set (or identified set) is within the confidence intervals of the controlled effect $\tilde{\beta}$, it implies that the omitted variables are unlikely to drive the results.

Meanwhile, Altonji et al. [2005] suggested a ratio of the impact of unobserved variables relative to the observed explanatory variables that would be needed to fully explain the treatment effect of MOB presence on some household welfare outcome measures. We denote this ratio by $\delta^{0.}$ A hypothetical $\delta^0 > 1$ suggests that the treatment effect can be considered robust to unobserved confounders and that the unobservables would have to be δ^0 times strongly correlated than observables for the unobservables to explain the treatment effects.[13]

4. Results and discussion

We present results from IPW DID-FE specification in Table 5 where the estimated coefficients for income and real expenditures have been transformed[14] to elasticities in percentage change for arcsinh-linear specification with dummy independent variables.

4.1. Effects of MOB presence on all income households

Panel A of Table 5 shows that there is no evidence of impact on real consumption for *continuing* households. Nonetheless, we see *immediate* gains of 2.80 percentage points on the likelihood of self-employment and of 0.44 percent on entrepreneurial income in 2006. These, however, regressed as an *incremental* reduction of 4.30 percentage points in the probability of self-employment and of 0.31 percent in entrepreneurial income in 2009 are noted. The *net* impact on self-employment is statistically not different from zero according to joint *F*-tests shown in Panel A of Table 5. This is probably because the typical businesses set up by microfinance clients in the Philippines are susceptible to closure because they are mostly small-scale production or distribution of goods and services (e.g., sari-sari store or small grocery/convenience store, ambulant/rolling stores, hair dressing, barbering, tailoring, tire repair, etc.),[15] which generates low, seasonal, or irregular income and faces stiff competition with big or organized establishments that offer comparable and lower-priced products and services [Milgram 2005].[16]

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[13] Khan et al. [2019] interpret $\delta<0$ as the coefficient increasing in magnitude due to the controls. And that while this does not indicate that the coefficient is unstable, it suggests that the method is not informative regarding omitted variable bias.

[14] See Bellemaret and Wichman [2020] for the derivation of elasticity. The non-transformed treatment effects are reported in Table 6.

[15] Karlan and Zinman [n.d.] contend that these are the usual clients of microfinance providers in the Philippines, such as First Macro Bank.

[16] We also conducted simulation on households that live in municipality with MOB only in 2006 (*dropouts*) and in 2009 (*newcomers*). Results in Panel A of Annex Table A4 show *total* (statistically significant joint *F*-test) positive effect of 3.11 percent on medical care and 1.55 percent on education spending among dropouts. However, no significant *total* impact is observed on entrepreneurial activities. It is also worth noting that there are negative *persistent* effects on the likelihood and income from wage work of 15.9 percentage points and 0.65 percent, respectively. As for newcomers, they do not enjoy any benefits from presence of MOBs in their municipalities (Panel B of Annex Table A4). Somewhat unexpectedly, however, a significantly positive impact on likelihood of being self-employed can be noted on newcomers even if they did not have access to microfinance in 2006. This is presumably because of the presence of self-selection. We examined this issue later (Section 5: Test on Omitted Variables). An exercise evaluating the variations in measures of household welfare induced by differences in the intensity of MOB presence in municipalities is likewise undertaken. The marginal effects of increased intensity are negligible.

TABLE 5. Effects of microfinance-oriented bank presence: IPW DID-FE

	Employment Status		Income		Real Expenditure			
	Employed	Self-employed	Wage & Salaries	Entrepreneurial Activities	Food	Medical Care	Alcoholic Beverage & Tobacco	Education
All income households								
Panel A: Treatment Group: Continuing Households (With MOB in 2006 and 2009)								
Control Group: Never Households (No MOB)								
CONTINUING x POST	-0.016	0.028*	0.079	0.444*	0.022	0.059	-0.069	0.002
	[-0.047, 0.014]	[-0.005, 0.061]	[-0.362, 0.520]	[-0.046, 0.933]	[-0.026, 0.069]	[-0.134, 0.253]	[-0.224, 0.086]	[-0.159, 0.162]
CONTINUING x POST x 2009	0.024	-0.043***	-0.015	-0.314**	-0.005	-0.001	-0.007	-0.034
	[-0.008, 0.055]	[-0.075, -0.011]	[-0.406, 0.376]	[-0.583, -0.046]	[-0.046, 0.037]	[-0.209, 0.206]	[-0.179, 0.166]	[-0.171, 0.103]
F-stat (test of joint significance)	0.16	0.68	0.11	0.00	0.48	0.31	0.73	0.13
R-squared	0.026	0.016	0.045	0.019	0.262	0.028	0.039	0.082
No. of Observations	18,825	18,825	18,825	18,825	18,825	18,825	18,825	18,825
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bottom 30 percent income households								
Panel B: Treatment Group: Continuing Households (With MOB in 2006 and 2009)								
Control Group: Never Households (No MOB)								
CONTINUING x POST	-0.043	0.071**	0.791	1.230**	0.052	-0.050	0.068	0.012
	[-0.100, 0.014]	[0.011, 0.131]	[-0.525, 2.107]	[0.006, 2.454]	[-0.038, 0.142]	[-0.284, 0.183]	[-0.226, 0.361]	[-0.192, 0.215]
CONTINUING x POST x 2009	0.058*	-0.047	-0.397*	-0.598***	-0.021	0.093	-0.036	0.052
	[-0.003, 0.118]	[-0.114, 0.019]	[-0.858, 0.063]	[-0.831, -0.365]	[-0.085, 0.043]	[-0.196, 0.382]	[-0.285, 0.212]	[-0.149, 0.254]
F-stat (test of joint significance)	0.25	0.56	0.04	0.12	0.70	0.08	0.05	0.36
R-squared	0.029	0.026	0.037	0.037	0.249	0.029	0.040	0.151
No. of Observations	6,234	6,234	6,234	6,234	6,234	6,234	6,234	6,234
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 5. Effects of microfinance-oriented bank presence: IPW DID-FE (continued)

	Employment Status		Income		Real Expenditure			
	Employed	Self-employed	Wage & Salaries	Entrepreneurial Activities	Food	Medical Care	Alcoholic Beverage & Tobacco	Education
				Upper 70 percent income households				
Panel C: Treatment Group: Continuing Households (With MOB in 2006 and 2009)								
Control Group: Never Households (No MOB)								
CONTINUING x POST	0.013	-0.004	-0.005	0.188	0.018	0.096	-0.091	0.043
	[-0.022, 0.049]	[-0.045, 0.038]	[-0.466, 0.455]	[-0.332, 0.708]	[-0.034, 0.070]	[-0.173, 0.364]	[-0.276, 0.094]	[-0.190, 0.276]
CONTINUING x POST x 2009	-0.010	-0.019	0.159	-0.193	0.000	-0.049	-0.037	-0.051
	[-0.044, 0.024]	[-0.056, 0.018]	[-0.396 0.713]	[-0.643, 0.257]	[-0.046, 0.046]	[-0.304, 0.206]	[-0.246, 0.171]	[-0.218, 0.115]
F-stat (test of joint significance)	0.04	0.94	0.42	0.02	0.34	0.10	1.23	0.01
R-squared	0.039	0.014	0.038	0.015	0.218	0.030	0.033	0.054
No. of Observations	12,591	12,591	12,591	12,591	12,591	12,591	12,591	12,591
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: MOB = Microfinance-Oriented Bank. DID-FE refers to difference-in-differences fixed effects. Treatment is defined as presence of MOBs in the municipality where the household is residing. Household expenditures are deflated by consumer price indices of the goods and services with base year of 2012. Weight is from logit model where the dependent variable is an indicator of whether the household stayed or not and the control variables are household head's age, sex, education, and family size as well as house ownership. The sample used to compute the weight includes households that dropped from the survey. Estimated coefficients for income and consumption are elasticities for the arcsinh-linear specification with dummy independent variables or in percentage change in the outcome variable due to the discrete change in treatment dummy = 0 to dummy = 1. The estimated coefficients for income and consumption expenditures that are not transformed into percentage change are presented in Table 6. Confidence intervals are in brackets. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

4.2. Heterogeneous effects of MOB presence

We now turn to the heterogeneous effects of MOB presence on poverty level of the household. A household is considered poor if it is categorized under the first to third national income decile. The PSA groups families into two income strata, the bottom 30 percent and the upper 70 percent. The bottom 30 percent grouping is used as a proxy for those falling below the poverty line. It refers to the lowest 30 percent of the total households in the per capita income distribution, arranged in descending order.

We assess whether the establishment of MOBs reduces poverty, as claimed by the proponents of microfinance under the impression that the poor are just financially constrained but can otherwise have high return to investment [Kaboski and Townsend 2012].

4.2.1. Bottom 30 percent income households

In Panel B of Table 5, it can be noted that there is also no significant effect on real expenditures of *continuing* households. They nonetheless enjoy an *immediate* increase in 2006 on the likelihood of being self-employed and in entrepreneurial income of 7.1 percentage points and 1.23 percent, respectively. However, a negative *incremental* effect on self-employment income of 0.60 percent is noted in 2009. And while households reap *incremental* increase in wage work of 5.80 percentage points in 2009, they experience *incremental* decrease in wage income of 0.40 percent. The immediate benefit of MOB presence on entrepreneurial activities is not unusual and consistent with the findings of Crèpon et al. [2015] suggesting that the lesser preference for wage work is a byproduct of increased income from self-employment activities because households in this circumstance have strong disutility with casual (day) labor or stable salaried work. That is, there is a change in household activity towards self-employment and away from wage work. Banerjee et al. [2015b] further explained that microcredit affords the poor more freedom in their choice of occupation.

Meanwhile, the incremental decrease in entrepreneurial and wage income as well as increase in likelihood of wage work are likely because households' microbusiness activities may have diminished, and salaried work is now preferred.[17]

[17] As for *dropouts*, Panel A of Annex Table A5 indicates that while there is an immediate increase in likelihood of wage work of 23.9 percentage points in 2006, wage income decreases by 0.85 percent. A *total* (statistically significant joint *F*-test) negative effect on income from entrepreneurial activities of 1.40 percent (-0.696 + -0.702) and persistent negative effect on food expenditure of 0.10 percent in 2009 are also observed. It is likewise interesting to note a *total* positive effect of 0.87 percent on medical care spending as well as an immediate negative effect of 0.54 percent in 2006 and persistent positive effect of 1.46 percent in 2009 on education spending. These imply that households possibly sacrifice their consumption on some goods and services as microfinance might not be large enough to fully cover the costs of establishing a business or even the borrowing cost (Augsburg et al. [2012]; Banerjee et al. [2015a]; Karlan and Zinman [2010]). Hence, we see more households working outside their homes to mitigate decreasing real expenditures as well as supplement their loan and reach the level of funds sufficient to finance an investment which can be unacceptably large [Banerjee et al. 2015b]. Another possible explanation for the dynamics that we observe

It is also plausible that, similar to the findings of Angelucci et al. [2015], presence of microfinance institutions increased the likelihood of informal household borrowing; or that of Tarozzi et al. [2015] wherein they showed that the assignment of households in rural Amhara and Oromiya, Ethiopia to a microfinance program crowded in borrowing and female-initiated household loans from credit sources such as informal lenders, non-governmental organizations (NGOs), banks, and cooperatives. The cost of borrowing from some of these institutions is occasionally either higher or more frequent payment schedules thereby reducing income from entrepreneurial activities.

4.2.2. Upper 70 percent income households

As for the impact on the upper 70 percent income or non-poor households, results in Panel C of Table 5 indicate that no significant impact on welfare measures—real expenditures on food, medical care, alcoholic beverage and tobacco, and education as well as likelihood of and income from entrepreneurial and wage and salary activities—of *continuing* non-poor households is recorded. These results may not be entirely surprising as microfinance does not have an effect on those who are too unproductive to be entrepreneurs and the funds lent are too small to substantially affect the livelihood of the highly skilled and non-poor borrowers [Buera et al. 2012].[18]

5. Tests on omitted variables

We investigate the robustness of our estimated coefficients to other unobserved factors that might contribute to the non-random selection of our households into our treatment group and MOB location using the Oster [2019] and Altonji et al. [2005] approaches. The estimated coefficients for income and real expenditures shown in Table 6 are not the elasticities or percent change but are for the arcsinh transformation. Overall, the value of several δ^0 and/or the coefficient bounds point to robustness in all our statistically significant estimates.

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in education spending is the labor demand effect of credit. If access to microfinance leads to investment in a household enterprise, and employing family member raises household productivity, then the opportunity cost of sending family members to school is high. On one hand, *newcomers* displayed immediate increase in real food spending of 0.10 percent, but entrepreneurial income decreased immediately by 0.56 percent (Panel B of Annex Table A5). We again note a significant effect in 2006 (e.g., real food and alcoholic beverage and tobacco expenditures) that may indicate potential presence of self-selection.

[18] Among *dropouts*, although they registered negative *total* impact of 0.93 percentage points on wage income, there are no significant effects on entrepreneurial activities, and *total* positive effect on medical care of 3.75 percent and on education spending of 1.83 percent (joint F-tests are statistically significant) are observed (Panel A of Annex Table A6). These results affirm the study of Kondo et al. [2008] in the Philippines that non-poor households benefit more relative to poor families. The cost and availability of microfinance products and services are not large enough for poor households to start a business that could have high returns. On one hand, *newcomers* suffer an immediate reduction of 0.31 percent in real spending on alcoholic beverage and tobacco (Panel B of Annex Table A6). We do not make any inference on the *total positive* effect on entrepreneurial income because it may be indicative of self-selection bias as one of the recorded impacts is noted in 2006 when no MOB has been established.

For instance, the coefficient bound interval (-0.043, -0.038) for the effect of MOB presence on likelihood of self-employment in Panel A of Table 6 does not contain 0 and is within the confidence interval of the controlled effect, which implies that the estimate is robust. Similarly, the value of $\delta_2{}^0 = 8.42$ indicates that unobservables must be 8.42 times as important as the control variables to drive the treatment effect to 0. Since this value is greater than 1, the effect can be considered robust to selection on unobservables. Regarding the other estimates that either have bound intervals containing 0 or have $\delta_0 < 1$, we still do not consider these a major enough concern for our results to be claimed false positive as they are insignificant coefficients.[19]

TABLE 6. Robustness to omitted variable bias of the effects of long-term microfinance-oriented bank presence

Dependent Variable	Identified Set $[\tilde{\beta}, \beta^{*\prime}(min\{1.3\ \tilde{R},1\}),1]$	Exclude Zero?	Within Confidence Interval?	δ^0 for β=0
	(1)	(2)	(3)	(4)
All income households				
Panel A: Treatment Group: Continuing Households (With MOB in 2006 and 2009)				
Control Group: Never Households (No MOB)				
Employment Status				
Employed				
CONTINUING x POST	(-0.016, -0.014)	Yes	Yes	6.221
CONTINUING x POST x 2009	(0.024, 0.022)	Yes	Yes	15.049
Self-employed				
CONTINUING x POST	(0.028*, 0.036)	Yes	Yes	-3.436
CONTINUING x POST x 2009	(-0.043***, -0.038)	Yes	Yes	8.421
Household Income				
Wages and Salaries				
CONTINUING x POST	(0.076, 0.105)	Yes	Yes	-2.699
CONTINUING x POST x 2009	(-0.015, -0.126)	Yes	Yes	-0.138
Entrepreneurial Activities				
CONTINUING x POST	(0.367**, 0.433)	Yes	Yes	-5.596
CONTINUING x POST x 2009	(-0.377*, -0.397)	Yes	Yes	-19.079

[19] The tables presenting the results for dropouts and newcomers are not included for brevity but are available from the authors upon request. Results suggest that all statistically significant coefficients are robust.

TABLE 6. Robustness to omitted variable bias (continued)

Dependent Variable	Identified Set $[\tilde{\beta}, \beta^{*\prime}$ $(min\{1.3\ \tilde{R},1\}),1]$	Exclude Zero?	Within Confidence Interval?	δ^0 for β=0
	(1)	(2)	(3)	(4)
Real Household Expenditure				
Food				
CONTINUING x POST	(0.021, 0.030)	Yes	Yes	-2.424
CONTINUING x POST x 2009	(-0.005, 0.000)	No	Yes	0.954
Medical Care				
CONTINUING x POST	(0.057, -0.002)	No	Yes	0.965
CONTINUING x POST x 2009	(-0.001, -0.031)	Yes	Yes	-0.041
Alcoholic Beverage and Tobacco				
CONTINUING x POST	(-0.072, -0.023)	Yes	Yes	1.483
CONTINUING x POST x 2009	(-0.007, -0.019)	Yes	Yes	-0.577
Education				
CONTINUING x POST	(0.002, 0.002)	Yes	Yes	-7.487
CONTINUING x POST x 2009	(-0.035, -0.019)	Yes	Yes	2.208
Bottom 30 percent income households				
Panel B: Treatment Group: Continuing Households (With MOB in 2006 and 2009)				
Control Group: Never Households (No MOB)				
Employment Status				
Employed				
CONTINUING x POST	(-0.043, -0.055)	Yes	Yes	3.463
CONTINUING x POST x 2009	(0.058*, 0.053)	Yes	Yes	11.853
Self-employed				
CONTINUING x POST	(0.071**, 0.097)	Yes	Yes	-2.700
CONTINUING x POST x 2009	(-0.047, -0.038)	Yes	Yes	5.171
Household Income				
Wages and Salaries				
CONTINUING x POST	(0.583, 0.585)	Yes	Yes	-286.197
CONTINUING x POST x 2009	(-0.507, -0.670)	Yes	Yes	-3.096
Entrepreneurial Activities				
CONTINUING x POST	(0.802***, 0.949)	Yes	Yes	-5.463
CONTINUING x POST x 2009	(-0.911***, -0.919)	Yes	Yes	-117.657

TABLE 6. Robustness to omitted variable bias (continued)

Dependent Variable	Identified Set [$\tilde{\beta}$, $\beta^{*\prime}$ ($min\{1.3\ \tilde{R},1\}$),1]	Exclude Zero?	Within Confidence Interval?	δ^0 for β=0
	(1)	(2)	(3)	(4)
Real Household Expenditure				
Food				
CONTINUING x POST	(0.051, 0.051)	Yes	Yes	-71.543
CONTINUING x POST x 2009	(-0.022, -0.023)	Yes	Yes	-18.610
Medical Care				
CONTINUING x POST	(-0.052, -0.110)	Yes	Yes	-0.889
CONTINUING x POST x 2009	(0.089, 0.063)	Yes	Yes	3.464
Alcoholic Beverage and Tobacco				
CONTINUING x POST	(0.065, 0.093)	Yes	Yes	-2.371
CONTINUING x POST x 2009	(-0.037, -0.077)	Yes	Yes	-0.918
Education				
CONTINUING x POST	(0.011, -0.010)	No	Yes	0.530
CONTINUING x POST x 2009	(0.051, 0.035)	Yes	Yes	3.126
Upper 70 percent income households				
Panel C: Treatment Group: Continuing Households (With MOB in 2006 and 2009)				
Control Group: Never Households (No MOB)				
Employment Status				
Employed				
CONTINUING x POST	(0.013, 0.022)	Yes	Yes	-1.496
CONTINUING x POST x 2009	(-0.010, -0.010)	Yes	Yes	-30.267
Self-employed				
CONTINUING x POST	(-0.004, -0.002)	Yes	Yes	1.862
CONTINUING x POST x 2009	(-0.019, -0.018)	Yes	Yes	15.431
Household Income				
Wages and Salaries				
CONTINUING x POST	(-0.006, 0.051)	No	Yes	0.098
CONTINUING x POST x 2009	(0.147, 0.043)	Yes	Yes	1.407
Entrepreneurial Activities				
CONTINUING x POST	(0.172, 0.217)	Yes	Yes	-3.908
CONTINUING x POST x 2009	(-0.214, -0.258)	Yes	Yes	-4.919

TABLE 6. Robustness to omitted variable bias (continued)

Dependent Variable	Identified Set $[\tilde{\beta}, \beta^{*\prime}$ $(min\{1.3\ \tilde{R},1\}),1]$	Exclude Zero?	Within Confidence Interval?	δ^0 for β=0
	(1)	(2)	(3)	(4)
Real Household Expenditure				
Food				
CONTINUING x POST	(0.018, 0.031)	Yes	Yes	-1.331
CONTINUING x POST x 2009	(0.000, 0.004)	Yes	Yes	-0.028
Medical Care				
CONTINUING x POST	(0.091, 0.020)	Yes	Yes	1.287
CONTINUING x POST x 2009	(-0.050, -0.088)	Yes	Yes	-1.319
Alcoholic Beverage and Tobacco				
CONTINUING x POST	(-0.096, -0.024)	Yes	Yes	1.332
CONTINUING x POST x 2009	(-0.038, -0.050)	Yes	Yes	-3.124
Education				
CONTINUING x POST	(0.042, 0.066)	Yes	Yes	-1.746
CONTINUING x POST x 2009	(-0.053, -0.031)	Yes	Yes	2.377

Notes: MOB = Microfinance-Oriented Bank. Results in column (1) reports the identified set and $\tilde{\beta}$ is the treatment effect. The treatment effect of income and consumption expenditures are not in percent change but for the arcsinh-linear specification with dummy independent variables from the IPW DID-FE regression. Column (2) indicates whether the identified set excludes zero and Column (3) reports whether the estimated biased-adjusted coefficient is within the confidence interval of the estimated controlled effect $\tilde{\beta}$. Column (4) is the computed $\delta^0 = [(\tilde{\beta} - \beta^*)(\tilde{R} - R^0)] / [(\beta^0-\tilde{\beta})(R_{max} - \tilde{R})]$ where β^0 is the treatment effect and R^0 is the R^2 value in the simple regression with no controls of outcome on treatment; $\tilde{\beta}$ and $\tilde{R}$ correspond to the regression with observable controls; and β^* is equal to zero [Khan et al. 2019]. δ^0 is the Altonji et al. [2005] coefficient of proportionality that would be required to attribute the treatment effect entirely to the influence of unobservables. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

6. Policy insights

While we cannot identify the root causes of the subtle impacts of MOB presence, it seems likely that the diminishing or regressive impacts of longer presence of MOBs may be attributable to the smaller amounts of loans offered to microfinance clients, which are not large enough to cover borrowing costs or expand existing microbusinesses, as well as unprofitable businesses that microfinance clients choose to open.

For instance, the principal amount of a microenterprise loan has been generally pegged at ₱150,000 since 2001 (see Circular No.272 issued in January 2001). And while Circular No. 744 dated December 28, 2011 increased the amount to ₱300,000, it is only made available to growing microenterprises that had "graduated" from the traditional microfinance loans of up to ₱150,000. More than a decade after, and amidst a backdrop of rising domestic prices and interest rates as well as depreciating peso, will this amount be sufficient to start, sustain, or even expand microbusiness? On one hand, another microfinance product—micro-agri loan of up to ₱150,000 and loans to start small and increase incrementally based on banks' policies—can't be accessed easily as it can only be obtained short term (up to 12 months) by those with multiple income generation activities (i.e., farm and off-farm), with farm activities of at least two years in operation, and by existing borrowers with good track record based on banks' policies.

As such, from a policy standpoint, there is a need to not only *facilitate graduation of microfinance* clients but also aim for microfinance borrowers to engage in activities that have absorptive capacity for additional capital so that microfinance products and services will not only assist them to raise their earnings above subsistence income. This kind of initiative is currently being implemented in the Philippines by CARD Mutually Reinforcing Institutions (CARD MRI), which provides microloans and assists clients who have evolved into medium- or large-scale entrepreneurs and are in need of larger loans from universal/commercial and thrift banks.

Second, *complement credit with client, entrepreneurship, or business development services.* Credit should be accompanied by complementary development services such as linking entrepreneurs to markets (e.g., agricultural value-chain financing, market matching, or trade fairs); training in product development and marketing; and entrepreneurship education. Such initiatives would foster product diversification, integrate microfinance borrowers into broader and high value markets, and enhance borrowers' business skills, thereby enabling borrowers to run their business profitably, increasing business opportunities, and avoid business closures.

7. Conclusion

This study utilizes a nationally representative panel dataset drawn from the 2003, 2006, and 2009 FIES for the Philippines to analyze whether MOB presence in municipalities affects various measures of household welfare such as engagement in wage work and self-employment activities, wage and entrepreneurial income, and real expenditure on food, medical care, alcoholic beverage and tobacco, and education.

Deviating from the previous literature, this study examines not only the impact of *long-term* MOB presence in a municipality but also the differentiation of the impact into *immediate*, *incremental*, or *total* (*net*) effects. Furthermore, heterogenous effects by poverty level are also examined. We employ DID-FE and IPW to control for endogeneity problem associated with self-selection as well as sample attrition.

Results suggest that long-term MOB presence has an immediate positive impact on households' engagement in and income from entrepreneurial activities. However, these benefits diminish or even regress over time. We find similar results among poor households. That is, there are immediate gains in entrepreneurial income and activities but the incremental effects either regress or wane. No significant effects are also noted on real expenditures of poor households. Lastly, no significant impact on real expenditures as well as likelihood of and income from wage and salary and entrepreneurial activities was observed among non-poor families.

These findings show that positive effects of MOB presence are not evenly distributed among households, which prompts a rethinking of the role of microfinance in basic development outcomes for poor households. For those households that reside in municipalities with MOBs, while it raises the likelihood of households being microentrepreneurs, it does not fuel an escape from poverty. Real expenditures do not increase for those who live in municipalities with long-term MOB presence. Similarly, income does not increase in the long run.

As such, MOB presence is not consequentially "transformative." Nevertheless, by providing immediate opportunities to open or expand existing microbusinesses, it reduces vulnerability of clients, who would otherwise have been wage workers had not they received it. It affords households the opportunity to make intertemporal choices, including the freedom to choose which income-generating activities to undertake.

This study establishes the role of MOB presence in reducing vulnerability of households. It is hoped that these findings will encourage further empirical studies on the issues involved in advocating microfinance as an effective tool for poverty reduction, and lead to better micro- and macro-prudential policies towards a financially self-sustainable microfinance industry that will provide a wide range of products and services.

We suggest examination of whether the magnitude will increase, and whether the direction of the impacts will be the same: (1) if actual MOB borrowing of households are used instead of MOB presence and (2) in the presence of NGO microfinance providers in municipalities where there are MOBs. Our study was not able to account for actual borrowing of households from MOBs and NGO microfinance providers due to the absence of readily available information about their locations.

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Annex

TABLE A1. Logit estimates of probability household stayed

Variable	Coefficients	Robust Standard Error
Household Head Sex (1=male; 0=female)	0.130***	0.040
Household Head Age	0.007***	0.001
Household Head Education	-0.003***	0.001
Family Size	0.055***	0.006
House and/or land ownership (1=yes, 0=no)	0.273***	0.031
No. of Observations	42,094	

Note: Statistically significant at ***1 percent, **5 percent, and *10 percent level.

TABLE A2. Balance in covariates across stayers and attritors after using inverse probability of treatment weights with the propensity score

	Mean in Stayers	Mean in Attritors	Standardized difference
Household Head Sex (1=male; 0=female)	0.84	0.84	-0.011
Household Head Age	46.37	46.27	0.007
Household Head Education	8.61	8.46	0.008
Family Size	4.84	4.84	0.002
Amount of financial assets owned	8,788.11	7,021.21	0.019
House and/or land ownership (1=yes, 0=no)	0.69	0.69	-0.007

TABLE A3. Balance in covariates across continuing and never households after using inverse probability of treatment weights with the propensity score

	Mean in Stayers	Mean in Attritors	Standardized difference
Household Head Sex (1=male; 0=female)	0.48	0.51	-0.072
Household Head Age	50.38	50.05	0.025
Household Head Education	7.67	8.31	-0.038
Family Size	51.27	50.62	0.030
Amount of financial assets owned	10,283.52	7,046.96	0.052
House and/or land ownership (1=yes, 0=no)	0.78	0.77	0.016

TABLE A4. Effects of microfinance-oriented bank presence on all income households: IPW DID-FE

	Employment Status		Income		Real Expenditure			
	Employed	**Self-employed**	**Wage and Salaries**	**Entrepreneurial Activities**	**Food**	**Medical Care**	**Alcoholic Beverage and Tobacco**	**Education**
Panel A: Treatment Group: Dropout Households (With MOB in 2006)								
Control Group: Never Households (No MOB)								
DROPOUT x POST	0.066	0.033	-0.028	0.351	0.046	2.693	0.144	0.590
	[-0.019, 0.150]	[-0.095, 0.161]	[-1.892, 1.836]	[-0.640, 1.343]	[-0.336, 0.429]	[-1.662, 7.047]	[-0.864, 1.153]	[-0.468, 1.649]
DROPOUT x POST x 2009	-0.159**	0.128	-0.654***	-0.183	-0.065	0.418	-0.277	0.956**
	[-0.297, -0.022]	[-0.033, 0.290]	[-1.076, -0.232]	[-1.324, 0.959]	[-0.215, 0.085]	[-0.144, 0.981]	[-0.618, 0.063]	[0.085, 1.826]
F-stat (test of joint significance)	2.24	1.40	1.10	0.03	0.04	8.44***	0.54	11.78***
R-squared	0.025	0.016	0.038	0.022	0.248	0.037	0.042	0.084
No. of Observations	11,901	11,901	11,901	11,901	11,901	11,901	11,901	11,901
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Treatment Group: Newcomer Households (With MOB in 2009)								
Control Group: Never Households (No MOB)								
NEWCOMER x POST	-0.033	0.076*	0.025	1.184	-0.044	-0.083	-0.032	0.055
	[-0.129, 0.063]	[-0.006, 0.157]	[-0.810, 0.861]	[-0.870, 3.238]	[-0.106, 0.018]	[-0.368, 0.201]	[-0.345, 0.281]	[-0.341, 0.450]
NEWCOMER x POST x 2009	-0.004	-0.051	-0.079	0.033	0.050	0.227	-0.061	0.057
	[-0.111, 0.103]	[-0.127, 0.025]	[-0.946, 0.787]	[-1.164, 1.230]	[-0.054, 0.154]	[-0.271, 0.726]	[-0.278, 0.157]	[-0.159, 0.274]
F-stat (test of joint significance)	0.56	0.39	0.01	2.29	0.00	0.20	0.59	0.31
R-squared	0.026	0.015	0.037	0.020	0.251	0.028	0.042	0.081
No. of Observations	12,279	12,279	12,279	12,279	12,279	12,279	12,279	12,279
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: MOB = Microfinance-Oriented Bank. DID-FE refers to difference-in-differences fixed effects. Treatment is defined as presence of MOBs in the municipality where the household is residing. Household expenditures are deflated by consumer price indices of the goods and services with base year of 2012. Weight is from logit model where the dependent variable is an indicator of whether the household stayed or not and the control variables are household head's age, sex, education, and family size as well as house ownership. The sample used to compute the weight includes households that dropped from the survey. Estimated coefficients for income and consumption are elasticities for the arcsinh-linear specification with dummy independent variables or in percentage change in the outcome variable due to the discrete change in treatment dummy = 0 to dummy = 1. The estimated coefficients for income and consumption expenditures that are not transformed into percentage change is available upon request from the author. Confidence intervals are in brackets. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

TABLE A5. Heterogeneous effects of microfinance-oriented bank presence on bottom 30 percent income households: IPW DID-FE

	Employment Status		Income		Real Expenditure			
	Employed	Self-employed	Wage and Salaries	Entrepreneurial Activities	Food	Medical Care	Alcoholic Beverage and Tobacco	Education
Panel A: Treatment Group: Dropout Households (With MOB in 2006)								
Control Group: Never Households (No MOB)								
DROPOUT x POST	0.239***	-0.063	-0.852**	-0.696**	0.029	0.699**	-0.461	-0.541**
	[0.068, 0.411]	[-0.316, 0.190]	[-1.332, -0.371]	[-1.227, -0.165]	[-0.230, 0.289]	[0.118, 1.281]	[-1.427, 0.505]	[-1.071, -0.012]
DROPOUT x POST x 2009	-0.122	0.006	7.545	-0.702**	-0.097**	0.175	0.307	1.455**
	[-0.534, 0.289]	[-0.071, 0.084]	[-6.238, 21.330]	[-1.276, -0.127]	[-0.179, -0.015]	[-0.636, 0.986]	[-0.222, 0.836]	[0.178, 2.733]
F-stat (test of joint significance)	0.19	0.20	0.03	20.97***	0.61	4.74**	0.10	0.07
R-squared	0.034	0.041	0.027	0.048	0.205	0.028	0.037	0.142
No. of Observations	3,817	3,817	3,817	3,817	3,817	3,817	3,817	3,817
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Treatment Group: Newcomer Households (With MOB in 2009)								
Control Group: Never Households (No MOB)								
NEWCOMER x POST	-0.087	0.098	0.059	0.468	-0.094**	-0.204	-0.255*	0.189
	[-0.266, 0.091]	[-0.074, 0.271]	[-1.152, 1.270]	[-1.960, 2.896]	[-0.173, -0.016]	[-0.531, 0.122]	[-0.529, 0.019]	[-0.298, 0.675]
NEWCOMER x POST x 2009	-0.000	-0.084	-0.360	-0.559*	0.102**	0.270	0.236	-0.028
	[-0.169, 0.168]	[-0.237, 0.068]	[-0.975, 0.256]	[-1.204, 0.086]	[0.002, 0.201]	[-0.279, 0.819]	[-0.102, 0.574]	[-0.305, 0.249]
F-stat (test of joint significance)	1.04	0.04	0.37	0.19	0.00	0.00	0.21	1.17
R-squared	0.037	0.037	0.025	0.039	0.205	0.027	0.037	0.142
No. of Observations	4,051	4,051	4,051	4,051	4,051	4,051	4,051	4,051
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: MOB = Microfinance-Oriented Bank. DID-FE refers to difference-in-differences fixed effects. Treatment is defined as presence of MOBs in the municipality where the poor household is residing. Household expenditures are deflated by consumer price indices of the goods and services with base year of 2012. Weight is from logit model where the dependent variable is an indicator of whether the household stayed or not and the control variables are household head's age, sex, education, and family size as well as house ownership. The sample used to compute the weight includes households that dropped from the survey. Estimated coefficients for income and consumption are elasticities for the arcsinh-linear specification with dummy independent variables or in percentage change in the outcome variable due to the discrete change in treatment dummy = 0 to dummy = 1. The estimated coefficients for income and consumption expenditures that are not transformed into percentage change is available upon request from the author. Confidence intervals are in brackets. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.

TABLE A6. Heterogeneous effects of microfinance-oriented bank presence on upper 70 percent income households: IPW DID-FE

	Employment Status		Income		Real Expenditure			
	Employed	Self-employed	Wage and Salaries	Entrepreneurial Activities	Food	Medical Care	Alcoholic Beverage and Tobacco	Education
Panel A: Treatment Group: Dropout Households (With MOB in 2006)								
Control Group: Never Households (No MOB)								
DROPOUT x POST	0.046 [-0.070, 0.162]	0.072 [-0.136, 0.281]	-0.113 [-1.852, 1.625]	0.687 [-0.593, 1.967]	0.030 [-0.419, 0.479]	3.428 [-2.306, 9.162]	0.273 [-0.813, 1.360]	1.006 [-0.530, 2.542]
DROPOUT x POST x 2009	-0.163 [-0.315, -0.011]	0.150 [-0.052, 0.353]	-0.816*** [-0.966, -0.667]	-0.028 [-1.060, 1.003]	-0.082 [-0.276, 0.112]	0.326 [-0.331, 0.983]	-0.235 [-0.833, 0.363]	0.825 [-0.616, 2.266]
F-stat (test of joint significance)	1.58	1.25	3.24*	1.15	0.22	10.28***	0.01	6.57**
R-squared	0.040	0.015	0.039	0.014	0.218	0.041	0.036	0.063
No. of Observations	8,084	8,084	8,084	8,084	8,084	8,084	8,084	8,084
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Treatment Group: Newcomer Households (With MOB in 2009)								
Control Group: Never Households (No MOB)								
NEWCOMER x POST	0.016 [-0.068, 0.101]	0.055 [-0.029, 0.138]	0.334 [-0.811, 1.480]	2.700 [-0.700, 6.100]	0.016 [-0.040, 0.072]	0.073 [-0.306, 0.452]	0.390 [-0.390, 1.171]	0.044 [-0.540, 0.627]
NEWCOMER x POST x 2009	0.033 [-0.103, 0.169]	-0.039 [-0.143, 0.065]	0.186 [-0.987, 1.360]	0.869 [-0.745, 2.482]	-0.021 [-0.138, 0.097]	0.086 [-0.652, 0.824]	-0.307* [-0.665, 0.052]	0.048 [-0.203, 0.298]
F-stat (test of joint significance)	1.24	0.17	0.67	18.62***	0.00	0.14	0.07	0.07
R-squared	0.039	0.012	0.037	0.016	0.220	0.031	0.035	0.059
No. of Observations	8,228	8,228	8,228	8,228	8,228	8,228	8,228	8,228
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: MOB = Microfinance-Oriented Bank. DID-FE refers to difference-in-differences fixed effects. Treatment is defined as presence of MOBs in the municipality where the poor household is residing. Household expenditures are deflated by consumer price indices of the goods and services with base year of 2012. Weight is from logit model where the dependent variable is an indicator of whether the household stayed or not and the control variables are household head's age, sex, education, and family size as well as house ownership.
The sample used to compute the weight includes households that dropped from the survey. Estimated coefficients for income and consumption are elasticities for the arcsinh-linear specification with dummy independent variables or in percentage change in the outcome variable due to the discrete change in treatment dummy = 0 to dummy = 1. The estimated coefficients for income and consumption expenditures that are not transformed into percentage change is available upon request from the author. Confidence intervals are in brackets.
***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively.