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Foreign direct investment inflow: The drivers and motivations in MENA Region

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Abstract

Purpose — Reasons why Multinational Enterprise (MNEs) engage in foreign direct investment (hereafter referred to as FDI) abroad have been of great interest to policy markets, academia and international portfolio investors. This examines FDI inflow motives to the Middle East and North Africa (MENA) region for the period 2005 to 2019.

Design/methodology/approach — This research paper applies both the static and dynamic panel methodologies such as SYS-GMM, fixed effects, and pooled OLS estimators to investigate the motivational factors of MNEs FDI inflows to MENA countries.

Findings — Although specificity applies to countries, estimated results suggest that MNEs in the MENA region are predominantly interested in serving both home and host markets. Other motives such as efficiency-seeking FDI vary across countries, indicating that FDI motives are not homogeneous among region members. This paper provides useful insight for both firms and host countries in the region.

Originality/value — This research paper investigates the factors that motivate MNEs to consider FDI decisions in MENA countries. Rather than investigate the individual countries within the region as done in existing literature, this research paper simultaneously examines MNEs' investment motivations in the MENA region. The findings are significant, plausible and in line with the economic development of most countries in the region.

Keywords — FDI motivation, marketing-seeking, resources-seeking, efficiency-seeking, MENA

Introduction

Foreign direct investments (hereafter referred to as FDI) play an important role in the economic prosperity of both the host and home economies. This has led to accelerated growth in FDI flows across the globe, with approximately an annual average of US$142 billion from 1985 to 1990 to about US$385 billion in 1996 and US$1.39 trillion in 2019 (UNCTAD, 2020). For this reason, the study on FDI has received much attention from academia, particularly students of international economics, investors, and policymakers in the past four decades. Figure 1 shows the percentage of the country's investments in the region, with Saudi Arabia and UAE controlling the largest investments in the region, respectively. However, due to the frequent social unrest, land/boundary dispute,s and tense political situation between countries in the region, many small business owners have lost their sustainable likelihood. Several foreign investors have diversified their investment to safer locations, stunted the region's economic growth. This corroborates with Figure 2 plots which

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show the investment inflow and outflow from the MENA region. The investments inflow (US$ million) has maintained a downward trend for more than a decade, whilst the outflow investments continue to fluctuate with recent values more than the inflow in the region. Thus, numerous research papers have argued that mineral deposit in the MENA region has been a curse rather than a blessing. To this end, economic scholars, private investors, and policymakers in the region are much concerned about the economic determinants or policies that encourage investment inflow to the MENA region. The relationship between FDI flows and its determinants has generated a plethora of empirical papers. Whilst most of these research papers explore the host country's quality of institutions as determinants to be studied for FDI inflow (Sabir, Rafique, & Abbas, 2019; Tomelin, Amal, Hein, & Carpes Dani, 2018), other studies focused on determinants associated with political risk indicators of the host country (Arel-Bundock, 2017). However, these research papers' model specifications and empirical results are mixed and vary from one country to the other.

Besides these various studies not considering the motives of MNEs investing in the MENA region, most of these papers have used static models such as OLS regression, pooled OLS regression, panel regression model, fixed model, gravity models etc. to examine FDI inflow in the region. Abonazel and Shalaby (2020) have documented their findings using the generalized methods of moments (GMM) to examine inward FDI in the region. Al-Khouri (2015) reveals that political risk factors such as law and order, ethnic tension and internal conflict significantly affect FDI, while the economic risk factor negatively affects FDI inflow substantially into the region. To this end, we used both the static and dynamic panel data econometric framework to examine the market seeking, resource seeking, and the efficiency-seeking motives of FDI inflow to the MENA region.

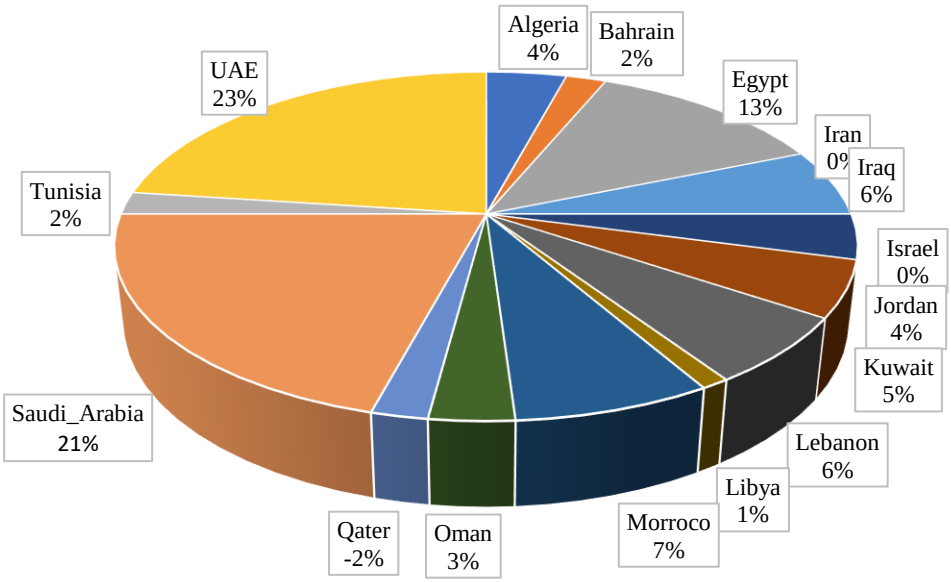

Figure 1. FDI inflows by MENA country destination (% of the total)
Source: https://unctad.org

MENA FDI location attractiveness is based on a two-dimensional viewpoint: Firstly, the MENA region is crucial for MNEs to maintain its numerous facilities at different locations to ensure efficient production of goods and services, particularly as it relates to oil and gas. Therefore, understanding the key drivers that improve or hinders its business operation in the region will be useful to management in the pre-investment decision. Secondly, the government are desirous of paying its debts and achieving its policies goals. Therefore, home policies need to be adjusted to attract potential investors to complement revenue generated through natural resources exportation. Therefore, this paper empirically examines the motives and drivers of foreign investment decisions in the MENA region.

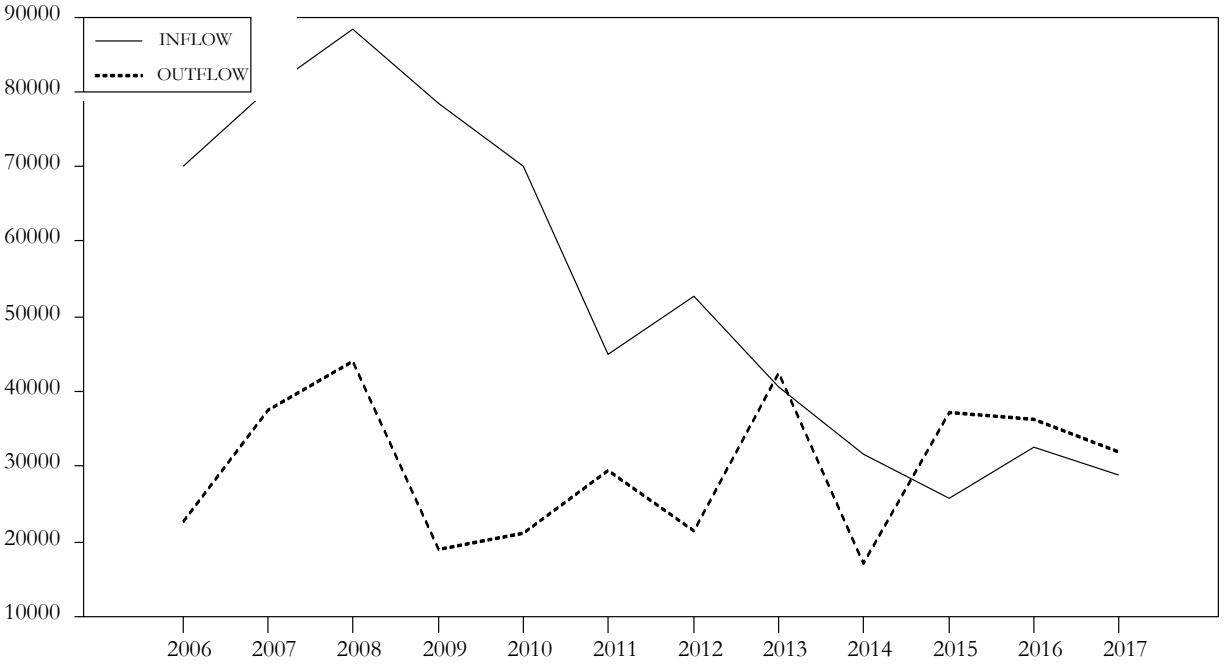

Figure 2. FDI inflows into and outflows from the MENA (US$ million, 2006-2017
Sources: OECD, Annual Investment Climate 2018 Report

Numerous studies on FDI determinants suggest that a plethora of factors can influence the decision of FDI location. Market size (GDP growth) is suggested as one of the most significant drivers determining FDI flow. For instance, using aggregate data with per capita GNP as a proxy for market size, empirical results reveal dominant variables that influence FDI in developing countries (Root & Ahmed, 1979). Factors such as availability, access to raw materials, cost, and labor supply strongly impacted FDI choice location (Dunning, 1988). However, another strand of studies has shown that a lower labour cost can also attract FDI inflow to a particular region or country. For example, Tsai (1994) study found that while higher labor costs discourage FDI inflow, lower labor costs attract more FDI to countries. Large numbers of studies have shown that political stability/instability can also influence the flow of investment (FDI) to location. Early studies such as Schneider and Frey (1985) and Bollen and Jones (1982) suggest that politically unstable countries are not attracted to foreign investments. In order words, their results suggest that political instability significantly reduces FDI inflow.

However, another strand of studies has also examined FDI locational flow to regions or groups of countries. For example, MNCs' motivations that significantly contribute to FDI inflow to invest in Vietnam service industries are marketing seeking, culture and government policies (Saleh, Anh Nguyen, Vinen, & Safari, 2017). Tax optimization, geographical distance and global production chain considerations are often one major motivation for firms entering Visegrad countries (Czech Republic, Hungary, Poland and Slovakia) to go through a country with a more favourable regulatory environment (Gubik, Sass, & Szunomár, 2020). Infrastructures such as roads, ports, and telecommunication predominantly contribute to FDI inflow across the Indian States. However, labor efficiency seems to motivate a firm more than other specific factors (Chakraborty, 2018). The motive for Chinese investment in the EU is market seeking. For most countries, technology integration and the consolidation of capacities across the supply chain were key motivations in most cases studied (Curran, Lv, & Spigarelli, 2017). However, Bartels, Alladina, and Lederer (2009) study showed that FDI location decision in ten (10) Sub-Saharan Africa (SSA) is influenced strongly by political economy considerations compared to labor and production input variables.

The plethora of empirical literatures on FDI has focused extensively on the determinants of FDI inflow to host countries. Most of these studies such as Minh (2019), Sabir et al. (2019), etc., explored these various determinants with a focus on the host institution. Minh (2019) paper

examines the effect of institutional quality on FDI inflows in Vietnam using different GMM estimations. Their results reveal that institutional quality is significant in explaining the FDI influx to Vietnam. An institution such as legal structure and strong property rights, freedom to trade, and civil liberty have a strong positive impact on inward FDI flows. Other studies on institutions and FDI relations Tomelin et al. (2018) etc.

In addition to examining how institutional factors, political risks, and microeconomics factors affect the influx of FDI to the region (Krajnakova, Pilinkiene, & Bulko, 2020; Mahmood, 2018), literature has examined some vital determinants as their effects on FDI inflow to countries. Hirsch, et al. (2020) used gravity analysis to examine the effect of water resources as a determinant for FDI on Land. Their experiment shows the importance of water resources in the production area and not only land abundance. Osei, Omar, and Joosub (2020) investigate the impact of colonial ties in attracting FDI to Ghana. Their experiment shows that colonial relations have limited influence on FDI inflow to Ghana. Radić (2018) study examines whether terrorism plays an important factor in the investment decisions of FDI in tourism. They employed the system GMM, and the results show that terrorism is insignificant to FDI inflow in the tourism industry.

Many methods have been used to examine the concept of Dunning's 1980 paradigm to explain FDI motivations in different economies. For instance, Okafor, Piesse, and Webster (2015) paper investigated four FDI motives for MNEs in sub-Sahara African (SSA) countries using panel data techniques such as OLS, FE, and GMM, Saleh et al. (2017) employed the structural equation modelling technique to show that the critical determinants of MNEs' incentives to invest in the service sector across Vietnam are market seeking government policies and culture. This research paper applies SYS-GMM, fixed effects, and pooled OLS estimators to investigate the motivational factors of MNEs FDI inflows to MENA countries. The dynamic panel equation has several econometric drawbacks: endogeneity, heterogeneity, simultaneity bias, omitted variable bias, reverse causality, etc. The empirical results from the regression model can yield inconsistent and biased estimates if Pooled OLS is applied. Although the Fixed effects models can address the issue of omitted variable bias, they still suffer numerous limitations such as low statistical power, time invariance, unobserved heterogeneity, measurement error, limited periods, etc. (Hill, Davis, Roos, & French, 2020). However, the SYS-GMM technique developed by Blundell and Bond (1998) accounts for the numerous econometric issues, reduces the finite sample bias, and has better precision of estimated coefficients due to its capacity to account for weakly exogenous instruments. Besides correcting heterogeneity and endogeneity problems in the panel, the SYS-GMM estimator also accounts for heteroskedasticity of unknown forms (Baiashvili & Gattini, 2020).

This paper uses the institutional factors as a proxy for efficiency-seeking indicators. Some of the institutional factors considered in this paper include the reliability of police, legal framework, intellectual property, the burden of government regulation and transparency of government policies. The motive of FDI inflow is examined in the context of the MENA region.

Methods

Preliminary Data Analysis

Table 1 shows the variables definition and data sources used in examining the drivers and motivations of FDI inflow in the MENA region were collated from different reliable sources. Nevertheless, due to the non-availability of data, this study dataset covers sixteen (16) countries in the MENA region from 2005 to 2019 with strongly balanced panel data, shown in Appendix Table A1. In Table 2, we showed the comparison of FDI inflow to the MENA region. The coefficient of variation confirms the uneven distribution of FDI inflows across MENA countries. Figure 3 shows the graph of FDI inflow for countries in the MENA region for the period 2005-2019. The trend of FDI inflow to Algeria, Egypt, Iraq, Kuwait, Oman, and Qatar confirms the results in Table 2 countries with more divestment economies. While some countries such as Jordan, Saudi Arabia, Qatar, Morocco, Lebanon, and Libya continue to experience a decline in inward FDI, few other countries (Tunisia, UAE, and Bahrain) have received almost predictable FDI inflow in recent years.

Table 1. Definitions of variables and data sources

Variables	Definitions of variables	Sources
IFDI	Foreign direct investment, net inflows (% of GDP)	WDI
Market seeking motives		
PO	Population growth of countries	WDI
EX	Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. Data are in constant 2010 U.S. dollars.	WDI
GD	GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. Data are in constant 2010 U.S. dollars.	WDI
Resource seeking motives		
IM	Imports of goods and services indicate the value of all goods and services received from the rest of the world. Data are in constant 2010 U.S. dollars.	WDI
QI	This is the overall quality of infrastructure in the country. This includes the quality of roads, railways, airports etc.	WEF
HR	This is the Human Development Index (HDI), a composite index measuring three basic dimensions, a long and healthy life, knowledge and a decent standard of living.	UNDP
NR	This is the abundance of natural resources. It is the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, forest rents etc.	WDI
IU	Internet users are individuals who have used the internet (from any location) in the last three months. The internet can be used via a computer, mobile phone, etc.	WDI
MS	Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service that provides access to the PSTN using cellular technology.	WDI
Efficiency seeking motives		
RP	Reliability of police services 1-7 (best)	WEF
LF	The efficiency of the legal framework in settling disputes 1-7 (best)	WEF
IP	Intellectual property protection 1-7 (best)	WEF
GR	The burden of government regulation 1-7 (best)	WEF
TG	Transparency of government policymaking, 1-7 (best)	WEF
Control variable		
IF	This is the inflation, a GDP deflator (annual %). Inflation is measured by the annual growth rate of the GDP implicit deflator. It shows the rate of price change in the economy as a whole.	WDI

Source: http://wdi.worldbank.org, https://www.undp.org/, https://www.weforum.org
Note: All the monetary measures are in US dollars, and the institutional factors are rated on a scale of 1 – 7

Table 2. Country Comparisons of FDI Inflows ($US billion, 2005 – 2019)

Variable	Mean	Std. Dev.	Coef. of var.	Min.	Max.
Algeria	1.032	0.539	0.290	-0.323	2.002
Bahrain	4.534	4.566	20.845	0.209	15.751
Egypt	3.613	2.759	7.614	-0.205	9.349
Iran	0.734	0.226	0.051	0.480	1.276
Iraq	-0.666	2.214	4.900	-4.337	1.561
Israel	4.225	1.760	3.098	1.954	9.346
Jordan	8.111	6.109	37.320	1.855	23.537
Kuwait	0.578	0.646	0.417	-0.015	2.115
Lebanon	8.484	3.949	15.593	4.276	14.881
Libya	2.392	1.776	3.155	1.002	6.945
Morocco	2.651	0.703	0.494	1.331	3.585
Oman	3.429	2.636	6.949	-3.176	7.918
Qatar	2.161	3.033	9.199	-1.600	8.308
Saudi Arabia	3.070	2.739	7.503	0.206	8.496
Tunisia	3.137	2.088	4.359	0.944	9.424
UAE	3.049	1.556	2.422	0.447	6.035

Note: 1. Source: Authors' calculations.
2. Data Source: World Bank Development Indicators.

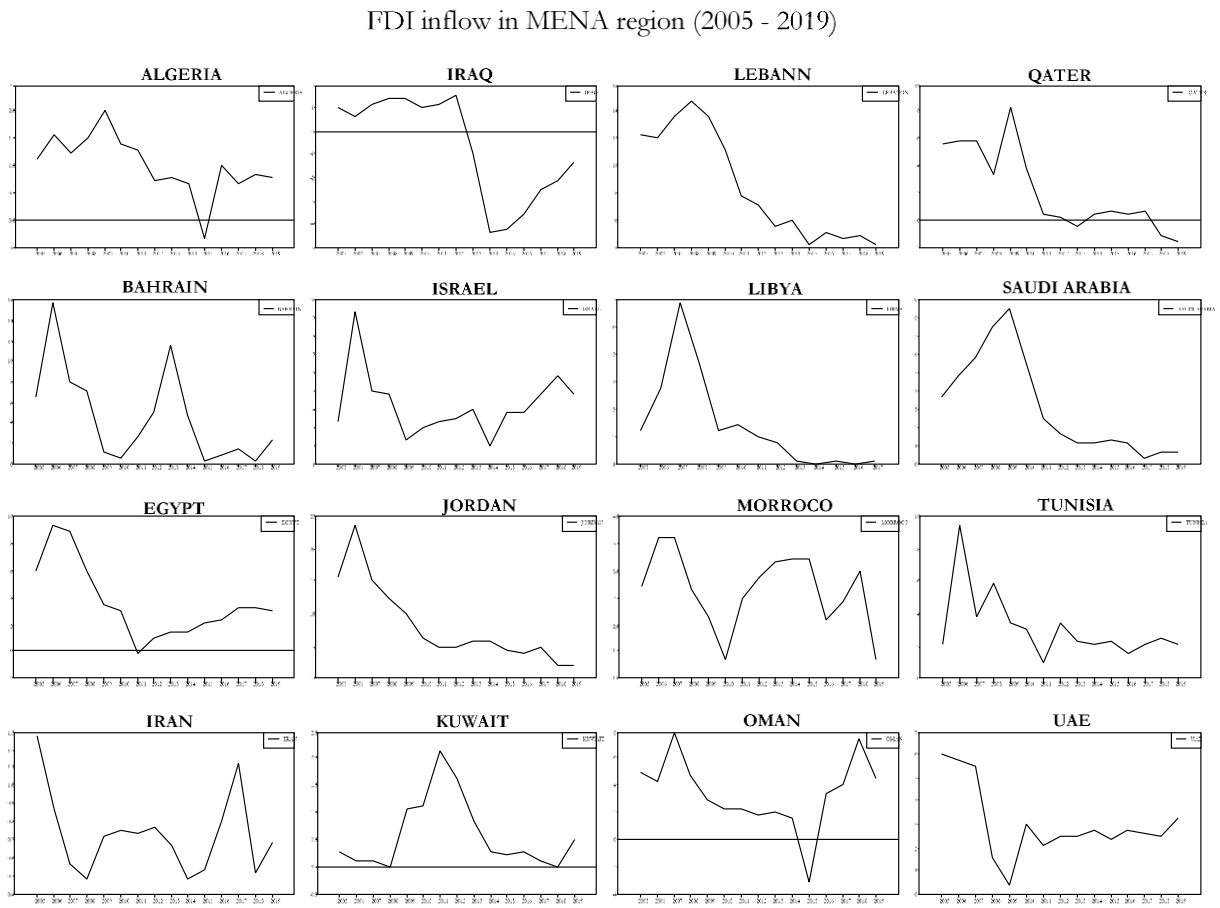

Figure 3. The yearly FDI inflow series plots of MENA countries (US$ billion, 2015-2019)

Model Specification

However, when one MNEs invests in a particular location or region, there is a tendency that other MNEs may follow. In order words, the inflow of FDI may induce additional FDI. For this reason, lagged FDI is included in the model, but this may lead to potential endogeneity problems and other econometric problems such as simultaneity bias, omitted variables and violate the OLS assumptions (Nickell, 1981). To this end, we used the dynamic System General Methods of Moments (SGMM) technique proposed by Arellano and Bover (1995) and Blundell & Bond (1998) which account for several econometric problems to determine the motives behind FDI flow to the MENA region.

$$FDI = f(Marketing\ seeking, Resources\ seeking, Efficiency\ seeking) \quad (1)$$

$$FDI_{it} = \beta_0 + FDI_{t-1} + \beta_1 Market\ seeking_{it} + \beta_2 Resource\ seeking_{it} + \beta_3 Efficiency\ seeking_{it} + \beta_4 Control\ variables_{it} + \gamma_t + \eta_i \quad (2)$$

Where,

γ_t indicates the unobserved effect across countries in the region, η_i indicates the unobserved country effects, which are constant over time and the variables indicating motives (market, resource and efficiency have been listed in Table 1). Thus, we specific the baseline model,

$$FDI_{it} = \beta_0 + FDI_{t-1} + \beta_1 PO_{it} + \beta_2 EX_{it} + \beta_3 GD_{it} + \beta_4 IM_{it} + \beta_5 QI_{it} + \beta_6 HR_{it} + \beta_7 NR_{it} + \beta_8 IU_{it} + \beta_9 MS_{it} + \beta_{10} RP_{it} + \beta_{11} IP_{it} + \beta_{12} GR_{it} + \beta_{13} TG_{it} + + \beta_{15} IF_{it} + \gamma_t + \eta_i \quad (3)$$

Where,

FDI_{it} indicates home country i investment inflow at time t in the region

PO_{it} indicates the population growth of home country i at time t in the MENA region,
EX_{it} indicates home country exports i at time t in the region,
GD_{it} indicates the GDP per capital of country i at time t in the region,
IM_{it} indicates home country imports i at time t in the region,
QI_{it} indicates the quality of infrastructure in country i at time t in the region,
HR_{it} is the human development index in country i at time t in the region,
NR_{it} indicates the natural resources in country i at time t in the region,
IU_{it} indicates the numbers of internets users in country i at time t in the region,
MS_{it} is the number of mobile telephone subscribers in country i at time t in the region,
RP_{it} indicates the reliability of police services in country i at time t in the region,
LF_{it} indicates the efficiency of the legal institution in country i at time t in the region,
IP_{it} indicates the intellectual property right in country i at time t in the region,
GR_{it} indicates government regulations in country i at time t in the region,
TG_{it} indicates transparency in government in country i at time t in the region,
γ_t indicates the unobserved effect across countries in the region,
η_i indicates the unobserved country effects, which are constant over time.

Results and Discussion

The highest value in our pairwise correlation matrix is 0.547, see Table A3. According to the rule of thumb, severe multicollinearity may be present if the correlation > 0.55. Hence, there is the absence of multicollinearity. However, some variables that were initially added to the group were expunged because the matrix values were more than the recommended rule of thumb. Table 3 reports the results of Im, Pesaran, and Shin (2003) and Levin, Lin, and James Chu (2002) panel unit root test at the level and first difference reject the null hypothesis of common unit root for almost all variables. The Hausman test result indicates the fixed effects as an appropriate model against the random effects estimations. According to Nickell (1981), the fixed and OLS estimators can be biased. To avoid potential econometric issues such as endogeneity, simultaneous bias, reverse causality, etc., this paper relies on the estimated results of the SYS-GMM technique to report firms' investment motivation in the MENA region.

Table 4 presents the results that explain the inward FDI flows into MENA countries using the One-step system GMM dynamic panel-data estimation. The Hansen test specification for override restrictions indicates that the chosen instruments for endogenous variables are valid. Besides the non-significance of the Hansen test, the autocorrelation of the first order is significant but insignificant in the second order. This strongly confirmed the consistency and reliability of the estimated coefficient, above all, justified the use of the SYS-GMM estimation technique. Expectedly, the GDP growth, population and export variables used for market seeking motivation of MNEs are positive and significant. The positive relationship of GDP growth with FDI inflow in the MENA region suggests that the market size of host countries significantly influences FDI location in the region. In order words, firms' investment decisions in MENA countries are partly driven by the host market's market size growth or GDP. Traditionally, the population of host countries is one of the motivations favouring a firm's location decision. Thus, the population's positive relationship with FDI inflow supports FDI inflows to countries in the MENA region. Export of goods and services from the region, probably exportation of oil and gas may be another reason for firm's relocation to MENA country. This indicates that firms consider these factors before deciding to invest in the MENA region. These results suggest that trade liberalization has improved, and governments of various countries and regions should continue to maintain and improve FDI policies in their countries. The fixed effect and Pooled OLS estimation results in Table 4 seem to be downward and upward biased of the estimated SYS-GMM coefficients. This appears to be within this Nickell (1981) assertion of lower and upper bound biases of estimates. This indicates the consistency of the estimated results.

Table 3. Panel unit root/stationarity test

Variables	Unit root tests	At Level		At first difference	
		Intercept	Intercept+Trend	Intercept	Intercept+Trend
FDI	LLC	-4.214***	-2.439***	-4.659***	-10.781***
	IPS	-0.251**	-0.437*	-1.937*	-1.353**
PO	LLC	-14.027**	7.184***	-52.231**	-93.611***
	IPS	-6.837*	-9.362**	-14.736	-13.771*
EX	LLC	91.835*	32.212***	-12.255***	-18.355***
	IPS	-22.425**	-26.718*	-17.236**	-16.283*
IM	LLC	-154.917***	-307.622***	-58.181***	-216.578***
	IPS	31.226	27.539*	19.357*	20.092
GD	LLC	-30.564***	-122.385*	-67.630***	-49.272***
	IPS	-11.272*	-13.563*	-14.836*	-17.530**
QI	LLC	12.765***	-20.683***	-4.210***	-20.008***
	IPS	3.673	5.902*	2.763*	4.125
IF	LLC	-1.918**	-0.816	-17.563***	-16.604***
	IPS	-0.342*	-0.738*	-0.219**	-0.811*
HR	LLC	-2.616***	-75.062***	-11.612***	-14.630***
	IPS	0.532*	0.663***	-0.362**	-0.183*
NR	LLC	3.366*	4.779*	-16.825***	-20.171***
	IPS	0.263***	0.346***	-9.452*	-7.185**
IU	LLC	-3.344***	-1.338*	-43.724***	-12.215***
	IPS	-0.863*	-0.463	-3.253*	-7.352**
MS	LLC	-9.321***	-9.486***	-11.470***	-20.749***
	IPS	-0.839**	-0.743**	-2.573**	-5.742**
RP	LLC	-267.372***	-1.368*	-10.687***	-9.296***
	IPS	-27.673	-21.509*	-4.252**	-2.647
LF	LLC	1.234*	-1.847***	-8.302***	-5.771***
	IPS	0.467	0.173*	-0.537	-0.462*
IP	LLC	-1.924**	0.997*	-4.340***	-9.015***
	IPS	0.374*	-0.684**	-0.363*	-0.211
GR	LLC	-6.904***	-1.011*	-8.519***	-9.752***
	IPS	-0.219**	-0.138	-7.282**	-5.273*
TG	LLC	-0.812*	-0.033**	-5.5987***	-7.758***
	IPS	-0.261**	-0.532*	-1.973*	-2.527**

Note:
1. Source: Authors' calculations.
2. *, ** and *** indicates 10%, 5% and 1% significance respectively
3. LLC indicates Levin et al. (2002), IPS indicates Im et al. (2003)

The import, human resources, an abundance of natural resources and mobile subscription variables significantly use the SYS-GMM. Still, only imports and human resources factors are significant when the fixed effects technique is used. The relationship between FDI flow and imports is negative and significant, which implies that imports of goods and services for countries in the MENA region are not an attracting factor for firms. Perhaps, these imports are not needed in MNEs investments in the region. The quality of infrastructures in the MENA region is MNEs specifics as reported by the fixed effects estimator. While some MNEs are motivated by the quality of infrastructures, others simply don't consider the quality of infrastructure in MENA countries during investments planning. These estimated results imply a need for the government of countries in the region to address the infrastructural deficit and coordinate the import activities of local firms and foreign firms so that imported produces can complement or be useful to other firms. Regarding transparency, the government should ensure a flow of information about its policies and programs to the citizens and foreign investors, as this will help eradicate or reduce the fear of expropriation or nationalization by the government. Although specificity exists for various countries, the government should 'roll out' necessary incentives such as tax reductions to encourage more mobile telecom firm investment in the region.

Table 4. Estimation results for the motivation of MNEs in MENA countries

Variables	SYS-GMM	Fixed Effect	Pooled OLS
Lagged FDI	0.516***	0.484***	0.801***
Market Seeking			
PO	0.618*	0.541****	0.639*
EX	0.591****	0.502**	0.734
GD	0.267**	-0.680*	0.321**
Resource seeking			
IM	-0.284**	-0.484*	-0.313
QI	-0.426	-0.393	-0.497
HR	0.626**	1.003**	1.101
NR	0.147***	0.058	0.193**
IU	-0.117	-0.130	-0.043
MS	0.204*	0.141	0.233
Efficiency seeking			
RP	0.334***	0.297***	0.362**
LF	0.159**	0.143	0.279*
IP	0.296	0.287*	0.307
GR	0.403**	0.324*	0.523*
TG	-0.452	-0.471	0.473
Control Variables			
IF	-0.197	-0.188	0.642
Constant	5.002***	4.277**	5.714*
Numbers of Observation	223	223	223
Numbers of groups	16	16	16
R Squared	-	0.571	0.826
Wald χ^2	527.3	-	-
Prob > χ^2	0.000	-	-
Arellano-Bond AR (1) (p-value)	-11.341 (0.000)	-	-
Arellano-Bond AR (2) (p-value)	-10.872 (0.309)	-	-
Hansen test (p-value)	7.306 (0.411)	-	-

Note:
1. Source: Authors' calculations.
2. Lagged IFDI is for one year
3. *, ** and *** indicates 10%, 5% and 1% significance respectively

The human resources and the abundance of natural resources determinants are positive and significant. This indicates that one of the numerous reasons for FDI flow in the region is the availability of these factors. Besides motivation due to the abundance of natural resources, the presence of human resources (in the form of professional or expertise) is another motivation for MNEs investment. This research paper has shown that the importation of goods and services by host countries motivates MNEs' investments. However, efficiency motives such as RP, LF, IP, and GR are also positively significant. Therefore, the government should sustain and improve these determinants to ensure an effective and efficient working environment that motivates investors. Previous studies by Duanmu (2012), Kinoshita and Campos (2003), etc., showed that institutional factors play a big role in FDI flow. Therefore, we used the institutional factors as proxies for efficiency-seeking FDI motivations in the MENA region. We employed host countries' institutional factors such as reliability of police services, the efficiency of the legal framework in settling disputes, intellectual property protection, the burden of government regulation and transparency of government policymaking. Empirical results shown in Table 4 revealed that the reliability of police services, the efficiency of the legal framework and government regulations are positive and significant. However, most studies often use Inflation as a substitute variable to capture efficiency-seeking FDI motivation; expectedly, the result shows that the relationship

between inflation and FDI in the MENA region is negative, see Table 4. The negative relationship of inward FDI-inflation indicates that a low inflation rate increases the influx of FDI into the region. This research controlled for the inflation variable; nevertheless, this factor is insignificant in relation to the inflow of FDI in the region.

Robustness Checks

To verify the consistency of the results of this research paper, we examined the adequacy of our model estimations by conducting a robustness check. The estimation of the lagged FDI variable for both the static and dynamic panel approach is positive and significant. This suggests that the demonstration effect of the FDI inflow into the region supports the three categories of FDI motives examined in this research paper. In the static models, the R squared values in the fixed effects model are shown to be 0.571, see Table 4. This indicates that the model explains about fifty-seven per cent (%) variations of the MNE's motives regarding FDI inflow to the MENA region. The pooled regression model estimation also reveals the value of R squared as 0.826, suggesting that the model's inputs explained more than eighty per cent (%) of the observed variation. The dynamic SYS-GMM model showed that the econometric problems connected with reverse causality, endogeneity, omitted variables bias, and instrument proliferation are controlled. The values of Arellano-Bond tests 1 and 2 and the Hansen test of override restrictions suggest that the dynamic panel data estimation results are robust and empirical results are reliable.

Conclusion

This research paper examines the market-seeking, resource-seeking, and efficiency-seeking motives of FDI inflow to the MENA region from 2005 to 2019. Empirical results suggest that besides other motives, resources and market-seeking remain the primary objectives amongst investors in the MENA region. This means that the MNEs in the MENA region are interested in supplying their home markets and their foreign affiliates with relevant goods and services. Still, they are also fascinated with securing dominant positions in the local markets to provide specific local market requirements for expanded customers overseas. The policy implication implies that countries in the region should ensure transparency in government policies, such as sharing information with their citizens and partners to make an informed decision and reduce risk. Foreign investors need transparent policies and information to make a quick decisions, especially during a crisis. Governments of host countries in the MENA region also need to improve the overall quality of infrastructure in their countries, as insufficient infrastructure is a disincentive for foreign investment. One of the limitations of this research paper is the inability to use the full panel of eighteen countries in the MENA region due to the non-availability of data. Nevertheless, for future research, we suggest that the externalities effect of these FDI motivations on local export should be examined.

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Appendix

Table A1. List of countries in the MENA region

S/No	Countries	S/No	Countries
1	Algeria	10	Libya
2	Bahrain	11	Yemen*
3	Egypt	12	Morroco
4	Iran (Islamic Republic of)	13	Oman
5	Iraq	14	Qatar
6	Israel	15	Saudi Arabia
7	Jordan	16	Syria*
8	Kuwait	17	Tunisia
9	Lebanon	18	United Arab Emirate

Note:
1. MENA countries listing according to USTR data
2. * Indicates countries not included in the final sample

Table A2. Descriptive statistics

Variable	Obs.	Mean	Std.Dev.	P25	P75	Min.	Max.	Skewness	Kurtosis
FDI	223	0.346	0.446	0.039	0.684	-1.029	1.372	-0.445	3.117
PO	240	4.081	0.496	5.002	4.577	2.837	5.112	0.127	2.832
EX	232	10.713	0.418	10.429	10.959	9.966	11.618	0.227	2.401
GD	240	4.022	0.449	3.634	4.395	3.332	4.843	0.276	1.668
IM	232	10.652	0.343	10.381	10.842	10.008	11.496	0.578	2.722
IF	193	0.740	0.535	0.437	1.164	-0.965	1.567	-0.893	3.377
IU	239	1.552	0.395	1.328	1.845	-0.046	2.000	-1.471	5.781
MS	240	7.035	0.533	6.650	7.517	5.855	8.072	-0.072	2.190
QI	230	0.616	0.126	0.552	0.701	0.184	0.811	-0.904	3.344
NR	224	0.807	1.171	0.529	1.573	-3.088	1.838	-1.895	6.060
HR	240	-0.120	0.044	-0.144	-0.089	-0.237	-0.037	-0.340	2.577
RP	192	0.669	0.101	0.611	0.752	0.302	0.811	-0.747	3.012
LF	159	0.599	0.089	0.535	0.664	0.383	0.765	-0.219	2.391
PR	182	0.642	0.090	0.576	0.716	0.361	0.777	-0.752	2.771
IP	170	0.588	0.117	0.494	0.686	0.250	0.777	-0.464	2.461
GR	183	0.541	0.094	0.469	0.615	0.305	0.728	0.011	2.281
TG	183	0.614	0.083	0.555	0.677	0.383	0.765	-0.426	2.556

Table A3. Correlation matrix coefficients for Inward FDI motive in MENA region

		PO	EX	FDI	GD	IM	IF	IU	MS	QI	NR	HR	RP	LF	IP	GR	TG
1	PO	1															
2	EX	0.126	1														
3	FDI	-0.165	0.002	1													
4	GD	0.473	-0.034	-0.150	1												
5	IM	0.146	0.295	0.039	-0.079	1											
6	IF	-	-0.025	0.002	-0.057	-0.045	1										
7	IU	-0.067	0.028	-0.062	0.422	0.039	-0.356	1									
8	MS	0.300	0.214	-0.251	-0.493	0.218	-0.003	-0.020	1								
9	QI	-0.025	0.022	-0.028	0.424	0.015	-0.085	0.386	-0.052	1							
10	NR	0.105	0.024	-0.455	0.202	-0.037	0.293	-0.227	0.192	0.252	1						
11	HR	-0.473	0.041	-0.009	0.436	0.015	-0.088	0.547	-0.350	0.402	-0.037	1					
12	RP	-0.134	-0.074	-0.026	0.195	-0.070	-0.098	0.395	0.083	0.505	0.167	0.215	1				
13	LF	-0.039	-0.009	-0.206	0.131	-0.009	-0.245	0.462	0.195	0.399	0.087	0.206	0.513	1			
14	IP	-0.139	-0.030	-0.151	0.201	-0.032	-0.184	0.457	0.150	0.484	0.124	0.245	0.444	0.340	1		
15	GR	-0.047	-0.066	-0.070	0.169	-0.062	-0.153	0.418	0.132	0.499	0.122	0.204	0.346	0.459	0.349	1	
16	TG	-0.104	-0.075	-0.086	0.164	-0.069	-0.165	0.417	0.139	0.493	0.112	0.200	0.356	0.463	0.347	0.486	1

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On the asymmetric effect of real exchange rate on growth: Evidence from Africa

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Abstract

Purpose — This study investigates the asymmetric effect of real exchange rates on the economic growth of twenty African countries for the period 2005 to 2019.

Design/Method/Approach — A refined method of Granger and Yoon (2002) was used to decompose real exchange into appreciation and depreciation. To address the problem of endogeneity and cross-sectional dependence, a two-steps system generalized method of moments, Driscoll-Kraay estimator, and Augmented Mean group were used.

Findings — This study established the presence of asymmetries in the real exchange rate in the region. Further, the study found that real exchange rate appreciation inhibits economic growth while real exchange rate depreciation is beneficial to growth in the region. The results are robust to different estimation techniques.

Practical Implications — The outcome of this study supports the traditional view of exchange rates on macroeconomic variables. Hence, findings from this study can help investors and policymakers in the region to better understand the dynamics of the exchange rate and its effect on economic growth.

Originality/Value — This study enriches the literature on the relationship between exchange rate and growth, especially in Africa using a refined approach to decompose exchange rate into appreciation and depreciation.

Keywords — Real exchange rate appreciation, real exchange rate depreciation, growth, Africa

Introduction

The importance of the exchange rate on macroeconomic variables has led to a subject of great debate among researchers, policymakers, and international bodies alike. Exchange rate management determined the performance and outcome of an economy since it serves as a vehicle that connects the local economy to the rest of the world (Dada, Olomola, & Adedokun, 2021; Iyke & Odhiambo, 2017; Olomola & Dada, 2017; Ozturk, 2006; Tiwari & Shahbaz, 2013). Further, a competitive exchange rate is needed especially in developing countries to achieve growth targets and desirable macro-economic objectives of government (Rapetti, Skott, & Razmi, 2012; Rodrik, 2008). In the literature, two views are broadly recognized as the effects of real exchange rates on macroeconomic variables. The traditional economists suggest that exchange rate depreciation is expansionary through an increase in net exports by substituting imports with

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home goods, thus boosting domestic production and putting the economy on a path of sustained growth (Dornbusch, 1988; Rodrik, 2008); while the reverse holds for exchange rate appreciation. On the other hand, the New Structuralists school of thought found that exchange rate depreciation could be contractionary instead of expansionary as suggested by the traditional school (Alexander, 1952; Dı´az-Alejandro, 1963; Krugman & Taylor, 1978). For instance, income could be redistributed from worker to producer as a result of the depreciation of currency thereby weakening the consumption component of aggregate demand through a reduction in marginal propensity to consume. In addition, depreciation of the exchange rate could increase the cost of imported factors of production, increase production cost and thereby reduce the effect on aggregate supply in the short run, and aggregate demand in the long run. This points to the fact that there are inherent asymmetric structures in the exchange rate (Mejıa-Reyes, Osborn, & Sensier, 2010; Parsley & Wei, 1993). That is, if depreciation improves economic growth, appreciation worsens it and its assumption does not hold in reality (Mohsen Bahmani-Oskooee & Fariditavana, 2016; Mohsen Bahmani-Oskooee, Halicioglu, & Neumann, 2018).

Scholars have identified four factors that could make the exchange rate exhibit asymmetry in its structures (Ahmad, Ahmad, & Ali, 2013; Y. Ahmad, Lo, & Staveley-O'Carroll, 2019; Cuestas, 2009; Dada et al., 2021; Juvenal & Taylor, 2008; Leon & Najarian, 2003; Sarantis, 1999; Sarno, Taylor, & Chowdhury, 2004). One, there are lots of trade barriers especially in developing countries such as transportation costs, tariffs, and other trade barriers which tend to be on the high side, thus, causing price gap among similarly traded goods (Bussiere, 2013; Dada et al., 2021; Peltzman, 2000). This price gap does not only occur in spatially separated markets but also the domestic market. Two, the intervention of monetary authority in exchange rate management and determination often leads to switching of the exchange rate from one regime to another one, usually an unstable regime (Arize, Malindretos, & Igwe, 2017; Chen & Lin, 2019; Dada, 2021). For instance, the desire of the apex bank to protect the export competitiveness of a country could force them to limit currency appreciations rather than depreciations, which has been termed the "fear of appreciation" hypothesis in literature. Three, the heterogeneous nature of market participants, their different perceptions, and imperfect information about the market could also make exchange rates exhibit asymmetry in their structures (Arize et al., 2017; Kilian & Taylor, 2003). Lastly, developing countries have witnessed a lot of structural breaks in their economies which may cause the exchange rate to adjust asymmetrically. However, earlier studies do not account for the asymmetric process in the exchange rate on macroeconomic variables (Mohsen Bahmani-Oskooee & Kandil, 2009; Christopoulos, 2004; McPherson & Rakovski, 1998).

Recent studies that have incorporated asymmetry into exchange rate have focused mainly on export (Adaramola, 2016; Oyovwi, 2012; Rahman & Serletis, 2009; Verheyen, 2013), pass through (Bussiere, 2013), trade balance (Arize et al., 2017; Mohsen Bahmani-Oskooee et al., 2018; Buba, Garba, & Guza, 2018; Dada & Olomola, 2017; Jibrilla Aliyu & Mohammed Tijjani, 2015; Kyophilavong, Shahbaz, Rehman, Souksavath, & Chanthasene, 2018; Nathaniel, 2020), reserve (Adler & Mora, 2011; Chen & Lin, 2019; Pontines & Rajan, 2011), inflation (Wimanda, 2014), etc. with little or no known study on the asymmetric effect of exchange rate on output especially in Africa which is one of the developing region and worst hit by factors that could make exchange rate respond asymmetrically. Further, exchange rate has a significant impact on developing economies rather than developed economies (Hussain, Hussain, Khan, & Khan, 2019; Stavárek, 2013). Previous studies that have assumed symmetric effect of exchange rate on macroeconomic variables especially growth are unable to differentiate the impact of depreciation from appreciation of exchange rate, which has important policy implications. Thus, the assumption of real exchange rate appreciation having opposite and equal effects as compared to real exchange rate depreciation on macroeconomic variables might be too restrictive. Succinctly put, economic agents react differently to exchange rate appreciation and exchange rate depreciation. It has equally been observed that human being tends to react more to positive shocks than negative ones (Granger & Yoon, 2002; Hatemi-J, 2012). Based on the foregoing, it is

imperative to allow for this new dimension by separating appreciation from depreciation in the link between exchange rate and output.

This study, therefore, contributes to the body of knowledge in the following areas. First, the study examines the asymmetric effect of real exchange rate on growth in African countries by decomposing exchange rate into both appreciations (negative shock) and depreciation (positive shock) since economic growth reacts differently to shocks from real exchange rate (Bahmani-Oskooee & Fariditavana, 2016). Second, the study adopts a robust method employed by Dada (2021), Granger and Yoon (2002), Hatemi-J (2012), dan Olaniyi (2019) to decompose exchange rate into appreciation and depreciation. This method helps to separate the impacts of positive changes from the negative ones and it is unique because economic agents in international markets react differently to appreciation and depreciation (good and bad news) (Gkillas, Vortelinos, & Suleman, 2018; Salisu & Umar, 2017). In addition, the approach helps to explore whether real depreciation or real appreciations, including their magnitudes, have different effects. The approach gives a better understanding of expansionary and contractionary policies in exchange rate management and gives better and more accurate policy options to policymakers in the region. Third, the study makes use of a technique that corrects for endogeneity in exchange rate-growth literature and spatial and cross-sectional dependence among the cross-sectional unit. Globalization of the world economies in the past few decades has made countries experience ever-increasing and knitted economic and financial integration, which is largely responsible for strong interdependencies among a cross-section of units (Ajide, Osinubi, & Dada, 2021; Akinlo & Dada, 2022; De Hoyos & Sarafidis, 2006; Sarafidis & Wansbeek, 2012). African countries, as cross-sectional units, are likely to be dependent on one another, given the level of economic integration in the region, thus, the need to consider cross-sectional dependence in the analysis arises.

Methods

To examine the asymmetric effect of exchange rate on economic growth in African countries, this study relies on modified Aggregate Demand (AD) framework to drive out the model. As stated by Mohsen Bahmani-Oskooee and Mohammadian (2017), the effect of exchange rate on output can be obtained from both the Aggregate Demand and Aggregate Supply sides of the framework. To avoid the problem of complexity in the relationship between forces of aggregate demand and aggregate supply; and also, the problem of multicollinearity among the variables, this study focuses mainly on the aggregate demand side. Adopting the study of Hussain et al. (2019), the modified aggregate demand model is stated thus:

$$GDP_{it} = f(RER_{it}, GEX_{it}, BM_{it}) \quad (1)$$

Where GDP is a proxy of output, RER is the real exchange rate, GEX is government expenditure and BM is the broad money supply. All variables are expressed in logarithms except the real exchange rate. The real exchange rate captures the interaction of the domestic economy with its foreign counterpart. It is incorporated into the model through the import-export sector of the economy. A rise in the value of the real exchange rate indicates depreciation of the domestic currency while a fall in its value signifies appreciation of the domestic currency. Government expenditure and broad money supply capture the fiscal and monetary policies respectively.

In specific terms, equation 1 can be expressed as:

$$GDP_{it} = \alpha_0 + \beta_1 RER_{it} + \phi_1 GEX_{it} + \eta_1 BM_{it} + \mu_{it} \quad (2)$$

Where μ_{it} is an error term.

From equation 2, the real exchange rate is separated into both depreciation (positive shock) and appreciation (negative shock) using the method developed by Granger and Yoon (2002) but later modified and used by Bahmani-Oskooee and Gelan (2008), Chen and Lin (2019), Dada (2021), Loretta and Liu (2007), and Maurizio, Elitza, and Livio (2016). The process of separating appreciation of real exchange rate from depreciation follows a random walk as explained thus:

$$RER_{it} = RER_{it-1} + \varepsilon_t = RER_0 + \sum_{j=1}^{t} \varepsilon_j \quad (3)$$

Where; t = 1, 2, 3,……T, the constant term RER_0 is the starting value of the variable while ε is the error term. The positive and the negative changes are stated as:

$$\varepsilon^+ = max(\varepsilon, 0) \quad (4)$$
$$\varepsilon^- = min(\varepsilon, 0) \quad (5)$$
Therefore, $\varepsilon = \varepsilon^+ + \varepsilon^-$ (6)

Substituting equations 4 and 5 in 3, it follows that:

$$RER_{it} = RER_{it-1} + \varepsilon_t = RER_0 + \sum_{j=1}^{p} \varepsilon_j^+ + \sum_{j=1}^{p} \varepsilon_j^- \quad (7)$$

Further, depreciation and appreciation of real exchange rate are defined as a cumulative sum:

$$POS = RER_{it}^+ = \sum_{j=1}^{p} \varepsilon_j^+ \quad (8)$$

$$NEG = RER_{it}^- = \sum_{j=1}^{p} \varepsilon_j^- \quad (9)$$

Where; POS is real exchange rate depreciation and NEG is real exchange rate appreciation.
Thus, appreciation (NEG) and depreciation (POS) of the real exchange rate in equations 8 and 9 are used to replace the real exchange rate in equation 2 (Arize et al., 2017; Mohsen Bahmani-Oskooee & Fariditavana, 2016; Dada, 2021; Hussain et al., 2019; Shin, Yu, & Greenwood-Nimmo, 2014).

$$GDP_{it} = \alpha_0 + \gamma_1 POS_{it} + \chi_1 NEG_{it} + \phi_1 GEX_{it} + \eta_1 BM_{it} + \mu_{it} \quad (10)$$

The a priori expectation of the variables are as follows:
The effect of the appreciation of real exchange rate (χ) and depreciation of real exchange rate (γ) on output is ambiguous (Arize et al., 2017; Dada, 2020), its effects could be negative or positive. If the coefficient of real exchange rate depreciation (γ) is positive (negative), then exchange rate depreciation increases (reduces) output. In contrast, the positive (negative) coefficient of exchange rate appreciation (χ) indicates that appreciation of real exchange rate improves (worsens) output. The positive effect of exchange rate appreciation and depreciation on output indicates that the exchange rate is expansionary, otherwise, contractionary. Government expenditure (ϕ) and broad money supply (η) are expected to have a positive effect on output.

To estimate equation 10, three different approaches namely, two-step system Generalised Method of Moments (GMM), Driscoll and Kraay (1998) (D-K), and Augmented Mean Group (AMG) are used. GMM accounts for the problem of endogeneity commonly found in the exchange rate-output relationship. D-K approach produces robust standard errors which correct for heteroskedasticity and autocorrelation in the error structure (Le & Tran-Nam, 2018). Furthermore, AMG account for both cross-sectional dependence and country-specific heterogeneity. Also, this study conducts a series of tests to determine the existence or otherwise of cross-sectional dependence. Similarly, the study adopts panel unit root tests that account for cross-sectional dependence.

The study period span 2005 to 2018. Twenty countries in Africa are selected based on the availability of data (see Appendix 1). Measurement and description of variables are presented in Appendix 2. The descriptive statistics of the variables are presented in Table 1. The result shows that output (GDP), government expenditure (GEX), and broad money supply (BM) are normally distributed since the measure of central tendency (mean and median) are very close. On the other hand, asymmetric components of real exchange rate i.e appreciation (NEG) and depreciation (POS) do not exhibit normal distribution in their mean and variance. This further laid claim to the presence of asymmetric structure in the real exchange rate in Africa. Furthermore, all the variables fall within their respective minimum and maximum values. The skewness statistics show

that all the variables are negatively skewed except exchange rate depreciation (POS). The synopsis of the correlation matrix in the lower part of Table 1 reveals the absence of multicollinearity among the variables.

Table 1. Descriptive Statistics and Correlation Matrix

	GDP	NEG	POS	BM	GEX
Mean	23.595	-18.612	16.176	36.129	106.002
Median	23.730	-11.158	12.618	35.438	107.226
Maximum	26.874	0.000	60.508	119.354	167.266
Minimum	20.457	-90.609	0.000	5.920	50.239
Std. Dev.	1.710	20.090	14.668	26.079	17.719
Skewness	0.142	-1.437	1.211	1.582	0.214
Kurtosis	2.218	4.436	3.688	4.886	5.209
GDP	1	-0.168	-0.052	0.418	-0.393
NEG		1	-0.340	-0.096	-0.116
POS			1	-0.336	0.045
BM				1	0.122
GEX					1

Where; GDP is output, NEG is an appreciation of real exchange rate, POS is exchange rate depreciation, BM is broad money supply and GEX is government expenditure.

Results and Discussion

Before examining the asymmetric effect of the real exchange rate on output in Africa, it is imperative to test for the presence of cross-sectional dependence among the countries. Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM and Pesaran CD were used to establish the existence or otherwise of cross-sectional dependence. The null hypothesis that the residuals are cross-sectional independence is tested against the alternative hypothesis that states the errors are cross-sectional dependence. The result of the cross-sectional dependence tests in Table 2 rejects the null hypothesis of cross-sectional independence among the countries using all four criteria. This result is not surprising, owing to several commonalities African countries shared such as trade, capital mobility, integrated financial systems, and exposure to common external shocks. Since the existence of cross-sectional dependence has been confirmed, first generational unit root tests are inept of addressing cross-sectional dependence, hence, second generational unit root tests such as cross-sectionally augmented Im, Pesaran, and Shin (CIPS) and cross-sectionally augmented Dickey-Fuller (CADF) are used. CIPS and CADF panel unit root tests are used to address the problems of cross-sectional dependence and heterogeneity in the data. CIPS is based on the null hypothesis of homogeneous non-stationary (Pesaran, 2007), while cross-section augmented Dickey-Fuller (CADF) rests on the null hypothesis that all the series are non-stationary in a heterogeneous panel with cross-sectional dependence. The unit root test presented in Tables 3 and 4 reveals that the variables are a mixture of both I(0) and I(1) variables using CIPS and CADF tests statistics.

Having established the presence of cross-sectional dependence, this study proceeds to examine the asymmetric effect of exchange rate on output in Africa using two-step system General Method of Moment (GMM), Driscoll-Kraay (D-K), and Augmented Mean Group (AMG) techniques. The estimates of the regression result are presented in Table 5. The results in Table 5 clearly show the evidence of asymmetric effect in the relationship between real exchange rate and output in Africa. From Table 5, appreciation of real exchange rate (NEG) exerts a negative and significant effect on output in the region. The negative impact of appreciation on output in Africa indicates that it requires more foreign currency to purchase a domestic product, thus, domestic product is relatively costly compared with their foreign counterpart. Furthermore, appreciation of domestic currency makes foreign goods cheaper to consume, hence, citizens with a taste for foreign goods will easily opt for it, thereby hurting domestic output since consumption of locally produced goods has reduced. This is in tandem with the studies conducted by Bahmani-Oskooee and Mohammadian (2017), Berg, Ostry, and Zettelmeyer (2008), Gala (2008)

who found a negative effect of exchange rate appreciation on output, but contrary to the findings of Dada et al. (2020), Mejıa-Reyes et al. (2010), and Schnabl (2008) who found that appreciation of exchange rate increases productivity and economic growth.

Table 2. Cross-sectional Dependence Test

	GDP	NEG	POS	BM	GEX
Breusch-Pagan LM	2023.726***	1881.489***	1941.056***	1054.808***	603.0243***
Pesaran scaled LM	94.068***	86.771***	89.827***	44.363***	21.187***
Bias-corrected scaled LM	93.298***	85.938***	88.993***	43.594***	20.418***
Pesaran CD	39.905***	43.021***	43.899***	24.640***	13.530***

Table 3. Unit Root Test with cross-sectional (Constant)

Variables	CIPS Test		CADF Test	
	Level	1st Difference	Level	1st Difference
GDP	-1.823	-2.687***	-1.880	-2.522***
NEG	-1.352	-2.659***	-1.673	-2.126*
POS	-2.113*		-2.064	-2.668***
BM	-2.465***		-2.440**	
GEX	-2.228**		-1.597	-2.571***
Critical values 10%	-2.11		-2.110	
5%	-2.22		-2.220	
1%	-2.45		-2.450	

Where *, ** and *** indicates 10%, 5% and 1% level of significant respectively

Table 4. Unit Root Test with cross-sectional (Constant and Trend)

Variables	CIPS Test		CADF Test	
	Level	1st Difference	Level	1st Difference
GDP	-1.982	-2.707*	-2.359	-2.685*
NEG	-1.729	-2.731*	-1.719	-2.631*
POS	-2.565	-3.280***	-2.565	-3.280***
BM	-2.792**		-2.792**	
GEX	-2.553	-4.296***	-2.553	-4.296***
Critical Values 10%	-2.65		-2.640	
5%	-2.77		-2.760	
1%	-3		-2.980	

Where *, ** and *** indicates 10%, 5% and 1% level of significant respectively

In contrast, depreciation of the exchange rate has a significant positive effect on output. This result reveals that the region will benefit from the depreciation of the real exchange rate since it increases output. Therefore, depreciation of the exchange rate is expansionary in Africa. This supports the Marshal-Learner condition. For African countries to fully benefit from the Marshal-Learner condition, the exchange rate must depreciate significantly so that the elasticity of export is more than import. In addition, depreciation of the exchange rate favors the tradeable sector through reallocation of resources, thereby increasing learning by doing and technological spillover in the economy (Eichengreen, 2008; Rodrik, 2008). The positive impact of the depreciation of the real exchange rate is confirmed by the theoretical work of Rodrik (2008). Rodrik (2008) postulates that real exchange rate depreciation is growth-enhancing in developing countries than developed countries. The outcome of this study conforms to the traditional school of thought. Other studies that found a positive effect of exchange rate depreciation on growth include Christopoulos (2004), Hausmann, Pritchett, and Rodrik (2005), and Rapetti et al. (2012), among others, but contrary to the studies of Ahmed (2003), Edwards (1986, 1989), Mejıa-Reyes et al. (2010), and Schnabl (2008).

Table 5. Estimation Results

Dependent Variable: GDP	Model 1 Two-Step GMM	Model 2 D-K	Model 3 AMG
GDP(-1)	0.031**		
	[-2.43]		
NEG	-0.012***	-0.008***	-0.010***
	[-6.94]	[-9.86]	[-5.12]
POS	0. 007	0.006***	0.004**
	[0.99]	[3.89]	[2.43]
GEX	3.812***	0.113**	0.034***
	[4.23]	[2.25]	[3.98]
BM	0.135***	0.023***	0.035*
	[5.21]	[10.29]	[1.683]
C	1.552***	2.786***	0.342***
	[3.41]	[4.03]	[4.49]
Observations	260	260	260
Number of groups	20	20	20
Wald Test	12.20***	19.67***	21.23***
Sagan Test	0.621		
AR(1)	0.002***		
AR(2)	0.274		
RMSE			0.0272

Where *, ** and *** indicates 10%, 5% and 1% level of significant respectively
[ ] are t-value
Wald Test is based on the null hypothesis of NEG=POS

The significant effect of exchange rate depreciation reveals that monetary authority in the region should not fear real exchange rate depreciation since it is beneficial to growth; on the other side monetary authority needs to fear exchange rate appreciation since its effect is significant and negative. This result further reveals that there will not be currency mismatch risk if the monetary authority in the region depreciates their currency. Comparing the magnitude of appreciation and depreciation of the exchange rate, the result shows that output responds more to appreciation than depreciation. This tallies with the studies conducted by Aguirre and Calderón (2005), Dhasmana (2015), Rahman and Serletis (2009), Razin and Collins (1999) that the response of output to exchange rate appreciation is more than that of exchange rate depreciation. Specifically, Razin and Collins (1999) found that the negative effect of overvaluation on growth is stronger than the positive effect of undervaluation, which suggests the existence of asymmetries in 93 countries (developed and developing countries). Contrarily, Arize et al. (2017) found that trade balance reacts more strongly to depreciations than to appreciations.

Besides, the nature of participants in the foreign exchange market could make depreciation and appreciation of the real exchange rate have a different effect on economic growth. For a risk-averse agent, depreciation of the real exchange rate will have much more effect on growth than appreciation of the real exchange rate. However, if economic agent in the foreign exchange market is risk-neutral, appreciation of the real exchange rate will be more felt than the depreciation of the real exchange rate. The outcome from this study reveals the importance of incorporating the asymmetric effect of the real exchange rate (appreciation/depreciation) into the exchange rate- output relationship since they have different magnitudes. Hence, previous studies on the relationship between output growth and exchange rate that was premised on a symmetric assumption, and the absence of cross-sectional dependence might have led to wrong policy prescription, especially in Africa. The fact that the null hypothesis of the coefficients of the asymmetric variables equals zero ($\chi_i = \gamma_i$) is rejected using the Wald test in all the regressions suggests that the difference between these two magnitudes is statistically significant, thus, establishing the need to incorporate asymmetric into the relationship.

Other control variables included in the model have a positive and significant effect on output in the region. Real activity responds positively to both fiscal and monetary policies. This result shows that government/monetary authority expansionary policies are beneficial to growth in Africa. This is in tandem with existing studies (Bahmani-Oskooee & Kandil, 2009; Hussain et al., 2019) that increase in government expenditure and money supply boost economic activities. Furthermore, the diagnostic indicators of the models are in the right magnitude. For instance, the Sargan test of over-identifying restrictions shows that the instruments used for the two-step GMM are valid and the model is free from second-order serial autocorrelation (AR(2)). Similarly, the root mean square error (RMSE) suggests that the error of the AMG model is minimized.

Conclusion

In this paper, one of the most important questions in monetary and international economics is being revisited; that is the effect of exchange rate on output, and whether output response to exchange rate asymmetrically in developing countries. Since it has been established in the literature that the impact of exchange rate is mostly felt by developing countries, this study focuses on twenty countries in Africa between 2005 and 2019. The real exchange rate was decomposed into appreciation (negative shocks) and depreciation (positive shocks) using a refined method of Granger and Yoon (2002). The objectives of the study are achieved using three estimation techniques, namely; two-step system General Method of Moment (GMM), Driscoll-Kraay (D-K), and Augmented Mean Group (AMG) which account for the problem of endogeneity and cross-sectional dependence.

The outcome of this study provides an interesting yet surprising result. The result reveals that the response of output to the depreciation of the real exchange rate differs significantly from the appreciation of the exchange rate in the region, thus confirming the presence of asymmetric structure in the real exchange rate in the region. Specifically, real exchange rate appreciation has a negative and significant effect on output, while on the other hand real exchange rate depreciation has a significant positive effect. This result shows that output in the region benefits from the depreciation of the exchange rate while appreciation hinders it. Further, the result shows that the region should not fear real exchange rate depreciation, rather real exchange rate appreciation should be dread in the region. The results are robust to different estimation techniques.

These results have some policy implications. First, the region needs to be fully liberalized and open to international trade to benefit from the depreciation of the real exchange rate. This will lead to an increase in the tradeable sector of the economy in the medium run, while in the long run, it will have a positive outcome on aggregate output. Similarly, overvaluation of the real exchange rate should be avoided, since it makes the region less competitive in terms of trade, thus, a decline in economic growth. However, caution needs to be taken in depreciating the real exchange rate beyond the threshold level, since most developing countries finance their project, and import most of their materials (raw and finished products) in foreign currency mainly US dollar which might likely have a recessionary impact on the economy. Lastly, policymakers should maintain competitive exchange rate policies that will stabilize the real exchange rate around its equilibrium level.

Also, it is imperative to note that this study has contributed significantly to the debate on the asymmetric effect of real exchange rate on output in African countries, however, non-availability of data on essential variables such as real exchange rate for some countries reduces the scope of study to twenty countries. Further, subsequent studies can extend this work to other developing countries and account for the cross-sectional dependence that is inherent in panel data.

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Appendix 1. List of Countries

Algeria	Burundi	Cameroon	Central African Republic
Congo	Cote d'Ivoire	Equatorial Guinea	Gabon
The Gambia	Ghana	Lesotho	Malawi
Morocco	Nigeria	Sierra Leone	South Africa
Togo	Tunisia	Uganda	Zambia

Appendix 2. Measurement and Description of Data

Variables Definition	Measurement	Source
Real Gross Domestic Product (GDP)	Constant 2005 in foreign currency unit ($)	World Development Indicator (WDI), 2018 edition
Real Effective Exchange Rate (RER)	Price of a US Dollar in terms of domestic currency (2010=100).	World Development Indicator (WDI), 2018 edition
Broad Money (BM)	Broad Money in terms of Domestic Currency as a percentage of GDP	World Development Indicator (WDI), 2018 edition
Government Expenditure (GEX)	Gross national expenditures as Percent of GDP	World Development Indicator (WDI), 2018 edition

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Does sectoral loan portfolio composition matter for the monetary policy transmission?

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Abstract

Purpose — The paper empirically explores the conditioning role of loan portfolio diversification in the monetary policy pass-through via the bank lending and risk-taking channels.

Methods — Data of Vietnamese commercial banks during 2007–2019 is employed to perform regression using the two-step system generalized method of moments in dynamic panel models. For robustness, we approach different choices of monetary policy indicators, ranging from interest-based tools to quantitative-based policy, and consider a rich set of sectoral exposure measures to proxy loan portfolio diversification.

Findings — Lower interest rates or greater liquidity injection during monetary expansion may increase bank lending and bank risk, thus confirming the working of the bank lending and risk-taking channels of monetary policy transmission. Notably, the potency of these banking channels may be weakened for banks diversifying loan portfolios more into various economic sectors.

Implication — The findings call for monetary authorities to concentrate on certain types of banks, depending on their loan portfolios when setting monetary policy. When managing banking supervision, banking supervisors should also acknowledge the tradeoff between bank lending and bank risk in response to monetary shocks.

Originality — For the first time, this paper explores the conditional role of loan portfolio composition and thus further supports the recent upsurge in empirical studies highlighting the role of business models in monetary policy pass-through.

Keywords — bank diversification, interest rates, liquidity injection, loan portfolios, monetary policy.

Introduction

Since the 2007–2009 financial crisis, a renewed interest has emerged in exploring banks' role in monetary policy transmission potency. This is specified under the bank lending channel as first Bernanke and Blinder (1988) first suggested, which asserts that monetary policy contraction cuts the number of loanable funds and potentially depresses lending activities if banks cannot gain new funds to reduce loanable ones. Besides quantity, credit quality has also received increasing attention, as monetary policy has often been one of the critical determinants of excessive bank risk-taking, despite the multifaceted causes of the crisis. Consequently, a growing line of research has referred to the monetary policy transmission through the bank risk-taking channel, which posits that

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decreased interest rates may enhance banks' risk tolerance. Fundamentally, this banking channel operates in several essential mechanisms, derived from bank incentives to "search for yield" (Rajan, 2006), investment valuation effects (Adrian & Shin, 2010), and communication policies (Borio & Zhu, 2012).

This paper relates to the literature streams on the bank lending and risk-taking channels of monetary policy pass-through. It is well established that if bank incentives are the core of these banking channels' functioning, it could be anticipated that bank characteristics would drive the link between bank lending/bank risk and monetary policy. Accordingly, most papers examine the extent to which banks' characteristics (such as bank size, capital, and liquidity) shape banks' reaction to monetary policy variations (Delis & Kouretas, 2011; Kashyap & Stein, 1995; Sáiz, Azofra, Olmo, & Gutiérrez, 2018). These studies indicate that financially weaker banks (i.e., smaller, less liquid, and more poorly capitalize more responsive to monetary shocks because of their limited access to alternative funding. However, in the period of financial innovation, these standard variables are considered inadequate to evaluate banks' ability to make additional loans as well as banks' incentives towards risk-take behavior. In addition to bank-level factors, some works also emphasize that reforms and changes in the financing may cause transformations in the potency of monetary policy pass-through, mainly through the bank lending channel (Hussain & Bashir, 2019; Leroy, 2014). Nevertheless, most patterns found are ambiguous and limited.

Our work aims to analyze further the interesting topics of the bank lending and risk-taking channels of monetary policy transmission by exploring the conditional role of loan portfolio diversification. Banks' loan portfolio behavior has attracted little attention in the existing monetary transmission literature. Prior research mostly examines the behavior components (for example, real estate loans, consumer loans and business loans) after monetary policy shocks (Den Haan, Sumner, & Yamashiro, 2009). In principle, banks' portfolio diversification matters for the behavior of their operations and thus could broadly influence the transmission effectiveness of monetary policy by weakening or strengthening the banking channels. The shifts towards diversified banking systems from increased market competition could ultimately lead to lower prices of financial products, better access to financing sources, and reduced informational asymmetries (Boot, 2000; Kashyap & Stein, 1995). Portfolio diversification might induce a detrimental effect on bank efficiency due to limited managerial expertise and experience, and it may force banks to engage in risk-taking strategies due to adverse selection (Acharya, Hasan, & Saunders, 2006). Moreover, banks diversify into various economic sectors to earn additional revenues and enhance their market position. Contrary to those that do not prefer diversification, they are more conservative and tend to conserve the outcomes by pursuing less risky projects (Căpraru, Ihnatov, & Pintilie, 2020).

We utilize the financial data of Vietnamese commercial banks during 2007–2019 to perform our empirical analysis. To guarantee the robustness of findings estimated by the generalized method of moments (GMM) estimator, we accept various alternative measures of crucial interest. For the diversification level of loan portfolios, we design a set of six sectoral exposure measures using the Herfindahl-Hirschman index (HHI) along with the Shannon Entropy (SE) index. We analyze both interest- and quantitative-based policy tools for monetary policy indicators, including short-term lending rates, refinancing rates, and security sales/purchases by open market operations. The growth rate of bank loan volume and the Z-score index are the fitted variables that capture bank lending and bank risk in the paper.

Vietnam displays some important features that make it an excellent laboratory to examine our research issue. First, commercial banks constantly hold a dominant position in the financial system and offer a major source of financing for the whole economy. Hence, the association between the banking sector and the monetary policy framework should be particularly conspicuous here (Dang & Dang, 2020; Dang & Huynh, 2021). Second, the State Bank of Vietnam (SBV) frequently combines many monetary policy tools to establish its multiple-goal mandate. In this regard, both interest- and quantitative-based tools are extensively utilized. Third, the influence of portfolio diversification strategies on the potency of monetary policy transmission should have taken much more attention due to the increasing reforms in Vietnam over the years. Concretely, the Vietnamese

banking system has considerably transformed from specialized segments to diversified operations, thereby reconstructing banks' exposures to all economic sectors (Huynh & Dang, 2021).

An emerging group of papers closely related to our work is Gambacorta and Marques-Ibanez (2011) and Dang and Dang (2021). They focus on the moderating role of business models in the association between monetary policy and lending activities. They reveal mixed results, i.e., the negative impact of monetary policy on bank lending is more pronounced for banks adopting a business model tilted towards non-traditional lines in advanced economies during the crisis (Gambacorta & Marques-Ibanez, 2011), whereas the potency of the bank lending channel is weaker as banks prefer non-interest segments in emerging markets during regular times (Dang & Dang, 2021). One key difference from our work is that they explore banks' revenue compositions, while we pay attention to loan portfolio diversification when approaching bank business models. Moreover, the two previous papers only study the bank lending channel. In contrast, we investigate bank lending and risk-taking behavior in reaction to monetary shocks to provide more insight into the moderating role of portfolio compositions in the pass-through mechanism.

The paper exhibits some contributions. While the existing documents favoring the bank-lending and risk-taking channels mainly focus on the conditional roles of multiple traditional bank-specific characteristics, we find no empirical evidence of these banking channels moderated by loan portfolio diversification. Our empirical paper is the first to fill in this gap and thus support the recent upsurge in empirical studies highlighting the importance of business models in the monetary policy pass-through analysis (Dang & Dang, 2021; Gambacorta & Marques-Ibanez, 2011). Additionally, we conduct more applicable to emerging economies by accounting for multiple different monetary policy tools, both interest- and quantitative-based, that the central bank employs to achieve its monetary targets. Considering a rich set of monetary policy indicators allows us to comprehensively assess the transmission effectiveness of monetary policy and the absorption of banks, as each specific policy tool might have different powers and economic outcomes (Varlik & Berument, 2017).

Methods

Model Specifications

In this paper, we follow the common logic of the existing literature to examine the heterogeneity across banks based on their different actions following monetary policy changes. In this vein, we specify our model as:

$$Y_{i,t} = a_0 + a_1 \times Y_{i,t-1} + a_2 \times MPI_{t-1} + a_3 \times MPI_{t-1} \times Portfolio_{i,t-1} + a_4 \times Portfolio_{i,t-1} + a_5 \times X_{i,t-1} + a_6 \times Z_{t-1} + u_{i,t} \quad (1)$$

where the subscript i capture banks and t illustrate years. Y is the dependent variable, representing bank lending and bank risk measures, separately. We utilize lagged dependent variable as a regressor to capture the persistence of bank behavior *MPI* stands for monetary policy indicators. *Portfolio* denotes the diversification degree of loan portfolios. X includes bank-specific control variables, Z consists of macroeconomic factors, and $u_{i,t}$ is the error term. The interaction term *MPI*×*Portfolio* is intended to indicate the marginal effects of loan portfolio composition on the monetary policy pass-through. We adopt one-period lagged macroeconomic and monetary policy variables since banks cannot react immediately to external shocks. Also, for an extra precaution, all bank-specific factors lagged by one year to defeat the potential endogeneity obstacle due to reverse causality.

We employ the GMM regression with the two-step system version to estimate our proposed dynamic panel model (Blundell & Bond, 1998). This setting accordingly could well tackle the endogeneity problem and offer efficient estimates. The consistency of the GMM estimator needs some diagnostic tests to justify, including the Hansen test for the joint validity of the instrument set, and the Arellano-Bond test for the first- and second-order autocorrelation, namely AR(1) and AR(2), respectively.

Variables

There are some concerns over using a specialized measurement for a particular type of bank risk. Consistent with the bank lending channel literature, we employ the annual percentage change of banks' customer loans as the dependent variable in the bank lending model. Next, given that a good proxy of bank risk is essential in conducting our analysis, we follow prior authors to use the Z-score index when reflecting bank risk (Beck, De Jonghe, & Schepens, 2013; Chen, Wu, Jeon, & Wang, 2017). Thus, the Z-score index comprehensively assesses a bank's financial stability or reverses overall riskiness. It is calculated by the sum of *ROA* (return-on-asset ratio) and *Capital* (equity-to-asset ratio) divided by *σ(ROA)* (standard deviation of return-on-asset ratio based on the three-year rolling time window) through the following formula specified as:

$$Z\text{-}score = \frac{ROA + Capital}{\sigma(ROA)} \tag{2}$$

We take the natural logarithm of (1+Z-score) in the regression stage to smooth higher values and evade the truncation of the Z-score index at zero.

In examining how monetary policy influences bank lending and bank risk, we apply monetary policy indicators based on two categories of interest- and quantitative-based policy tools. For the former, we employ short-term interest rates, including average lending rates and refinancing rates, which is a type of policy rate that the central bank uses to charge banks for short-term loans (Dang & Dang, 2020; Rafique, Quddoos, Ali, Aslam, & Ahmad, 2021). For the latter, we focus on the security sales/purchases through open market operations, proxied by the SBV's claims on domestic real nonfinancial sectors as suggested by the previous literature (Mamatzakis & Bermpei, 2016). Not only could the interest rate framework be altered, but the SBV could also use quantitative tools to adjust the liquidity created in the economy.es We take the level values of selected interest rates to produce interest-based monetary policy indicators (with a more significant value suggesting monetary co. In comparison, we concretely build the quantitative-based monetary policy proxy by the SBV's claims relative to GDP (with a higher value implying monetary expansion).

As a striking point of this paper, we follow Huynh and Dang (2021) by shaping multiple proxies to estimate the diversification level of loan portfolios in Vietnam. The first proxy is the HHI, defined as follows:

$$HHI = 1 - \sum_{s=1}^{n} x_s^2 \tag{3}$$

The second proxy is the SE index, calculated as follows:

$$SE = \sum_{s=1}^{n} x_s \times ln\left(\frac{1}{x_s}\right) \tag{4}$$

In the two equations above, x_s determines the relative exposure of each sector s, and n is the number of sectors. A higher value in these two indicators suggests a higher level of loan portfolio diversification. From an empirical perspective, we divide loan portfolios of Vietnamese banks into six sectoral exposures, containing the top five sectoral exposures (with the highest proportions), and the sixth one is the sum of all remaining exposures. To check whether the estimation results are robust to altering the number of economic sectors, we also consider alternative eight and ten sectoral exposures (see Table 1 for a specific list of alternative portfolio diversification variables).

Supported by the well-known literature on bank lending and risk determinants, we control key bank-level characteristics, including bank size, and capitalization, and liquidity levels (Vo, 2018). These variables have also been widely considered in the literature segment on the bank lending and risk-taking channels. Apart from internal variables, we also allow some macroeconomic factors to control changes in demand-side effects besides the supply-side bank lending and risk-taking channels. These macroeconomic variables introduce economic cycles, inflation, and stock markets (Chen et al., 2017; Dang & Dang, 2021). Please refer to Table 1 for the specific construction of all control variables.

Sample Data

We obtain data on commercial banks operating in Vietnam during 2007–2019 from their annual financial reports, especially grasping statement footnotes to gain breakdowns of sectoral loan portfolios. Some banks differ in operating regimes to ensure comparability, i.e., acquired banks/banks subject to special control by the SBV are not included. As a result, we produced unbalanced panel data from 31 Vietnamese commercial banks. The monetary policy and macroeconomic data are collected from the SBV (for refinancing rates), the International Financial Statistics (for average lending rates and the SBV's claims), and the World Development Indicators (for inflation rate and GDP growth), and the Vietstock (for VNindex).

Table 1. Definitions and summary statistics of variables

	Obs	Min	Max	Mean	SD	Definitions
Bank lending and bank risk measures						
Lending growth	391	−5.159	111.120	29.533	29.671	The annual growth rate of customer loans (%)
Overall riskiness	356	2.625	5.892	3.951	0.875	Natural logarithm of *(1 + Z-score)*
Portfolio indexes						
HHI10	391	0.579	0.870	0.770	0.081	HHI portfolio diversification index from each bank's ten sectoral exposures
SE10	391	1.098	2.161	1.770	0.301	SE portfolio diversification index from each bank's ten sectoral exposures
HHI8	391	0.579	0.859	0.766	0.078	HHI portfolio diversification index from each bank's eight sectoral exposures
SE8	391	1.098	2.013	1.701	0.260	SE portfolio diversification index from each bank's eight sectoral exposures
HHI6	391	0.578	0.816	0.747	0.067	HHI portfolio diversification index from each bank's six sectoral exposures
SE6	391	1.098	1.737	1.549	0.182	SE portfolio diversification index from each bank's six sectoral exposures
Bank-specific characteristics						
Size	391	29.943	34.269	31.972	1.233	Natural logarithm of total assets
Capital	391	4.939	21.884	10.072	4.647	Equity/Total assets (%)
Liquidity	391	5.570	38.193	17.453	9.594	Liquid assets/Total assets (%)
Monetary policy indicators						
Lending rates	391	6.960	16.954	10.400	3.328	Average short-term lending rates (%)
Refinancing rates	391	6.000	15.000	8.042	2.547	Refinancing rates announced by the SBV (%)
Central bank assets	391	0.174	4.205	1.419	1.239	SBV's claims on domestic real nonfinancial sectors/GDP (%)
Macroeconomic factors						
Stock market	391	−65.953	56.761	7.425	29.655	The annual growth rate of the VNindex (%)
Inflation	391	0.631	23.115	7.495	6.226	Annual inflation rate (%)
Economic cycles	391	5.247	7.130	6.245	0.642	The annual growth rate of GDP (%)

Notes: We drop some observations for the Z-score index due to its computation applying the three-year rolling time window.

Results and Discussion

Preliminary Statistical Analysis Results

We report the summary statistics for our variables in Table 1. Looking into the distributions of bank-level variables, we recognize their large ranges of extreme values and high standard deviations. This note indicates substantial variations in different features across banks, especially lending expansion, risk profiles, and loan portfolio compositions of main interest. For monetary policy indicators, through their large standard deviations for both interest- and quantitative-based tools, we document

some sizable adjustments in interest rates and money supply during the research time.

We also compute the pairwise correlations between variables (not presented for brevity). For monetary policy indicators and portfolio diversification measures, high correlation coefficients emerge for the variables capturing the same aspect. This observation justifies using different diversification measures as alternative variables and confirms that the SBV combines multiple monetary tools simultaneously when setting its policy framework. For remaining independent variables, they are found not to be excessively highly correlated with each exception for the inflation rate and monetary policy interest rates. Hence, we will proceed to the regression stage without the inflation rate to assure that our estimation design does not cause severe multicollinearity.

Estimation results for the bank lending channel

Employing different monetary policy interest rates in the bank lending model, we obtain groups of results reported in Tables 2–3. Most coefficients on both lending rates and refinancing rates are negative and statistically significant, revealing the presence of the bank lending channel: lower interest rates amid monetary policy expansion boosts banks' lending activities. Next, for the interaction term of monetary policy indicators and portfolio diversification, its coefficient is positive and statistically significant in most columns. These results imply that increased portfolio diversification in the banking market is linked with a weaker bank lending channel.

Table 2. Estimation results for the bank lending channel using lending rates as a monetary policy indicator

	Dependent variable: Bank loan growth					
	(1) HHI10	(2) HHI8	(3) HHI6	(4) SE10	(5) SE8	(6) SE6
Lagged dependent variable	0.361***	0.360***	0.358***	0.368***	0.365***	0.359***
	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)
Lending rates	−3.873***	−3.868***	−3.820***	−3.911***	−3.886***	−3.774***
	(0.379)	(0.380)	(0.382)	(0.363)	(0.369)	(0.378)
Lending rates*Portfolio diversification	1.138***	1.133***	1.083**	0.524***	0.525***	0.497**
	(0.427)	(0.432)	(0.437)	(0.182)	(0.190)	(0.202)
Portfolio diversification	−23.273***	−25.312***	−32.715***	−6.145***	−7.675***	−11.135***
	(3.647)	(3.719)	(3.124)	(1.452)	(1.538)	(1.340)
Size	1.760	1.803*	1.875*	1.669	1.768	1.760
	(1.079)	(1.075)	(1.056)	(1.096)	(1.086)	(1.079)
Capital	1.740***	1.750***	1.781***	1.697***	1.720***	1.743***
	(0.192)	(0.194)	(0.189)	(0.193)	(0.199)	(0.198)
Liquidity	0.854***	0.862***	0.872***	0.836***	0.848***	0.858***
	(0.085)	(0.085)	(0.084)	(0.084)	(0.084)	(0.088)
Economic cycles	−5.483***	−5.467***	−5.472***	−5.586***	−5.541***	−5.593***
	(1.106)	(1.087)	(1.034)	(1.145)	(1.090)	(1.006)
Stock market	−0.142***	−0.142***	−0.143***	−0.141***	−0.141***	−0.144***
	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)
Number of observations	360	360	360	360	360	360
Number of banks	31	31	31	31	31	31
Number of instruments	30	30	30	30	30	30
AR(1) test (p-value)	0.047	0.047	0.046	0.047	0.047	0.047
AR(2) test (p-value)	0.725	0.726	0.724	0.720	0.724	0.733
Hansen test (p-value)	0.326	0.318	0.303	0.350	0.337	0.321

Notes: The portfolio diversification measure (HHI and SE) is displayed at the top of each column. ***, ** and * denote the significance levels of 1%, 5% and 10%, respectively.

Table 4 presents the estimation results for the bank lending model when using the central bank's assets as the monetary policy indicator. Our results exhibit a positive relationship between bank lending and liquidity injection by the SBV, as captured by the positive and statistically significant coefficient on the stand-alone monetary policy indicator. Consequently, an increase in the money supply by the central bank leads to a higher growth rate of bank loans. Further analysis with marginal effects shows that this higher loan growth could be mitigated if banks grant loans to more economic sectors since the interaction term enters all regressions negatively and significantly.

Table 3. Estimation results for the bank lending channel using refinancing rates as a monetary policy indicator

	Dependent variable: Bank loan growth					
	(1) HHI10	(2) HHI8	(3) HHI6	(4) SE10	(5) SE8	(6) SE6
Lagged dependent variable	0.225***	0.224***	0.221***	0.228***	0.226***	0.223***
	(0.016)	(0.017)	(0.017)	(0.015)	(0.016)	(0.017)
Refinancing rates	−5.783***	−5.441**	−2.764	−5.636***	−5.859***	−3.583*
	(2.049)	(2.163)	(2.428)	(1.191)	(1.434)	(1.936)
Refinancing rates*Portfolio diversification	5.514**	5.117*	1.785	2.282***	2.503***	1.364
	(2.504)	(2.663)	(3.057)	(0.615)	(0.776)	(1.155)
Portfolio diversification	−58.459***	−58.318***	−42.502*	−19.252***	−22.662***	−18.394**
	(18.859)	(19.851)	(22.029)	(4.783)	(5.877)	(8.339)
Size	0.670	0.722	0.891	0.486	0.604	0.720
	(0.945)	(0.938)	(0.907)	(0.965)	(0.947)	(0.910)
Capital	1.299***	1.308***	1.341***	1.261***	1.282***	1.296***
	(0.210)	(0.212)	(0.211)	(0.203)	(0.206)	(0.203)
Liquidity	0.496***	0.499***	0.492***	0.503***	0.514***	0.497***
	(0.096)	(0.097)	(0.097)	(0.096)	(0.098)	(0.098)
Economic cycles	−7.739***	−7.670***	−7.410***	−7.930***	−7.801***	−7.485***
	(0.806)	(0.813)	(0.831)	(0.771)	(0.783)	(0.798)
Stock market	−0.210***	−0.209***	−0.204***	−0.215***	−0.213***	−0.206***
	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
Number of observations	360	360	360	360	360	360
Number of banks	31	31	31	31	31	31
Number of instruments	30	30	30	30	30	30
AR(1) test (p-value)	0.008	0.008	0.008	0.008	0.009	0.006
AR(2) test (p-value)	0.857	0.858	0.875	0.834	0.832	0.856
Hansen test (p-value)	0.192	0.193	0.201	0.192	0.192	0.202

Notes: The portfolio diversification measure (HHI and SE) is displayed at the top of each column. ***, ** and * denote the significance levels of 1%, 5% and 10%, respectively.

Considering our estimation results at face values, assuming that the SBV relaxes monetary policy associated with a one percentage point drop-in lending rates, we infer that bank lending growth tends to increase by 3.873% accordingly (column 1 of Table 2). Similarly, if the central bank's asset ratio increases by one percentage point, bank lending will likely increase by 6.957% (column 4 of Table 4). Further elaborated, these influence magnitudes might be reduced by about 0.092% (~0.081×1.138) and 0.315% (~0.301×1.046), respectively, when loan portfolio diversification surges by one standard deviation. These patterns highlight our findings' economic plausibility. We thus gain solid evidence that increased loan portfolio diversification makes bank lending less responsive to monetary policy adjustments. These findings could be explained as follows. When banks diversify their credit portfolios to a more significant extent, they might enjoy lower expenses of handling informational asymmetry, involved in raising loanable funds, or gaining more accessible access to substitute funding sources (Boot, 2000; Kashyap & Stein, 1995). Thus, their lending activities tend to be less dependent on the monetary policy stance relative to their specialized counterparts.

Table 4. Estimation results for the bank lending channel using the central bank's claims as a monetary policy indicator

	Dependent variable: Bank loan growth					
	(1) HHI10	(2) HHI8	(3) HHI6	(4) SE10	(5) SE8	(6) SE6
Lagged dependent variable	0.211***	0.209***	0.204***	0.210***	0.207***	0.200***
	(0.018)	(0.018)	(0.017)	(0.019)	(0.020)	(0.018)
Central bank assets	6.881***	6.883***	6.888***	6.957***	6.978***	6.906***
	(0.405)	(0.407)	(0.402)	(0.406)	(0.409)	(0.418)
Central bank assets*Portfolio diversification	−2.686***	−2.694***	−2.756***	−1.046***	−1.078***	−1.246***
	(0.735)	(0.749)	(0.786)	(0.317)	(0.341)	(0.387)
Portfolio diversification	−13.450***	−15.864***	−24.704***	−1.333	−2.998	−7.446***
	(4.859)	(4.866)	(5.198)	(1.726)	(1.952)	(2.386)
Size	−0.537	−0.524	−0.477	−0.954	−0.989	−0.636
	(0.673)	(0.683)	(0.701)	(0.910)	(0.926)	(0.689)
Capital	0.712***	0.713***	0.744***	0.559*	0.540	0.702***
	(0.266)	(0.269)	(0.267)	(0.338)	(0.343)	(0.254)
Liquidity	−0.038	−0.036	−0.032	−0.058	−0.055	−0.047
	(0.065)	(0.066)	(0.068)	(0.058)	(0.062)	(0.068)
Economic cycles	−5.145***	−5.153***	−5.178***	−5.125***	−5.143***	−5.091***
	(0.746)	(0.749)	(0.759)	(0.740)	(0.736)	(0.744)
Stock market	−0.160***	−0.160***	−0.158***	−0.167***	−0.166***	−0.161***
	(0.015)	(0.015)	(0.015)	(0.017)	(0.016)	(0.014)
Number of observations	360	360	360	360	360	360
Number of banks	31	31	31	31	31	31
Number of instruments	30	30	30	30	30	30
AR(1) test (p-value)	0.046	0.046	0.046	0.044	0.044	0.049
AR(2) test (p-value)	0.812	0.813	0.823	0.789	0.789	0.809
Hansen test (p-value)	0.189	0.184	0.168	0.204	0.194	0.179

Notes: The portfolio diversification measure (HHI and SE) is displayed at the top of each column. ***, ** and * denote the significance levels of 1%, 5% and 10%, respectively.

Estimation Results for the Bank Risk-Taking Channel

We check whether the association between bank risk and monetary policy varies based on different credit portfolio diversification degrees. Tables 5–6 show that the coefficient on lending and refinancing rates is significantly positive, regardless of the portfolio diversification measures employed. Table 7 reports that the central bank's claims are negatively associated with bank stability as captured by the Z-score index, mainly through SE diversification measures. We gain evidence to confirm that the bank risk-taking channel operates in Vietnam. Banks react to monetary policy relaxing, either when the central bank cuts interest rates or purchases more securities in the open market, by reducing their financial stability or, in other words, suffering more overall risks.

Turning to the estimation results of interest, as most columns of Tables 5–6 indicate, the coefficients on the interaction terms between interest rates and portfolio diversification are significantly negative. In contrast, the interaction terms of the central bank assets and loan portfolios are significantly positive in Table 7. The signs of all these interaction terms are opposite to those of stand-alone monetary policy indicators. The two categories of monetary policy tools collectively provide complementary evidence that bank credit portfolio diversification undermines the working of the bank risk-taking channel. From an economic standpoint, the significance of our interaction terms' results is also appropriate. For instance, the coefficients in column 2 (Table 6) and column 5 (Table 7) suggest that a one standard deviation rise in loan portfolio diversification measure could alleviate the impacts of a one-percentage-point change in refinancing rates on bank risk by approximately 0.022% (~0.078×0.278), and also diminish the effects of a variation of one percentage point in the central bank's asset ratio on bank risk by approximately 0.032% (~0.260×0.124), respectively.

Table 5. Estimation results for the bank risk-taking channel using lending rates as a monetary policy indicator

	Dependent variable: The natural logarithm of (1 + Z-score)					
	(1) HHI10	(2) HHI8	(3) HHI6	(4) SE10	(5) SE8	(6) SE6
Lagged dependent variable	0.424***	0.419***	0.411***	0.438***	0.432***	0.420***
	(0.020)	(0.020)	(0.019)	(0.026)	(0.024)	(0.021)
Lending rates	0.110***	0.122***	0.175***	0.025	0.042	0.088**
	(0.041)	(0.045)	(0.068)	(0.032)	(0.028)	(0.037)
Lending rates*Portfolio diversification	−0.130**	−0.147**	−0.222**	−0.011	−0.021	−0.052**
	(0.053)	(0.058)	(0.089)	(0.018)	(0.016)	(0.023)
Portfolio diversification	1.916***	2.091***	2.940***	0.327**	0.461***	0.863***
	(0.294)	(0.309)	(0.446)	(0.148)	(0.116)	(0.138)
Size	0.048*	0.048*	0.043	0.060**	0.057**	0.051*
	(0.026)	(0.027)	(0.028)	(0.027)	(0.028)	(0.027)
Capital	0.009	0.009	0.006	0.014**	0.012**	0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Liquidity	0.003	0.003	0.003	0.002	0.002	0.003
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Economic cycles	0.244***	0.241***	0.230***	0.230***	0.228***	0.228***
	(0.043)	(0.043)	(0.045)	(0.040)	(0.039)	(0.040)
Stock market	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of observations	325	325	325	325	325	325
Number of banks	31	31	31	31	31	31
Number of instruments	30	30	30	30	30	30
AR(1) test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test (p-value)	0.182	0.162	0.115	0.194	0.163	0.142
Hansen test (p-value)	0.570	0.567	0.536	0.521	0.533	0.541

Notes: The portfolio diversification measure (HHI and SE) is displayed at the top of each column. ***, ** and * denote the significance levels of 1%, 5% and 10%, respectively.

Table 6. Estimation results for the bank risk-taking channel using refinancing rates as a monetary policy indicator

	Dependent variable: The natural logarithm of (1 + Z-score)					
	(1) HHI10	(2) HHI8	(3) HHI6	(4) SE10	(5) SE8	(6) SE6
Lagged dependent variable	0.429***	0.426***	0.427***	0.438***	0.433***	0.432***
	(0.016)	(0.017)	(0.018)	(0.016)	(0.016)	(0.016)
Refinancing rates	0.245***	0.252***	0.329***	0.116***	0.127***	0.195***
	(0.081)	(0.088)	(0.124)	(0.040)	(0.043)	(0.066)
Refinancing rates*Portfolio diversification	−0.267***	−0.278**	−0.388**	−0.045**	−0.053**	−0.102**
	(0.103)	(0.112)	(0.162)	(0.023)	(0.025)	(0.042)
Portfolio diversification	2.132***	2.246***	3.079***	0.425***	0.553***	0.975***
	(0.682)	(0.706)	(0.816)	(0.128)	(0.142)	(0.212)
Size	0.049**	0.049**	0.047*	0.052**	0.046**	0.041*
	(0.023)	(0.024)	(0.026)	(0.022)	(0.023)	(0.024)
Capital	0.004	0.004	0.003	0.007	0.006	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Liquidity	0.000	0.000	0.000	0.000	0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Economic cycles	0.248***	0.246***	0.236***	0.247***	0.242***	0.235***
	(0.049)	(0.049)	(0.049)	(0.047)	(0.047)	(0.047)
Stock market	0.002***	0.002***	0.003***	0.002***	0.002***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of observations	325	325	325	325	325	325

	Dependent variable: The natural logarithm of (1 + Z-score)					
	(1) HHI10	(2) HHI8	(3) HHI6	(4) SE10	(5) SE8	(6) SE6
Number of banks	31	31	31	31	31	31
Number of instruments	30	30	30	30	30	30
AR(1) test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test (p-value)	0.331	0.322	0.291	0.353	0.312	0.302
Hansen test (p-value)	0.771	0.759	0.735	0.714	0.688	0.677

Notes: The portfolio diversification measure (HHI and SE) is displayed at the top of each column. ***, ** and * denote the significance levels of 1%, 5% and 10%, respectively.

Table 7. Estimation results for the bank risk-taking channel using the central bank's claims as a monetary policy indicator

	Dependent variable: The natural logarithm of (1 + Z-score)					
	(1) HHI10	(2) HHI8	(3) HHI6	(4) SE10	(5) SE8	(6) SE6
Lagged dependent variable	0.443***	0.442***	0.446***	0.437***	0.435***	0.439***
	(0.025)	(0.025)	(0.023)	(0.029)	(0.028)	(0.025)
Central bank assets	−0.115	−0.137	−0.056	−0.158**	−0.210***	−0.171*
	(0.095)	(0.093)	(0.112)	(0.080)	(0.076)	(0.090)
Central bank assets*Portfolio diversification	0.146	0.176	0.069	0.089**	0.124***	0.110*
	(0.124)	(0.122)	(0.155)	(0.044)	(0.043)	(0.060)
Portfolio diversification	0.924**	0.931**	1.409***	0.102	0.123	0.344**
	(0.370)	(0.382)	(0.445)	(0.109)	(0.121)	(0.163)
Size	0.060**	0.060**	0.056**	0.067**	0.062**	0.058**
	(0.024)	(0.024)	(0.023)	(0.026)	(0.026)	(0.024)
Capital	0.008	0.008	0.007	0.008	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Liquidity	0.003	0.003	0.003	0.003	0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Economic cycles	0.239***	0.239***	0.237***	0.240***	0.236***	0.232***
	(0.043)	(0.043)	(0.042)	(0.044)	(0.043)	(0.042)
Stock market	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of observations	325	325	325	325	325	325
Number of banks	31	31	31	31	31	31
Number of instruments	30	30	30	30	30	30
AR(1) test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test (p-value)	0.344	0.334	0.333	0.353	0.313	0.333
Hansen test (p-value)	0.573	0.579	0.585	0.552	0.582	0.596

Notes: The portfolio diversification measure (HHI and SE) is displayed at the top of each column. ***, ** and * denote the significance levels of 1%, 5% and 10%, respectively.

We could suggest some possible mechanisms of our results. First, banks with more diversified portfolios may reach more opportunities to earn higher profits; thus, they have lower incentives to search for yield by high risk high return projects, even when interest rates are decreased amid monetary policy expansion (Rajan, 2006). Second, as also implied by the literature, informational asymmetries are less severe due to increased diversification in banks' activities (Boot, 2000). So, banks could mitigate the harmful impacts of monetary policy on bank risk after the central bank injects liquidity by asset purchases or raises interest rates in the economy.

Conclusion

We explore how bank loan portfolio diversification plays a crucial role in moderating the bank lending and risk-taking channels of monetary policy transmission in Vietnam during 2007–2019. Consistent with the theoretical and empirical works on the bank lending and risk-taking channels

of monetary policy, we find that lower interest rates or more liquidity injection during monetary expansion boost bank lending and bank risk. Furthermore, as a unique contribution of this study, we find that the potency of these banking channels may be weakened for banks diversifying their loan portfolios more into various economic sectors. These findings are robust across different choices of monetary policy indicators, ranging from interest-based tools (short-term lending rates and refinancing rates) to the quantitative-based policy (security sales/purchases by open market operations), and across a rich set of sectoral exposure measures to proxy the diversification level of loan portfolios.

Identifying the modifying condition in this paper for the link between monetary policy and bank lending/bank risk will be beneficial in deriving policy implications. Accordingly, our findings call for monetary authorities to concentrate on certain types of banks, depending on their compositions of loan portfolios that they hold when setting monetary policy using both complementary tools of interest rates and liquidity injection. They also suggest that banking supervisors should acknowledge the potential tradeoff between bank lending and bank risk in response to monetary shocks when managing banking supervision. For example, higher loan portfolio diversification is found to dampen the bank risk-taking channel, thus calling for policies to encourage more diversification in the banking sector. However, these policies should be accompanied with caution because more diversifications tend to attenuate bank lending activities when monetary policy is relaxed.

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Foreign direct investment, efficiency, and total factor productivity: Does technology intensity classification matter?

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Abstract

Purpose — We examine whether the foreign direct investment (FDI) in promoting technical efficiency is controlled by the sector classifications based on the technology intensity (High Technology, Medium-High Technology, Medium-Low Technology, and Low Technology).

Methods — We use the Indonesian firm-level dataset of the large and medium manufacturing survey from 2007 to 2015 and employ the time-varying stochastic production frontier.

Findings — We reveal that FDI, technology intensity and absorptive Capacity significantly affect firms' production and efficiency. We also found that the Indonesian manufacturing industry from 2007 to 2015 experienced positive Total Factor Productivity growth, where High-Technology sectors experienced the largest magnitude among others. Meanwhile, technological progress stemming from FDI is enjoyed more by Low Technology sectors. Meaning to say, technology intensity classification does not matter to technological progress.

Implication — The host country's government should focus on industries with high technical capabilities to accelerate FDI gains for the firms. Simultaneously, human capital improvement also needs to be intensified, for instance, through training or human development, so that firms with lower technical capability can catch up and, consequently, receive similar benefits from FDI activities.

Originality — Our study accommodates the research gap by including the FDI effect in both productivity and efficiency in a single equation. Many studies merely categorize technology intensity following the stochastic production frontier estimation to obtain technical efficiency or TFP growth. In this sense, those studies did not control the impact of the technology-specific effect.

Keywords — FDI, manufacturing, Indonesia, stochastic production frontier.

Introduction

The debate on whether foreign investment benefits the host's economy in the form of technology diffusion has attracted many researchers. Most of them claimed that foreign investment is a major channel of technology transfers from developed countries to developing countries (Baltabaev, 2014; Zhao & Zhang, 2010). In terms of more technical issues, some studies also suggested that the benefits of FDI can be effectively gained to develop advanced managerial expertise and scale-

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production knowledge that lead to production efficiency improvement (Mastromarco & Ghosh, 2009; Sari, 2019; Smeets, 2008; Yang, Chen, & Huang, 2013).

However, theoretical arguments indicate that the effect of technology diffusion stemming from FDI might be conditional and complementary to other factors such as human capital investment and specified subsector characteristics. The high quality of human capital will promote FDI benefits as it increases absorptive capacity, enabling technology diffusion to be quickly taken in (Carbonell & Werner, 2018). For the case of subsector characteristics, there may be different effects resulting from FDI upon high and low technology intensity sectors. The technology diffusion caused by FDI is greater in the high technology sectors than in low-technology ones as it relies on technology creation and research and development (R&D) intensity (Keller, 2010). In this sense, technological progress and the appropriateness of technology are claimed as sector-specific (Fu & Gong, 2011). Therefore, the conventional approach to identifying the effect of technology diffusion caused by FDI on economic performance without considering specific technology intensity may be unclear.

Given any considerable potential effect of FDI on economic performance, a systematic analysis that distinguishes technology intensity is essential. However, there are not many previous robust studies that have devoted efforts to investigating any detected FDI's effect on technology intensity in the case of Indonesia. The United Nations Conference on Trade and Development (UNCTAD) recorded that, as of 2014, the Indonesian global FDI inflows were noted in the 14th place with more than 23 billion USD (Gopalan, Hattari, & Rajan, 2016). This amount increased by approximately 20% compared to that in 2013. Therefore, this evidence raises urgent questions–*"In the case of the Indonesian manufacturing sector, do large FDI inflows matter?*" If it does matter, "*is it technology-intensity sectors oriented?*"

This study investigates the effect of FDI on firms' technical efficiency and production distinguished in high-, medium-high, medium-low and low-technology sectors in Indonesia. FDI's effect on technical efficiency helps measure total factor productivity (TFP) growth decomposed from technological change and scale efficiency change. To acknowledge the composition of TFP growth, this study prefers stochastic frontier estimation because it recognises 'the best practice' aligning the frontier at which well-performed firms will stay, leading to more variation in productivity scores (Farrell, 1957).

This study contributes to the literature in several ways. Firstly, unlike many prior studies examining the FDI effect on firms' productivity or efficiency, our study accommodates the research gap by including the FDI effect on productivity and efficiency in a single equation. This model refers to the study of (Sari, Khalifah, & Suyanto, 2016). Secondly, many studies, notably for Indonesian cases, merely categorize technology intensity following the stochastic production frontier estimation to obtain technical efficiency or TFP growth. In this sense, those studies did not control the impact of the technology-specific effect. This approach leads to FDI bias that may affect efficiency and productivity and the firms' technology intensity classification. In this study, we include technology-specific to avoid this bias.

Methods

Data

This study uses firm-level data from the large and medium manufacturing sector (IBS) annually surveyed by the Indonesian Central Bureau of Statistics from 2007 to 2015. The Indonesian Central Bureau of Statistics defines manufacturing firms as large and medium firms which empower more than 100 labourers for large firms and between 20 to 99 labourers for medium firms. The number of firms may change over time due to some exiting the industry. Nonetheless, selecting balanced panel data may limit the number of firms estimated in this study. Therefore, the unbalanced-panel data consists of 120,477 observations with a minimum number of 12,418 manufacturing establishments in 2010 and a maximum number of 13,850 establishments in 2011.

There are two divisions of variables in this study. The first division includes the main variables, e.g. total output, capital (approximated by the fixed assets of a firm such as land, building,

machinery, equipment, and vehicles), number of labourers, energy (approximated by fuel and lubricants used in a year) and raw material. Except for the number of labourers, all variables are in Rupiah. The second division has two sub-divisions, namely the key exogenous variables: a foreign firm that proxies FDI, dummies of technology intensity (high, medium-high, medium-low, and low intensity) and absorptive Capacity. There are other exogenous variables referred to in some previous studies: age of firm (Machmud, Nandiyanto, & Dirgantari, 2018; Suyanto & Salim, 2010), export (Atkin, Khandelwal, & Osman, 2017; De Loecker, 2013; Mok, Yeung, Han, & Li, 2010), imported raw material intensity obtained from the ratio of imported raw material and total materials (Sari, 2019; Sari et al., 2016), and firm size obtained from the market share of the firm in the industry. Table 1 reports the statistics descriptive of all variables employed in this study.

Table 1. Descriptive Statistics

Variables	Units		2007	2008	2009	2010	2011	2012	2013	2014	2015
The Main Variables											
Output (Y)	Billion Rupiah	Mean	14.85	31.79	43.50	41.86	51.49	58.09	109.63	68.87	74.91
		Std. Deviation	154.28	509.07	439.54	516.98	542.31	441.01	864.95	568.98	696.00
Capital (K)	Billion Rupiah	Mean	7.3	15.0	1010.7	52.8	74.9	103.6	161.9	486.9	116.0
		Std. Deviation	98.7	292.2	105598.8	1928.4	2418.1	4924.4	8162.6	15054.4	4809.2
Labour (L)	Workers	Mean	134.3	148.3	154.9	172.8	180.4	189.8	194.3	193.7	189.3
		Std. Deviation	544.3	579.6	591.2	665.0	642.0	657.1	671.1	759.4	793.2
Material (M)	Billion Rupiah	Mean	8.3	17.7	24.5	23.5	28.6	30.7	57.0	34.0	35.3
		Std. Deviation	51.3	225.1	250.4	387.5	377.8	198.3	518.3	255.9	268.2
Energy (E)	Billion Rupiah	Mean	0.37	0.89	1.02	0.79	1.17	1.40	2.36	1.73	1.71
		Std. Deviation	5.50	24.51	17.74	12.03	19.68	17.90	30.02	30.44	25.98
Exogenous Variables											
Technology Intensity	Dummy	High Technology	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
		Std. Deviation	0.11	0.12	0.13	0.13	0.13	0.13	0.13	0.13	0.13
		Medium-High Technology	0.05	0.06	0.06	0.07	0.07	0.07	0.08	0.08	0.08
		Std. Deviation	0.22	0.24	0.24	0.26	0.26	0.26	0.27	0.27	0.27
		Medium-Low Technology	0.18	0.19	0.19	0.19	0.19	0.20	0.20	0.19	0.19
		Std. Deviation	0.38	0.39	0.39	0.39	0.39	0.40	0.40	0.39	0.39
		Low Technology	0.74	0.72	0.71	0.71	0.70	0.70	0.69	0.70	0.70
		Std. Deviation	0.43	0.44	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Foreign Direct Investment/Foreign Ownership	Dummy	Mean	0.06	0.07	0.07	0.08	0.08	0.09	0.08	0.09	0.10
		Std. Deviation	0.23	0.26	0.26	0.27	0.28	0.28	0.28	0.29	0.29
Absorptive Capacity (absp)	Ratio	Mean	14.97	15.18	15.65	15.51	14.81	16.24	16.79	16.06	16.19
		Std. Deviation	1.06	1.06	0.95	0.93	2.13	0.70	0.65	0.76	0.74
Age of Firm (age)	years	Mean	15.52	16.71	17.81	18.95	20.10	21.18	22.27	23.17	24.10
		Std. Deviation	11.62	11.78	11.89	11.96	12.18	12.21	12.29	12.21	12.19
Export (expr)	Dummy	Mean	0.19	0.17	0.15	0.14	0.14	0.12	0.14	0.12	0.13
		Std. Deviation	0.40	0.38	0.35	0.35	0.35	0.32	0.35	0.32	0.34
Imported Raw Material (imp)	Ratio	Mean	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08
		Std. Deviation	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08
Firm Size (Fsize)	Ratio	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Std. Deviation	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Number of Observations			12,418	13,814	13,737	13,071	13,850	13,585	13,360	13,337	13,305

Note: Mean=arithmetical average, Std. Dev.=standard deviation.

FDI can be set in some proxies to capture the foreign diffusion in the firm. In this study, the percentage of foreign-capital ownership share is considered as the proxy of FDI (see: Sari, 2019; Sari et al., 2016; Yasin, 2021). The percentage of foreign share ownership in a firm consists of several categories: 5% (Haddad & Harrison, 1993), 10% (IMF, 2004), 20% (Djankov & Hoekman, 2000), or at least any amount of positive foreign ownership in a firm (Narjoko & Hill, 2007). This study only refers to the 20% to estimate TFP growth and decomposition. However, the 5% indicator is also considered to examine the robustness check of the estimated model.

The dummy variables of high, medium-high, medium-low, and low technology stem from the sector classification based on technology intensity proposed by OECD (2011). The classification is referred to in the two digits of the Indonesia Standard Industrial Classification

(ISIC) of 2009. It is worth noting that IBS data before 2010 referred to ISIC 2005, while ISIC 2009 was referred to in the 2010 IBS and later. During this transition, a firm might change its industrial classification. Therefore, this study's 2007-2009 observations need to be converted into ISIC 2009. The classification is summarised in Table 2.

Table 2. Classification of High-Technology and Low-Technology

High Technology		Medium-High Technology		Medium-Low Technology		Low Technology	
Code	Subsector	Code	Subsector	Code	Subsector	Code	Subsector
21	Pharmaceutical Industry	20	Chemical Industry	23	Fabricated Metal Industry	10	Food Industry
26	Computers, Electronics, and Optics Industry	27	Electrical Equipment Industry	24	Metal Base Industry	11	Beverage Industry
		28	Machinery Industry	25	Metals Industry	12	Tobacco Industry
		29	Motor and trailers Industry	22	Rubber and Plastic Industry	13	Textile Industry
		30	Other Transport Equipment Industry	19	Products from Coal and Oil Refinery Industry	14	Apparel Industry
						15	Leather and Footwear Industry
						16	Wood Industry
						17	Paper and Printing Industry
						18	Printing and Recording Media Industry
						31	Furniture Industry
						32	Other Manufacturing Industry

Source: OECD (2011)

Empirical Strategy

This study uses Transcendental Logarithmic (Translog) as the main stochastic production frontier model. The use of Translog is more flexible as it recognises a non-fixed substitution elasticity and fewer constraints than those recognised in a general logarithm linear model, e.g. Cobb-Douglas (Christensen, Jorgenson, & Lau, 1973). Moreover, the Translog function does not inflict constant elasticity substitution as Cobb-Douglas does (Kumbhakar & Wang, 2005; Wang & Wong, 2012). Therefore, Translog conveys more insights into the estimation. The stochastic production frontier for panel data with the exogenous variable in this study can be specified as follows:

$$y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n xn_{it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm}\, xn_{it} xm_{it} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{m=1}^{N} \beta_{nt}\, xn_{it} t_{it} + \sum_{k=1}^{K} \beta_k Zk_{it} + v_{it} - u_{it} \quad (1)$$

Where y is the total output, xn and xm represent inputs consisting of capital (k), labour (l), energy (e) and raw materials (r). All output and inputs are expressed in the natural logarithm (ln) and deviation from their geometric means. The subscript i and t denote i-th firm and t-the year. Zk represents exogenous variables such as the dummies of technology intensity (High, Medium-High, Medium-Low, and Low Technology), FDI, absorptive Capacity, the interacting variable of technology intensity with FDI and absorptive Capacity, the interacting variable of FDI with absorptive Capacity, age of firm, dummy export, imported material intensity and firm size. v_{it} is the SF model's random variable assumed as $iid.N(0, \sigma_v^2)$, and u_{it} is a non-negative random variable assumed as the half-truncated normal $(N^+(\mu_i, \sigma_u^2))$ in distribution. u_{it} is also the inefficiency parameter that captures the inefficiency effects specified below.

$$u_{it} = \delta_0 + \sum_{k=1}^{K} \delta_k Zk_{it} + \omega_{it} \quad (2)$$

Where δ_k represents the coefficients of inefficiency effects that consist of all exogenous variables, and ω_{it} is an error term in the inefficiency equation.

The stochastic frontier approach is challenging to estimate as it requires precise specification forms and causes instability of numerical and statistical samples in the infinite samples (Sari, 2019). To maintain the stability of the numerical and statistical samples, an additional test, e.g. the generalised log-likelihood test (Kumbhakar et al., 2015), is needed to select the proper specification, rather than the Translog function, of the stochastic production function. This study refers to another alternative of the production function: Cobb-Douglas (CD). A null hypothesis (H_0) is the CD model that omits the coefficients of time, time-squared and interacting input with time ($\beta_{nm} = \beta_{nt} = \beta_{tt} = \beta_t = 0$). The log-likelihood test is decided by comparing the likelihood ratio statistic from each model. The log-likelihood statistic is determined from $\lambda = -2[l(H_0) - l(H_1)]$, where $l(H_0)$ is the log-likelihood statistic of the CD model and where $l(H_1)$ is the log-likelihood value of Translog. The null hypothesis is rejected if the λ statistic is less than the χ^2 table with degrees of freedom equal to the number of parameters involved in the restrictions.

The estimated coefficients in Eq. (1) cannot be directly interpreted (Sari et al., 2016), but these coefficients can be used to measure the output elasticity of each input. The calculation is specified as follows:

$$\varepsilon_{nit} = \frac{\partial y_{it}}{\partial x n_{it}} = \beta_n + \frac{1}{2}\Sigma_{n=1}^{4}\Sigma_{m=1}^{4}\beta_{nm} x m_{it} + \beta_{nt} t \tag{3}$$

Where ε_{nit} is the elasticity for each input at each data point. From each output elasticity, the standard return to scale elasticity can be calculated as follows:

$$\varepsilon_{Tit} = \Sigma_{n=1}^{N}\varepsilon_{nit} \tag{4}$$

Where ε_{Tit} is the total elasticity of inputs for each firm and period.

Some studies in the literature emphasised that high technology may generate not only technological progress but also develop managerial expertise and scale-production knowledge, which contributes to enhancing both technical efficiency and scale efficiency (Kokko & Kravtsova, 2008; Sari et al., 2016; Smeets, 2008). In this sense, different technology intensities may affect scale efficiency change. Following the example of the study of Kumar and Russell (2002) and Sari et al. (2016), this study depends on the decomposition of TFP growth: Technical Efficiency Change (TEC), Technical Change (TC) and Scale Efficiency Change (SEC).

The first component of TFP growth is technical efficiency change (TEC) obtained from the growth of technical efficiency (TE). Obtained from the stochastic production frontier in Eq. (1), technical efficiency measures the ratio of the realised output to the maximum potential output. The estimation of TE is illustrated in Eq. (5a-5d):

$$TE_{it} = \frac{y_{it}}{\hat{y}_{it}} \tag{5a}$$

$$= \frac{f(x_{it}, z_{it}; \beta).\exp(v_{it} - u_{it})}{f(x_{it}, z_{it}; \beta).\exp(v_{it})} \tag{5b}$$

$$= \exp(-u_{it}) \tag{5c}$$

$$= \exp(-\delta_k Z k_{it} - \omega_{it}) \tag{5d}$$

Where y_{it} is the realised output and $\hat{y}_{it}$ is the maximum potential output. As TE is the ratio of y_{it} and $\hat{y}_{it}$, it ranges between 0 and 1. When TEs are closer to 1, the realised outputs are closer to their optimal output value. Then, TEC can be defined as follows:

$$TEC_{it,t-1} = \ln\left(\frac{TE_{it}}{TE_{it-1}}\right) \times 100\% \tag{6}$$

Where $\ln\left(\frac{TE_{it}}{TE_{it-1}}\right)$ is the natural logarithm of the technical efficiency of firm i at the period t over the technical efficiency of the period $t-1$.

The second component of TFP growth is technical change (TC), which captures the condition of the production frontier's shifting. This shifting reflects the technological progress

embodied in the capital and labour input to depict the effect of technology in improving factor productivity over time (Sengupta, 1995). TC can be functionally derived from the partial derivative with respect to time, as follows:

$$\frac{\partial y_{it}}{\partial t} = \beta_t + \beta_{tt}t + \beta_{nt}xn_{it} \quad (7)$$

Then, TC can be formed by:

$$TC_{it,t-1} = 0.5\left[\left(\frac{\partial y_{i,t-1}}{\partial t}\right) + \left(\frac{\partial y_{i,t}}{\partial t}\right)\right] \times 100\% \quad (8)$$

The third component of TFP growth is scale efficiency change (SEC), which is associated with a firm's production scale. SEC considers the elasticity of output from each input in Eq. (3) and total elasticity in Eq. (4) to construct a scale factor that is functioned as follows:

$$SF_{it} = \frac{\varepsilon_{Tit}-1}{\varepsilon_{Tit}} \quad (9)$$

at each data point. SEC between periods t and $t-1$ is calculated from the summation of the average of the scale factor between two periods multiplied by the change in the respective input usage. It can be formulated as follows:

$$SEC_{it,t-1} = \frac{1}{2}\sum_{n=1}^{N}[(SF_{it}\varepsilon n_{it} + SF_{it-1}\varepsilon n_{it-1})(xn_{it} - xn_{it-1})] \times 100\% \quad (10)$$

Therefore, TFP growth can be calculated as follows:

$$TFPg_{it,t-1} = TEC_{it,t-1} + TC_{it,t-1} + SEC_{it,t-1} \quad (11)$$

Results and Discussion

Table 3 documents the generalised log-likelihood test decision to choose this study's most suitable production frontier. By referring to α =1% in χ^2 table, the result shows that λ>χ^2 table, which therefore determines the Translog specification as a suitable model to be furtherly analysed.

Table 3. Hypothesis testing of various production functions

Model	CD (df=16)
	$\boldsymbol{H0: \beta_{nt} = 0}$
Translog (H1)	38499.89
Critical Value of $\boldsymbol{\chi^2}$ at $\boldsymbol{\alpha = 1\%}$	5.81
Decision	Translog

Table 4 and Table 5 report the estimated coefficients on the production function and inefficiency effects of the exogenous variables from 3 different models[1]. Model 1 refers to the Translog production function using foreign ownership (FOR) 20%, Model 2 refers to the Translog production function using FOR 5%, and Model 3 refers to the Cobb Douglas production function using FOR 20%. The focus is firstly on identifying the main exogenous variables. The Coefficients of technology intensities, namely Medium-High Technology, Medium-Low Technology, and Low Technology, show the negative significance for all models in the production function. This finding implies that the firms' production categorized as high technology sector are averagely higher than that firms categorized as Medium-High Technology, Medium-Low Technology, and Low Technology. However, this result contrasts the inefficiency effects functions in Table 5, where the coefficients of Medium-High Technology, Medium-Low Technology, and Low Technology reveal significant and negative magnitude. These results conclude that firms categorized as High Technology sector are less efficient than that Medium-High Technology, Medium-Low Technology, and Low Technology firms. The coefficients of FDI from Model 1 and Model 2 are

[1] The results for input coefficients are reported in the Appendix to save space.

identified as positively significant in promoting productivity. Accordingly, the magnitude of FDI in Model 1 is larger than that in Model 2. This finding suggests that foreign firms have larger output production than local firms. However, there is no significant effect of FDI. It affects inefficiency partially.

Table 4. The Estimation of Stochastic Production Frontier on The Production Function

	Dependent Variable= Firms' Outputs					
	Model 1		Model 2		Model 3	
	Coeff	Standard Error	Coeff	Standard Error	Coeff	Standard Error
Medium-High Technology (MHT)	-0.882***	0.239	-1.475***	0.229	-1.981***	0.285
Medium-Low Technology (MLT)	-1.015***	0.223	-1.408***	0.220	-1.295***	0.258
Low Technology (LT)	-0.832***	0.222	-1.248***	0.217	-1.888***	0.254
Foreign Direct Investment (FDI)	0.838***	0.127	0.720***	0.122	0.200	0.149
FDI × MHT	0.111**	0.050	0.088*	0.050	-0.008	0.057
FDI × MLT	0.037	0.049	0.061	0.046	-0.089	0.056
FDI × LT	-0.045	0.048	-0.014	0.043	-0.075	0.053
Absorptive Capacity (Absp)	0.076***	0.014	0.051***	0.013	0.051***	0.016
FDI × Absp	-0.038***	0.007	-0.033***	0.007	0.007	0.008
Absp × MHT	0.049***	0.015	0.084***	0.014	0.113***	0.017
Absp × MLT	0.044***	0.014	0.067***	0.014	0.063***	0.016
Absp × LT	0.034***	0.014	0.058***	0.013	0.095***	0.015
Age	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
Export	0.012**	0.006	0.007	0.006	-0.005	0.007
Import	0.125***	0.010	0.138***	0.010	0.064***	0.012
Firm Size	15.668***	0.518	17.635***	0.544	10.747***	0.434

Note: *** is significance at 1%, ** is significance at 5%, * is significance at 10%.

Table 5. The Estimation of Stochastic Production Frontier on The Inefficiency Function

	Dependent Variable= Inefficiency					
	Model 1		Model 2		Model 3	
	Coeff	Standard Error	Coeff	Standard Error	Coeff	Standard Error
Medium-High Technology (MHT)	-19.632***	0.706	-20.926***	0.721	-21.431***	0.795
Medium-Low Technology (MLT)	-23.783***	0.573	-22.780***	0.586	-25.226***	0.576
Low Technology (LT)	-22.692***	0.529	-22.699***	0.518	-24.708***	0.548
Foreign Direct Investment (FDI)	-0.360	0.652	1.042	0.640	-5.480***	0.735
FDI × MHT	0.818***	0.174	0.891***	0.192	1.727***	0.195
FDI × MLT	3.356***	0.171	3.518***	0.178	2.854***	0.212
FDI × LT	2.300***	0.177	2.365***	0.190	2.294***	0.191
Absorptive Capacity (Absp)	-1.021***	0.032	-0.968***	0.032	-1.142***	0.034
FDI × Absp	0.252***	0.037	0.165***	0.036	0.499***	0.040
Absp × MHT	1.000***	0.043	1.062***	0.043	1.045***	0.049
Absp × MLT	1.040***	0.035	0.974***	0.035	1.140***	0.034
Absp × LT	0.969***	0.032	0.963***	0.032	1.109***	0.033
Age	0.011***	0.001	0.010***	0.001	0.003***	0.001
Export	0.220***	0.045	0.097**	0.049	0.025	0.035
Import	3.415***	0.047	3.346***	0.047	3.325***	0.051
Firm Size	39.492***	0.575	41.825***	0.599	30.161***	0.537

Note: ***, **, * denote significance at 1%, 5%, and 10% level respectively. Standard errors are in parenthesis.

A similar finding is also shown by the coefficient of Absorptive Capacity, which is positive for the production function in all models. This result implies that a higher allocation of labour costs, such as wages, overtime, accident allowance and training, fosters a firm's productivity. This effect is strengthened by the result of the inefficiency effects function, where absorptive Capacity

has a negative impact on technical inefficiency. This suggests that a higher labour cost will boost a firm's technical efficiency. Mastromarco and Ghosh (2009) and Henry, Kneller, and Milner (2009) argued that the existing number of human capital is an essential factor for higher technology absorption as the quality of workers will be assessed by this indicator. Since absorptive Capacity also includes the cost of training, spending on labour training might also positively contribute to promoting firms' efficiency and productivity.

The interacting variables between technology intensity & FDI, technology intensity & absorptive Capacity, and absorptive Capacity & FDI are robust impacts on the production function. According to Model 1, the interacting variable between FDI and MHT is found significant, but it is discovered insignificant on the MLT and LT. This finding can be interpreted as a higher FDI does not affect Medium-Low and Low Technology sectors in promoting firms' production. The result of Model 2 strengthens this finding. The inefficiency effect function demonstrates that most of the coefficients of interacting terms between technology intensity and FDI are positive. It means that the effect of FDI in promoting efficiency is primarily effective for the High Technology sector as a benchmark. This result supports the finding of Walheer and He (2020) using the observation of the high technology firms. They argued that firm ownership is essential in explaining Chinese manufacturing firms' technical efficiency and technology gap. Foreign-owned firms not only shape the sectoral technology metafrontier but also set the standard for technical efficiency.

The effects of the interaction variable between technology intensities and absorptive capacity positively affect firms' production in all models. This can be interpreted as the allocation of labour cost is effective in encouraging production for only Medium-High, Medium-Low, and Low Technology sectors. Conversely, these effects are not pertinent in terms of technical efficiency. The coefficients of technology intensities and absorptive capacity in the inefficiency equation are significantly positive. This concludes that the more allocation of labour costs is more effective for High Technology in improving technical efficiency. This finding is not surprising as an increase in labor cost per worker often represents the increasing ability of workers to absorb external knowledge and technologies (Orlic, Hashi, & Hisarciklilar, 2018). In this regard, a higher-skilled labor allocation in the High Technology group leads to greater efficiency as skilled professionals are required for research and development (R&D). Meanwhile, lower technology groups are found less rigorous, signalling that those groups are less engaged in R&D and advanced production activities than higher-tech firms.

The last variable to be analysed is the interaction variable between absorptive Capacity and FDI. Surprisingly, the result in the production function shows a negative coefficient for Model 1 and Model 2, which suggests that a higher absorptive capacity for a foreign firm will decrease productivity. However, this study observed a different effect of the interaction between FDI and absorptive Capacity on technical inefficiency. Similarly, the inefficiency function reveals that FDI and higher absorptive Capacity will decrease technical efficiency by 25.2%, 16.5%, and 49.9%, respectively, for each model. This finding indicates that foreign firms are relatively not benefited by a higher allocation of labour costs to boost efficiency. The plausible reason for this finding is referred to the study by Javorcik et al. (2012), revealing that foreign firms have offered higher salaries to attract skilled workers. In this regard, foreign firms do not require to allocate more costs for training that will reduce their efficiency performance.

The other exogenous variables in this study show relatively the same effect among the three models. First, the coefficient of firm age in the production function is negative, which means an older firm tends to experience decreasing productivity. This impact is also evidently found in the inefficiency effects equation by which the firm's age positively impacts technical inefficiency. In other words, an older firm tends to be less efficient than a younger one. This finding is in line with the hypothesis of the liability of obsolescence. According to this hypothesis, the effect of firm age decreases firms' efficiency due to their failure to adapt to the environmental evolution in the industry, like failing to adopt a newer technology which might lead to inefficient production (Coad, 2018; Le Mens, Hannan, & Pólos, 2015).

Surprisingly, an exporting firm tends to reduce technical efficiency less than a non-exporting firm does. This finding aligns with Mok et al. (2010), arguing that exporters will benefit from export activities if only they take up a dominant portion of their total sales. Otherwise, exporters will handle large costs of transactions and demanding technical barriers to the trade, decreasing their benefits. The coefficient of *Imp* shows a significant positive effect on the production function of all models. Still, the positive impact of imported material intensity on technical efficiency can not be captured. This result supports the finding of Yasin (2021), revealing that more intensity of imported materials leads to less efficient performance. The finding related to firm size is relatively not surprising as it shows a vigorous positive impact on productivity. However, a larger firm is found less efficient than a smaller one; thus, this effect does not promote firms' technical efficiency.

The coefficients of inputs are reported in Appendix Table 8. These coefficients are not directly interpretable in the economy, but they can be used to estimate the output elasticity with respect to each input. Table 6 conveys output elasticity that captures how much output will increase if the level of input increases. By comparing the elasticity of output with respect to capital (EK), labour (EL), energy (EE) and raw material (EM), it is found that output is mainly more driven by material than by capital, energy, or labour.

Table 6. Elasticity of Output

		Domestic Firm	Foreign Firm
High Technology	EK	0.055	0.044
	EL	0.278	0.241
	EE	0.082	0.065
	ER	0.637	0.667
	Etotal	1.051	1.017
Medium-High Technology	EK	0.048	0.036
	EL	0.260	0.212
	EE	0.082	0.068
	ER	0.661	0.691
	Etotal	1.050	1.006
Medium-Low Technology	EK	0.065	0.043
	EL	0.311	0.235
	EE	0.104	0.077
	ER	0.602	0.667
	Etotal	1.082	1.022
Low Technology	EK	0.053	0.048
	EL	0.279	0.253
	EE	0.076	0.076
	ER	0.660	0.648
	Etotal	1.067	1.023

Note: EK, EL, EE, and ER denote output elasticity with respect to capital, labour, energy and raw material. Etotal=EK+EL+EE+ER. The measurements are obtained from the unbalanced panel observation.

The following analysis concerns the estimation of TFP growth and its decompositions: technical efficiency change (TEC), scale efficiency change (SEC) and technical change (TC). Table 7 reports this estimation for foreign and domestic firms and the categories of R&D intensity.

The result reported in Table 7 reveals that, on averagely, the manufacturing industry in Indonesia from 2007-2015 experienced a positive TFP growth of 3.59%. This magnitude stems from the component of TC at 2.8%, TEC by 0.99% and SEC by 0.68%. Looking at the capital ownership for the whole period, the result shows that the TFP growth of foreign firms categorized as High Technology is the largest amongst all categories at 7.07%. However, by dividing TFP growth into the foreign and domestic firms, the domestic firms have a higher TFP than foreign firms by 3.64%.

Table 7. The Average of Total Factor Productivity Growth and Its Components

Firm	Technology Intensity	TFPg	TC	TEC	SEC
Foreign Firms	HT	7.077	2.985	3.897	0.194
	MHT	3.429	2.296	1.237	-0.105
	MLT	2.056	2.636	-0.648	0.065
	LT	2.816	3.554	-0.881	0.150
	All Foreign Firms	3.073	3.048	-0.051	0.079
Domestic Firms	HT	3.750	3.100	-0.066	0.715
	MHT	3.552	2.304	0.716	0.532
	MLT	3.727	3.241	-0.325	0.812
	LT	3.625	2.718	0.185	0.729
	All Domestic Firm	3.643	2.802	0.112	0.733
All Firms		3.596	2.822	0.991	0.680

Note: TEC, TC, SEC, and TFPg are the arithmetic average of the annual rate in percentage. HT denotes High Technology, MHT denotes Medium High Technology, MLT denotes Medium Low Technology, and LT denotes Low Technology.

Table 8. The Estimation of Stochastic Production Frontier

	Model 1		Model 2		Model 3	
	Coeff	SE	Coeff	SE	Coeff	SE
k	0.054***	0.002	0.054***	0.002	0.056***	0.001
l	0.174***	0.005	0.176***	0.005	0.271***	0.002
e	0.070***	0.002	0.069***	0.002	0.088***	0.001
r	0.701***	0.002	0.701***	0.002	0.643***	0.001
k^2	0.006***	0.000	0.006***	0.000	-	-
l^2	0.041***	0.002	0.040***	0.002	-	-
e^2	0.018***	0.000	0.018***	0.000	-	-
r^2	0.072***	0.000	0.073***	0.000	-	-
$k \times l$	0.028***	0.001	0.030***	0.001	-	-
$k \times e$	0.006***	0.000	0.006***	0.000	-	-
$k \times r$	-0.039***	0.001	-0.040***	0.001	-	-
$l \times e$	0.013***	0.001	0.014***	0.001	-	-
$l \times r$	-0.116***	0.001	-0.120***	0.001	-	-
$e \times r$	-0.045***	0.001	-0.046***	0.001	-	-
t	0.062***	0.003	0.062***	0.003	-	-
$t \times k$	-0.003***	0.000	-0.003***	0.000	-	-
$t \times l$	-0.001***	0.000	-0.001***	0.000	-	-
$t \times e$	0.018***	0.001	0.018***	0.001	-	-
$t \times r$	0.002***	0.000	0.002***	0.000	-	-
t^2	-0.008***	0.000	-0.008***	0.000	-	-
Sigma-Square (σ^2)	4.960***	0.019	5.030***	0.021	3.705***	0.008
Gamma (γ)	0.971***	0.000	0.971***	0.000	0.941***	0.000
Log-Likelihood Ratio	-84155.51		-84091.98		-103405.46	

Note: Models 1-3 refer to Translog model with foreign ownership (FOR) 5% (Model 1), 10% (Model 2), and 20% (Model 3). Models 4-6 refer to Hick-Neutral, Cobb-Douglas, and No Technological Progress with FOR 5%. ***, **, * denote significance at 1%, 5%, and 10% level respectively. Standard errors are in the parenthesis.

Both foreign firms categorized as Medium-Low and Low Technology averagely experience negative TEC. In terms of this indicator, foreign firms show an averagely lower magnitude than domestic firms. The result shows that foreign firms in the High Technology category have the largest average of TEC among others at 3.89%. In comparison, foreign firms in the Low Technology category show the lowest growth by -0.88%. This finding strengthens Table 5, revealing that foreign firms with high technology perform better efficiently. This finding is consistent with Fu and Gong (2011), who employed a Chinese-firm-level dataset despite using

different observations. Although FDI does not contribute to higher technical efficiency for foreign High Technology sectors (see the inefficiency equation in Table 5), foreign firms in High Technology sectors tend to grow faster than others during the periods of interest.

Foreign and domestic firms are relatively different in scale efficiency change (SEC). Foreign firms experience a positive SEC of 0.07%, whereas the negative SEC is experienced by the Medium-High Technology sector at -0.10%. Meanwhile, domestic firms averagely show a positive SEC of 0.73%, whereas Medium-Low Technology sectors contribute 0.81% on this magnitude.

This study addresses the finding regarding the technical change, which can reflect how the technological progress of firms developed. The results related to technical change in foreign and domestic firms show that the technological progress experienced by foreign firms is relatively larger than that experienced by domestic ones. This is not surprising as foreign firms may have more advanced technology to produce outputs, and thus, their shifting frontier process is faster.

However, an intriguing result reveals that the Low Technology sectors enjoy foreign ownership benefits mainly. This finding is surprising since, according to some studies, the technology diffusion caused by FDI is associated with high-technology intensity (Keller, 2010). There are three possible reasons for this result. The first plausible reason is the low technical capabilities of human resources in Indonesia. The investment of multinational enterprises (MNEs) can take place anywhere. Still, the investment in the High Technology sectors surely needs more stringent standards that might lead to a slower shifting of high-technology firms. In this sense, theories of human capital investment as a complementary factor to foreign investment are, indeed, relevant (see: Carbonell & Werner, 2018; Lucas, 1988; Rebelo, 1991; Romer, 1986).

The second reason is that the Low Technology sectors have received many foreign investments. This means that more foreign support is given through, for instance, High Technology transfer to Low Technology sectors. This is in accordance with the studies of Kokko (1994) and Liu, Siler, Wang, and Wei (2000), concluding that regardless of the classification of the industry (e.g. low-technology industry or high-technology industry), firms' technical capabilities are more likely to determine the effectiveness of the technology transfer obtained from FDI activities.

The third reason is related to the type of foreign firms. Foreign firms are more likely to affiliate with parent companies headquartered in foreign countries. In this case, a parent company may give its subsidiaries the access merely to apply and adapt advanced technology (Fu & Gong, 2011). Meanwhile, the parent company continues its core technology development in the headquarters. In this sense, a foreign High Technology sector cannot achieve a higher technical change.

Conclusion

This study has demonstrated the effects of FDI (represented by the incoming foreign firm), technology intensity (i.e. High, Medium-High, Medium-Low, and Low Technology sectors) and absorptive Capacity on the technical efficiency and productivity of the manufacturing firms in Indonesia. The stochastic production frontier estimation reveals that FDI, technology intensity and absorptive capacity alone promote firms' production, but only absorptive capacity promotes technical efficiency. The models adopted in this study concluded that the interacting term between technology intensity and FDI has a negative impact on firms' technical inefficiency. It means that sectors categorized as High Technology incorporated with foreign ownership tend to have higher technical efficiency. The result shows that, on averagely, the manufacturing industry in Indonesia from 2007 to 2015 experienced positive TFP growth. The result also shows that the technological progress experienced by foreign firms is relatively larger than that experienced by domestic ones. In this sense, international technology diffusion through FDI might successfully occur because foreign firms can make a faster frontier shifting process.

Finally, this study has many important implications. Obtaining FDI benefits, such as transfer of knowledge or technology diffusion, is not a simple matter. It requires many complementary factors, such as technical capabilities or absorptive Capacity, even if a firm is categorised as a High Technology sector. Firms with lower technical capability can catch up and receive similar benefits from FDI activities. In this sense, the host country's government should

focus on the industries that have had high technical capabilities to accelerate FDI gains for the firms. However, simultaneously, human capital improvement also needs to be intensified, for instance, through training or human development.

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Forecasting inflation in Turkey: A comparison of time-series and machine learning models

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Abstract

Purpose — This paper aims to analyze inflation in Turkey. For this purpose, the accuracy of some Machine Learning (ML) models in forecasting inflation have been tested a new and complementary approach has been tried to be given to time series models.

Methods — This paper forecasts inflation in Turkey by using time-series and machine learning (ML) models**.** The data spans from the period 2006:M1 to 2020:M12.

Findings —According to the root mean squared error and R-square evaluation criteria, the forecasts obtained from the ML algorithms were less accurate than the forecasts obtained from the VAR model. However, it has been observed that the findings obtained from the MLP algorithm, which takes into account nonlinear relationships, give more accurate results compared to the forecasts obtained from linear-based Lasso and Ridge models. From this point of view, it is suggested that nonlinear ML should be evaluated as a complementary method for inflation forecasting.

Implication — According to the study's findings, the nonlinear ML algorithms can be thought of as a complementary method to forecast inflation in emerging economies with volatile inflation rates. Central banks and policymakers can benefit from computational power and big data for inflation forecasting.

Originality — We evaluate the forecasting performance of ML models against each other and a time series model and investigate possible improvements upon the naive model. So, this is the first study in the field that uses both linear and nonlinear ML methods to compare the time series inflation forecasts for Turkey.

Keywords — inflation forecasting, time series models, machine learning models, emerging economies

Introduction

Inflation is one of the most crucial indicators that reflects the status of the Economy. Contracts are usually set in nominal terms, so the level of inflation significantly impacts the behaviour of the economic agents such as households, firms, and investors. Furthermore, policymakers direct the Economy using monetary policy, which needs a reliable inflation forecast. In case of failure in inflation forecasting, large welfare losses occur (Barkan et al., 2021). Lastly, since the debt and interest payment levels are being affected by the level of inflation, governments need accurate forecasts for choosing appropriate fiscal policies. This fact is especially crucial in emerging

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economies such as Turkey, with high public debt levels. (According to the Central Government Budget, Turkey has nearly 7,597 billion TL foreign debt stock in the first quarter of 2021 (MTFRT, 2021) (Republic of Turkey Ministry of Treasury and Finance)).

Turkey has experienced high and persistent inflation rates since the 1970s. Especially after the 1994 crisis, the inflation rates have gone through the ceiling and exceeded 120%. Although a series of stabilization programs supported by the IMF have been implemented in recent years, inflation remains a crucial problem for the Turkish Economy. To reduce inflation, CBRT started to adopt an explicit inflation-targeting regime in 2006. Adapting this regime and ongoing high inflation has made forecasting inflation in Turkey more important for CBRT (The CPI inflation in Turkey is 20.3%, 11.84%, and 14.6% in 2018, 2019, and 2020 respectively.)

Despite its needfulness, forecasting inflation is a challenging task. Today, even Central Banks sometimes make projections that do not systematically fit the actual values. Recently, even European Central Bank has overestimated the inflation values (Medeiros et al., 2021). The CBRT likewise, has underestimated most of the level of inflation in the recent 10 years. From this point of view, researchers began to look for a new and applicable methodology to forecast inflation more accurately. Due to improvements in computational power and size of the datasets, ML models have recently come to be seen as the solution to tackle difficult forecasting tasks. As big data accumulated in the field of economics, ML algorithms became used in forecasting inflation, too. However, studies using machine learning methods to estimate inflation are noteworthy that studies are generally conducted in developed countries. Studies based on machine learning algorithms have remained limited in developing countries such as Turkey, as the data volume is newly developing, and researchers have turned to conventional methods.

To fill this gap, Özgür and Akkoç (2021), for the first time, performed a comparative analysis using ML and time-series algorithms simultaneously to predict inflation in Turkey. As an ML algorithm, they used Ridge, Lasso and derivatives of Lasso and elastic net algorithms. The ML findings were compared to the results of the random walk, ARIMA, and multivariate VAR models. The study filled an important gap in the literature in that it uses machine learning algorithms that do not require assumptions about the relationships of independent variables with a large data set and compare the findings with the results obtained from time series models (Özgür & Akkoç, 2021). Their ML methodologies were also able to choose the most appropriate measures of inflation. However, only linear models were used in the study. However, there may be nonlinear relationships between inflation and other economic variables. This situation is critical in developing economies such as Turkey, where uncertainty is relatively high.

This paper aims to make an empirical and methodological contribution to the literature by using a nonlinear ML algorithm while comparing ML and time series models in forecasting inflation in Turkey. For that purpose, the predictions obtained from neural network algorithm (multilayer perceptron model) with different tuning parameters have been used in addition to shrinkage models. The results have been compared with the findings from the time series model, namely the VAR model. This study is the first study in the field that uses both linear and nonlinear ML methods to compare Turkey's time series inflation forecasts

There is a vast literature on inflation forecasting. Preliminary empirical studies that predict inflation are based on three main models: the mark-up models (e.g. Brouwer & Ericsson, 1998; Banerjee et al., 2001; Christopher & Jansen, 2004; Bennouna, 2015), the monetary models (e.g. Callen & Chang, 1999; Altimari, 2001; Jonsson, 2001), and the Phillips curve (e.g. Coe & McDermott, 1997; Önder, 2004; J. H. Stock & Watson, 2013; Chen, 2019; Ball & Mazumder, 2019, 2020). However, as the available data and computational power increase, machine learning algorithms have started to be a preferred method in inflation forecasting. ML algorithms have been used in forecasting different economic variables, but this study does not attempt to present all of them. Instead, focus on studies that apply ML algorithms to inflation forecasting. In this section, the studies with the ML approach are mentioned, and studies based on conventional econometric techniques are excluded.

Firstly, it is noteworthy that most of the studies dealing with the ML algorithm in inflation forecasting focus on the US. Stock and Watson (1999) is one of the pioneer studies that

handle forecasting inflation in the US using neural network approaches. They compare the forecasts at the one, six, and twelve-month horizons for monthly US economic time series. The results indicate that most nonlinear methods, including the ANN method, produce worse forecasts than the linear AR methods (J. Stock & Watson, 1999). Nakamura (2005), in a later study, forecast a new US inflation by using a neural network approach. The author uses the GDP deflator as the indicator of inflation. The neural networks outperform univariate autoregressive models such as AR models with different baselines (Nakamura, 2005).

Ülke, Sahin, and Subasi (2018) use different indicators such as CPI for all items, core-CPI, the personal consumption expenditure deflator (PCE), and the core-PCE, for inflation forecasting in the US. They use AR, random walk, ARDL, VAR models as benchmark models and the SVR as the ML approach. The results indicate the outperformance of the SVR model in forecasting core-PCE inflation, and the ARDL model provides the best results in forecasting core-CPI inflation (Ulke, Sahin, & Subasi, 2018). Almosova & Andresen (2019) show that the artificial neural network gives better results than the linear AR and random walk models. Medeiros et al. (2021) similarly note the outperformance of the ML models against univariate benchmarks for inflation forecasting in the US, such as random walk and AR (Medeiros et al., 2021). They find that the performance of using ML methods can be as better as 30% in terms of mean squared errors. They also pay special attention to the nonlinear random forest model, which gives more accurate results than the other ML algorithms such as Lasso, adaptive Lasso, and Ridge regression. Barkan et al. (2021) improve the forecasts of the US by using the disaggregated indexes that comprise CPI. They use AR and VAR models as time series benchmarks and test the performance of ML models such as KNN and neural network approaches. The results demonstrate the superiority of the neural network model, especially in low levels of CPI hierarchy (Barkan et al., 2021).

Some other studies handle inflation in different countries. For example, Medeiros, Vasconcelos, and De Freitas (2016) use LASSO regression to forecast inflation in Brazil. They also use linear autoregressive and factor models based on principal components as the benchmark specifications. Their results indicate that the LASSO results are more accurate than the benchmark specifications in short-horizon forecasts. However, the results differ in long-horizon forecasts. Another important finding of the study is the relevance of the variables. The most important variables selected by the LASSO regression are related to government debt and money instead of unemployment and production (Medeiros et al., 2016). So, the authors' findings do not support the Phillips curve mechanism. In a later study, Garcia, Medeiros, and Vasconcelos (2017) re-estimate the inflation rates in Brazil by using ML algorithms. They employ linear shrinkage models such as the Lasso and the adaptive Lasso, including random forest as an alternative nonlinear ML model. They compare their results with the AR and the random walk model. The results differ according to the period considered (Garcia et al., 2017).

Chakraborty and Joseph (2017) forecast CPI inflation in the UK on a medium-term horizon of two years by using various modelling approaches, such as artificial neural networks, tree-based models, support vector machines, recommender systems, and different clustering techniques. The results indicate the high performance of the ML models (Chakraborty & Joseph, 2017). Similar findings are being obtained by Baybuza (2018) for Russian inflation forecasts, too. The author compares the Russian inflation forecasts of different time series methods to the results of ML algorithms such as Lasso and Ridge regressions, elastic net model, and random forest model. Rodríguez-Vargas (2020) compares the performance of ML models in forecasting inflation in Costa Rica. The results point out the extended short-term memory network, univariate KNN, and random forests as the best-performing models (Rodríguez-Vargas, 2020). In conclusion, ML methods can improve the quality of forecasting Russian inflation compared to univariate time series models (Baybuza, 2018).

To the best of our knowledge, the paper of Özgür and Akkoç (2021) is the first and unique study that tries to forecast inflation in Turkey using ML techniques and compares the results with some time series benchmark models. The algorithms they employ are Ridge regression, Lasso regression, and elastic net algorithms. They state that shrinkage methods such

as Lasso and elastic net algorithms outperform conventional econometric methods (Özgür & Akkoç, 2021).

On the other side, this study aims to enrich the literature by adding the nonlinear predictions from the neural network algorithm. That way, this study is the first to forecast the inflation in Turkey, a developing country, with linear ML models such as Lasso and Ridge regression and nonlinear ML models such as multilayer perceptron algorithm, and to compare the results with the findings of time series model. The second contribution of the study is methodological, which evaluates ML models' forecasting performance against each other and a time series model and thereby investigates possible improvements upon the naive model. The third contribution of the model is about data. This study makes use of the current data set covering the period 2006:M1-2020:M12. We also eliminate the variables with missing data since it can cause bias in the model.

Methods

This section will forecast the inflation rates using both time series regression and different ML algorithms. This study uses the multivariate VAR methodology for the benchmark time series analysis and benefits from different supervised ML algorithms with a labelled dataset. These algorithms consist of linear shrinkage models such as Ridge regression, Lasso regression, and a neural network algorithm.

The data spans from the period 2006:M1 to 2020:M12 based on the availability of the data. We use the conventional 75%-25% division for the train/test splitting of the data. So, each model is being trained over the period 2006:M1 to 2017:M3. The rest of the dataset covering the period 2017:M4 to 2020:M12 is being used as the test dataset to measure the accuracy of the predictions. The root means squared error (RMSE) and the square of correlation coefficient (R^2) values are being used as the evaluation metrics. We benefit from the Python software as the development environment.

In the benchmark VAR model, the CPI variable shows the consumer price index based on 2003. The CBRT also uses the annual change in CPI for inflation targeting. Based on monetary models (e.g. Altimari, 2001; Callen & Chang, 1999; Jonsson, 2001), the exchange rate (EXC), the stock market index (BIST), and the money supply (M2) series have been used as the explanatory variables. EXC is the sale price of the US dollar. BIST is the 2003 based stock market index of Borsa Istanbul. And M2 is the money supply that includes term deposits.

All of the VAR model datasets have been obtained from the Central Bank of Turkey (CBRT, 2021). The definitions and the sources of the variables are given in Table 1.

Table 1. Variable Definitions and Data Sources

Name	Description	Source
CPI	consumer price index (2003=100)	CB of Turkey
EXC	US dollar (sale price)	CB of Turkey
BIST	Stock market index (January 1986=100) (according to closing price)	CB of Turkey
M2	M2 money supply (level)	CB of Turkey

On the other hand, the ML algorithm is a method that learns from data, and it creates its own algorithm from a large number of variables. For this reason, 28 different features thought to affect inflation were considered, and the choice of the model to be used was left to the method itself. Following Özgür and Akkoç (2021), these data include groups of features such as production indicators, the quantity of money supply, gold prices, exchange rates, interest rates, government budget indicators, and so on. However, it eliminated the variables with missing values. The CPI is used as the indicator of the output. The definitions and the sources of the variables are given in the table in Appendix 1. The complete data set has been obtained from the CBRT database. The program codes and data set are available upon request from the authors.

Benchmark Model

We used the VAR model, developed by Sims (1980), as the benchmark model to evaluate the accuracy of the forecasts of the ML algorithms. The VAR is a widely used model in forecasting variables when two or more time series are expected to influence each other. One of the advantages of the VAR model is that it does not require the endogenous and exogenous distinction between the variables (Wojciech & Derek, 1992). In addition, since only the lagged values of the variables are included in the analysis, the success of the future forecasts increases (Kumar et al., 1995).

In the VAR model, the variables are modelled as a weighted combination of their own past values and the past values of other signals in the model plus an error term (Chang et al., 2012). Therefore, the VAR model can be specified as:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + C x_t + \varepsilon_t \quad (1)$$

where $y_t = (y_{1t}, y_{2t}, \ldots, y_{kt})'$ is a *k**1 vector of endogenous variables, $x_t = (x_1, x_{2t}, \ldots, y_{dt})'$ is a *d**1 vector of exogenous variables, $A_1, \ldots, A_p$ are *k*k* matrices of lag coefficients, C is a matrix of exogenous variable coefficients and ε_t is the *k*1* vector of error terms which are considered white noise.

Since all the variables in the VAR system must be stationary, it is necessary to test the stationarity of the data in the first stage and make the necessary transformation for non-stationary series. The augmented Dickey-Fuller test developed by Dickey and Fuller (1979) is a widely used statistical procedure that tests whether a time series contains a unit root.

For an equation of a time series (Y_t) as follows:

$$Y_t = \rho Y_{t-1} + u_t \quad (2)$$

where u_t is a white noise error term, the stationarity can be tested with the following hypothesis:

$$H_0: \rho \geq 1$$
$$H_1: \rho < 1 \quad (3)$$

If the t-stat is less than the critical values, then the null hypothesis is rejected, and the time series are accepted to be stationary (Dickey & Fuller, 1979). If the variables are not stationary, the analysis is repeated by taking the differences. This process continues until there is no nonstationary variable left.

The next step in the VAR estimation process is determining the lag length. At this stage, benefiting from information criteria such as Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQIC) is very common. AIC focuses on finding the lag length that minimizes the means squares of error. On the other hand, BIC and HQIC focus on finding a consistent model. The criteria are calculated as follows:

$$AIC = \left(\frac{2n}{f-m-1}\right) m - 2ln[L_{max}]$$
$$BIC = ln[f]m - 2ln[L_{max}]$$
$$HQIC = 2ln\big[ln[f]\big]m - 2ln[L_{max}] \quad (4)$$

where *f* is the number of observations, *m* is the number of parameters to be estimated and L_{max} is the maximized value of the log-likelihood for the estimated model. The coefficients of m show the degree to which the number of model parameters is being penalized. So, BIC and HQIC are more stringent than AIC in penalizing the loss of degrees of freedom.

Among the alternative models, the one with the minimum information criteria provides a good balance between fit and complexity. Finally, the selected model can be tested in terms of autocorrelation. Although many tests are used to test the presence of autocorrelation, the Durbin-Watson (DW) test is the most used. Where σ is the autocorrelation coefficient, the null and alternative hypotheses for the DW test are as follows:

$$H_0: \sigma = 0$$
$$H_1: \sigma \neq 0 \quad (5)$$

The DW test statistic is calculated as follows:

$$DW = \frac{\sum_{t=2}^{t=n}(\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^{t=n}(\hat{u}_t)^2}$$

or as;

$$DW = 2(1-\sigma) \quad (6)$$

If σ=-1, DW will be equal to 4, and there is negative autocorrelation. If σ=0, DW will be equal to 2, and there is no autocorrelation. If σ=1, then DW will be equal to 0, and there is positive autocorrelation. After calculating the value of the DW test statistic (*d*), it is compared with the lower bound (d_l) and upper bound (d_u) critical values to determine whether there is an autocorrelation problem. The decision mechanism is as follows:

If $0< d < d_l$, then the null hypothesis is rejected.

If $d_l \leq d \leq d_u$, then the test is inconclusive.

If $4 - d_l < d < 4$, then the null hypothesis is rejected.

If $4 - d_u \leq d \leq 4 - d_l$, then the test is inconclusive.

If $d_u \leq d \leq 4 - d_u$, then the null hypothesis cannot be rejected.

If there is no autocorrelation problem, the model indicated by the information criteria will be preferred.

Machine Learning Models

Econometric methods are frequently being used in the estimation of economic variables. However, these methods are generally estimated with models being created in line with economic theories. As mentioned in the literature review section, different economic theories have been developed for the estimation of inflation. However, there is no consensus on the determinants of inflation. At this point, the existence of a method that creates its own algorithm from a large data set containing different variables is important. In addition, as the data volume increases in the future, the accuracy of the forecasts will increase.

The ML algorithms are generally sensitive to the scaling of the data. Therefore, standard normalization that gives data with zero mean and unit variance has been used. Then the forecasts were made with both linear and nonlinear models.

Linear models

Shrinkage methods are being widely used to estimate the parameters in high-dimensional datasets. Among these algorithms, Lasso (Least Absolute Shrinkage and Selection Operator), proposed by Tibshirani (2016), and the Ridge regression proposed by Hoerl & Kennard (1970), have received particular attention.

Lasso regression algorithm is an ML algorithm that uses linear models but also satisfies an additional constraint. It uses l1 regularization, which minimizes the sum of the coefficients' absolute values and shrinks coefficients for some features that have a low contribution to the prediction task. Thus, some coefficients become exactly zero.

The solution to a minimization problem defines the Lasso estimator:

$$\hat{\beta} = \arg\underbrace{min}_{\hat{\beta}} \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j)^2,$$

$$\text{subject to } \sum_{j=1}^{k}|\beta_j| \leq t \quad (7)$$

where β's are the estimated coefficients.

The Ridge regression algorithm is again a widely used linear model, but it uses l2 penalty, which minimizes the square of the magnitude (Euclidean length) of the coefficients (min $\sum(\beta_i)^2$)

to shrink coefficients. Therefore, the magnitudes of the coefficients are restricted to be small as possible. However, none of them become exactly zero.

The solution to a minimization problem defines the Ridge estimator:

$$\hat{\beta} = \arg\underbrace{min}_{\hat{\beta}} \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{k} x_{ij}\beta_j)^2,$$
$$\text{subject to } \sum_{j=1}^{k} \beta_j{}^2 \leq t \tag{8}$$

where β's are the estimated coefficients.

Evaluation metrics

In order the examine the performance of the models, this study benefits from two different evaluation metrics: root mean squared error (RMSE) and the square of correlation coefficient (R^2) value (or the test set accuracy) RMSE is given by:

$$\text{RMSE}= \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \hat{x}_t)^2} \tag{9}$$

where x_t indicates the monthly change in time t, and $\hat{x}_t$ indicates the relevant prediction.

The R^2 value lies between 0 and 1, where higher values indicate a better data performance to fit the model.

$$R^2 = \frac{\hat{\beta}_1^2(\sum \hat{Y}_i^2)}{\sum Y_i^2 - (\sum Y_i)/n} = \frac{\sum(Y_i - \hat{Y}_i)^2 - \sum(\hat{\varepsilon}_i)^2}{\sum(Y_i - \hat{Y}_i)^2} \tag{10}$$

Neural Networks

In this paper, a relatively simple multilayer perceptron's (MLP) method for regression can be seen as a generalization of linear models that perform multiple stages with hidden layers. The perceptron model was developed by an American psychologist Rosenblatt (1958), who is acknowledged as a pioneer in the training of neural networks. In this algorithm, the input features are weighted by the learned coefficients, and computing the weighted sums is repeated by multiple times (Muller & Guido, 2017).

The first layer includes input features for each predictor variable, the second layer is the hidden layer, and there is one output layer. Each feature is weighted by the learned coefficients and connected to nodes in the hidden layer. Each node in the hidden layer is also multiplied by a weight, and the weighted values are added together to produce the output.

In addition to the computation of the weighted coefficients by multiple times, the MLP algorithm also uses a nonlinear function such as rectifying nonlinearity (relu) and the hyperbolic tangent (tanh), thereby giving more powerful results than a linear model.

Results and Discussion

In the first step, the VAR model is employed to forecast inflation. As the series affect each other, it is modelled by the system of equations with one equation for each variable:

$$CPI_t = \alpha_1 + \beta_{11,1}CPI_{t-1} + \cdots + \beta_{p1,1}CPI_{t-p} + \beta_{12,1}EXC_{t-1} + \cdots + \beta_{p2,1}EXC_{t-p} + \beta_{13,1}BIST_{t-1} + \cdots + \beta_{p3,1}BIST_{t-p} + \beta_{14,1}M2_{t-1} + \cdots + \beta_{p4,1}M2_{t-p} + \varepsilon_{1t}$$

$$EXC_t = \alpha_2 + \beta_{11,2}CPI_{t-1} + \cdots + \beta_{p1,2}CPI_{t-p} + \beta_{12,2}EXC_{t-1} + \cdots + \beta_{p2,2}EXC_{t-p} + \beta_{13,2}BIST_{t-1} + \cdots + \beta_{p3,2}BIST_{t-p} + \beta_{14,2}M2_{t-1} + \cdots + \beta_{p4,2}M2_{t-p} + \varepsilon_{2t}$$

$$BIST_t = \alpha_1 + \beta_{11,3}CPI_{t-1} + \cdots + \beta_{p1,3}CPI_{t-p} + \beta_{12,3}EXC_{t-1} + \cdots + \beta_{p2,3}EXC_{t-p} + \beta_{13,3}BIST_{t-1} + \cdots + \beta_{p3,3}BIST_{t-p} + \beta_{14,3}M2_{t-1} + \cdots + \beta_{p4,3}M2_{t-p} + \varepsilon_{3t}$$

$$M2_t = \alpha_1 + \beta_{11,4}CPI_{t-1} + \cdots + \beta_{p1,4}CPI_{t-p} + \beta_{12,4}EXC_{t-1} + \cdots + \beta_{p2,4}EXC_{t-p} + \beta_{13,4}BIST_{t-1} + \cdots + \beta_{p3,4}BIST_{t-p} + \beta_{14,4}M2_{t-1} + \cdots + \beta_{p4,4}M2_{t-p} + \varepsilon_{4t} \quad (11)$$

In the first step, the series have been tested for stationarity by using Augmented Dickey-Fuller (ADF) test. The null hypothesis of the test states that the data has a unit root. The results are given in Table 2.

Table 2. Augmented Dickey-Fuller Test on Variables

Variable Name	BIST	EXC	M2	CPI
Test stat	0.471	3.237	6.250	4.536
No. lags chosen*	14	5	0	5
Critical value 1%	-3.471	-3.469	-3.467	-3.469
Critical value 5%	-2.879	-2.878	-2.878	-2.878
Critical value 10%	-2.576	-2.576	-2.575	-2.576
p-value	0.984	1.000	1.000	1.000

*The optimal lag length has been chosen according to the Akaike Information Criteria.

According to the ADF test, the t-stats of all variables are greater than all of the critical values. Therefore, the null hypothesis cannot be rejected. So, none of the series is stationary at level. Therefore, take the variable into the first differences of all series and test the stationarity of the new series. The results are shown in Table 3.

Table 3. Augmented Dickey-Fuller Test on the First Differenced Variables

Variable Name	BIST	EXC	M2	CPI
Test stat	-3.431	-6.773	-0.6221	-3.168
No. lags chosen*	14	2	11	4
Critical value 1%	-3.471	-3.468	-3.471	-3.469
Critical value 5%	-2.879	-2.878	-2.879	-2.878
Critical value 10%	-2.576	-2.576	-2.576	-2.576
p-value	0.010	0.000	0.866	0.022

*The optimal lag length has been chosen according to the Akaike Information Criteria.

In the following result of the ADF test in the first differences variables in table 3, all of the series except the first difference of M2 are stationary at a 5% level of significance (t-stat of M2 (-0.6221)>t-critical (-2.879)). However, all of the series in the MVAR model should have the same number of observations. Therefore, the second difference of all series is used and re-run the ADF test.

According to Table 4, the t-stats of all variables are greater than the critical values. Therefore, all of the variables are stationary in their second differences. So, the analysis continues with the second differenced series. In the next step, split the dataset into training data for the period of 2006:M1 to 2017:M3 and the last forty-five observations as the test data. The forecasts obtained from test data will be compared against the actual values of CPI.

Table 4. Augmented Dickey-Fuller Test on the Second Differenced Variables

Variable Name	BIST	EXC	M2	CPI
Test stat	-4.997	-7.223	-5.375	-7.439
No. lags chosen*	13	9	14	10
Critical value 1%	-3.471	-3.471	-3.471	-3.471
Critical value 5%	-2.879	-2.879	-2.879	-2.879
Critical value 10%	-2.576	-2.576	-2.576	-2.576
p-value	0.000	0.000	0.000	0.000

*The optimal lag length has been chosen according to the Akaike Information Criteria.

Determining lag length (p) before estimating a VAR model is very important. Benefiting from information criteria such as Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQIC) is very common. The three methods are used to determine the lag length. Table 5 shows the results.

Table 5. The Lag Length Selection

p	AIC	BIC	HQIC
0	42.10	42.18	1.927e+18
1	40.11	40.47	2.619e+17
2	39.52	40.17*	1.455e+17
3	39.33	40.27	1.207e+17
4	38.95*	40.18	8.233e+16*

*highlights the minimums.

According to Table 5, AIC and HQIC reach their minimum level at a lag order of 4. Therefore, lag 4 chooses as the lag length and trains our model of p=4. Table 6 shows the results of the VAR model for the equation CPI.

Autocorrelation problems were checked by using Durbin-Watson test statistics. The test statistic is 2.15, and the autocorrelation coefficient is found to be -0.075. As the autocorrelation coefficient is greater than d_u and is less than 4-d_u, the null hypothesis cannot be rejected, there is no serial correlation, and the VAR(4) model can be used in forecasting.

Table 6. The VAR model results for equation CPI

	Coefficient	Standard Error	T-Statistic	Probability
Constant	0.040	0.142	0.282	0.778
L1.BIST*	0.002	0.004	0.686	0.492
L1.EXC*	-0.655	3.335	-0.196	0.844
L1.M2*	0.000	0.000	1.711	0.087
L1.CPI*	-0.388	0.090	-4.293	0.000
L2.BIST*	0.003	0.005	0.532	0.595
L2.EXC*	5.956	4.074	1.462	0.144
L2.M2*	0.000	0.000	0.517	0.605
L2.CPI*	-0.605	0.097	-6.254	0.000
L3.BIST*	0.006	0.005	1.243	0.214
L3.EXC*	1.262	4.078	0.309	0.757
L3.M2*	0.000	0.000	-0.480	0.632
L3.CPI*	-0.163	0.098	-1.671	0.095
L4.BIST*	-0.002	0.004	-0.465	0.642
L4.EXC*	4.914	2.859	1.719	0.086
L4.M2*	-0.000	0.000	-0.393	0.694
L4.CPI*	-0.437	0.090	-4.858	0.000

Note: * indicates that the second difference of the variable is taken.

As shown in Table 6, the CPI variable is being affected by its own one and two-term lags at a 5% level of significance. It is also being affected by its own three-term lag at a 10% significance level. In addition, it is affected by one term lag of M2 and four terms lag of EXC at a 10% level of significance. This finding is consistent with the Monetarist and Keynesian views about inflation. According to these views, the increase in money supply will increase aggregate demand, production will rise above the natural level in the short run, and then the aggregate supply will decrease due to rising wages arising from unemployment falling below the natural level. Although the natural output is restored, this process ends with a price increase. If the money supply increases, the increase in the price level will also continue. Thus, the main inflation factor is seen as rapid monetary expansion (Mishkin, 2000). The finding is also consistent with studies advocating the importance of monetary variables in determining inflation (e.g. Altimari, 2001; Callen & Chang, 1999; Jonsson, 2001).

In the next step, by use the last four observations to forecast the following 45 observations, which also consist of our test dataset. The results can be seen in Figure 1.

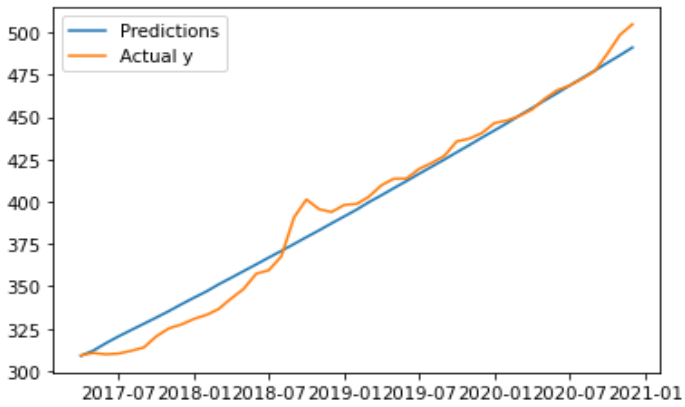

Figure 1. Forecasted and Actual Values for CPI (2019:M7-2020:M12)

In Figure 1, the orange line shows the actual values of the CPI during 2017:M4-2020:M2. On the other hand, the straight blue line shows the forecast results of the VAR(4) model for that period. Although the forecasts of the VAR model deviate from the actual values in periods when inflation is volatile, it can be argued that it provides accurate forecasts in general.

In the second step, make inflation forecasts using ML algorithms. First, the forecast used standard normalization that gives data with zero mean and unit variance for that purpose. Table 7 shows the magnitudes of the coefficients obtained from the Lasso and Ridge models. By looking at the magnitudes of the coefficients, the most important features are selected by the algorithm.

Table 7. Coefficients of Lasso and Ridge Regression

Feature	Lasso regression	Ridge regression
ind	0.00e+00	0.149
int	0.00e+00	-1.655
dur	0.00e+00	0.354
nondur	0.00e+00	1.427
enr	-1.82e-01	0.580
cap	0.00e+00	-0.076
ltech	0.00e+00	-0.717
mltech	-1.02e-02	0.603
mhtech	0.00e+00	2.080
htech	0.00e+00	-1.214
min	-6.39e-01	-0.471
man	0.00e+00	0.125
mes	1.17e+00	2.304
eftrans	8.57e-01	3.823
cbtrans	-5.34e+00	-6.409
cumh	0.00e+00	9.903
bist	0.00e+00	0.644
usds	0.00e+00	3.097
usdb	0.00e+00	3.068
r1	0.00e+00	-0.180
r2	0.00e+00	-1.763
dep	4.59e+01	27.449
cred	2.74e+01	17.996
M2	2.27e+01	18.558
asset	0.00e+00	6.174
budrev	5.15e-01	5.915
budexp	0.00e+00	5.606
build	0.00e+00	-0.377

We can also plot the coefficients of the different models to see the most important features. Figure 2 shows the coefficient magnitudes for Lasso and Ridge regression.

As shown in Table 7 and Figure 2, only ten coefficients are different from zero in Lasso regression. Therefore, the Lasso model uses only ten of the features. Among these automatically selected features, the most important ones are dep (deposit account (TRY)), cred (Total credits (TRY)), and M2 (M2 money supply (TRY)). It is noteworthy that monetary variables are found to be relatively important. Furthermore, this finding confirms monetarist and Keynesian views about inflation.

The finding is again consistent with studies advocating the importance of monetary variables in determining inflation (e.g. Altimari, 2001; Callen & Chang, 1999; Jonsson, 2001). Additionally, the finding is consistent with Medeiros et al. (2016). By addressing the Brazilian Economy, they drew attention to the relative importance of monetary variables such as money supply and public debt instead of unemployment and production in determining inflation in emerging economies. Some studies draw attention to the importance of monetary variables in determining inflation in the Turkish Economy (e.g. Bulut, 2016; Gungor & Berk, 2006; Lim & Papi, 1997).

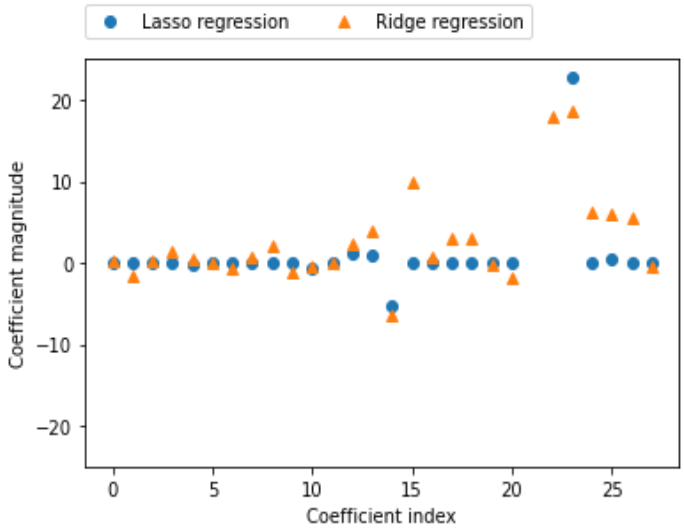

Figure 2. Comparing Coefficient Magnitudes for Ridge and Lasso Regression

The forecasting results obtained from the Lasso and Ridge regression can be visualized as shown in Figure 3.

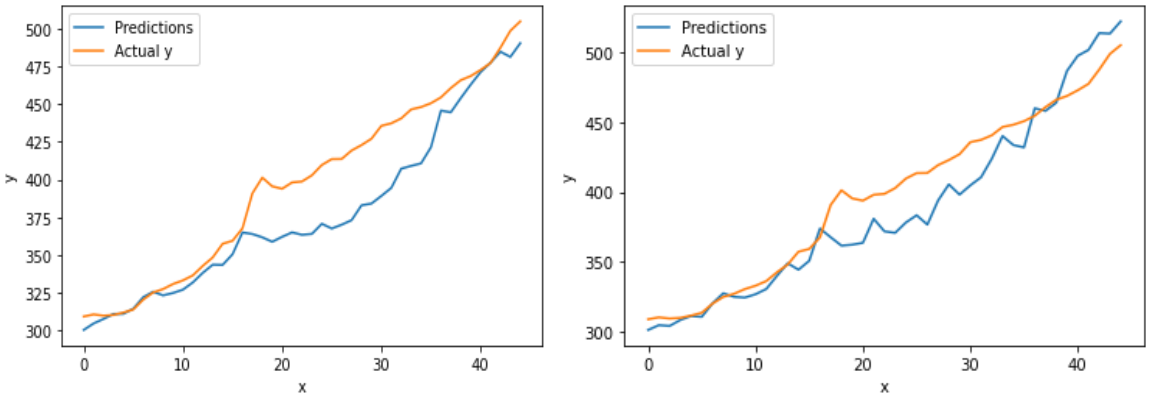

Figure 3. Lasso and Ridge Regression Forecasts and Actual Values for CPI (2017:M4-2020:M12)

In Figure 3, the orange curves show the actual values of the CPI during 2017:M4-2020:M2. On the other hand, blue curves show the forecasts obtained from Lasso and Ridge models, respectively. Visually, both algorithms perform worse than the VAR model, especially in periods of high inflation. This finding is consistent with Medeiros et al. (2016) and Ülke et al. (2018). While Medeiros et al. (2016) argued that the time series model outperforms the LASSO model in forecasting inflation for Brazil, Ülke et al. (2018) found the forecasts of the time series model for the US to be more accurate than the forecasts of support vector regression.

Comparing this result with the findings of the Ozgur and Akkoc (2021) study, which is the only similar study for Turkey, some differences can be discussed. Namely, Ridge regression gives more accurate forecasts than the VAR model in the related study, while Lasso regression produces less accurate predictions. It is thought that this difference is due to the fact that the variables with missing values were not included in the data set in our study. It should be noted that there may be a nonlinear relationship between inflation and other economic variables. The existence of uncertainty may also stimulate nonlinearities. Therefore, in the next step to enhance the forecasts, the benefit from a nonlinear ML model is employed.

A multilayer perceptron algorithm employed the nonlinear ML method and benefited from two hidden layers and the "relu" as the activation function. The analysis used 15 nodes for the first hidden layer and 3 nodes for the second one. The complexity of the neural network has been regulated by using an l2 penalty that shrinks the weights towards zero as well. Figure 4 gives the MLP results for different alpha values.

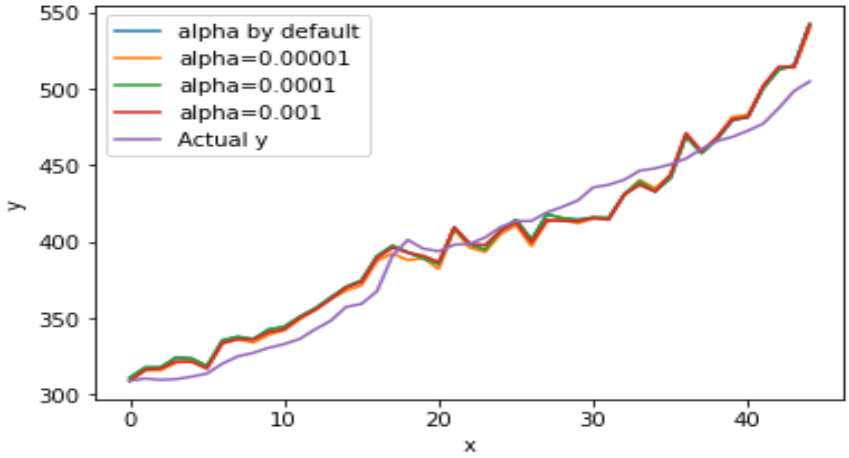

Figure 4. MLP Forecasts and Actual Values of CPI (2017:M4-2020:M12)

In Figure 4, the purple curve shows the actual values of the CPI during 2017:M4-2020:M2. The curves in other colours show the forecasts obtained from MLP algorithm with different alpha values. Visually, the forecasting results obtained from MLP seem to be more accurate than the linear ML algorithms in general.

The MLP model seems to be more successful in approximating actual values during periods of sudden ups and downs in inflation. This finding is particularly important for developing countries with volatile inflation rates. The relative success of the MLP model also supports the existence of nonlinear relationships between inflation and other economic variables. It is thought that the MLP algorithm can be an important useful method since it will be difficult to forecast inflation with linear models in periods of increased uncertainty. Lastly, tuning the parameter alpha seems to have no radical effect on the results. This result is consistent with the findings of Gungor and Berk (2006), who found the prediction power of the MLP model to be reasonably good. It is also in line with the findings of the study by Medeiros et al. (2021), which indicate that the nonlinear model outperforms the Lasso and Ridge models.

Consequently, comparing the results in the ML algorithms that observe the forecasting performance of the MLP algorithm is more accurate than the linear-based Lasso and Ridge

regression algorithms. On the other hand, by only looking at Figures 3 and 4, it is hard to compare the results of the MLP algorithm and the VAR model. Therefore, we benefited from some evaluation metrics.

Table 8. Performance Metrics of Different Models

Algorithm	Test Set Accuracy	RMSE
Time Series Model		
VAR (4)	0.993	8.61
ML Models		
Ridge Regression	0.890	13.39
Lasso regression	0.810	25.79
MLP(alpha by default)	0.948	13.45
MLP(alpha=0.00001)	0.951	13.05
MLP(alpha=0.0001)	0.948	13.45
MLP(alpha=0.001)	0.949	13.28

Table 8 shows the evaluation metrics for different algorithms. The table shows that the time series model provides more significant performance than the ML models. The test set accuracy (0.9927) is higher in VAR(4) model than in the ML models. This means that the output estimations of the VAR model are more accurate in the data set that is not used for training purposes. Similarly, the RMSE value (8.61) is lower in VAR(4) model than in the ML models. Accordingly, the forecasts obtained from the VAR model were found to be closer to the actual values. These findings are consistent with Medeiros et al. (2016) and Ülke et al. (2018), which handle Brazil and the US, respectively.

On the other hand, using nonlinear ML algorithms seems to improve the forecasting performance compared to linear ML models. Namely, the MLP model reaches nearly 95% accuracy, which seems quite good. Additionally, MLP forecasts were more successful in approximating actual values during periods of volatile inflation. Since inflation is more volatile in developing countries, it is relatively important to use algorithms that take into account nonlinear relationships in estimating inflation in such countries. This finding confirms the results of Gungor and Berk (2006) and Medeiros et al. (2021).

The relative success of the MLP model also supports the existence of nonlinear relationships between inflation and other economic variables. As the linear relationships are damaged with increasing uncertainty, it is thought that the MLP algorithm can be an important useful method for forecasting inflation. Lastly, it is good to be reminded that the performance of the ML algorithms may increase with the progress in the computational power and the data size. So, the performance of the MLP may increase in the future. We also believe that considering other explanatory variables, increasing the volume of the data and also tuning parameters in different ways may be helpful to increase the accuracy even more.

Conclusion

Inflation forecasts have crucial effects on the behaviour of economic agents. Policymakers also need accurate inflation forecasts in steering the Economy by using fiscal and monetary policies. However, forecasting inflation is challenging, and there is no consensus on the best methodology. We, in this paper, have included assessments of different ML methods, compared the results with time-series forecasts, and contributed to the debate by providing an enlightening guide for forecasting inflation in a more accurate way. The results can be summarized as follows.

Firstly, it was observed that the forecasts obtained with the monetary model-based VAR model showed a high performance in forecasting the real inflation level for the 2017:M4-2020:M12 period. Secondly, according to the results of Lasso and Ridge regression, dep (deposit account (TRY)), cred (Total credits (TRY)), and M2 (M2 money supply (TRY)) variables were found to have the highest coefficients. Therefore, the monetary variables were found to be more effective on the level of inflation. Furthermore, this finding is consistent with the

monetary models of inflation. On the other hand, the forecasts obtained from linear-based Lasso and Ridge regression were found to be less accurate than the results of the VAR model. Thirdly, although the performance of the MLP model in forecasting inflation was found to be less than the VAR model, it was found to be higher than the linear-based Lasso and Ridge regression. This result was interpreted as taking into account that the nonlinear relationships between the variables positively affected performance.

In sum, in a pseudo-out-of-sample forecasting experiment using recent Turkish data, the performance of the VAR model is found to be better than the ML algorithms. However, although the Lasso and Ridge regression algorithms use variable selection mechanisms, the MLP model seems to outperform due to potential nonlinearities. As uncertainty is thought to induce nonlinearities, the performance of the nonlinear ML models is expected to be better, especially in periods of high uncertainty. Since inflation is more volatile and uncertain in developing economies, the MLP algorithm is thought to be an important useful method for forecasting inflation. The performance of the method will increase further in the future, depending on the progress in the computational power and data volume.

From this point of view, it can be said that policymakers can benefit from ML algorithms that take nonlinear relationships into account in forecasting inflation. In the cases such as the inability to create a data set suitable for time series analysis and the inability to determine explanatory variables that will affect the output, the MLP method will solve the problem by deriving its own algorithm. In this context, it is suggested that nonlinear ML models should be considered as an alternative method for estimating inflation.

While a nonlinear machine learning algorithm is found to approach the performance of time series estimations, several caveats for future research remain. Firstly, the results are sensitive to train and test split. We used the conventional 75%-25% division for the train/test splitting of the data. But the researchers may re-forecast the inflation rates for the short and medium-term by choosing a shorter period for test data.

Another limitation of the study is the dataset size that benefits from the dataset over the period 2006:M1-2020:M12. However, the performance of the empirical methods increases with the size of the data. Especially in the ML methodology, many variables are being used, and it can be argued that as the data size increases, the forecasting performance and accuracy will increase.

As Baybuza (2018) states, the most significant disadvantage of ML models is the loss of interpretability in the classical sense (Baybuza, 2018). However, forecasts obtained from the ML algorithms would be beneficial to both academics and practitioners aiming at a specific inflation target level. The results of this study will be expected to be useful as a guide for central banks and policymakers in developing countries with volatile inflation rates.

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Appendix 1. Variable Definitions and Data Sources

Name	Description	Source
ind	Industry production index-Total industry	CB of Turkey
int	Industry production index -intermediate goods	CB of Turkey
dur	Industry production index-durable consumer product	CB of Turkey
nondur	Industry production index-nondurable consumer product	CB of Turkey
enr	Industry production index-energy	CB of Turkey
cap	Industry production index-capital good	CB of Turkey
ltech	Industry production index- low technology	CB of Turkey
mltech	Industry production index- medium-low technology	CB of Turkey
mhtech	Industry production index-medium high technology	CB of Turkey
htech	Industry production index-high technology	CB of Turkey
min	Industry production index-mining and quarrying	CB of Turkey
man	Industry production index-manufacturing industry	CB of Turkey
mes	Eft transactions- the quantity of payment messages (number)	CB of Turkey
eftrans	Eft transactions- total payment (TRY)	CB of Turkey
cbtrans	Eft transactions-total outflow from CB (number)	CB of Turkey
cumh	Cumhuriyet gold(coin) sale price (TRY)	CB of Turkey
bist	BIST-100 index according to closing price (January, 1986=0.01)	CB of Turkey
usds	USD dollar sale price (TRY)	CB of Turkey
usdb	USD dollar buying price(TRY)	CB of Turkey
r1	interest rate up to 1 year (TRY deposits) (%)	CB of Turkey
r2	interest rate for 1 year and more (TRY deposits) (%)	CB of Turkey
dep	deposit account (TRY)	CB of Turkey
cred	Total credits (TRY)	CB of Turkey
M2	M2 money supply (TRY)	CB of Turkey
asset	CB balance sheet-assets (TRY)	CB of Turkey
budrev	Central government-budget revenues (TRY)	CB of Turkey
budexp	Central government-budget expenditures (TRY)	CB of Turkey
build	Construction- building with 2 or more apartments (number)	CB of Turkey
CPI	Consumer price index (2003=100)	CB of Turkey

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Nonlinear effects of ıncome ınequality on economic growth: A comparative analysis of selected countries

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Abstract

Purpose — The paper queries the impacts of income inequality on economic growth in selected advanced and emerging market economies by adopting nonlinearity and endogeneity.

Methods — This research analysis is based on a balanced panel from 1996 to 2018 and employs the dynamic panel threshold analysis after baseline estimations with the fixed-effect, system Generalized Method of Moments, and difference Generalized Method of Moments.

Findings — This study finds a nonlinearity between income inequality and economic growth. Income inequality has a significant threshold effect on the growth of both panels. Besides, the threshold effect of emerging market countries is higher than the level for advanced countries. This means emerging market economies are negatively affected above the estimated threshold value according to the advanced economies.

Implication — This paper supports that inequality may harm much more economic growth above a specific level. On the other hand, these distorting effects are related to the other economic issues of countries, such as government spending, inflation, export of goods and services, gross fixed capital formation, and foreign direct investment.

Originality — This paper contributes to the literature by focusing on the nonlinear effects of income inequality and different aspects of economic growth above or below the estimated threshold value, thereby providing cross-country comparability and endogeneity.

Keywords — Income inequality, economic growth, threshold analysis, dynamic panel, nonlinearity

Introduction

Theoretical discussions on the relationship between income inequality and economic growth and empirical studies after the middle of the last century are quite intense. The overall conclusion is that it could be solved by increasing welfare or by distributing wealth generated in an economy/society. On the other side, it is revealed that somewhat inequality can increase economic capacity favoring some income groups (high-income groups) that inequality can be reduced with economic growth so that disadvantaged low-income groups can have their share. It is desirable to implement an optimal policy combination that simultaneously reduces income inequality and increases economic growth and expected results may not occur due to many political, economic, global, and social factors. So, interest in the inequality-growth nexus requires determining the extent

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of the relationship. Early and classical theoretical and empirical studies on the effect of income inequality on economic growth find out that inequality positively or affects economic growth, while subsequent modern theories and empirical studies conclude with the negative inequality impact on economic growth. Later empirical studies have determined that the direction of the relationship diversifies and is not linear. However, the existence of incompatible results and the probable multiple and nonlinear relationship correlation lead to the questioning that inequality can affect economic growth through different channels such as macroeconomic, socio-economic, and political issues.

The first study, the cornerstone of empirical studies and modelling, belongs to Kuznets (1955). Kuznets addresses how income is distributed among the population and inequality in terms of how total income is earned among low, middle, and high-income groups in the economy. Although the period conditions pose difficulties in obtaining reliable data, Kuznets' study is a major starting point for some implications (Kuznets, 1955; Todaro & Smith, 2012). Kuznets states that inequality initially increases as economic growth increases in different income groups, then decreases and takes the form of an inverted U curve. This is expressed as the Kuznets inverse U curve theoretically (Lahouij, 2017). It is stated that high and low GDP is correlated with low-income inequality, and a medium level GDP is correlated with high-income inequality (Kuznets, 1955). The Kuznets curve is no longer efficient, while the global income inequality is detailed. It is stated that this curve transforms into the shape of Kuznets waves that increase and decrease inequality will not be efficient to determine inequality alone (Milanovic, 2016). Thomas Piketty criticizes Kuznets' study. Piketty states that the reduction of inequality does not result from social mobility. Piketty has claimed that these is the historical or periodic effects of world wars and the fiscal tightening of high US revenues between 1913-1948 was due to these effects (Piketty, 2014).

Many studies indicate that the income inequality and economic growth relationship is negatively related. Studies by Alesina & Perotti (1994) state that the nexus is negatively correlative. Alesina and Rodrik (1994) assume that the relationship between inequality and growth is negative. Birdsall et al., 1995 and Birdsall et al., 1996 conduct a specific study on Latin America and East Asian countries. It is indicated that there is a negative relationship between income inequality and economic growth in Latin America in contrast to the previous study. Knowles (2005) states a negative relationship between inequality and growth and emphasizes income inequality after redistribution for the period 1960-1990. Wahiba and Wariemmi (2014) estimate the relationship between income inequality and economic growth for Tunisia under the period 1984-1995 and 1996-2011. It is concluded that income inequality is negatively associated with economic growth (Wahiba & Wariemmi, 2014). Cingano (2014) has estimated the period between 1970 and 2010 with 5-year average growth data for 31 OECD countries. The results show that inequality harms economic growth (Cingano, 2014). Lahouij (2017) focuses on selected oil-importing MENA countries. Income inequality slows the rate of economic development; that is, it slows down economic growth (Lahouij, 2017). Michálek and Výbošťok (2019) observe changes in economic growth expressed by real gross domestic product and inequality ratio in the reduction of relative poverty for 28 European Union countries from 2005 to 2015 (Michálek & Výbošťok, 2019). The findings reveal that economic growth is connected to reducing poverty and inequality. Strong economies can better combat inequality and poverty during a crisis. As income inequalities increase, poverty also rises. The negative coefficient of the Gini indicates that inequality hurts economic growth (Michálek & Výbošťok, 2019).

There are also studies reaching positively related findings. Saint-Paul and Verdier (1993) suggest that higher economic growth rates can occur in an unequal economy. Li and Zou (1998) predict that there should be a positive relationship between income inequality and economic growth by classifying government expenditures related to their structures for production and consumption. Forbes (2000) estimates 30 years between 1966-1995 and five years of average growth data and dummy variables for 45 countries. A positive correlation has been confirmed between income inequality and economic growth (Forbes, 2000). Chletsos and Fatouros (2016) test the relationship between 1968 and 2007 with panel data analysis for 126 countries. It is stated that income inequality may enhance while economic growth goes up (Chletsos & Fatouros, 2016).

Yang and Greaney (2017) estimate the short and long-term relationship between income inequality, economic growth, and redistribution over the period 1960-2014 for China, Japan, South Korea, and the USA. A general conclusion is revealed that increasing income inequality promotes economic growth (Yang & Greaney, 2017).

Some studies state that the inequality-growth nexus cannot be *single-sided* and *linear*. Banerjee and Duflo (2003) conclude a nonlinear relationship between inequality and growth for 45 countries. It is stated that high inequality encourages growth in more egalitarian societies (Banerjee & Duflo, 2003). Khalifa and El Hag (2010) reveal that the inequality-growth relationship is negative and significant below the income per capita threshold. The relationship is positive but less significant above the threshold (Khalifa & El Hag, 2010). Cho, Kim, and Rhee (2014) state that income inequality has nonlinear effects on economic growth by using the panel regression model. It is stated that inequality prevents economic growth in most countries and accelerates economic growth only in Denmark where the level of inequality is very low (Cho et al., 2014). Delbianco, Dabús, and Caraballo (2014) argue that inequality supports economic growth for the wealthiest 10% of higher-income countries. Fawaz, Rahnama, and Valcarcel (2014) determine that income inequality contributes to economic growth in high-income countries and the contrary exists for low-income countries with a threshold effect. Kolev and Niehues (2016) state that economic growth is negatively connected with net income inequality for countries with low GDP per capita. However, the impact is weakening as GDP increases and is positive even for developed countries (Kolev & Niehues, 2016). As a recent study, Aktas (2019) analyzes the relationship utilizing Hansen (1999) which enables us to consider nonlinearity. The study evaluates whether income inequality will lead to economic growth by using Hansen (1999) threshold analysis. The analysis covers 11 separate panels. A balanced panel is developed with annual and five-year average data from 1996 to 2016 for 60 countries. The findings of the analysis vary in terms of the threshold effect of income inequality on economic growth, reaching significant and insignificant results in separate panels.

By extension of Aktas (2019), the economic growth impact of income inequality is evaluated using the dynamic panel data threshold analysis proposed by Kremer, Bick, and Nautz (2013) in this paper. Our study considers nonlinearity and provides a dynamic framework that avoids endogeneity. Contributing to this wide literature, we develop a nonlinear framework by examining the impact of income inequality on economic growth for 60 advanced and emerging market economies over 1996 and 2018. It is of great importance to consider the relationship between income inequality and economic growth in a dynamic framework because growth is based on the economic performances of previous periods. Furthermore, the method of the study provides the elimination of problems such as endogeneity, multicollinearity, and autocorrelation. We implement the panel threshold methodology for three country groups. More clearly, after examining all countries in a single panel, estimations have been made in two more panels for 32 emerging markets and 28 advanced economies under the International Monetary Fund (IMF) classification. We also avoid methodological issues such as endogeneity using a dynamic approach. Our paper is organized as follows. In the first part, we emphasize the theoretical and empirical background. Then, we present data and methodology. In the succeeding part, we address empirical findings. Finally, we conclude with specific policy implications.

Methods

Data

Our sample covers 60 advanced and emerging market countries as shared in Appendix 1. IMF classifies 189 economies whole over the world as follows: Advanced Economies, Euro Area, Major Advanced Economies (G7), Newly Industrialized Asian Economies, Other Advanced Economies (excluding G7 and Euro Area), European Union, Emerging and Developing Economies, Central and Eastern Europe, Commonwealth of Independent States, Developing Asia, ASEAN-5 Countries, Latin America, and the Caribbean, the Middle East and North Africa, Afghanistan, Pakistan, Sub-Saharan Africa, and G-20 (Group of 20). The countries that obtained data mostly dissipation less is annexed to the data set, and the countries are split as 32 advanced and 28

emerging market economies following the IMF classification. Income inequality data has some limitations, such as measurement problems, sparse coding, and limited comparability across countries and over time. Income inequality calculations of the Standardized World Income Inequality Database (SWIID), which has been widely used in recent years, are utilized in our study. The database has a comparative advantage over other alternatives since it meets the requirements of the researchers by maximizing the comparability of income inequality data while maintaining the widest possible coverage across countries and over time. SWIID filters the Gini coefficients based on the relative values of income from different sources (Solt, 2020). We utilize the Gini Market variable in our models to focus on the inequality effect. Following empirical literature, control variables are preferred from among investment, consumption, capital, and trade variables that are assumed to affect economic growth. All control variables are obtained from the World Bank database. All data include annually between 1996 and 2018. Table 1 represents the detailed information of the data.

Table 1. Data information

Variables	Index/Indicator	Basic theory or study on which it is based	Source
Explanatory Variable: Income Inequality	Gini inequality index is equalized with household disposable income (before taxes and transfers) *(GINI)*	Yang and Greaney (2017)	Standardized World Income Inequality Database (SWIID)
Dependent Variable: Economic Growth	The growth rate of GDP per capita (annual %) (y)	Alberto Alesina and Rodrik (1994); Cingano (2014); Delbianco et al. (2014); Khalifa and El Hag (2010); Knowles (2005); Kolev and Niehues (2016)	World Bank Open Data
Control Variables			
Export	Exports of goods and services (% of GDP) *(EXP)*	Cho et al. (2014); Lahouij (2017); Wahiba and Wariemmi (2014); Yang and Greaney (2017)	World Bank Open Data
Investment	Foreign direct investment, net inflows (% of GDP) *(FDI)*	Alesina and Perotti (1994); Chletsos and Fatouros (2016); Lahouij (2017)	World Bank Open Data
Capital	Gross fixed capital formation (% of GDP) *(INV)*	Alesina & Perotti, (1994); Nancy Birdsall et al., (1995); Lahouij, (2017); Li & Zou, (1998); Yang & Greaney, (2017)	World Bank Open Data
Expenditure	Government consumption of expenditure (% of GDP) *(GOV_SPE)*	Alesina & Rodrik, 1994; Birdsall et al. (1995); Li and Zou (1998); Lahouij, (2017); Yang and Greaney (2017)	World Bank Open Data
Inflation	Inflation, consumer prices (annual %) *(INF)*	Alesina & Perotti, 1994; Chletsos & Fatouros, 2016; Lahouij, (2017)	World Bank Open Data

Note: Created by the authors.

As can be seen from the summary statistics reported in Table 2, no significant variations in the measurement of income inequality (Gini coefficient) and GDP per capita are not found. The mean and standard deviation of the Gini coefficients for emerging markets and advanced economies are close to each other. From control variables, inflation and export differ greatly across the countries. Diversification in other control variables is negligible.

Table 2. Summary statistics

Variable	All Economies		Emerging Market Economies		Advanced Economies	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
(y) (annual %)	2.77	3.59	2.13	3.41	3.23	3.87
(GINI)	46.11	6.45	46.41	5.70	46.09	7.14
(EXP)	47.05	32.38	104.55	79.38	86.56	37.65
(FDI)	5.54	8.21	7.41	10.92	4.35	5.36
(INV)	22.71	5.09	23.24	4.94	24.51	6.46
(GOV_SPE)	16.16	5.07	18.97	4.33	14.24	4.62
(INF)	7.20	31.61	2.18	2.23	12.18	44.04

Note: Listed by the authors.

This paper uses a panel threshold regression modelling proposed by Hansen (1999) to assess the hypothesis that income inequality plays an important role in economic growth. Then, a dynamic panel threshold model is designed by expanding Hansen (1999) original model setup and following Caner and Hansen (2004) and Kremer et al. (2013). A model is designed where GMM type estimators are brought to a dynamic setting. Besides, as shown by Doytch and Uctum (2011), the Generalized Method of Moments which is used in this paper within the framework of dynamic panel data analysis, has the advantage of eliminating the autocorrelation, endogeneity, and multicollinearity problems that can be arisen in large panels. The threshold estimation analysis is employed because this methodology is more flexible to accommodate the possible contingency effect in the inequality-growth link. This procedure allows the data to determine the numbers and locations of the threshold points endogenously. We argue that the model is well suited to capture the presence of contingency effects and offers a rich way of modelling the influence of income inequality on economic growth.

Baseline Model

Within the scope of our study, we implement a model to investigate the nexus between economic growth and income inequality empirically. A baseline model is set up before the dynamic panel threshold model (Delbianco et al., 2014). The baseline model of the relationship is represented by equation (1).

$$y_{it} = \alpha_i + \lambda_t + \beta 1 g_{it-1} + \beta 2 g_{it-1}^2 + \beta 3 y_{it-1} + X_{it}\gamma + u_{it} \quad (1)$$

i = 1, . . . , N and t = 1, . . . , T

y_{it} is the growth rate of GDP per capita (annual %) for each country *i* at time *t*. g_{it} denotes the measurement of income inequality as the Gini coefficient. u_{it} shows the error term, α_i, and λ_t present the country, and time-specific effects (fixed effects), X_{it} is a vector of control variables. Besides, the quadratic term of the Gini coefficient g_{it}^2 is defined under the assumption that income inequality on growth is linear or nonlinear. Three estimation models that are frequently used in the growth and inequality literature represent the baseline results under equation (1). The fixed-effects model may result in inconsistent estimates in the presence of time-varying omitted factors that affect inequality and growth. On the other hand, it may not estimate the causal effect of income inequality on economic growth and cause the lagged dependent variables to be related to the transformed error term. This eliminates a significant portion of changes in income inequality and other explanatory variables and causes significant measurement errors. The generalized method of moments (GMM) estimator allows the endogeneity of income inequality that can result from reverse causality and measurement errors. The GMM estimators are preferred more frequently because the fixed effects model may decrease the significance of the findings. Consequently, baseline estimation regressions are conducted under the three estimation methods which are panel fixed-effect, system GMM, and difference GMM. The heterogeneity between countries and the nonlinearity of the relationship is also a common challenge in the inequality-growth literature. Thus, we implement a dynamic threshold regression to overcome the mentioned problems.

Threshold Regression

Unlike traditional theories, Hansen (1999) offers an asymptotic distribution theory that can estimate the threshold regression models using the bootstrap method. This approach develops the existing theory by using threshold regression techniques. Threshold regression models state that individual observations can be divided into classes according to the value of an observed variable. The study describes the econometric techniques appropriate for threshold regression with panel data. For model estimation, first, a two-stage ordinary least squares model is used, where the sum of error squares is calculated independently for each of the possible threshold values, and secondly, these values are minimized. In the final step, coefficient parameters are estimated in identified different regimes based on the threshold value (Caner & Hansen, 2004; Hansen, 1999, 2000). It is possible to consider the panel threshold model put forward by Hansen (1999) within the framework of the purpose and variables of this study. Hansen (1999) original threshold model can also be used in a dynamic context under the orthogonal deviation transformation (Kremer et al., 2013). The following threshold model of the growth-inequality nexus:

$$y_{it} = \begin{cases} \delta_i + \alpha_1 X_{it} + \beta_1 GINI_{it} + e_{it}, GINI_{it} \leq \lambda \\ \delta_i + \alpha_2 X_{it} + \beta_2 lnGINI_{it} + e_{it}, GINI_{it} > \lambda \end{cases} \quad (2)$$

The significance of the threshold effect test is necessary to determine whether the relationship is linear or not. Hansen (1999) evaluates the aspect of the effect below and above the threshold value if a significant threshold effect is identified. After estimation with the baseline model, it is necessary to re-estimate the model with a dynamic panel threshold analysis to compare the (non)linearity and endogeneity. If the p-value is smaller than the desired critical value, the null hypothesis of no threshold effect is rejected. If a significant threshold effect is identified (F-statistics of the threshold effect test), the existence of a nonlinear relationship is accepted in two different regimes. In the case of identifying the threshold effect, two and three threshold modelling can be done.

The methodology provides a convenient framework to examine the study's research questions: Is the nexus between growth and inequality linear or nonlinear? If the nexus is nonlinear, does income inequality have a significant threshold effect on economic growth? If it has, what is the aspect of the relationship (negatively or positively related to growth) under and below the threshold level of inequality? The model figured in this framework allows the determination of threshold values by dividing the sample internally into subgroups to analyze the growth effects of income inequality. Thus, the relationship can be identified in various ways depending on the threshold value. In the model established with a balanced panel data set and containing individual effects *(i)* and time effects *(t)*; y_{it} shows the economic growth, which is defined as the annual growth rate of GDP per capita, the $GINI_{it}$ is the explanatory variable which is the indicator of income inequality, and the threshold variable which is assumed not to be constant over time, and X_{it} is the other control variables vector. λ shows the estimated threshold value. δ_i denotes the fixed effects representing the heterogeneity of the countries with different inequality levels, and e_{it} refers to the error term assumed to be distributed independently and identically with zero mean and infinite variance. The slope parameters (β_1, β_2) in the equation reveal the effect of income inequality in different regimes, in other words, below and above the threshold value. The income inequality variable ($GINI$) is defined as both the threshold variable and the regime-dependent variable.

A model is designed where GMM type estimators are brought to a dynamic setting. Then, a dynamic panel threshold model is designed by expanding Hansen (1999) original model setup in addition to the linear model. Besides, as shown by Doytch and Uctum (2011), the Generalized Method of Moments used in this paper within the framework of dynamic panel data analysis has the advantage of eliminating the autocorrelation, endogeneity, and multicollinearity problems that can be arisen in large panels.

$$y_{it} = \mu_i + \beta_1 z_{it} I(GINI_{it} \leq \gamma) + \beta_2 z_{it} I(GINI_{it} > \gamma) + + \varepsilon_{it} \quad (3)$$

Υ is the fixed threshold that is estimated through least squares for the ultimate model. μ_i shows the country fixed effect. z_{it} is a multi-dimensional vector of explanatory variables, and it may involve lagged values of other endogenous variables. The error term is ε_{it}. y_{it} denotes the GDP per capita growth rate and $GINI_{it}$ is the threshold variable. Υ determines the growth effect of inequality under and above $GINI_{it}$. *I* is the indicator function determined depending on the regime. We consider endogenous regressors, including the lagged of dependent variable GDP per capita (annual %), and employ the threshold model of Caner and Hansen (2004) to allow endogeneity. We also apply the dynamic panel threshold model which is developed by Kremer et al. (2013). The essential problem is transforming the panel threshold model to eliminate country-specific fixed effects (Hansen, 1999). There should not be an autocorrelation in the error terms.

For this reason, it is not applicable to eliminate the standard fixed effects in dynamic panels with the first difference. This difficulty is solved by using advanced orthogonal deviation transformation, which eliminates the fixed effects proposed by Arellano and Bover (1995). It also prevents serial correlation in the transformed errors (Caner & Hansen, 2004; Kremer et al., 2013):

$$Var(\varepsilon_i) = \sigma^2 I_T \text{ and } Var(\varepsilon_i^*) = \sigma^2 I_{T-1}. \quad (4)$$

The conversion (transformation) of the error term is as follows (Kremer et al., 2013, p. 18).

$$\varepsilon_{it}^* = \sqrt{\frac{T-t}{T-t+1}} \left[\varepsilon_{it} - \frac{1}{T-t}(\varepsilon_{i(t+1)} + \cdots + \varepsilon_{iT}\right] \quad (5)$$

$$\widehat{\Upsilon} = \min(\Upsilon \epsilon \Gamma)\, S_n(\Upsilon) \quad (6)$$

Equation (6) represents the determination of the threshold level. The threshold level is computed by the two-stage least squares method. $S(\Upsilon)$ represents the sum of squared residuals from the (2SLS) method. First, reduced form regression is estimated for the endogenous variables z_{it}, as a function of the instruments x_{it}. Υ is chosen as the connected one with the smallest sum of squared residuals. Once $\widehat{\Upsilon}$ is identified, the slope coefficients can be estimated by using the generalized method of moments. $\Gamma = \{\Upsilon : LR(\Upsilon) \leq C\}$ shows the confidence interval for the threshold estimate. C presents the 95% confidence interval. $LR(\Upsilon)$ percentile of the asymptotic distribution of the likelihood ratio statistic (Caner & Hansen, 2004; Hansen, 2000; Kremer et al., 2013).

Results and Discussion

Table 3 presents the baseline estimation results given in Equation (1). Three estimation models that are frequently used in the growth and inequality literature represent the baseline results. In GMM estimations, AR(1) test proves first-order autocorrelation, and AR(2) test proves second-order autocorrelation. The AR(1) test result is expected to be statistically significant, while the AR(2) test result is expected to be statistically insignificant. In other words, even if there is first-order autocorrelation in the model, it means that there is no second-order autocorrelation problem. According to the results, there is first-order and no second-order autocorrelation in first-differenced residuals. Whether the estimation results of the GMM method are valid or not can be analyzed with different post-estimation tests such as the Sargan test, Hansen-J test, and autocorrelation test. With the Sargan and Hansen-J tests, the validity of the estimations is tested with the instrument variables, and it is measured whether the instrument variables fully reflect the actual variables. The results obtained from the Sargan and Hansen-J tests are used to determine whether the instrument variables used for GMM estimation are valid or not. If the instrumental variables are used exogenous, the residuals are uncorrelated with the explanatory variables. If there is heteroscedasticity in the model, the difference in the Hansen-J test is used. In addition, the externality of the instrumental variables can be tested with several Hansen tests. On the other hand, in GMM estimations, the Hansen-J test checks over-identification constraints, and the difference in the Hansen-J test checks the externality of instrumental variables. It is accepted that the number of instruments should not exceed the number of units in GMM estimations, as excessive instrument usage leads to biased results, as a rule of thumb.

Table 3 reflects the p-values of all these diagnostic tests. According to the results in both tests, the high exact probability value indicates that the instruments are valid. Besides, the Sargan test results show that overidentifying restrictions are valid. The effect of inequality on growth is highly significant in the three models. The square of the GINI coefficient is defined under the assumption that growth will be adversely affected if the inequality is high. Therefore, the quadratic term of the Gini coefficient is determined for testing (non)linearity in the inequality-growth nexus. The inequality coefficients in the three model results are initially positive. The coefficients of the square of the GINI coefficient are negative. These results indicate that if income inequality is extremely high, economic growth may be affected negatively, and nonlinearity in the nexus of the inequality-growth should be retested. The results are similar to Cho et al. (2014) and Fawaz et al. (2014). Coefficients of control variables are significant. As Cho et al. (2014) and Delbianco et al. (2014) have claimed, expenditure and inflation harm growth.

Table 3. Baseline estimation results for all sample economies

Dependent Variable: (y)	Fixed Effect		System GMM		Difference GMM	
	Coefficient	Standard Errors	Coefficient	Standard Errors	Coefficient	Standard Errors
L1			0.169***	0.009	0.181***	0.026
L2			-0.113***	0.005	-0.071***	0.025
(GINI)	1.763***	0.589	0.619***	0.145	0.785***	0.202
$(GINI)^2$	-0.019***	0.006	-0.018***	0.005	-0.079***	0.012
(EXP)	0.011**	0.005	0.001	0.003	0.037**	0.015
(FDI)	0.073***	0.014	0.068***	0.010	0.079***	0.016
(INV)	0.114***	0.024	0.224***	0.014	0.159***	0.038
(GOV_SPE)	-0.438**	0.052	-0.753***	0.036	-0.056***	0.088
(INF)	-0.007***	0.002	-0.027***	0.001	-0.028***	0.010
R^2	0.061					
Number of observations	1380		1260		1200	
Number of countries	60		60		60	
Arellano-Bond test for AR(1) (p-value)			0.005		0.025	
Arellano-Bond test for AR(2) (p-value)			0.998		0.869	
Sargan test of joint validity of instruments (p-value)			0.839		0.736	
Hansen-J test (p-value)			0.613		0.529	
Difference in Hansen-J test (p-value)			0.165		0.891	
Number of instruments			47		49	
Periods	1996-2018		1996-2018		1996-2018	

Notes: ***, ** and * indicate the significance at 1, 5, and 10% levels, respectively. Variable names ending in L1 and L2 indicate lagged copies of the dependent variable.

The dynamic panel threshold estimation results for advanced, emerging markets and all sample economies are summarized in Table 4, following the panel threshold model represented in Equation (7). We aim to estimate the long-term impact of income inequality and the economic growth relationship by considering the nonlinearity. The model refers to a Generalized Method of Moments (GMM) type estimator to account for endogeneity by following Caner and Hansen (2004) and Kremer et al. (2013). We apply the dynamic panel threshold model to analyze the inequality effect on growth in all sample economies, advanced economies, and emerging market economies. The new (dynamic) model of the inequality-growth nexus is as follows:

$$y_{it} = \mu_i + \beta_1 x_{it} I(\delta_{it} \leq \Upsilon) + \beta_2 x_{it} I(\delta_{it} > \Upsilon) + \varepsilon_{it} \quad (7)$$

x_{it} denotes the vector of control variables that intervene in the nexus between growth and inequality. The dependent variable (y_{it}) is the lagged value of GDP per capita (annual %). δ_{it} is

the threshold variable that represents the heterogeneity of the countries with different inequality levels, and beyond (γ), which its impact on economic growth can alternate. β_1, β_2 are the vector of regime-dependent slope parameters that reveals the effect of inequality on growth. ε_{it} is the error term and μ_i presents the country fixed effect. Control variables are included in the estimated model as shown in Table 1. The threshold variable is the Gini coefficient as Gini Market. As the value of the Gini coefficient comes close to 0, the inequality decreases. The Gini coefficient $GINI_{it}$ is both the threshold variable and the regime-dependent variable and the estimated Gini coefficient threshold corresponds to 95% confidence intervals.

As shown from Table 6, the threshold level of the Gini coefficient is nearly 40 for all sample countries, is nearly 36 for advanced economies, and is approximately 40 for emerging market economies. So, the nonlinearity effect has been detected. The threshold level is lower for advanced economies than the level for emerging market economies. This indicates that income inequality has a more positive effect on economic growth in advanced economies than in emerging market economies (35.65 < 39.59). If the measure of inequality reaches a higher level than the threshold level, it can be said that inequality has an adverse (negative) effect on economic growth. We conclude that the level of inequality differently affects economic growth in the two regimes. In other words, as the measure of inequality increases, economic growth is negatively affected. β_1, β_2 present the estimated threshold value. The marginal effect of income inequality on growth in the low-inequality and high-inequality regimes, respectively. Although the coefficients are not statistically significant in the high inequality regime for advanced and emerging market economies, the signs of the coefficients are in line with the expectation. This means economic growth is positively affected in the low-inequality regime ($\gamma \leq$ 39.59-35.65), and negatively affected in the high-inequality regime ($\gamma >$ 39.59-35.65). Findings show that the negative impact of income inequality is stronger when income inequality is high. This explains the reasons for the incoherent findings achieved in the literature with linear modelling. The higher inequality thresholds for emerging market economies and all sample economies may be associated with insufficient convergence, excess because the coefficient of the initial income is positive.

Most of the control variables are statistically significant for advanced and emerging market economies. The coefficients of the variables are with the expected sign. Inflation and expenditure negatively affect economic growth. Capital, investment, and export positively affect economic growth. The coefficient of the inflation variable is not significant for advanced and emerging market economies. It has the expected negative sign. The coefficient of the initial income variable is not significant for only advanced economies. The studies of Banerjee and Duflo (2003); Cho et al. (2014); Delbianco et al. (2014); Fawaz et al. (2014;) Khalifa and El Hag (2010); Kolev and Niehues (2016) find that inequality and growth nexus is nonlinear, or the aspect of the relationship changes based on the initial income. The impact(s) of Gini_mkt on economic growth in two different regimes, as noted in Table 3 for whole country groups, are similar to these studies. In another saying, the determined inequality threshold levels (39.59, 35.65, 39.59) explain the nonlinearity in the inequality-growth nexus by dividing the link into two regimes (negative aspect below the threshold level and positive aspect above the threshold level). However, when inequality is too high, the economy can be disrupted through rent-seeking activities.

The distribution of factors can also disrupt it before taxes, transfers and redistribution policies after taxes and transfers. The high level of income inequality can lead to social unrest and conflicts arising from inequality in society. This may discourage investment and latent economic growth. The countries with income inequality above a threshold level of Gini coefficients are more likely to experience a negative impact on the long-term growth rate of the GDP per capita. In brief, the relationship between income inequality and economic growth is negative at higher income inequality levels and positive at lower inequality levels. The aspect of the inequality effect (the signs) turns negative from positive when the Gini coefficient is almost 40 for all sample and emerging market economies and almost 36 for advanced economies. These results show that income inequality harms economic growth above the threshold value in three panels. The threshold inequality level is higher for emerging market economies compared to advanced economies.

Table 4. Dynamic Panel Threshold Estimation Results

All Economies			Advanced Economies			Emerging Market Economies		
Threshold variable: Gini_mkt			Threshold variable: Gini_mkt			Threshold variable: Gini_mkt		
Threshold estimate: 39.59			Threshold estimate: 35.65			Threshold estimate: 39.59		
(95% confidence interval)			(95% confidence interval)			(95% confidence interval)		
Impact of Gini_mkt			Impact of Gini_mkt			Impact of Gini_mkt		
	Coefficient	Standard Errors		Coefficient	Standard Errors		Coefficient	Standard Errors
Regime 1: β_1	1.344*	0.065	Regime 1: β_1	0.574**	0.256	Regime 1: β_1	1.492***	0.087
Regime 2: β_2	-0.135**	0.055	Regime 2: β_2	-0.042	0.110	Regime 2: β_2	-0.114	0.075
Impact of covariates			Impact of covariates			Impact of covariates		
(y)	0.041***	0.013	(y)	0.060	0.051	(y)	0.058***	0.020
(INF)	-0.006***	0.002	*(INF)*	-0.043	0.097	*(INF)*	-0.005	0.001
(INV)	0.110***	0.034	*(INV)*	0.172***	0.068	*(INV)*	0.103***	0.041
(FDI)	0.069***	0.022	*(FDI)*	0.077***	0.030	*(FDI)*	0.055*	0.029
(GOV_SPE)	-0.463***	0.066	*(GOV_SPE)*	-0.818***	0.102	*(GOV_SPE)*	-0.315***	0.084
(EXP)	0.010*	0.006	*(EXP)*	0.018*	0.009	*(EXP)*	0.013***	0.009
Number of observations	1380		Number of observations	644		Number of observations	736	
Number of countries	60		Number of countries	28		Number of countries	32	

Notes: ***, **, and * indicate the significance at 1, 5, and 10% levels, respectively.

Conclusion

Income inequality is a concept that has aroused much interest recently, supported by previous studies and theories that it has a clear impact on economic growth. A few studies survey the threshold regression in the inequality-growth nexus. This paper examines the income inequality impact on economic growth and queries whether the relationship between inequality and growth diversifies with the threshold level of inequality or not. The relationship between income inequality and economic growth is evaluated in two different regimes depending on the income inequality threshold in this study based on Hansen (1999) threshold value approach. Thus, the broad panel used in the study is divided based on the IMF per capita income level, and the relationship is analyzed in this context. More specifically, dynamic panel threshold analysis improved by Kremer et al. (2013) is used for the estimation under Hansen (1999) and Caner and Hansen (2004) panel threshold method. All panels cover annual data for 60 countries between 1996 and 2018 to identify the long-term inequality effect on growth. After baseline estimation, we find a nonlinear relationship between economic growth and income inequality. The estimation results indicate that nonlinearity and heterogeneity in the inequality-growth nexus need to be considered, as inequality may lead to economic growth with a lower-inequality level, particularly in the emerging market economies rather than the advanced economies. This study has some limitations, such as the study results cannot be generalized because different developing countries, and country groups, have different economic features. The inequality-growth nexus should be evaluated with attentive considerations of important specification issues and data limitations in cross-country panel data, such as nonlinearity and the efficiency of covariates. Moreover, other channels through which inequality and growth are correlative can be analyzed.

Estimation results show that the negative impact of inequality on economic growth is more significant when the income inequality level is above the estimated threshold level for all panels. The findings that growth rates of high-income countries may slow down in the face of an increase in inequality and that emerging market economies can achieve growth even at a higher-inequality level reveal that policymakers should consider the economic conditions during the decision-making process and its' implementation. A redistribution policy may significantly affect whether inequality will generate growth since the Gini market coefficient, which is equalized with household disposable income before taxes and transfers, is identified in the estimation. A social welfare policy that redistributes income may increase economic growth, but this depends on the proper definition and quality of the implementation. On the other hand, if income inequality increases depending on the country's income level and development level, the redistribution policy may also slow down economic growth. Therefore, it becomes more noteworthy that future studies

should evaluate tax and transfers. Economic growth can be another solution to reduce income inequality. However, economical solutions that will be effective in increasing economic growth should be well determined by policymakers. As can be seen from the signs of the coefficients of the control variables, the economic efficiency depends on the main factors such as the increase in export, realization of the expenditures and investments in productive areas, the increase of foreign direct investments, the formation and accumulation of domestic capital and low inflation.

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Appendix 1

Table 1. List of sample countries

Canada*	Greece*	Armenia**	Ecuador**
Denmark*	Netherlands*	Hungary**	Mexico**
Finland*	Portugal*	Colombia**	Peru**
Hong-Kong*	Slovenia*	Panama**	Romania**
Ireland*	Spain*	Poland**	Bolivia**
Israel*	Sweden*	Costa Rica**	Georgia**
South Korea*	Italy*	Kazakhstan**	Belarus**
Austria*	France*	Malaysia**	Kyrgyzstan**
New Zealand*	Germany*	Namibia**	Moldova**
Norway*	Estonia*	Paraguay**	Vietnam**
Belgium*	Czechia*	Russia**	Bangladesh**
Singapore*	Lithuania*	Turkey**	El Salvador**
Taiwan*	Puerto Rico*	Honduras**	Mongolia**
The United Kingdom*	Dominican Republic**	Bulgaria**	Sri Lanka**
The United States of America*	Indonesia**	Uruguay**	Ukraine**

Note: *, ** present the advanced and emerging market economies, respectively.

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Analysing network structures and dynamics of the Pakistan stock market across the uncertain time of global pandemic (Covid-19)

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Abstract

Purpose — The global pandemic COVID-19 has attracted considerable interest from researchers globally. However, there is very little systematic work on the impact of the COVID-19 crisis on the local stock markets. This paper proposes a complex network method that examines the effects of global pandemic COVID-19 on the Pakistan stock market to fill in these gaps.

Methods — Firstly, correlograms are plotted to inspect the correlation matrices of the overall and two sub-sample periods. Secondly, correlation threshold networks and topological properties are examined for different threshold levels. Finally, this paper uses evolving MSTs to construct a dynamical complex network and presents dynamic centrality measures, normalised tree, and average path lengths.

Findings — The findings show that COVID-19 related certainty and crisis lead to low volatility and a star-like structure, resulting in a quick flow of information and a strong correlation among the Pakistan stock market.

Implication — This analysis would help investors and regulators to manage the Pakistan stock market better. In addition, the comprehensive study solely on the Pakistan stock market will be helpful for Pakistan government officials and stock market participants to assess and predict the risks of the Pakistan stock market associated with the global pandemic COVID-19.

Originality — This paper addresses both classes of the networks. To the best of our knowledge, the static and dynamic evolution of the Pakistan stock market around the global pandemic COVID-19 has not been performed yet.

Keywords — COVID-19, stock network, threshold network, network topology, minimum spanning tree, emerging market.

Introduction

A distressing global pandemic as COVID-19, which rattled the stock markets throughout the globe, brought the businesses and economies to a standstill, having a considerable impact that no country was prepared for. According to World Health Organisation (WHO)[1], there are currently 67 Million confirmed cases and 1.5 Million deaths (as of December 8, 2020) due to Coronavirus disease (COVID-19) globally. The novel coronavirus declared as a pandemic by WHO in March 2020 has already contained the economy due to its contagious human to human transmission, due to which

[1] Please see: WHO Coronavirus Dashboard available at: https://covid19.who.int/

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authorities of the world have forced stringent quarantine of their population and business activity shut down (Topcu & Gulal, 2020). The international monetary fund (IMF) predicted a shrink in the world GDP by 3% during the year. Given the significant impact on the world economy, developing countries like Pakistan will suffer the worst pandemic.

The global pandemic COVID-19 has attracted significant interest from researchers worldwide within a short period. In a survey, (Goodell, 2020) assessed several pandemics and mentioned that the COVID-19 could have an extensive impact on the financial markets, mainly comprising stock markets and institutions. Therefore, it is a promising area for future study. Ashraf (2020) found an adverse reaction of stock markets from 64 countries towards an increase in the number of COVID-19 cases and thus concluded that markets reacted quickly to the pandemic. Al-Awadhi, Alsaifi, Al-Awadhi, and Alhammadi (2020) applied the panel testing technique to examine 1,579 stocks listed in the Chinese stock market between January 2020 and March 2020, and their results similarly found significant adverse effects of a pandemic on stock returns of entire companies.

Additionally, He, Sun, Zhang, and Li (2020) applied the classical event study methodology to several industries of the Chinese stock market. He found a few industries worst affected, along with the negative impact of a pandemic on stock prices of the Shanghai stock market. On the contrary, Alam, Alam, and Kavita (2020) examined the Indian stock market reaction during the COVID-19 lockdown using the event study methodology. Their results found positive average abnormal returns (AAR) during the lockdown period compared to negative AAR before the lockdown period. Salisu, Ebuh, and Usman (2020) applied Panel vector autoregressive (pVAR) on oil and stocks to examine its impact on the pandemic related shocks. Their results suggested extended impacts on oil and stocks during the pandemic compared to the period before the pandemic. Various other methods have been employed to examine the effects of a global pandemic on stock markets, such as the dynamic Spatial Durbin Model (DSDM) (Alexakis, Eleftheriou, & Patsoulis, 2021), Complex network methods (Aslam et al., 2020; Zhang, Hu, & Ji, 2020), and panel data techniques (Cepoi, 2020; Salisu, Sikiru, & Vo, 2020). However, this study examines Pakistan's stock market reaction to the global pandemic Covid-19 by using complex network methods.

Pakistan reported the first case of coronavirus on February 26, 2020. The number of confirmed cases in Pakistan comprises 0.625% of the global confirmed cases to 0.42 Million, along with 8,398 pandemic related deaths (as of December 8, 2020). Following others, the authorities of Pakistan ordered a strict lockdown resulting in the shutdown of businesses throughout the country to curb the impact of a pandemic. The country's stock market witnessed a significant decline, with foreign investors pulling off the money and industries being affected; the stock index reached the bottom level on March 19 in the past five years (Waheed, Sarwar, Sarwar, & Khan, 2020). A country struggling to manage its balance of payment crisis and in economic crisis (Memon, Yao, Aslam, & Tahir, 2019), the impact of the pandemic is vast. Therefore, the IMF approved $1.386 Billion for Pakistan to manage COVID-19 related shock. In addition, authorities in Pakistan limited the lockdown duration option and resumed the industry through intelligent lockdown measures that improved the country's stock market index. Previous studies either focused on examining the impact of global pandemic COVID-19 on developing stock markets, such as Albulescu, (2021); Baker et al. (2020); Mazur, Dang, and Vega (2021); Mittal and Sharma (2021); Narayan, Devpura, and Wang (2020), or global stock indices (see: Ashraf, 2020a; Aslam et al., 2020; Zhang et al., 2020). However, this pioneering study focuses on the Pakistan stock market state and structure changes around COVID-19 through the application of network-based methods, using an expansive timeline. In addition, past studies mentioned adverse effects of COVID-19 on stock markets, such as Huo and Qiu (2020); Liu, Manzoor, Wang, Zhang, and Manzoor (2020); Takyi and Bentum-Ennin (2021). Therefore, this study will assist various stakeholders of stock markets in analysing and postulating the impact of COVID-19 on developing economies. Moreover, the comprehensive research solely on the Pakistan stock market will be helpful for Pakistan government officials and stock market participants to assess and predict the risks of the Pakistan stock market associated with the global pandemic COVID-19.

The network methods are valuable tools for studying stock market patterns and revealing evolving trends in the stock tree topology Field (Chakrabarti, Chakraborti, & Chatterjee, 2006; Memon & Yao(Chakrabarti, Chakraborti, & Chatterjee, 2006; Memon & Yao, 2021). After the seminal work of Mantegna (Mantegna, 1999), empirical analysis of stock markets through applications of complex networks has been a critical motive for the researchers throughout the world (Kazemilari, Mohamadi, Mardani, & Streimikis, 2019; Memon, Yao, & Tahir, 2020; Tang, Xiong, Jia, & Zhang, 2018; Wiliński, Sienkiewicz, Gubiec, Kutner, & Struzik, 2013; Yao & Memon, 2019). Financial network analysis offers an unparalleled outlook revealing fresh perspectives on examining the stock market stability, risk, shock dissemination, and contagion (Taylor et al., 2015). In addition, network analysis through the application of the minimum spanning tree provides the interdependency and dynamic evolution of the market, which is essential for institutional investors and hedge fund operators in modelling risks and providing an interactive outlook of the stock market. Under empirical network analysis, two sub-classes are performed, commonly known as static and dynamic networks. Previous work mainly focuses on exploring static properties of the stock markets (Huang, Zhao, Su, Yang, & Yang, 2020). However, a significant issue about the static network is the avoidance of time evolution, which a few studies have addressed recently by analysing both the static interdependence and dynamic development of the stock market networks (Cao & Wen, 2019; Memon & Yao, 2019). This paper addresses both classes of the networks. To the best of our knowledge, the static and dynamic evolution of the Pakistan stock market around the global pandemic COVID-19 has not been performed yet.

The rest of the paper is organised as follows: Section 2 contains the methodology and data used in the paper. Section 3 presents empirical findings and a discussion of the study. Finally, the conclusion, limitations and future research are provided in Section 4.

Methods

Given the time series of N number of stocks, we can calculate the correlations among any pair of stocks at a specific time window with a length or size of L. Consider $r_i(t)$ and $r_j(t)$ are the returns calculated as $r_i(t) = \ln P_i(t) - \ln P_i(t-1)$, and $r_j(t) = \ln P_j(t) - \ln P_j(t-1)$ at time t of two stocks S_i and S_j respectively. The Pearson correlation coefficient among two stocks can be calculated (Mantegna, 1999):

$$C_{ij} = \frac{\langle r_i\, r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\left(\langle r_i^2 \rangle - \langle r_i \rangle^2\right)\left(\langle r_j^2 \rangle - \langle r_j \rangle^2\right)}} \tag{1}$$

where $<..>$ signifies the statistical mean. This study comprises $N = 67$ top stocks of the Pakistan stock market, and hence the correlation matrix C represents an outlook of complex system between $67(67-1)/2$ pair of stock edges. The correlation coefficient C_{ij} satisfies $-1 \leq C_{ij} \geq 1$, and threshold network Θ can be created by mentioning certain value Θ, for example if $C_{ij} > \Theta$ among two stocks, an undirected edge is drawn among stocks i and j. Specifically, at any point of threshold value Θ, we can get numerous number of links (Lee & Nobi, 2018; Memon & Yao, 2019).

By following Mantegna (1999), the correlation matrix C_{ij} is transformed into a distance matrix d_{ij} among pair of stocks i and j as:

$$d_{ij} = \sqrt{2\left(1 - C_{ij}\right)} \tag{2}$$

The rolling window technique is largely used in literature to construct dynamic network (Jia, An, Sun, Huang, & Wang, 2017; Khuntia & Pattanayak, 2020; Memon et al., 2019). While relying on complex network theory, the study links entire pair of nodes conforming to the distance matrix $D^m = (d_{i,j}^m)$. Thereafter, the dynamic minimum spanning trees of various length L are obtained by dividing the timeline through rolling window technique, in our study L is one month. The MST can be defined as (Mantegna, 1999):

$$T = \sum_{(i,j)\epsilon T} d_{ij} \quad (3)$$

In addition, this paper uses various topological properties to access the static and dynamic structures of Pakistan stock market network. While describing the information linkages among networks, density (average number of links per node) is used against various threshold levels Θ, can be calculated as follows:

$$C = \frac{2M}{N(N-1)} \quad (4)$$

where M represents number of edges, and N is the number of nodes of the network. The average path length (APL) is defined as the mean distance among two stocks in a network, and can be expressed as:

$$L(t) = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \geq j} d_{ij} \quad (5)$$

where $d_{ij}$is the shortest distance among the stocks i and j. The clustering coefficient is a criterion that assesses the degree of a group. For a given node i, its clustering coefficient C_i is the probability of connection among any two points associated with node i. The formula for computing clustering coefficient is as follows:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \quad (6)$$

where E_i represents number of links that exists in the network among the nodes associated with node i, and k_i, is the degree of node i. For a whole Pakistan stock market network, the clustering coefficient is described as the average of entire nodes' clustering coefficients, calculated as

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i \quad (7)$$

where N is total number of nodes of the network. Node degree is used to simplify a network containing $N \times N$ edges, which is massive number for a large N, therefore for simplification the weakest linkages are taken out (Onnela, Chakraborti, Kaski, & Kertész, 2003). Node degree can be calculated as

$$k_i^m = \sum_{j=1}^{N} A_{i,j}^m \quad (8)$$

where $A_{i,j}^m$ represents the adjacency matric of the mth minimum spanning tree. In order to measure intermediary role of a certain node i in the overall network, betweenness centrality $B(i)$ measure is used (Barthélemy, 2004). For a node i, the betweenness centrality is calculated as follows:

$$B(i) = \sum_{k \neq i \neq h} \frac{\sigma_{kh}(i)}{\sigma_{kh}} \quad (9)$$

where $\sigma_{kh}(i)$ represents shortest paths among nodes k and h that pass-through node i, and σ_{kh} symbolizes aggregate number of shortest paths among k and h. Further, to access the dynamic properties normalized tree length (NTL) denoted as $L(t)$ is applied:

$$L(t) = \frac{1}{(N-1)}\sum_{(i,j)\epsilon T^t} d_{ij} \quad (10)$$

To examine the impact exerted by COVID-19 on the network structure and dynamics of the Pakistan stock market, we use a wide timeline covering 328 trading days, from July 1, 2019 to October 22, 2020. In addition to the overall analysis, we further divide the timeline into two sub-periods of pre-and during-COVID-19 by country-specific pandemic conditions and confirmed cases. Pakistan, a neighboring country of China, where the pandemic began, and Iran, another bordering country with the highest death rates due to COVID-19, reported their first confirmed case on February 26, 2020, (Waris, Atta, Ali, Asmat, & Baset, 2020). Soon after this, the country started reporting regular confirmed and suspected cases, and within a short span of fifteen days, the confirmed cases reached 20, along with 471 supposed cases (Saqlain, Munir, Ahmed, Tahir, &

Kamran, 2020). Therefore, the study investigates network structures and topological evolution during COVID-19 (February 26, 2020, to October 22, 2020) and Pre-COVID-19 (July 1, 2019, to February 25, 2020), where both sub-sample periods contain 164 trading days. The analysis utilises closing prices of the top 67 companies from 21 industry sectors listed in the Karachi Stock Exchange 100 Index (KSE-100). The time-series data has been gathered from investing (https://www.investing.com/). Appendix A lists all the top 67 companies acting as nodes of the networks categorised in their respective industry sectors.

Results and Discussion

The entire sample investigation period of correlation is presented in Figure. 1, along with two sub-sample periods of pre-and during COVID-19 in Figure. 2, and Figure. 3, respectively. The red colour in the correlogram plots shows positive correlation values. In contrast, blue color represents less or negative correlation, and the x and y axes vales offer each of the top 67 stocks of the Pakistan stock market. While looking at three figures, the initial observation shows visible changes in the correlation structures during these periods. The results in Figure. One further reveals the average correlation among stocks of 0.365, along with the maximum correlation among two cement sector nodes of DG khan cement and maple leaf cement of 0.849. This pair also has the most significant correlation of 0.894 during the COVID-19 period.

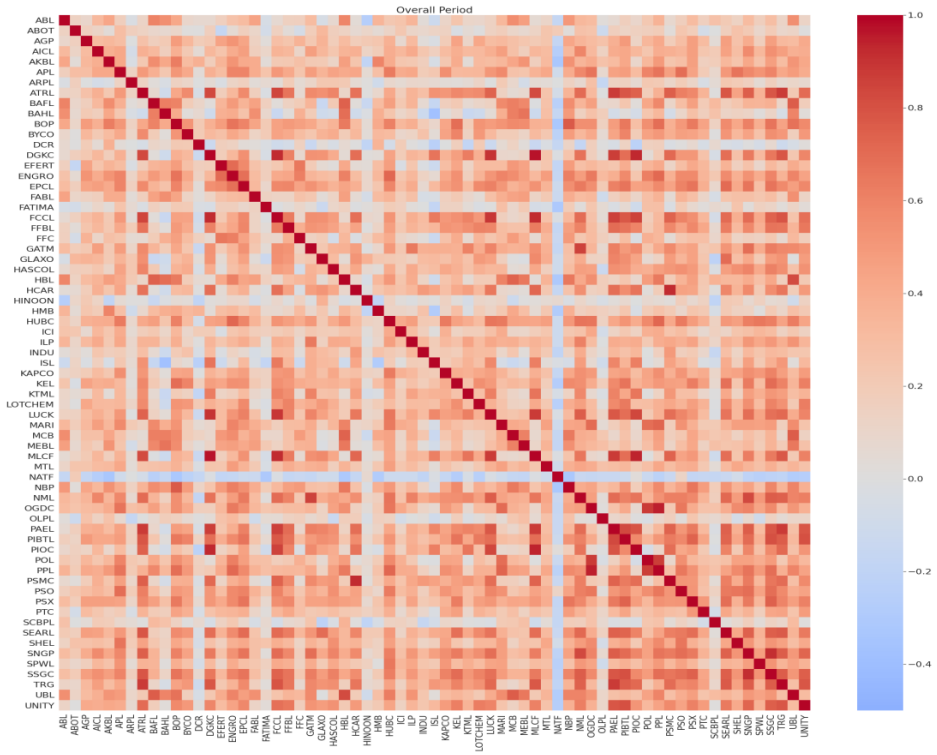

Figure 1. Overall period correlogram for the Pakistan stock market

While accessing the changes during two sub-sample periods in Figure. 2, and Figure.3, the results show that the pre-COVID-19 period has lower average correlation values, thus highlighting relatively weak clusters. The moderate correlation (0.391) during COVID-19 is higher than pre-COVID-19 (0.335). This shows that uncertain times during COVID-19 force stocks to move in one direction, similar to previous studies that reported a tighter correlation among stocks during crisis period (Lee & Nobi, 2018; Memon & Yao, 2019; Yao & Memon, 2019). The uncertainty of the health-related COVID-19 crisis implied into broader crisis among the Pakistan stock market due to the vulnerability of investors in decision making. In addition, total positive correlation values during COVID-19 remained at 2,209 (out of 2,211 network links), compared to 2,195 in the pre-COVID-19 period. Similar results of higher positive correlation values during the COVID-19 period have been obtained by Aslam et al. (2020) for the world stock market indices. The stocks

that changed significant correlation values during-COVID-19 are NATF, SCBPL, POL, BYCO, HBL, FATIMA, UNITY, and EFERT. Moreover, the negative correlation values during-COVID-19 period have dropped to just two, compared with sixteen values in the pre-COVID-19 period.

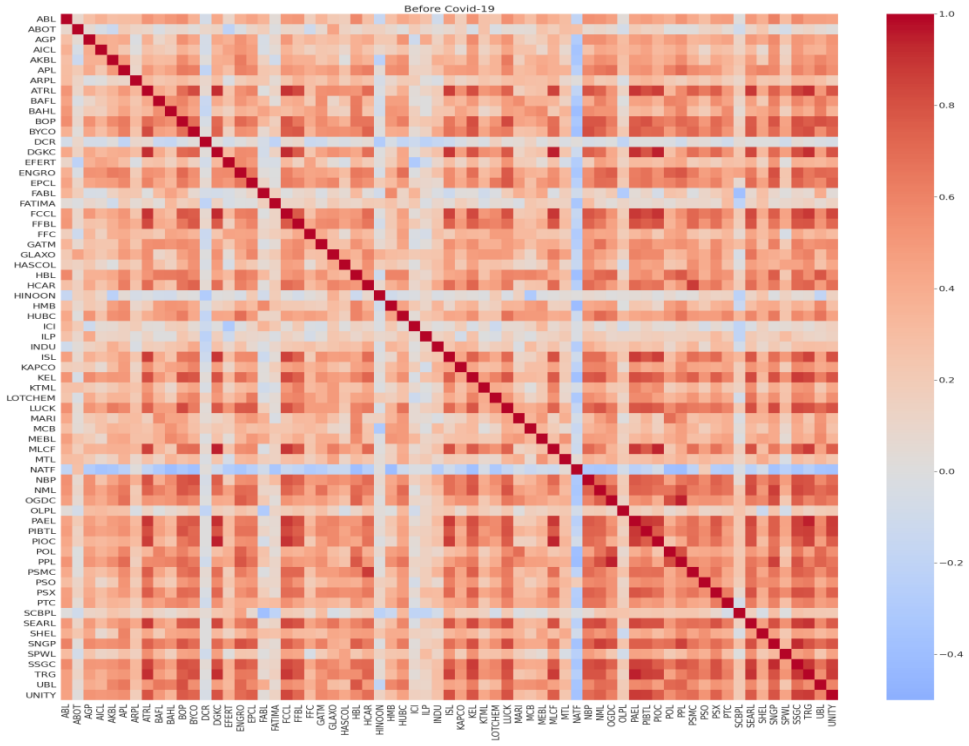

Figure 2. Pre-Covid-19 correlogram for the Pakistan stock market

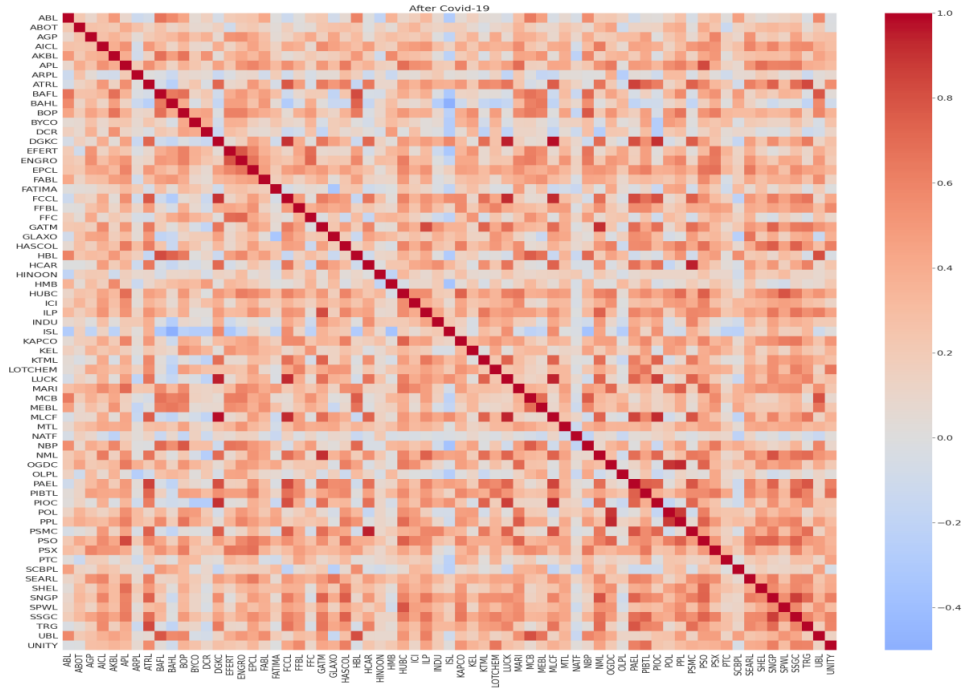

Figure 3. During-Covid-19 correlogram for the Pakistan stock market

The paper generates threshold networks of the Pakistan stock market by associating certain values Θ of correlation coefficient (Lee & Nobi, 2018; Memon & Yao, 2019). In threshold networks of overall and two sub-sample periods, a node (V) comprises a stock, and (E) is an edge joining the two stocks weighted through a cross-correlation coefficient. Similarly, the topological properties of eight threshold networks of the Pakistan stock market for overall, pre-, and during-COVID-19

periods against various Θ levels are presented in table 1. The results show a higher mean correlation against many correlation threshold levels during the COVID-19 period, representing a stronger association among stocks than in other periods. In addition, the density of the network at lower threshold levels is greater for all the periods, and the edge links and density keep on reducing when the threshold level enhances (Dimitrios & Vasileios, 2015). Moreover, the results show high density even at a higher threshold level of Θ greater than 0.4 during the COVID-19 period, compared to pre-COVID-19 and overall period, owing to the herd behaviour due to uncertainty and crisis in Pakistan stock market. Regarding connectivity, cement and oil & gas marketing sector nodes of a Maple leaf (MLCF), DG khan cement (DGKC), Oil & Gas Development Company (OGDC), and Pakistan petroleum limited (PPL) are essential nodes in the pre-and during COVID-19 period.

Table 1. For the Pakistan stock market network, the existing number of edges$|e|$, the network edge density$|e|_{density}$, and the mean degree $< c >$ are mentioned for various correlation threshold levels

Time Period	θ	>0.1	>0.2	>0.3	>0.4	>0.5	>0.6	>0.7	<0
Overall	Edges	2192	2057	1571	818	269	53	16	0
	Density	0.9914	0.9303	0.7105	0.3700	0.1217	0.0240	0.0072	0
	Mean	0.3682	0.3817	0.4200	0.4845	0.5659	0.6666	0.7468	0
Before	Edges	2114	1839	1268	691	292	88	14	16
Covid-19	Density	0.9561	0.8318	0.5735	0.3125	0.1321	0.0398	0.0063	0.0072
	Mean	0.3480	0.3762	0.4318	0.5009	0.5774	0.6567	0.7517	-0.0262
During	Edges	2194	2100	1687	1039	416	96	17	2
Covid-19	Density	0.9923	0.9498	0.7630	0.4699	0.1882	0.0434	0.0077	0.0009
	Mean	0.3936	0.4038	0.4397	0.4954	0.5702	0.6623	0.7881	-0.0442

To investigate the transitivity and network span of Pakistan stock market, average clustering coefficient $< C >$ and average path length $< L >$ are applied to the correlation threshold network. The average clustering coefficient shows a fluctuating descending trend as threshold level increases, inversely, average path length shows an increasing trend with an increase in the threshold level. However, the $< C >$ becomes larger and inversely $< L >$ decreases at a very higher threshold level. While comparing the two sub-sample periods, the $< C >$ for all threshold levels during COVID-19 remain 1.77% higher to 0.805, compared with pre-COVID-19 average of 0.791. This implies that the crisis of COVID-19 contributes to some extent of fluctuation and transitivity among stocks of Pakistan stock market. In addition, Zhu, Kou, Lai, Feng, and Du (2021) also found higher clustering coefficient during the COVID-19 period, possibly reflecting close-world network features. An appealing concept linked with clustering coefficient is small world network, which is simply the ratio of the path length upon the clustering coefficient (Xu, Wong, Chen, & Huang, 2017). However, this paper uses average path length as replacement variable against different threshold levels for all the periods. Moreover, <*L*> shows that both networks of sub-sample periods are different. The transmission efficiency enhances due to higher network density, and lower threshold levels corresponds to COVID-19 related crisis, with majority investors become enormously thoughtful to the information resulting in spillover effect of various markets being clearly improved. Further, the COVID-19 related uncertainty and crisis leads to low volatility resulting in quick flow of information and strong correlations among Pakistan stock market.

Further, we use moving window correlation coefficients to examine the evolving correlations between stocks of the Pakistan stock market. The window length has been set to 1 month, resulting in 16-time windows. After the formation of evolving MSTs, the following sub subsections present an analysis of Pakistan stock market concerning highest evolving node degree, highest evolving betweenness centrality, dynamic normalised tree length, and dynamic average path length.

The centrality measures are helpful in representing the influence of critical nodes among a network. The highest centrality measure of node degree and betweenness centrality are presented in Figure 5. As shown in Figure. 5, the highest number of nodes in Pakistan stock market network increased from six in the month of July-2019 to eight in February 2020. In other words, the network

structure represents a star-like structure during the time when Government of Pakistan has verified COVID-19 cases. Another peak in the highest node degree of eight was also noticed during October 2020, when the total number of COVID-19 cases reached 332,993, including 6,806 COVID-19 related deaths[2]. Previous studies found star-like structure of MST just before a crisis event that changed to chain-like during the crisis (Kumar & Deo, 2013; Zhao, Li, & Cai, 2016). In addition, the corresponding stocks with the highest betweenness centrality in the MST vary over time. The tremendous global influence and highest betweenness centrality among the Pakistan stock market stocks of 1,763 are noticed for October-2020.

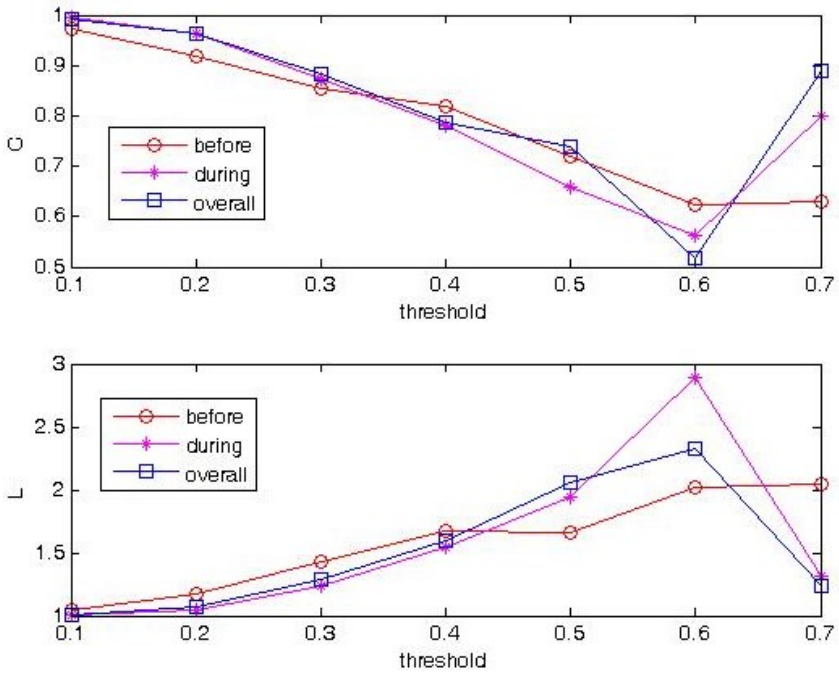

Figure 4. Average clustering coefficient <C> and average path length <L> of Pakistan stock threshold network

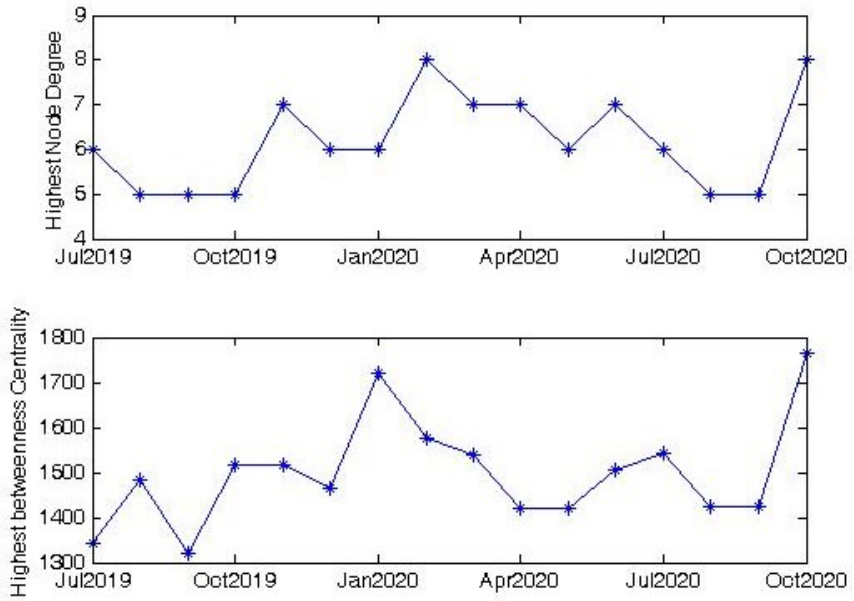

Figure 5. Dynamic highest node degree and highest betweenness centrality of Pakistan stock market

[2] Please see (https://reliefweb.int/report/pakistan/pakistan-covid-19-external-update-october-2020)

Furthermore, Table 2 show top Stocks of Pakistan stock market based on highest degree and betweenness centrality score during each period. The results show varied stocks appear on top spot in accordance with their relative industry sector. In terms of highest node degree, stocks from cement sector such as: DGKC, MLCF, and LUCK dominating on the overall network structure followed by oil and gas marketing nodes of SHEL, PSO, and SSGC. This indicates that these two industries have become more active and attractive to investors, representing to higher centrality in the Pakistan stock market. Before COVID-19 commercial banking sector nodes appear twice on the most influential hub positions, which has been changed during COVID-19 period to varied sector nodes as the Pakistan stock market network reduced connectivity to the financial sector. With regard to betweenness centrality, oil and gas marketing sector is most significant, followed by engineering sector having highest number of short routes and reflecting strong intermediary role. This also shows crucial role of these sectors for Pakistan economy. Moreover, an increase in the average intermediary routes for engineering sector node of International steel (ISL) has also been noted for the two consecutive months of July and august 2020 during COVID-19 period.

Table 2. Top stocks of Pakistan stock market with highest values of degree and betweenness

Time	Highest Node Degree			Highest Betweenness Centrality		
	Ticker	Name	Industry	Ticker	Name	Industry
Jul-19	PPL	Pakistan Petroleum Limited	Oil & Gas Exploration Companies	PPL	Pakistan Petroleum Limited	Oil & Gas Exploration Companies
Aug-19	HUBC	Hub Power Company	Power Generation & Distribution	SSGC	Sui Southern Gas Company Limited	Oil & Gas Marketing Companies
Sep-19	DGKC	D.G. Khan Cement Company	Cement	TRG	TRG Pakistan Limited	TECHNOLOGY & COMMUNICATION
Oct-19	UBL	United Bank Limited	Commercial Banks	LUCK	Lucky Cement Limited	Cement
Nov-19	FABL	Faysal Bank Limited	Commercial Banks	MEBL	Meezan Bank Limited	COMMERCIAL BANKS
Dec-19	ISL	International Steels Limited	Engineering	ISL	International Steels Limited	Engineering
Jan-20	PSX	Pakistan Stock Exchange Limited	Inv. Banks/Inv. Cos./Securities Cos.	PSX	Pakistan Stock Exchange Limited	Inv. Banks/Inv. Cos./Securities Cos.
Feb-20	PSMC	Pak Suzuki Motor Company	Automobile Assembler	PSMC	Pak Suzuki Motor Company	Automobile Assembler
Mar-20	MLCF	Maple Leaf Cement Factory Limited	Cement	FFBL	Fauji Fertilizer Bin Qasim Limited	FERTILIZER
Apr-20	SHEL	Shell Pakistan Limited	Oil & Gas Marketing Companies	SHEL	Shell Pakistan Limited	Oil & Gas Marketing Companies
May-20	LUCK	Lucky Cement Limited	Cement	LUCK	Lucky Cement Limited	Cement
Jun-20	PSO	Pakistan State Oil Company Limited	Oil & Gas Marketing Companies	PSO	Pakistan State Oil Company Limited	Oil & Gas Marketing Companies
Jul-20	DGKC	D.G. Khan Cement Company	Cement	ISL	International Steels Limited	Engineering
Aug-20	SEARL	The Searle Company Limited	Pharmaceuticals	ISL	International Steels Limited	Engineering
Sep-20	MCB	MCB Bank Limited	MCB Bank Limited	LOTCHEM	Lotte Chemical Pakistan Limited	CHEMICAL
Oct-20	SSGC	Sui Southern Gas Company Limited	Oil & Gas Marketing Companies	SSGC	Sui Southern Gas Company Limited	Oil & Gas Marketing Companies

Figure. 6 shows the highest fall of the normalised tree length (NTL) of the Pakistan stock market during the month of March 2020, soon after Pakistan confirmed the cases of COVID-19. The value of NTL dropped from 0.7146 in the month of January 2020 before COVID-19 to 0.5440 in the month of March 2020, the maximum shrinkage of tree structure among all the periods. Previous studies mention shrinkage in the tree length typically during crisis period, representing chaos and uncertainty due crisis-related shocks that lead to contraction and smaller MST of stock markets (Lee & Nobi, 2018; Memon & Yao, 2019). Since then, the NTL improved instantly and reached its highest level of 0.9105 during the month of July 2020 and during the COVID-19 period. The measures are taken by the government of Pakistan to restrict the impact of COVID-19, such as: shortening the duration of complete lockdowns, implementing smart lockdowns, approval of fiscal stimulus package, and compensation towards various industries, resulted in the expansion of network structures.

Consequently, the NTL decreased sharply due to the Pakistan stock market confronted with extreme risk. Furthermore, the dynamic average path length is used to assess the network transfer efficacy among all the periods of the Pakistan stock market. The APL shows a fluctuating downward trend from July 2019 to January 2020, before COVID-19. The lowest APL of 5.7069 was noted during January 2020, representing an early indication of crisis, with entire investors becoming highly thoughtful of the information and spillover effect of the Pakistan stock market. The transmission efficacy enhanced afterwards, with the highest APL of 8.1655 recorded during the month of June 2020. However, the APL decreases slightly thereafter as the Pakistan stock market gradually becomes sparse again.

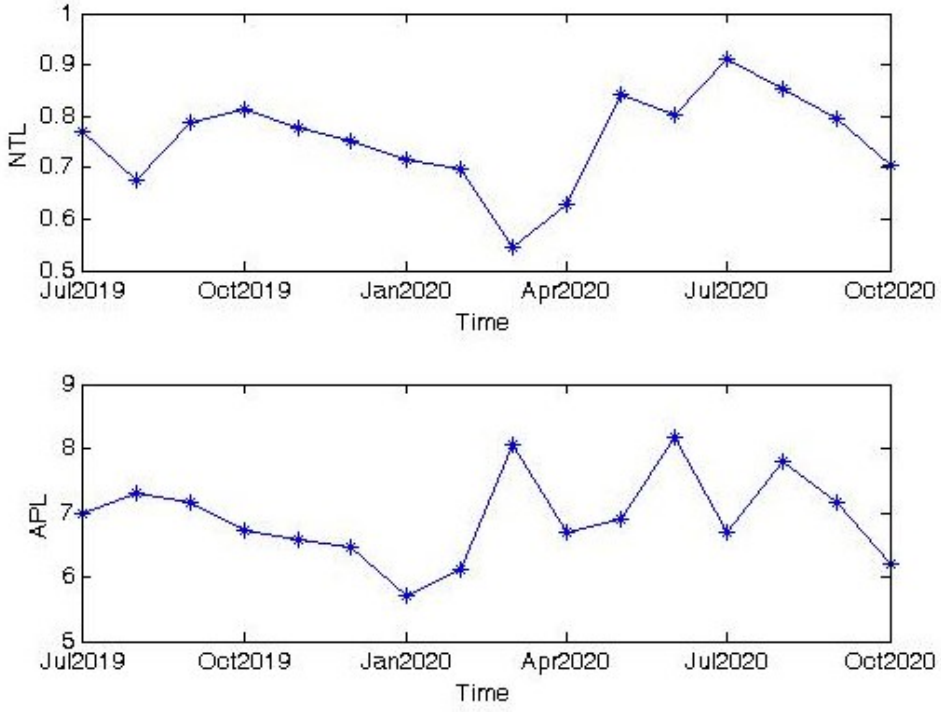

Figure 6 Dynamic normalised tree length and average path length of Pakistan stock market

Conclusion

This paper presented a detailed analysis of the blue-chip stocks of the Pakistan stock market in the pre-, during COVID-19 and total sample period through complex network methods. The dynamic and static characteristics of network structures provided us with a comprehensive outlook of the Pakistan stock market, particularly during the crisis and uncertain time of COVID-19. This would be useful to the investors of the Pakistan stock market for opting for correct decisions related to their portfolios and managing risks, further to the regulators for accessing stock market stability and control.

The analysis of correlation matrices revealed visible changes among the correlation structures in all the study periods. However, low clusters and weak correlation are observed in the pre-Covid-19 period, followed by an increase in the correlation coefficients during the COVID-19 period, reflecting uncertainty of the health-related COVID-19 crisis. About the threshold networks, the results showed an interconnected and dense network of the Pakistan stock market during the COVID-19 period in almost all the threshold levels. The results further revealed highly connected MLCF, DGKC, OGDC, and PPL nodes during the two sub-sample periods. The threshold topological properties of clustering coefficient and average path length showed that the COVID-19 crisis added some extent of fluctuation and transitivity to the Pakistan stock market stocks.

To examine the dynamic structures of the Pakistan stock market, this paper constructed sixteen monthly MSTs covering both sub-sample periods. The results of dynamic MSTs revealed a star-like system during the month when the government of Pakistan identified confirmed cases of COVID-19. The topological properties of node degree showed important nodes on hub position mostly from two sectors of cement and oil and gas marketing. In addition, stocks from the oil and gas marketing sector have the most significance, followed by the engineering sector having the highest number of short routes and reflecting a robust intermediary role. This information can provide investors and regulators with better risk and portfolio management in the stock market.

The NTL decreased rapidly during the crisis and uncertain time during COVID-19 and recovered back where it reached its maximum level throughout the period. In addition, NTL has proposed a good indication for the investors to monitor and analyse the changing trend from the period before and during-COVID-19 the crisis time. Although this paper has addressed many issues related to the analysis of the Pakistan stock market, for future work, an assessment of south Asian stock markets can be performed by extending the application of complex network methods in a broader data, and by comparing the results achieved in this paper.

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Appendix

Table A1: Complete list of Companies and their respective industry sector, used in this study.

Ticker	Company name	Sector
KEL	K-Electric	Power Generation & Distribution
HUBC	Hub Power Company	Power Generation & Distribution
KAPCO	Kot Addu Power Company	Power Generation & Distribution
SPWL	Saif Power Limited	Power Generation & Distribution
OGDC	Oil and Gas Development Company	Oil & Gas Exploration Companies
PPL	Pakistan Petroleum	Oil & Gas Exploration Companies
POL	Pakistan Oilfields	Oil & Gas Exploration Companies
MARI	Mari Petroleum Company	Oil & Gas Exploration Companies
BYCO	Byco Petroleum Pakistan	Refinery
ATRL	Attock Refinery	Refinery
SCBPL	Standard Chartered Bank	Commercial Banks
BOP	Bank Of Punjab	Commercial Banks
NBP	National Bank Of Pakistan	Commercial Banks
BAFL	Bank Al-Falah	Commercial Banks
FABL	Faysal Bank Limited	Commercial Banks
HBL	Habib Bank Limited	Commercial Banks
MEBL	Meezan Bank Limited	Commercial Banks
AKBL	Askari Bank Limited	Commercial Banks
UBL	United Bank Limited	Commercial Banks
MCB	MCB Bank Limited	Commercial Banks
ABL	Allied Bank Limited	Commercial Banks
BAHL	Bank Al-Habib Limited	Commercial Banks
HMB	Habib Metropolitan Bank Limited	Commercial Banks
PTC	Pakistan Telecommunication Company Limited	Technology & Communication
TRG	TRG Pakistan Limited	Technology & Communication
DCR	Dolmen City Reit	Real Estate Investment Trust
FATIMA	Fatima Fertilizer Company Limited	Fertilizer
EFERT	Engro Fertilizers Limited	Fertilizer
FFC	Fauji Fertilizer Company Limited	Fertilizer
FFBL	Fauji Fertilizer Bin Qasim Limited	Fertilizer
ENGRO	Engro Corporation Limited	Fertilizer
PIBTL	Pakistan International Bulk Terminal Limited	Transport
LOTCHEM	Lotte Chemical Pakistan Limited	Chemical
EPCL	Engro Polymer and Chemicals Limited	Chemical
ICI	I.C.I. Pakistan Limited	Chemical
ARPL	Archroma Pakistan Limited	Chemical
FCCL	Fauji Cement Company Limited	Cement
MLCF	Maple Leaf Cement Factory Limited	Cement
DGKC	D.G. Khan Cement Company Limited	Cement
LUCK	Lucky Cement Limited	Cement
PIOC	Pioneer Cement Limited	Cement
HASCOL	Hascol Petroleum Limited	Oil & Gas Marketing Companies
SSGC	Sui Southern Gas Company Limited	Oil & Gas Marketing Companies
SNGP	Sui Northern Gas Pipelines Limited	Oil & Gas Marketing Companies
PSO	Pakistan State Oil Company Limited	Oil & Gas Marketing Companies
SHEL	Shell Pakistan Limited	Oil & Gas Marketing Companies
APL	Attock Petroleum Limited	Oil & Gas Marketing Companies
ILP	Interloop Limited	Textile Composite
GATM	Gul Ahmed Textile Mills Limited	Textile Composite
NML	Nishat Mills Limited	Textile Composite
KTML	Kohinoor Textile Mills Limited	Textile Composite
PSX	Pakistan Stock Exchange Limited	Inv. Banks/Inv. Cos./Securities Cos.
UNITY	Unity Foods Limited	Vanaspati & Allied Industries
PAEL	Pak Elektron Limited	Cable & Electrical Goods
ISL	International Steels Limited	Engineering
AICL	Adamjee Insurance Company Limited	Insurance
GLAXO	GlaxoSmithKline (Pakistan) Limited	Pharmaceuticals
AGP	AGP Limited	Pharmaceuticals
SEARL	The Searle Company Limited	Pharmaceuticals
ABOT	Abbot Laboatories (Pakistan) Limited	Pharmaceuticals
HINOON	Highnoon Laboratories Limited	Pharmaceuticals
OLPL	Orix Leasing Pakistan Limited	Leasing Companies
NATF	National Foods Limited	Food & Personal Care Products
HCAR	Honda Atlas Cars (Pakistan) Limited	Automobile Assembler
PSMC	Pak Suzuki Motor Company Limited	Automobile Assembler
INDU	Indus Motor Company Limited	Automobile Assembler
MTL	Millat Tractors Limited	Automobile Assembler

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Revisiting the macroeconomic variables and economic growth nexus: A Markov regime-switching approach

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Abstract

Purpose — Current paper assesses the impact of macroeconomic variables on Pakistan's economic growth.

Method — This study analyzed the data using the Markov Regime switching (MS) model using monthly data for 1981-2020. Firstly, BDS and CUSUM square tests were applied to detect the non-linearity of the model.

Results — The model is non-linear, so the Markov regime-switching model is used for analysis. Each regime's mean and variance are highly significant and show a high growth regime with high volatility and a low growth regime with low volatility. Furthermore, the results show that inflation, interest rate, and trade openness negatively impact while real effective exchange rates positively affect development in both regimes. The negative effect of interest rate, exchange rate, inflation, and trade openness become more pronounced in low growth regimes.

Implication — This study suggests that policymakers should consider the non-linear behaviour of macroeconomics. This will help to formulate better policies for the economy's economic growth.

Originality — The current research adds to the existing literature by identifying the non-linear effect of growth indicators on economic growth, which was previously neglected in the case of Pakistan.

Keywords — macroeconomic variables, economic growth, nexus, non-linear, Markov switching model, Pakistan.

Introduction

Stable economic growth is an important prerequisite for sustainable economic growth (Semuel & Nurina, 2014). Economic growth comes under the prime priority of macroeconomic policy of any economy (Chowdhury, Hamid, & Akhi, 2019) as an increase in economic growth more than a population, specifies that there is an increase in GDP per capita and hence an improvement in living standard (Anaripour, 2011). Most countries strive to achieve rapid and sustainable economic growth, but achieving this goal is a problem as many factors affect economic growth. Macroeconomic management is of primary concern in promoting economic development (Van Dan & Binh, 2019). The correct knowledge about the effectiveness of the macroeconomic variables is the main issue for policymakers for the successful implementation of economic policies to achieve sustainable economic growth (Fasanya, Onakoya, & Agboluaje, 2013).

Pakistan is on the way to attaining long-term sustainable economic growth, but it is very difficult to say which factors determine economic growth (Javed, Nabi, Yasin, & Razzaq, 2018).

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However, according to Romer (1990) and Solow (1956), economic growth combines different macroeconomic variables. Pakistan experiences a weak and decreasing trend in economic growth. The weak economic situation is mainly due to high inflation (Hussain & Malik, 2011), mounting fiscal deficit (G. Fatima, Ahmed, & Rehman, 2011), expanding debt (Akram, 2011), fluctuating exchange rate (Mohsin, Majeed, & SobiaNaseem, 2018), trade balance (Koukouritakis, 2004), interest rate and money supply (Anowor & Okorie, 2016; Precious & Makhetha-Kosi, 2014). The gross domestic product of Pakistan reached almost $1.08 trillion in 2019/20, and it has been continuously decreasing due to the effect of various economic factors. Pakistan's current economic growth rate is around -0.4 per cent in 2019/20, reflecting an alarming situation. The current economic growth situation is calling to re-investigate the macroeconomic variables-growth nexus.

The macroeconomic variables-growth nexus has recently gained attention, and many academics are trying to understand such an economic growth relationship. Empirical findings, however, are mixed regarding the overall macroeconomic variables – growth nexus conclusions. For example, certain degrees of inflation is needed for sustainable economic growth (Temple, 2000). The main objective of macroeconomic policy is to keep the inflation rate low, providing a favourable climate for increased economic growth. Low inflation boosts economic growth by promoting capital investment and price stability. However low inflation is important for maintaining macroeconomic stability, but it is not suitable for sustained economic growth (Fischer, 1983). An interest rate increase generally allows people to invest more, as the former contributes to higher wages. However, an increase in the interest rate also increases capital costs, contributing to decreased investment within the economy. Austrian, some ecological economists, and even post-Keynesian economists assume that lower interest rates increase economic growth (Lee & Werner, 2018). Empirical research presents contradictory findings on the impact of trade terms (TOT) on economic growth. Several researchers (Bleaney & Greenaway, 2001; Cakir, 2009; Chang, Kaltani, & Loayza, 2009; Dollar & Kraay, 2004; Frankel & Romer, 1999; Grimes, 2006; Jawaid & Raza, 2013; Jawaid & Waheed, 2011) have found a positive relationship between trade openness and economic growth. The variation can explain the positive impact of trade openness in trade terms caused by an increase in the export price relative to the import price.

In comparison to imports, this will increase export revenues, boosting the balance of payments and economic growth (Blattman, Hwang, & Williamson, 2003; Bleaney & Greenaway, 2001; Ijaz, Zakaria, & Fida, 2014). Studies have also reported a negative effect of trade terms on production growth (N. Fatima, 2010; Kalumbu & Sheefeni, 2014; Wong, 2010). Theoretically, it has been proven that free trade can improve economic trade in the long term. Free trade can increase access to goods and services, achieving resource allocation efficiencies and increasing the economy's overall production (Barro, 1996; Rivera-Batiz & Romer, 1991). Therefore, trade openness enables countries to outperform in relative terms. Most research has focused on the relationship between real exchange rates (RER) and economic development (Ghosh, Ostry, & Qureshi, 2015; Klein & Shambaugh, 2012; Rose, 2011). The exchange rate is an endogenous variable for most economists, which can be difficult to eliminate from growth. Indeed, whether exchange rate understatement promotes long-term growth remains curiously unanswered in the literature.

Various studies have been done in the literature to study the drivers of economic growth, with little attention paid to the views' distinct theoretical and methodological aims. We have recorded that no discussion was agreed to find out which measures of economic indicators are most important in different regimes. Because of socio-economic conditions, the components of economic development can differ in developed and developing countries. Further, in the existing literature, the impact of macroeconomic variables is assumed to be linear, but the impact is asymmetric, and it varies according to regimes. As a result, the current study adds to the existing literature by identifying the effect of growth indicators such as inflation, interest rate, trade openness, and exchange rate on economic growth using a non-linear model of regime transition.

There has been substantial disagreement about the macroeconomic variables-growth nexus for many years. Before delving into the empirical findings of the current study, it will be very instructive to shed light on past literature on the relationship between macroeconomic variables and economic growth.

Agalega and Antwi (2013) discovered a positive association between inflation and economic growth in Ghana but a negative relationship between interest rates and economic growth. On the other hand, Salian and Gopakumar (2008) discovered that inflation affects economic growth negatively in the long term. It revealed that a moderate inflation rate leads to high economic growth and vice versa. The negative impact of inflation rate fluctuations was also found by Umaru and Zubairu (2012) on productivity and the overall output level of the economy. Chughtai, Malik, and Aftab (2015) examined the impact of macroeconomic variables impact on the economic growth of Pakistan over a period from 1981 to 2013. They discovered that both the inflation rate and the interest rate affect economic growth negatively, whereas the exchange rate has a favourable impact on economic growth. Khan and Khan (2018) looked at how inflation affects economic growth in five Asian countries: Bangladesh, Iran, Indonesia, Malaysia, and Pakistan. They used primary data spanning the years 1973 to 2016. They established a neoclassical relationship between inflation and economic growth. Mbulawa (2015) discovered that Foreign Direct Investment (FDI) and the inflation rate had a considerably beneficial impact on GDP, while gross capital formation had a positive but negligible impact on Botswana's economic growth.

Ristanović (2010) found that budget consumption, private expenditure, export, and imports are considered major macroeconomic variables that affect economic growth. Similarly, Muhammad, Lakhan, Zafar, and Noman (2013) attempted to find the nexus between the interest rate and investment. They found that investment was the main variable that can boost the economy of Pakistan, while investment is directly associated with interest rate. Fluctuations in interest rates change investment and savings as well. Interest rate fluctuations negatively affect the investment sector (Bader & Malawi, 2010); however, the investment sector is positively associated with the economy's income level. According to Khawaja and Din (2007), there is a link between interest rates and economic growth. They further found that a high interest rate disrupts the economy's saving and investment patterns, potentially affecting economic growth. Bashir, Ahmed, and Khan (2017) used maximum entropy bootstrap to investigate the causal relationship between interest rates and economic growth from 1960 to 2017. They discovered a unidirectional causal association between economic growth and interest rates.

Ahmad, Ahmad, and Ali (2013) found that a high exchange rate significantly impacted economic growth. Devaluation has a persistent effect on economic growth in a model of increasing return to scale. High productivity in the trading sector would incentivise maintaining relative prices high enough. This will create an incentive to shift resources into the tradable sector. Therefore, a weak exchange rate is recommended to enhance the tradable sector (Aizenman & Lee, 2008; Benigno, Converse, & Fornaro, 2015; Di Nino, Eichengreen, & Sbracia, 2011).

Zoramawa, Ezekiel, and Kiru (2020) found the impact of exchange rate on economic growth by using the Johanson Cointegration and ECM model from 1980 to 2019. Their findings show that the exchange rate has a favorable impact on economic growth. In contrast, a weak exchange rate leads to higher savings and, hence, higher investment and low labor costs (Glüzmann, Levy-Yeyati, & Sturzenegger, 2012). According to Krueger (1978), trade liberalization frequently increases specialization in sectors where the economy has economies of scale. This specialization, as a result, contributes to the enhancement of efficiency and productivity. Countries with trade openness are more flexible towards the diffusion of advanced technologies, and this technology transfer will lead to more productivity and hence economic growth (Coe & Helpman, 1995; Romer, 1994). Rigobon and Rodrik (2005) investigate that TOT had a significantly negative impact on economic output growth.

Similarly, Fenira (2015) found that TOT hurts economic growth. Asfaw (2014) reviewed that trade openness can boost economic output growth and investment. Khan, Anwar, and Anwar (2020) found a positive relationship between trade openness and economic growth in the case of Pakistan. They further found that there exists a bidirectional Granger causality between selected variables. The literature shows that the variables are linearly correlated, and different authors used different linear methods to analyze the relationship among macro variables. Our stance is that if we had a better understanding of the phenomena, it would help make policies that are more effective and help improve the economy's economic condition, as the linearity may mislead the results and lead to a wrong policy decision.

Methods

Our main goal of the study is to investigate the effect of a macroeconomic variable on economic growth. Several macroeconomic variables affect the growth, but we only consider inflation (INF), interest rate (INT), trade openness (OPEN), and real effective exchange rates (REER) as independent variables and GDP (Output) as a dependent variable.

$$output = f(INF, INT, OPEN, REER)$$

Large scale manufacturing is used as a proxy for economic growth. The manufacturing sector is divided into two sub-sectors, i.e., Large-Scale Production and Small-Scale Production. The productivity of the industrial sector, which usually involves mining, manufacturing, services, and, in some cases, construction, is determined by industrial production. The industrial output measure is generally given in volume terms as an index. Variation in industrial production usually reflects the changes in the volume of industrial output compared to the previous time.

The WPI is used as a proxy for inflation. The wholesale price index measures the average changes in prices of goods before goods reach the retail level. Goods included in WPI are sold in bulk and traded between entities or businesses only. In WPI, the overall costs of goods in one year are compared to the overall costs of goods in the base year. On the scale, the total prices for the base year are equal to 100. The difference between the current and base years is represented as a percentage of change.

The RER is a weighted average of domestic currency with other trading partners ' currencies. The partners are those with whom most of the trade occurs, and their currency fluctuations affect the domestic country's trade. The weights are determined by comparing a country's relative trade balance to each country in the index. In the case of Pakistan, the weighted average of 24 major currencies is used.

Open is used as a proxy for trade openness. Trade openness is one indicator of a country's participation in the global trading system. It is calculated as a ratio between export plus imports and GDP. An investment decision is highly correlated with trade openness. Investors pay close attention to foreign markets' trade openness for future investment decisions.

CMR is used as a proxy for the interest rate. The call money rate is when short-term funds in the money market are borrowed and lent. The call money rate is the borrowing rate usually used by investors to pay on margin in their trading. Borrowed Capital boosts investment in the economy.

Structural stability test

Parameters' stability is checked through CUSUM and CUSUM square tests. The results showed that the model is not stable. Figure 1 revealed that the blue line is not within the boundary of a 5 per cent level of significance, so it is concluded that the model is not linear.

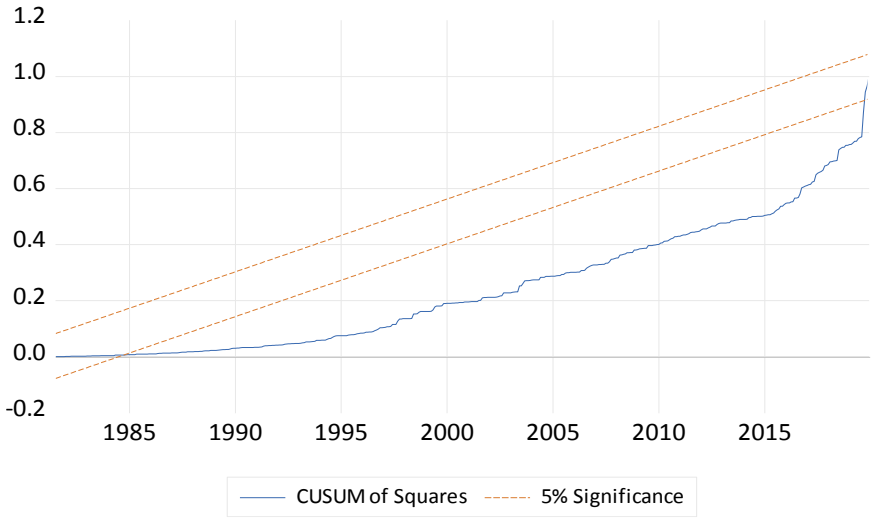

Figure 1. The figure of CUSUM Square

BDS test

Broock, Scheinkman, Dechert, and LeBaron (1996) proposed a nonparametric test of correlation integral. The basic idea is that the evolution of two values of the block, which are close to some metric, should also be close to the block metric. An observed series at the correlation integral C (l, t) is given below as

$$c_n(l,t) = \frac{2}{(t_n*(t_n-1)} \sum_{t<s} I_t\,(x_t^n, x_s^n)$$

where

$x_t^n = (x_t, x_{t+1}, \ldots\ldots\ldots\ldots\ldots x_{t+n-1})$
$x_s^n = (x_s, x_{s+1}, \ldots\ldots\ldots\ldots\ldots x_{s+n-1})$

Are called n-histories. The correlation integral is estimated the probability that any two n histories are within l of each other. If this is white noise then

$$c_n(l,t) \to c_1(l,t)^n, ast \to \infty$$

And

$$w_n(l,t) = \frac{\sqrt{t}(c_n(l,t)-c_1(l,t)^n)}{\sigma_n(l,t)}$$

The BDS test the null hypothesis that series are white noise. Because this is a diagnostic test, rejecting the null hypothesis indicates data reliance. The BDS test in chaos theory demonstrates that the results are based on the spatial correlation principle, meaning that the time series exhibits non-linear and deterministic behaviour. BDS measures non-linearity since the first natural logarithmic distinction removed any linear dependence on the results. BDS test null hypothesis is that the series is distributed independently and identically. Still, if we reject the null hypothesis, the series had some chaotic behaviour which means that the series is dependent and not identically distributed. BDS used by Kanzler, Kuschert, Liu, and Mallo (1998); Sharma and Panagiotidis (2005); Winker, Gilli, and Jeleskovic (2007). A time-series non-linearity test was performed using a BDS test presented in Table 1. To complete the test, by using 2-6 dimensions and 0.7 distance were chosen for estimation.

Therefore, we can conclude that the MS method is suitable for examining the relationship between variables.

Table 1. Results of BDS Test

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.032	0.004	7.144	0.000
3	0.064	0.007	8.983	0.000
4	0.088	0.008	10.276	0.000
5	0.099	0.008	11.148	0.000
6	0.104	0.009	11.996	0.000

Markov Regime-Switching Technique

Hamilton (1990) proposes the regime-switching model, a non-linear extension of the ARMA model that incorporates the dynamics, including asymmetry and heteroscedasticity. Y_t is a two-state Markov process of economic growth where Ω_i (where i=0,1) parameter takes on one of two values depending on the realization of discrete-valued unobserved state variable may be written as

$$\Delta y_t = \Omega_i + \beta_i x_t + \varepsilon_t \quad (1)$$

where

$$p(y_t = 1/y_{t-1} = 1) = pp(y_t = 0/y_{t-1} = 1) = 1 - pp(y_t = 1/y_{t-1} = 0) = 1 - qp(y_t = 0/y_{t-1} = 0) = q$$

In equation (1), y_t is the change in the large scale manufacturing industry index, which is used as a proxy of the economy's output where the state variable x_t changes according to a two-state Markov process. It includes macroeconomic variables of the economy like inflation, interest rate, real effective exchange rate, and trade openness. Where $\varepsilon_t \; iid \sim N(0, \sigma^2{}_\varepsilon)$.

$$p_r = \begin{pmatrix} p_{11}\, p_{12} \\ p_{21}\, p_{22} \end{pmatrix}$$

The probability of remaining in that state is o and 1, and to switch from one to another; regime probabilities are captured in p_r column. State one has high growth, and high volatility and state 2 is low growth and low volatility. The important element of this technique is that the switching probabilities of one another regime are endogenously modelled.

P11= prob (state 1=high output regime given that high output regime)
P12= prob (state 2=high output regime given that low output regime)
P21= prob (state 1=low output regime given that high output regime)
P22= prob (state 1=high output regime given that high output regime)

Results and Discussion

Unit root test

We employed stationary variables in the MS model, and stationarity was confirmed using the PP (Phillips-Perron) and ADF (Augmented Dickey-Fuller) tests, and the results are shown in Table 2. The results show that all series are stationary at the significance levels of 1%, 5%, and 10%, respectively.

Table 2. Unit Root Results

At Level	With Constant				With Constant & Trend			
	ADF		PP		ADF		PP	
Variables	t-Stats		t-Stats		t-Stats		t-Stats	
Output	-0.77	n0	-1.48	n0	-1.64	n0	-6.85	***
D(INF)	-2.12	n0	-7.75	***	-4.17	***	-7.78	***
INT	-3.34	**	-19.82	***	-3.36	*	-19.88	***
OPEN	-1.30	n0	-1.99	n0	-3.21	*	-1.68	n0
REER	-2.16	n0	-5.67	***	-1.89	n0	-9.52	***
At First Difference								
d(Output)	-5.30	***	-36.86	***	-5.27	***	-36.45	***
d(DINF)	-13.98	***	-79.07	***	-13.97	***	-78.94	***
d(INT)	-15.09	***	-251.93	***	-15.07	***	-264.94	***
d(OPEN)	-6.13	***	-15.34	***	-6.15	***	-15.27	***
d(REER)	-15.28	***	-73.59	***	-15.32	***	-79.12	***

Note: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%

Regime Switching Model

The effect of macroeconomic variables on economic growth was investigated using the Markov switching approach. We used a non-linear regime-switching strategy to better understand the relationship between macroeconomic variables and economic growth. We defined two regimes: one with great economic growth and the other with low economic growth and minimal volatility. According to Fallahi (2011), the two-regime model is more suited to macroeconomic connections. Table 3 presents the results of the regime change model, showing that the coefficients (μ1; μ2; σ1 and σ2) are highly significant. Results indicate that regime 1 is a low economic growth regime and regime 2 is a high one. Regime 1 refers to a period of low growth with a mean (μ1) is 1.6019 and relatively low variance (σ1) of 0.4997. Regime 2 is a high-growth regime in which economic activities expand considerably, with a high mean (2) of 6.196 and a variance (2) of 1.560. Because of the high mean value and low volatility, this regime corresponds to an era of economic growth.

The result reveals that μ2> μ1 and σ2 <σ1. As a result, it is possible to conclude that the high-growth regime is more unpredictable and turbulent.

Regression parameters suggest that the CPI has had a negative but marginal effect on economic growth in both regimes. Inflation is a major problem in Pakistan and affects the everyday life of people, such as wages, purchasing power, literacy rate, money supply, etc., all of which have different effects on Pakistan's economic growth in some way and that further impact the development of the country. Regression parameters suggest that the CPI in both regimes had a negative but marginal effect on the economic development of the economy. These results are evidence that there exists a tradeoff between GDP growth and inflation. Inflation in Pakistan's economy is detrimental to GDP growth. This statistically important finding shows that economic growth is hurt by a steady rise in the average price level. Such findings are consistent with those of Ahmad et al. (2013) and Ayyoub, Chaudhry, and Farooq (2011). The interest rate harmed economic growth in both regimes but with different magnitude. The result indicates that in high growth time, if the interest rate becomes high so there is the chance to reduce investment which costs more as compared to the time in which the economy is less responsive to the interest rate with a low opportunity of growth of other variables as mentioned by Harswari and Hamza (2017).

The interest rate is a barrier to economic investment, affecting growth and vice versa. Trade openness has hindered economic growth. The findings are consistent with those of Ali and Abdullah (2015). As Pakistan is a developing country with low economic development and high inflation, openness has a detrimental impact on economic growth. According to the literature (Keho, 2017; Kim, Lin, & Suen, 2012), the true effects of trade on economic growth are determined by the level of financial development and inflation. As Pakistan experienced low financial development and high inflation, that could lead to a negative impact on trade openness as Huang and Chang (2014) found that in developing countries growth effect of trade depends upon the extent of stock market development. Results also showed that the exchange rate positively impacts economic growth in both regimes with different magnitudes. Results confirm that currency depreciation can affect economic growth in the long term through export income elasticity of demand. Strong exchange can lead to expensive exports and cheaper imports, resulting in less demand for exports.

Table 3. Results of Markov Regime switching Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
MEAN(μ1)	1.601	0.839	1.908	0.056
Output (-1)	0.205	0.025	8.153	0.000
Output(-12)	0.838	0.026	32.231	0.000
D(INF)	-0.409	0.309	-1.323	0.185
INT	-0.150	0.043	-3.457	0.000
OPEN	-0.072	0.016	-4.380	0.000
REER	0.014	0.004	3.329	0.000
Variance (σ1)	0.499	0.061	8.192	0.000
		Regime 2		
MEAN(μ2)	6.196	4.210	1.472	0.141
Output (-1)	0.346	0.047	7.334	0.000
Output (-12)	0.657	0.043	15.240	0.000
D(INF)	-0.612	0.411	-1.489	0.137
INT	-0.527	0.116	-4.545	0.000
OPEN	-0.133	0.050	-2.658	0.008
REER	0.063	0.042	1.500	0.134
Variance(σ2)	1.560	0.053	29.322	0.000

Duration of Regime Classification

Table 4 presents the length of the regime classification relating to MS. The findings indicate that since the conditional probabilities are .972 to stay regime one in state one and the probability of regime two is.966 to stay in state two. Both the probabilities of regimes are persistent.

Table 4. Conditional Probabilities

	1	2
1	0.972	0.028
2	0.034	0.966
Expected. Duration		
	1	2
	35.13	29.05

Table 5 shows that the expected duration in state one is 35 months and 13 days and probably 29 months and five days for state two. Its average time is three years for low growth and two year and six months for high growth—the probability of switching from one state to another. The probability of state one staying in-state one is p11. The probability of state two staying in-state one is p21.

Table 5. Transition Matrix Parameters

P11-C	3.53	0.44	8.03	0.00
P21-C	-3.35	0.48	-7.01	0.00

The probabilities of a smooth transition from one regime to another are persistent and given in Figure 2.

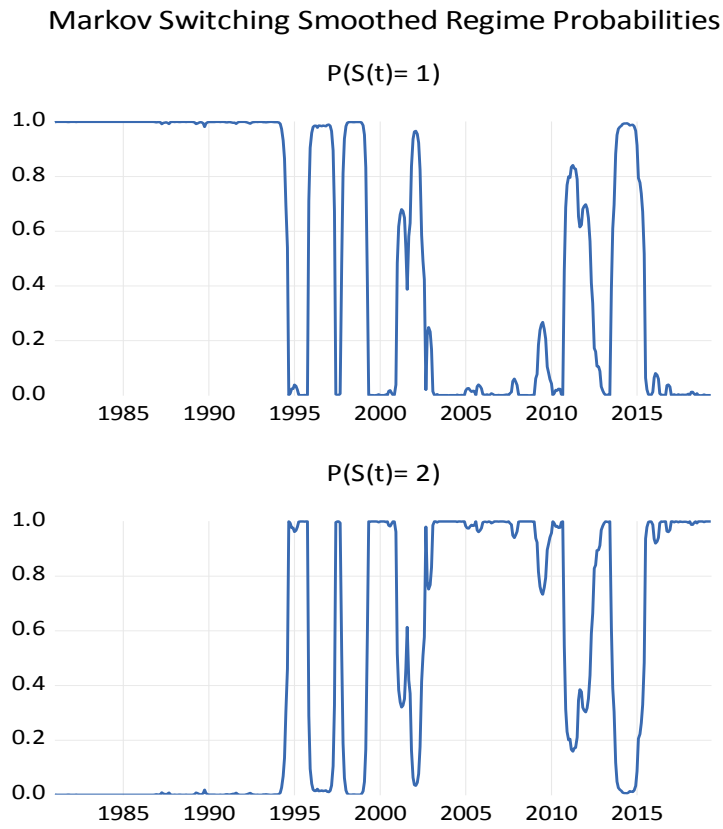

Figure 2. The figure of Smooth Probabilities of MS Model

Conclusion

This research was conducted to explore the non-linear relationship between economic growth and macroeconomic variables in the case of Pakistan. This non-linear relationship is investigated by the non-linear regime-switching model proposed by Hamilton (1990). In this study, monthly data was used from 1980 to 2020. The findings confirm that the series is non-linear, and regime-switching modelling effectively examines the link between macroeconomic variables and economic growth.

The MS results demonstrate two economic growth regimes: high and low. In both regimes, interest rate, inflation, and TOT negatively affect economic growth. The impact of macroeconomic variables is asymmetric in size across regimes.

In contrast, the exchange rate positively influenced economic growth in both low and high regimes. This study suggests that policymakers should consider the non-linear behaviour of macroeconomics. This will help to formulate better policies for the economy's economic growth.

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Islamic banks credit risk performance for home financing: Before and during Covid-19 pandemic

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Abstract

Purpose — This study aims to assess the home financing credit risk performed by Islamic banks in Indonesia.

Methods — A panel dynamic analysis is adopted to measure the bad loan performance before and during the Covid-19 pandemic. The observation period started from January 2016 to September 2020 with 1,881 observation periods of monthly panel data from the province level.

Findings — The study finds a difference in bad loan performance before and during the Covid-19 pandemic. Before this pandemic, inflation has a positive and significant influence on non-performing financing in real estate, rental business, and company service. However, during the Covid-19 pandemic, a substantial and positive effect of inflation is found on the bad loan for personal flat and apartment ownership. On the other hand, a significant and negative impact of inflation is found on the bad home loan for personal business shop ownership.

Implication — This analysis could trigger the government to provide financial assistance for those affected by the Covid-19 crisis. In addition to that, an Islamic bank is also expected to give financing allowances for them by providing an option of debt restructuration and rescheduling.

Originality — This paper analyses the Islamic bank's credit risk performance for home financing before and during the Covid-19 pandemic. This issue has not been presented in the literature to the best of our knowledge.

Keywords — credit risk, islamic banks, home financing, panel dynamic, inflation

Introduction

The COVID-19 pandemic comes as a surprise to all countries in the world, without the exception of Indonesia. Many countries could not predict how severe the effects of this virus are on the health, social, or economic condition. Particularly in Indonesia, a massive spread of COVID-19 from early March 2020 has caused a decline in economic activity and disrupted many macroeconomic indicators at the national level, including household consumption, investment, financing, inflation, and so forth (Statistics Indonesia, 2020). It has been hard for analysts and economists to forecast the national economic growth considering the unprecedented nature of the Covid-19 crisis. While few optimists hope to have moderately positive economic growth, a majority group merely forecasts a contraction.

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One of the indicators is the inflation rate in Indonesia. Claeys, Bénassy-quéré, Demertzis, and Zenios (2020) emphasise that inflation can be part of the main objective for the central bank to conduct monetary policy. In addition, inflation is one of the robust indicators utilised to explain the current economic circumstance. Bohl and Siklos (2018) state that inflation reflects what is happening in the real market in terms of goods and service conditions. An increase in inflation explains that there is a rise in prices for goods and services in the market, and it can be caused by two things which are cost-pull inflation and demand-pull inflation. A dramatic increase in inflation occurred during financial crises such as the Asian financial crisis in 1998 due to the cost-pull inflation Field (Mishkin, 1999). It also happened in the global financial crisis in 2008. It impacted the real market because a rocketed inflation rate made a sound, and services were less affordable.

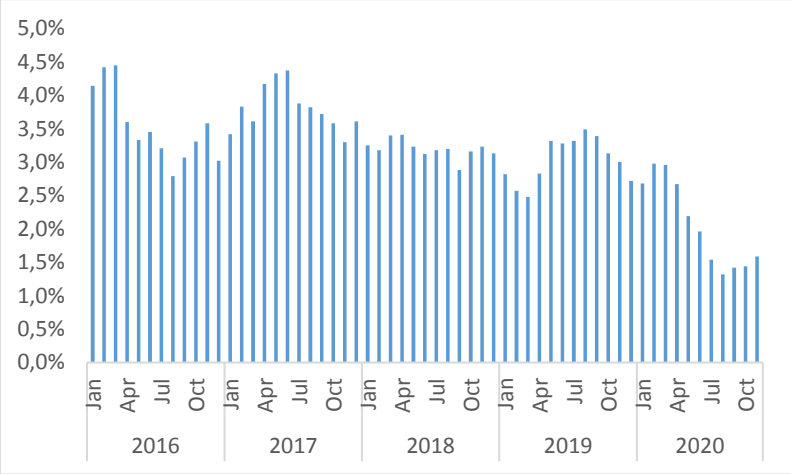


Figure 1. Inflation Rate in Indonesia
Source: Central Bank of Indonesia (2020)

On the other hand, financial turmoil can cause low inflation that sheds light on a lower purchasing power of society in Indonesia; this condition is shown in Figure 1, which expresses, in general, an upward movement of inflation after March 2020. Sukharev (2020) demonstrates that a hit in the real and financial sectors during the Covid-19 pandemic is possibly impacted the inflation rate to be lower than in the normal situation. A lower inflation rate which means a fall in purchasing power, confirms that the people tend to postpone their spending on non-primary needs goods and service. On a large scale, it significantly impacts production activities that provide non-primary needs products, and in the end, it creates a supply shock in economic activities (Claeys et al., 2020).

Even though less purchasing power appears in the society, according to Statistics Indonesia in August 2020, several sectors recorded positive growth, including information and communication, water supply, health services, and real estate. Notably, for real estate, a capital-extensive sector with a huge multiplier effect to more than 170 sub-sectors still appears as a positive driver of the national economy even in times of crisis like today. Despite many challenges brought by this pandemic, such as a fall in demand due to a weakened purchasing power as well as the ability to repay, the housing sector is shown to have a strong resilience by contributing a positive growth of 2.3% to the national Gross Domestic Product in the second quarter of 2020 (Statistics Indonesia, 2020). It could not be denied that the growth of the housing sector in 2020 heavily depends on the coordinated steps taken by the government, including a new housing loan subsidies of IDR 1.5 trillion (US$89.7 million) for 175,000 low-income families nationwide and other financing allowances provided by banks as the significant financial institutions (The Jakarta Post, 2020).

As home to the largest Muslim population and the most significant number of Islamic financial institutions globally, Islamic banks indeed play a crucial role in assisting society in financing their housing needs. Based on Law No. 21 of 2008, Islamic Bank can be defined as a bank that carries out business operations complying with Islamic principles, which are reflected in the fatwa of the Indonesian *Ulama* Council. Islamic banks in Indonesia provide Sharia-compliant

financing through various types of Sharia contracts according to the purpose of the funding including property financing. In a report released by Financial Services Authority (2020), Islamic Banks have provided financing to 18 industrial sectors in Indonesia. The financing of the 18 sectors is carried out by both Islamic Commercial Banks (BUS) and Islamic Business Units (UUS).

The covid-19 pandemic severely impacted almost all industries, not to exclude Islamic banking, which holds a crucial function as an intermediary that connects surplus funds and deficit funds. As a response, various urgent changes have been immediately implemented to allow this industry to survive the battle against the Covid-19 pandemic. When major industries need faster and easier access to capital, the role of Islamic banking is increasingly significant. However, on the one hand, Islamic banking must also remain cautious in carrying out its operations because the inevitable exposure to the risk is getting bigger amidst the uncertainty at the macroeconomic level arising from the Covid-19 pandemic.

Especially for home financing activities, being prudent is a key to maintaining the quality of financing activities. Ahmed (2010) explains that imprudent financing in the home financing or mortgage sector can be a preliminary cause to make the banks have a higher opportunity to default. This condition once occurred during the global financial crisis in 2008 that was started due to excessive and imprudent financing to the banking customers. Cheng, Cen, Wang, and Li (2020) add that the subprime mortgage crisis impacted the business cycle activities in the international market, creating a slowdown movement in trading activities.

Some previous research, including Field Ghosh (2016), shows that macroeconomic variables greatly determine banking performance in a dual banking system. It is also in line with the result of Fakhrunnas, Dari, and Mifrahi (2018), which confirms that in a dual banking system like Indonesia, a bank's risk-taking behaviour would be affected by macroeconomic indicators over a long period. Nonetheless, there is a distinct response between conventional and Islamic banks as the former are more exposed to the interest rate. Mohamad, Hasbulah, and Razali (2015) and Aviliani, Siregar, Maulana, ad Hasanah (2015) find that inflation impacts the banks' performance, which may increase the cost of business operation. In addition, the banks also need to adjust their expected return when the inflation rate goes up.

In addition to that, Zarrouk, Ben Jedidia, and Moualhi (2016) reveal a direct effect of economic growth on the performance of Islamic banking. The result also shows that Islamic banks will tend to provide a large number of financing and ultimately contribute more to the economic growth on the condition of good economic signals. Furthermore, Iriani and Yuliadi (2015) find that bank performance in form of non-performing financing (NPF) ratio is significantly affected by bank behaviors and macroeconomic indicators. The level of inflation held by a nation will affect the performance and the risk of banking activities in the future (Lin, Farhani, & Koo, 2016).

Research on Islamic banking is one of the most popular topics published in reputable journals both nationally and internationally. However, when it comes to a study on Islamic banking during the Covid-19 pandemic we find that there is still limited number research discussing this topic. Several existing studies such as Ningsih and Mahfudz (2020) and Ubaidillah and Syah Aji (2020) show that at the beginning of 2020 all banks, including Islamic banks, experienced turmoil in their intermediary function both from collecting and distributing funds which aggressively showed a downward trend. Other research such as Fitriani (2020) explains that the effect of the Covid-19 pandemic differs between the banks as her study reveals significant differences in financial performance between Islamic banks in Indonesia, in terms of NPF, ROA, and BOPO ratios.

On the other hand, several studies such as Hachicha and Amar (2012), Farahani and Dastan (2013), and Rosylin and Bahlous (2013) discuss the impact of Islamic bank's financing on economic growth. These studies find that the financing carried out by Islamic banks has a positive impact on the long-term economic growth, especially for the financing under Profit-Loss-Sharing (PLS) scheme. Further research related to the impact of macroeconomic variables on the performance of Islamic banking has also been carried out by Karim, Al-Habshi, and Abduh (2016), Louhichi and Boujelbene (2016), Trad, Trabelsi, and Goux (2017) and Srairi (2013).

As far as the authors are concerned, there are only few studies have used banking financial statement data to analyze the impact of the Covid-19 pandemic on Islamic bank's financing, in

particular the housing financing. Secondly, the use of regional macroeconomic variables will analyze more objectively the characteristics of Islamic banking in the selected provinces. Thirdly, the use of a dynamic panel approach will provide more information about the dynamic impact of Islamic banking financing on regional macroeconomic variables.

Based on the abovementioned explanations, this study aims to assess the Islamic Banks' credit risk performance for home financing before and during the Covid-19 pandemic. This paper will firstly present an introduction which covers the factual background and the literature review supporting this research. It is then followed by the method used in this study. Afterward, it will provide the results and discussion prior to presenting the conclusion and the recommendations for related stakeholders.

Methods

Data

The study uses panel data analysis that comprises cross-section data of 33 Indonesian provinces which provide Islamic banks financing service for home financing. The data is retrieved from Indonesian Financial Service Authority (FSA) which provides Islamic banks financial performance on monthly basis. The period is started in January 2016 and ended in September 2020. The study-time-period is applied because it is the maximum data that is able to be analyzed. Totally, there are 1881-year-observation periods. Table 1 describes the variable and its explanation.

Table 1. The Variables Definition

Variable(s)	Definition(s)	Source (s)
NPREU	The percentage of Islamic banks' bad loan for real estate, rental business and company service in each province	Financial Service Authority
NPRT	The percentage of Islamic banks' bad loan for personal residential ownership in each province	Financial Service Authority
NPFA	The percentage of Islamic banks' bad loan for personal flat and apartment ownership in each province	Financial Service Authority
NPR	The percentage of Islamic banks' bad loan for personal business shop ownership in each province	Financial Service Authority
INF	The percentage of inflation rate in each province	Statistics Indonesia
FDR	The ratio of total financing to third-party funding of Islamic banks in each province	Financial Service Authority
Ln_FIN	The log of total financing of Islamic banks in each province	Financial Service Authority
Ln_ASSET	The log of total asset of Islamic banks in each province	Financial Service Authority

Empirical Model

The study aims to assess the impact of the Covid-19 pandemic on the performance of Islamic banks' home financing by looking at regional inflation as its determinant. To understand the impact of the Covid-19 pandemic, the study segregates time-frame analysis by separating the analysis to be all observation period bases, before Covid-19 pandemic period basis and during Covid-19 pandemic basis. The general model used in the analysis is as below;

$$CHF = f(INF, FDR, Ln\_FIN, Ln\_ASSET) \quad (1)$$

Moreover, the formula can be explained as,

$$CHF_{it} = \beta_0 + \beta_1 INF_{it} + \beta_2 FDR_{it} + \beta_3 Ln\_FIN_{it} + \beta_4 Ln\_ASSET_{it} + \varepsilon_{it} \quad (2)$$

β_0 expresses the constant in the model while β_1 to β_4 reflect estimated parameters. Moreover, the symbol of *i* and *t* describe the cross-sectional and time-series data respectively then ε_{it} is a symbol for the error term. To specify the analysis, CHF is split into NPREU, NPFA, NPRT, and NPR for the following estimation model.

Estimation Model

To attain the objective, a dynamic panel data analysis is utilized with following Holtz-Eakin, Newey, and Rosen (1988) approach to adopt Panel Vector Autoregression (PVAR) that also allows time-series effect within panel data. In addition, PVAR analysis deal with the endogeneity issue among the variables and unobserved individual heterogeneity in panel data is permissible to exist. Moreover, the use of PVAR also provides the opportunity for the researcher to examine the Variance Decompositions (VDs) and Impulse Response Factors (IFRs) that explain multivariate causalities among the observed variables (Anarfo, Abor, Osei, & Syeke-Dako, 2019; Fakhrunnas, 2020).

Love and Zicchino (2006) stated that the use of PVAR model in economic and finance research can utilize the formula as follows:

$$Y_{it} = \tau_1 Y_{it-1} + f_i + d_t + e_{it} \quad (3)$$

In which Y_{it} describe the observed variable using PVAR approach that is while f_i explains a fixed effect of an unobservable time-invariant effect specific to each province. Furthermore, d_t is a time dummy for each provinces-specific then e_{it} is defined as a random error term iid.

Derived from the formula, this study uses four models which are;

Model 1,

$$NPREU_{it} = \sum_{j=1}^{p} \emptyset_{1j} NPREU_{it-j} + \sum_{j=1}^{p} \emptyset_{2j} INF_{it-j} + \sum_{j=1}^{p} \emptyset_{3j} FDR_{it-j} + \sum_{j=1}^{p} \emptyset_{4j} Ln\_FIN_{it-j} + \sum_{j=1}^{p} \emptyset_{5j} Ln\_ASSET_{it-j} + f_i + d_t + e_{it} \quad (4)$$

Model 2,

$$NPRT_{it} = \sum_{j=1}^{p} \emptyset_{1j} NPRT_{it-j} + \sum_{j=1}^{p} \emptyset_{2j} INF_{it-j} + \sum_{j=1}^{p} \emptyset_{3j} FDR_{it-j} + \sum_{j=1}^{p} \emptyset_{4j} Ln_{FIN\,it-j} + \sum_{j=1}^{p} \emptyset_{5j} Ln_{ASSET\,it-j} + f_i + d_t + e_{it} \quad (5)$$

Model 3,

$$NPFA_{it} = \sum_{j=1}^{p} \emptyset_{1j} NPFA_{it-j} + \sum_{j=1}^{p} \emptyset_{2j} INF_{it-j} + \sum_{j=1}^{p} \emptyset_{3j} FDR_{it-j} + \sum_{j=1}^{p} \emptyset_{4j} Ln\_FIN_{it-j} + \sum_{j=1}^{p} \emptyset_{5j} Ln\_ASSET_{it-j} + f_i + d_t + e_{it} \quad (6)$$

Model 4,

$$NPR_{it} = \sum_{j=1}^{p} \emptyset_{1j} NPR_{it-j} + \sum_{j=1}^{p} \emptyset_{2j} INF_{it-j} + \sum_{j=1}^{p} \emptyset_{3j} FDR_{it-j} + \sum_{j=1}^{p} \emptyset_{4j} Ln_{FIN\,it-j} + \sum_{j=1}^{p} \emptyset_{5j} Ln_{ASSET\,it-j} + f_i + d_t + e_{it} \quad (7)$$

To conduct PVAR analysis, a Panel Unit Roots Test suggested by Pesaran (2012) and Pedroni (2000, 2004) must be firstly exercised then it is followed by PVAR analysis. Qu and Perron (2007) suggest using lag selection criteria to optimize the analysis by generating robust results. Lastly, VDs and IRFs can be conducted to examine the impact of independent variables on dependent variables by capturing the time-variant effect.

Results and Discussion

Table 2. Data Description

Variable	Mean	Median	Maximum	Minimum	Std. Dev.
NPREU	7.9 %	3.6%	198.7%	0%	12.9%
NPRT	3.9%	2.9%	47.6%	0%	03.4%
NPFA	4.8%	1.8%	308.7%	0%	11.2%
NPR	5.1%	3.2%	71.3%	0%	6.8%
INF	0.317%	0.25%	4.2 %	-3.03 %	0.705%
FDR	111.91%	103.36%	256.60%	26.7 %	0.424%
FIN	IDR 8416 bn	IDR 2985 bn	IDR 158743 bn	IDR 93.12 bn	IDR 21938 bn
ASSET	IDR 16292 bn	IDR 3745 bn	IDR 403995 bn	IDR 171.3 bn	IDR 54192 bn

Table 2 highlights the descriptive data from all 33 provinces in Indonesia during observation period which is starting from January 2016 to September 2020. According to the table, the minimum score of NPREU, NPRT, NPFA, and NPR is zero which reflects that in certain provinces and time there was inexistence of bad loan for home financing in several provinces in Indonesia during the observation period. In contrast, Islamic banks once had a maximum bad loan for home financing in NPFA variable which reached 308.7% in a month which was in West Sumatra Province on September 2017. This high percentage reflected that at that moment the number of bad loan is higher than total financing for personal flat and apartment ownership.

For inflation, the average inflation rate during the observation period in all provinces was 1.124% while the highest percentage of inflation rate was 4.2% occurred in Yogyakarta Province in December 2017. Jakarta province had the highest amount of total financing that was IDR 158,743 bn in May 2020 while the lowest number was IDR 2985 bn performed in Jambi Province in February 2019. Lastly, in average the total amount of Islamic banks' assets was IDR 16,292 bn in all provinces over the observation period.

Panel Unit Roots Test Results

To begin the analysis, Panel Unit Roots test is firstly conducted to check the level of stationary. Referring to Table 3, the panel unit roots test is divided by using three categories which are intercept, trend and intercept, and none. This paper adopts the approach Pesaran (2012) and Pedroni (2000, 2004) to use ADF-statistics and PP-statistics to be a benchmark to determine the level of stationary for each variable. The result of the test shows that all variables are stationary in the first level at 1% level of significance. Then, according to the result, Panel Vector Autoregression (PVAR) can be applied.

Panel VAR results

Table 4 shows the result of Panel VAR that consists of four models with the condition of all periods by using all samples, before the Covid-19 pandemic and during the Covid-19 pandemic. In all periods, it can be seen that inflation has significant influence to NPFA that reflects the bad loan for real estate, rental business, and company service. In the lag 2, the inflation has negative impact to NPFA which also means a home financing for business purposes. It also highlights that a decrease in inflation will increase bad loan rate.

Table 3. The Results of Panel Unit Roots Test

Variable	Intercept				Trend and Intercept				None			
	At Level		First Difference		At Level		First Difference		At Level		First Difference	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP	ADF	PP
NPREU	297.9***	435.0***	952.3***	1132.6***	226.3***	358.8***	814.0***	1039.4***	265.7***	413.6***	2036.7***	6277.8***
NPRT	301.7***	522.0***	1130.4***	1206.6***	245.7***	485.6***	986.1***	1071.6***	136.0***	195.2***	2770.1***	7885.8***
NPFA	287.2***	425.0***	1047.6***	1110.2***	269.4***	438.0***	903.7***	1058.9***	248.8***	365.0***	2263.3***	7045.6***
NPR	225.4***	353.7***	967.8***	1170.7***	202.5***	355.0***	825.8***	1072.9***	199.1***	300.1***	1933.9***	5867.8***
INF	781.0***	1350.7***	984.4***	712.4***	674.2***	1102.1***	1205.***	949.5***	712.5***	1087.1***	4567.8***	8170.9***
FDR	154.0***	192.7***	839.7***	1280.1***	129.1***	165.9***	697.2***	1154.5***	51.8841	56.7315	1406.2***	4140.9***
Ln_Fin	92.4***	101.5**	679.2***	1147.6***	67.85***	81.5***	545.7***	1031.8***	15.1099	14.7441	994.3***	2547.8***
Ln_Asset	106.8***	149.4***	780.7***	1220.2***	81.4**	126.2***	644.3***	1093.7***	12.0781	10.7297	1215.4***	3130.2***

Note: The symbol of ***,** and * describe the level significance in 1%, 5% and 10% respectively.

The finding in line with Iriani and Yuliadi (2015) and Lin, Farhani, and Koo (2016) who also conclude that macroeconomic variables including inflation has a significant relationship to the banks' performance. Moreover, a lower rate of inflation reflects less purchasing power for the market and hits the supply side which makes the business activities are disrupted due to less product that can be produced (Mishkin, 1999). In contrast, Islamic banks' home financing for personal home ownership as shown in model 2 to model 4 which are NPRT, NPFA and NPR do not have any significant relationship with inflation rate.

When the period is separated into before the Covid-19 pandemic and during the Covid-19 pandemic, the findings of this study are different. Before the Covid-19 pandemic, inflation has positive and significant influence to NPREU. An increase 1% in the inflation rate will increase

0.006% of monthly non-performing financing in real estate, rental business, and company service. Before Covid-19, in a stable economic condition, an increase in inflation will tend to make the bad loan rate increase. It possibly occurs because inflation will increase the price of the product which will raise the cost of production of business activities. It means that an additional cost for Islamic banks' customers is needed to operate the business activities which possible loss their potential return. This result is supported by Aviliani et al. (2015) lso explains that an increase of inflation which means a reduction for the real profit of the banks tend to encourage the banks to increase their return by offering more profitable contract while they are giving financing to customers. In other words, the price of the property sold by Islamic banks to the customers will be higher.

During the Covid-19 pandemic, which started in Indonesia from March 2020, the impact of inflation to Islamic banks' home financing is different. Inflation does not influence anymore to NPREU which reflects financing activities in business sectors performed by the company. It has a shift of influence that is previously from Islamic banks' home financing for business purposes to home financing for personal ownership. The findings are exhibited by the significant influence of inflation to the bad loans of Islamic banks' home financing in model 2 and 4.

In model 2, inflation significantly impacts positively to NPFA which is the bad loan of home financing for personal flat and apartment ownership in 5% level of significance. A rise in the inflation rate will increase the bad loan rate for personal flat and apartment ownership. It indicates that a high inflation will encourage Islamic banks to have more profit in financing during the Covid-19 pandemic in Indonesia. Mohamad, Hasbulah, and Razali (2015) and Aviliani et al. (2015) state that a high inflation rate will deduct real return for the bank. Then, to respond to this condition, Islamic banks possibly attempt to generate more return in their financing activities which still has a positive growth during the Covid-19 pandemic especially for home financing in personal flat and apartment ownership.

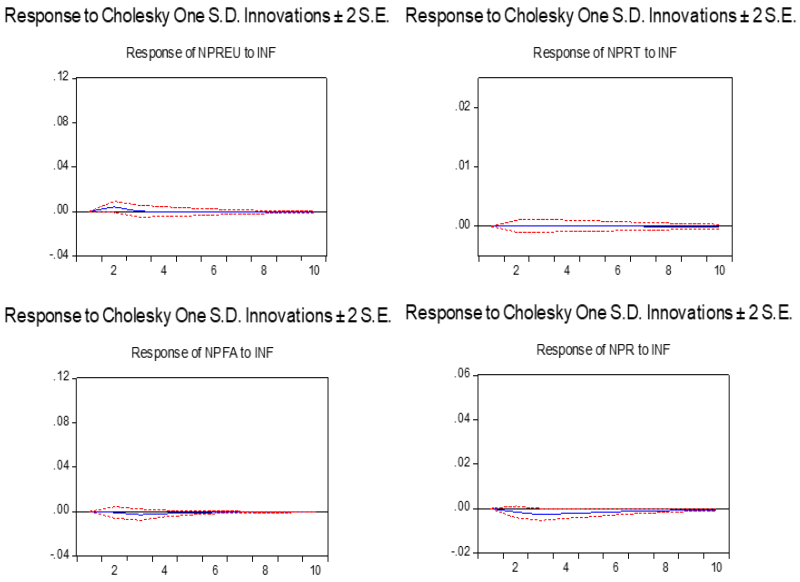
As consequence, an increase in profit demand from Islamic banks' side is equivalent to the rise of price in the home financing from customers' side. Finally, it gives more possibility for customers to fail to return the financing funds from Islamic banks and it also means that the default risk exposure is increasing. The influence of inflation to Islamic banks' performance is also supported by the previous findings performed by Karim et al. (2016), Louhichi and Boujelbene (2016), Trad et al. (2017) and Srairi (2013)

Table 4. The Results of PVAR

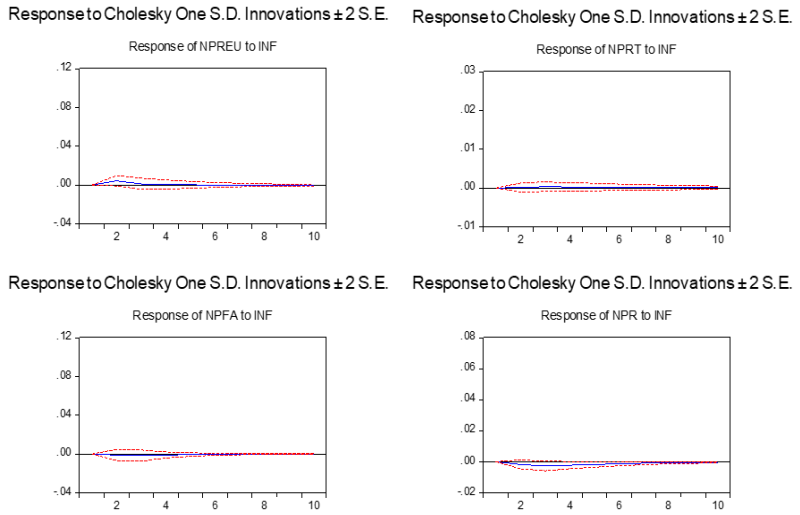
Indicators/Variables	All Periods				Before Covid-19				During Covid-19			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
HF(-1)	0.483***	0.485***	0.208***	0.415***	0.492***	0.47***	0.195***	0.390***	0.341***	0.646***	0.578***	0.964***
	[20.72]	[21.49]	[8.868]	[18.29]	[19.62]	[19.72]	[7.779]	[16.01]	[4.102]	[8.219]	[7.253]	[12.91]
HF(-2)	0.153***	0.285***	0.113***	0.233***	0.123***	0.29***	0.103***	0.213***	0.469***	0.266***	0.258***	-0.022
	[6.578]	[12.69]	[4.813]	[10.24]	[4.841]	[11.99]	[4.099]	[8.734]	[5.617]	[3.429]	[3.064]	[-0.300]
INF(-1)	0.006**	0.001	-0.001	-0.002	0.006**	0.000	-0.001	-0.002	0.008	0.002**	0.007	0.005**
	[1.716]	[0.042]	[-0.310]	[-1.170]	[1.625]	[0.175]	[-0.334]	[-1.165]	[0.478]	[1.59330]	[0.940]	[2.052]
INF(-2)	-0.005*	0.001	-0.003	-0.002	-0.004	0.000	-0.001	-0.002	-0.004	-0.001	-0.006	-0.005***
	[-1.322]	[0.167]	[-0.864]	[-1.168]	[-0.887]	[0.437]	[-0.317]	[-1.016]	[-0.278]	[-0.854]	[-0.858]	[-2.654]
FDR(-1)	-0.0506**	-0.002	0.026	0.003	-0.051**	-0.000	0.029	0.003	0.010	0.0011	0.013	-0.016
	[-1.839]	[-0.360]	[0.992]	[0.234]	[-1.699]	[-0.386]	[0.992]	[0.214]	[0.079]	[0.106]	[0.248]	[-1.013]
FDR(-2)	0.057**	0.003	0.018	0.001	0.061**	0.00	0.017	0.002	-0.026	0.002	-0.010	0.013
	[2.078]	[0.548]	[0.688]	[0.113]	[2.044]	[0.567]	[0.575]	[0.137]	[-0.207]	[0.163]	[-0.201]	[0.8010]
LN_FIN(-1)	-0.015	-0.006	-0.017	-0.001	-0.010	-0.00	-0.018	-0.001	-0.501*	-0.003	-0.079	-0.014
	[-0.391]	[-0.773]	[-0.439]	[-0.015]	[-0.231]	[-0.699]	[-0.436]	[-0.056]	[-1.297]	[-0.095]	[-0.500]	[-0.294]
LN_FIN(-2)	0.0360	0.005	-0.011	0.008	0.027	0.01	-0.010	0.009	0.558	-0.006	0.0810	0.02
	[0.981]	[0.677]	[-0.281]	[0.441]	[0.695]	[0.681]	[-0.254]	[0.427]	[1.453]	[-0.195]	[0.513]	[0.410]
LN_ASSET(-1)	-0.001	0.005	0.017	0.004	-0.007	0.00	0.018	0.005	0.2675	-0.011	0.087	-0.046
	[-0.036]	[0.659]	[0.450]	[0.192]	[-0.172]	[0.609]	[0.435]	[0.221]	[0.576]	[-0.279]	[0.457]	[-0.774]
LN_ASSET(-2)	-0.021	-0.006	0.007	-0.010	-0.012	-0.00	0.007	-0.011	-0.328	0.019	-0.090	0.041
	[-0.573]	[-0.746]	[0.196]	[-0.551]	[-0.314]	[-0.772]	[0.169]	[-0.544]	[-0.707]	[0.496]	[-0.470]	[0.692]
C	0.035**	0.018***	-0.003	0.006	0.032*	0.02***	0.001	0.010	0.090	0.005	0.012	0.004
	[1.652]	[3.983]	[-0.122]	[0.558]	[1.406]	[3.788]	[0.060]	[0.783]	[1.183]	[0.688]	[0.384]	[0.445]
R-squared	0.3636	0.587	0.10205	0.356	0.345	0.57	0.091	0.303	0.516	0.873	0.604	0.962
Adj. R-squared	0.360	0.584	0.09701	0.352	0.3408	0.57	0.085	0.298	0.484	0.864	0.577	0.959
F-statistic	101.8***	253.1***	20.27***	98.66***	82.02***	211***	15.63***	67.68***	15.91***	102.4***	22.71***	376.5***

Note: The symbol of ***,**, and * describe the level significance in 1%, 5%, and 10% respectively.

All Periods



Before Covid-19 Pandemic



During Covid-19 Pandemic

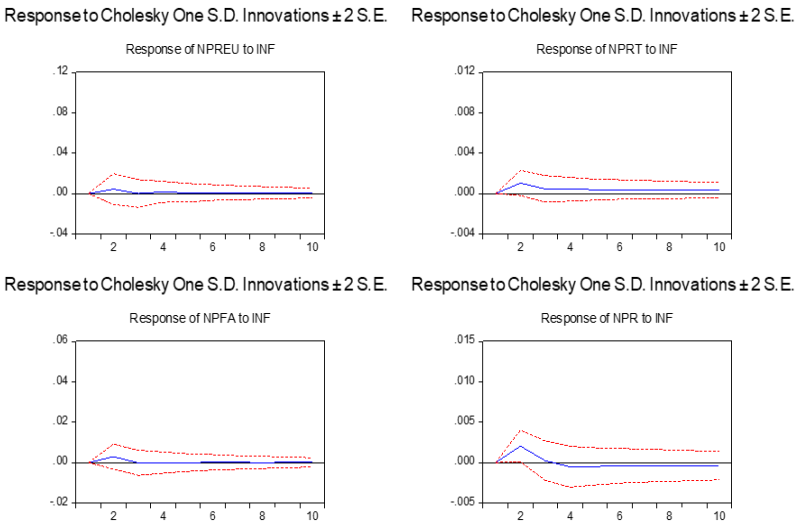


Figure 2. The Results of IRFs

In model 4, inflation has a significant and negative impact to NPR which stands for the percentage of Islamic banks' bad loans for personal business shop ownership in lag two. A decrease in inflation of 1% will increase the percentage of bad loans in personal business shop ownership by 0.005%. As mentioned above, a lower inflation rate possibly reflects a lower purchasing power of the society. Further, this condition may influence the supply side including personal business activities that are not able to sell and to produce the products and services at the maximum level. A lower income from business activities lessens the amount of the profit and the default risk of the customers will increase.

IRFs and VDs results

As adopted by Rosylin and Bahlous (2013) and Love and Zicchino (2006), Impulse Response Factors (IRFs) can be utilized to assess the movement of independent variables to dependent variables. By using IRFs, the movement and direction of independent variables can be examined over the observation periods. According to Figure 2, the movement of inflation through Islamic banks' home financing in all periods and before the Covid-19 period have a similar direction. At first, inflation increases the percentage of bad loans of NPREU in the first-two period and after that, it declines and remains stable to move around zero line after the first-three period. Inflation affects NPRT around the zero line and very less fluctuation occurs during the observation period. It goes the same with the influence of inflation to NPFA. In addition, inflation decreases the percentage of bad loans of NPRT in the first-three period and after that, it has an upward trend and remains stable to move around zero line after the first-five period.

The impact of inflation to Islamic banks' financing during the Covid-19 pandemic is more fluctuating than before the Covid-19 pandemic. It can be seen from the same figure in which NPREU and NPFA have an identical direction which has upward movement in the first-two period then it goes down and tends to move similar roughly near to zero line. For NPRT, a rise of bad loan percentage exists in the first-two period and mostly it is stable to move slightly above zero line. The most dynamic response is NPR that experiences a rise in the one to two early periods and then it decreases significantly until slightly below zero line then it constantly moves in the same direction. The difference of fluctuation as well as the movement of the direction depicts the different reactions before and during the Covid-19 pandemic in terms of the rate of the bad loans in Islamic banks' home financing.

Furthermore, the result for Variance Decompositions (VDs) is highlighted in Table 5. VDs shed light on how the independent variables affect the value of dependent variables along the observation period in the short-run (Mohd. Yusof & Bahlous, 2013). Based on Table 5, it is separate among observation periods which consists of all periods, before the Covid-19 period and during the Covid-19 period. In all periods and before the Covid-19 period, the influence of inflation to home financing value in all models is roughly similar. In model 1, either all periods or before the Covid-19 period, the influence of inflation to NPREU score is less than 0.2%. The influence of inflation to NPRT in the model 2 is almost the same for the two observation periods which are the value near to zero. In model 3, the highest inflation rate influence to NPFA is 0.113% in the period of 10 in all period groups, while in the group of before the Covid-19 period, the highest value is 0.037% and it can be seen in the period of 10. Lastly in model 4, the average influence of inflation to NPR is around 0.5% in all periods and 0.4% before the Covid-19 period.

The influence of inflation during the Covid-19 pandemic is higher than that in the other periods. Generally, in all models, inflation almost has zero influence in the 1st period. In model 1, inflation has the highest effect on period 4 reaching 0.16% of NPREU then it tends to fall for the rest of the period and finally the score of influence becomes 0.145% in the period of 10. NPRT has the highest influence from inflation that is able to deduct the value of NPRT by more than 1% in almost all period of time. The highest value is in the 2nd period that attains 1.3%. Furthermore, in model 3, the influence of inflation to NPFA reaches its peak in the 2nd period which is 0.44% and it ends in the 10th period that is only 0.233%. Finally, for model 4, inflation is able to deduct the NPR value which is almost 1.5% in the 2nd period but the downward trend of the influence appears in the next period.

Table 5. The Results of VDs

All Period												
Period	Model 1			Model 2			Model 3			Model 4		
	S.E	NPREU	INF	S.E	NPRT	INF	S.E	NPFA	INF	S.E	NPR	INF
1	0.104059	100	0	0.0215	100	0	0.1082	100	0	0.054685	100	0
2	0.115901	99.4894	0.1332	0.0239	99.9317	0	0.1106	99.9416	0.005	0.059235	99.9109	0.065
3	0.122652	99.4844	0.1195	0.0264	99.90724	0	0.112	99.7267	0.07	0.063297	99.708	0.241
4	0.125633	99.4859	0.1139	0.0278	99.86989	0	0.1123	99.5309	0.094	0.064979	99.5589	0.346
5	0.127132	99.4412	0.112	0.0287	99.80767	0	0.1124	99.3376	0.104	0.065979	99.432	0.415
6	0.127889	99.3851	0.1116	0.0293	99.73066	0	0.1125	99.1565	0.109	0.066504	99.3239	0.455
7	0.128296	99.3091	0.112	0.0298	99.63414	0	0.1126	98.9873	0.111	0.066805	99.2243	0.479
8	0.12853	99.2237	0.1127	0.0301	99.52306	0	0.1127	98.8304	0.112	0.06698	99.1299	0.493
9	0.128681	99.1317	0.1135	0.0303	99.39825	0	0.1128	98.6851	0.112	0.067088	99.0388	0.501
10	0.128789	99.037	0.1143	0.0305	99.26251	0	0.1129	98.5507	0.113	0.067159	98.9505	0.506

Before Covid-19												
Period	Model 1			Model 2			Model 3			Model 4		
	S.E	NPREU	INF	S.E	NPRT	INF	S.E	NPFA	INF	S.E	NPR	INF
1	0.106296	100	0	0.0227	100	0	0.1146	100	0	0.057816	100	0
2	0.118741	99.4984	0.1374	0.0252	99.92534	0	0.1168	99.9303	0.008	0.062096	99.9004	0.075
3	0.124851	99.4762	0.1339	0.0278	99.8844	0	0.118	99.7543	0.027	0.065656	99.7025	0.245
4	0.127392	99.4678	0.1303	0.0291	99.84051	0	0.1183	99.5688	0.034	0.066993	99.5641	0.341
5	0.128567	99.411	0.1282	0.0301	99.76574	0	0.1184	99.3814	0.036	0.067725	99.451	0.398
6	0.129125	99.3399	0.1271	0.0307	99.67673	0	0.1185	99.203	0.037	0.068078	99.3566	0.427
7	0.129415	99.2493	0.1265	0.0312	99.56541	0	0.1186	99.0364	0.037	0.068268	99.2702	0.443
8	0.129585	99.1503	0.1262	0.0315	99.43829	0	0.1187	98.882	0.037	0.068374	99.1887	0.451
9	0.129701	99.0463	0.1261	0.0317	99.29594	0	0.1188	98.7396	0.037	0.068439	99.1103	0.455
10	0.129792	98.9415	0.126	0.0318	99.14176	0	0.1189	98.6082	0.037	0.068483	99.0349	0.457

During Covid-19												
Period	Model 1			Model 2			Model 3			Model 4		
	S.E	NPREU	INF	S.E	NPRT	INF	S.E	NPFA	INF	S.E	NPR	INF
1	0.094195	100	0	0.0077	100	0	0.0386	100	0	0.01198	100	0
2	0.100064	98.9362	0.203	0.0093	98.39659	1.3	0.0446	99.4121	0.442	0.017021	98.0956	1.463
3	0.114096	98.9579	0.1563	0.0106	98.44215	1.2	0.0499	99.5128	0.353	0.020268	97.912	1.046
4	0.119351	98.8227	0.1655	0.0116	98.3174	1.1	0.0534	99.557	0.309	0.022799	97.6838	0.879
5	0.12502	98.7944	0.1543	0.0125	98.20833	1.1	0.0559	99.5854	0.281	0.024861	97.5432	0.776
6	0.128433	98.7608	0.1536	0.0131	98.02998	1.1	0.0578	99.602	0.263	0.026568	97.434	0.701
7	0.131338	98.7372	0.1498	0.0137	97.83379	1.1	0.0592	99.6111	0.251	0.028003	97.3293	0.65
8	0.133404	98.7164	0.1481	0.0142	97.60529	1	0.0602	99.6149	0.243	0.029226	97.2239	0.615
9	0.135051	98.694	0.1462	0.0146	97.35449	1	0.061	99.6145	0.237	0.030278	97.1166	0.59
10	0.1363	98.6708	0.1448	0.0149	97.07933	1.1	0.0616	99.6109	0.233	0.031191	97.0059	0.571

Conclusion

The Covid-19 pandemic has disrupted the global economy at an unprecedented scale. As the macroeconomic indicators have been hit on account of low business activity, it becomes more challenging for the society to fulfill their basic necessity including the housing needs. As depicted in this study, in general there is a bigger impact of inflation toward bad loans during the Covid-19 pandemic, compared to that in the other periods. Further, it is interesting to note the distinct impact of inflation to the Islamic bank's home financing based on its specific purposes. Prior to this pandemic, inflation has positive and significant influence to non-performing financing in real estate, rental business, and company service (NPREU). However, during the Covid-19 pandemic, inflation no longer has an influence to NPREU and even reflects a shift of influence from business purposes to personal ownership. Inflation is found to have a significant and positive impact toward bad loan of home financing for personal flat and apartment ownership.

Considering the fact that this pandemic has forced millions of people lost their job and hence significantly reduced the income of many households, it would be very hard for them to pay for the home loan. Therefore, this result could trigger the government to provide financial assistance for those people affected by the Covid-19 crisis. In addition to that, Islamic bank is also expected to give financing allowances for them by giving an option of debt restructuration and rescheduling. In addition to that, inflation is also found to have a significant and negative impact to bad loans for personal business shop ownership (NPR). It can be justified with the fact that

during pandemic there is a monthly financial injection given by the government to the personal business categorized as Micro, Small, and Medium Enterprises (MSMEs). It is a good signal for the government that their program is effective enough to cater the bad home financing for personal business, thus the program is recommended to be continued. For future research, this paper recommends to extend the current study by examining other financing sectors affected by the Covid-19 pandemic. Hence, the effect of macroeconomic variables on Islamic bank's financing during the Covid-19 pandemic can be comprehensively informed in order to formulate an effective strategy to tackle the Covid-19 effect on our economy.

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Trade liberalization, financial development, and economic growth: A panel data analysis on Turkey and the Turkic Republics

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Abstract

Purpose — In this study, 5 Turkic Republics (Azerbaijan, Kazakhstan, Kyrgyzstan, Uzbekistan and Turkmenistan) and Turkey are analysed to investigate the impact of trade liberalisation and financial development on economic growth.

Methods — In this study, long-term relationships among trade liberalisation, financial development, and economic growth are analysed by applying unit root, cointegration and causality tests for panel data analysis study for the period 1998 to 2017.

Findings — The findings reveal a strong cointegration relationship between trade liberalization, financial development, and economic growth. It was understood that trade liberalisation positively affected economic growth, and financial development negatively affected economic growth in the long term for the whole panel. However, when the variables are analysed for each country in the panel, it is seen that the sign and severity of the coefficients change. Also, according to panel causality test results, it was understood that there was no causal relationship between variables.

Implication — This paper supports the notion that the direction of the relationship among trade liberalisation, financial development, and economic growth change according to countries in Turkey and the Turkic Republics.

Originality — This paper contributes to the literature by the general view that trade liberalisation and financial development are the driving force of economic growth; these relations may vary according to the country group examined in the studies, the period handled, and the econometric method applied.

Keywords — Trade liberalisation, financial development, Turkic Republics, Turkey, panel data analysis

Introduction

After the dissolution of the USSR in 1991, countries of the Union entered the transition period. Although the Turkic Republics started reforms later than other countries in this process, they are implementing structural reforms to transition to a planned market economy. Turkic Republics and Turkey should develop their financial systems and determine appropriate policies to ensure sustainable economic growth (Djalilov & Piesse, 2011).

International trade and financial markets are the driving forces of the economic growth process. While international trade is an area for the exchange of goods and services, the financial

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markets constitute the demand side of the economy through money. Although the groups that will benefit from economic growth are domestic residents, economic growth is determined by the competitiveness in international markets (Menyah, Nazlioglu, & Wolde-Rufael, 2014). Therefore, the question of how much and how the tradable goods will be subject to international trade becomes essential.

Although the role of financial markets in the economy cannot be ignored, another critical question is whether financial development supports economic growth. Gains from financial development are stable as the level of confidence in financial markets is high, generally due to the robust financial markets of developed countries. On the other hand, despite the increase in financial development in developing countries, it does not have a significant impact on economic growth due to the low level of confidence and the unstable gains from financial markets (Agayev, 2012).

Recent studies reveal that trade liberalisation and financial development may affect economic growth. Especially developing countries liberalise both their trade openness and financial systems to increase economic growth. Countries with strong financial markets can attract foreign direct investments more because they are considered safe environment for investors. The essential functions of the financial system are to produce and distribute information, monitor companies and implement corporate governance, reduce risks, bring savings together, and implement changes that will contribute to the economic growth (Agayev, 2012). Therefore, financial development contributes to countries' economic growth by increasing the performance of foreign direct investments.

The study aims to investigate the effect of trade liberalisation and financial development on economic growth. The study's novelty is that it deals with trade openness, financial development and economic growth in the context of the Turkic Republics. In this context, the effects of trade liberalisation and financial development on economic growth are analysed empirically in the 5 Turkic Republics and Turkey for 1998-to 2017 with annual data.

The effects of trade liberalisation and financial development on economic growth have been debated in the literature for many years. Especially in the last two decades, although there are many studies focusing on transition economies, the Turkic Republics have been ignored due to the lack of information. Although there is a general view that trade liberalization and financial development are the driving force of economic growth, these relations may vary according to the country group examined in the studies, the period handled and the econometric method applied (Gries, Kraft, & Meierrieks, 2009).

The traditional trade theory suggests that international trade stems from external differences among countries. Reallocation of national resources increases productivity and leads to an increase in national income. Trade liberalization both diversifies the increasing consumer goods and lowers the balance price due to the increasing competition (Krugman, 1980). Also, the increase in the size of the market brings along the phenomenon of scale economies.

The theoretical framework of the relationship between trade liberalization and economic growth is based on the Neoclassical growth theory. According to the theory, increasing trade liberalization increases the integration of countries into the world economy. Higher trade liberalization increases competition among countries and therefore the amount of exports and imports. This, in turn, could increase exports and thus economic growth as a result of falling prices of goods by specializing in the production of goods. Gül, Kamacı, and Konya (2013) examined the Turkic Republics and Turkey for the period 1994-2010 in their study and found that foreign trade a positive relationship between long-term economic growth. Silajdzic and Mehic (2018) discussed Transition economies for the period 1995-2013 and examined the relationship between trade liberalization and economic growth by PCSE and LSDVC methods. As a result of the study, they concluded that trade liberalization positively affects the economic growth in countries with high technology production. Erkişi and Ceyhan (2019) analyzed the 13 Transition economy for the period 1995-2016 and stated that trade liberalization positively affected economic growth in both the short and long run.

Financial markets are where borrowers and lenders meet and capital is reallocated. In the literature, there are two different aspects on the relationship between financial development and

economic growth. The first one argues that financial development increases economic growth due to resource allocation. The first view in the literature is that as the level of financial development increases, resource allocation becomes more efficient and this affects economic growth positively. Agayev (2012) examined 20 transition economies for the period 1995-2009 and found that there is a unidirectional causality relationship from financial development to economic growth. Asghar and Hussain (2014) analyzed 15 developing countries for 1978-2012 using the panel cointegration method and concluded that there is a long-term relationship between financial development and economic growth. The second one argues that economic growth will increase the ease of access to financial instruments and external financing. Financial development negatively affects economic growth in low-income countries and transition economies due to insufficient resources. Artan (2007) examined 79 countries for the period 1980-2002 and stated that financial development negatively affected economic growth in low-income countries. Djalilov and Piesse (2011) in his study on the Central Asian countries found that the effects of financial institutions and financial regulations are different, although the direction of these relations changes, but there is a generally negative relationship. Gries et al. (2009) and Menyah et al. (2014) highlighted the complex relationship between financial development and economic growth. Gries et al. (2009) discussed 13 Latin American and Caribbean countries and the period 1960-2004 and stated that while there was a mutual causal relationship between financial development and economic growth, there was no relationship in the long term. Menyah et al. (2014) studied on 13 African countries and found that trade liberalization and financial development had a limited impact on economic growth.

Current studies in the literature have reached the conclusion that both financial development and trade openness increase economic growth. Estrada, Park, and Ramayandi (2010) researched 116 countries and the period 1987-2008 and found that both trade liberalization and financial development positively affected economic growth. Le and Tran-Nam (2018) used the FGLS method in their study of 14 Asia-Pacific countries and concluded that there is a causal relationship from financial development to economic growth, from commercial liberalization to economic growth and from commercial liberalization to financial development. On the other hand, Tufaner (2020) discussed the relationship among trade liberalization, financial development and economic growth in the context of the Fragile Five countries. In this study, which examined the period of 1980-2017, it was found that both financial development and trade liberalization positively affect economic growth. In addition, it was emphasized that policymakers should contribute to the development of the financial system by making financial regulations and that both public and private sectors should make efforts to contribute to financial development. The common point of the current studies is that while the increase in trade openness increases economic growth through specialization in production, financial development increases economic growth through efficiency in resource allocation.

Methods

The motivation for this study is to reveal whether there is a long-term relationship among trade openness, financial development and economic growth, given the limited and contradictory results of previous studies. The inconclusive nature of the studies investigating the relationship between financial development and economic growth motivated to overcome the limitations of previous studies by using both cointegration and causality tests by including all three variables in the model.

The basic model used for empirical analysis is shown in equation (1) below;

$$EcoGro_{it} = \alpha_{it} + \beta_i TradeLib_{it} + \gamma_i FinDev_{it} + \varepsilon_{it} \quad (1)$$

i = 1, 2, ..., N denotes the countries in the panel, and t = 1, 2, ..., T denotes the time. EcoGroit represents economic growth, TraLibit represents trade liberalization and FinDevit represents financial development variable, while ε_{it} it expresses the classical error term. 5 Turkic Republic (Azerbaijan, Kazakhstan, Kyrgyzstan, Uzbekistan, and Turkmenistan) and Turkey are analyzed with annual data for the 1998-2017 period in the study. The countries and the period range in the sample were selected considering the data availability. For economic growth (EcoGro) variable, the

natural logarithm of GDP per capita is used. For the trade liberalization (TraLib) variable, the logarithm of the export and import total in US dollars is used.

There is a discussion in the literature on the variables used for financial development. Although the ratio of M2 money supply to GDP or liquid liabilities to GDP ratio is used to measure the level of financial development, there is no consensus on which indicator is superior. Therefore, for the Financial Development (FinDev) variable, the financial development index, which is accepted as an indicator of financial development, is used in current studies. The financial development index consists of two components: financial institutions and financial markets. Financial institutions and financial markets are divided into three components: depth, accessibility, and efficiency. EcoGro and TraLib variables were obtained from the World Bank (World Development Indicators) dataset and FinDev variable was obtained from the IMF (Macroeconomic & Financial Data) dataset. Table 1 shows the country averages of the variables used in the study.

Table 1. Averages of Variables by Country

Variables (Level)	EcoGro	TraLib	FinDev
Azerbaijan	3671.907	27.5026	0.1413738
Kazakhstan	6534.726	79.146	0.2813643
Kyrgyzstan	756.7178	5.0244	0.1788924
Uzbekistan	1269.663	16.9866	0.2393554
Turkey	8304.855	292.9446	0.4458459
Turkmenistan	3604.242	16.03	0.1237967

In the study, the panel data method is used to investigate the relationships among economic growth, trade liberalization and financial development in 5 Turkic Republics and Turkey. Panel data consists of N units and T number of observations corresponding to each unit. Panel data has many advantages over sectional or time data. Using the panel data method for short time series allows more observation by collecting time-series data among countries and stronger results for the Granger causality test. Also, panel data are subjected to cross-sectional dependence testing, providing more informative data, greater variability, concurrency between variables, higher degree of freedom and more effectiveness (B. Baltagi, 2005).

Panel data models created using panel data are estimated by various methods, depending on the size of the unit and time dimension and whether the model provides some assumptions. If there is a cross-sectional dependence in the error term, first-generation estimators are insufficient because they do not consider this correlation. In the new generation panel data analysis developed in recent years, it is suggested that the cross-sectional dependency may exist among the countries that make up the panel and that the correlation among units is tested first. In case of cross-sectional dependence, new generation panel data analysis methods that consider this should be used.

Breusch and Pagan (1980) LM test can be used to test the cross-sectional dependence in fixed effects model. Null hypothesis is;

H_0: cov (u_{it}, u_{jt}) = p_{ij} = 0 (i≠j for all ts)

The LM test statistic is calculated as in equation (2);

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{ij}^2 \quad (2)$$

Where $\hat{p}_{ij}^2$; i, j is the correlation coefficient between of the residuals.

$$\hat{p}_{ij} = \hat{p}_{ji} = \frac{\sum_{t=1}^{T} e_{it}\, e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{1/2}} \quad (3)$$

e_{it} are residuals estimated from each unit by the appropriate method.

The Pesaran (2004) CD test uses the residues obtained from the estimation of the ADF regression to test the cross-sectional dependence. The correlation of each unit with all units other than itself is calculated. Hypotheses are established as follows;

H_0: $p_{ij} = 0$
H_1: $p_{ij} \neq 0$

P_{ij} refers to the correlation coefficient of residuals. Pesaran test is defined as in equation (4) for balanced panel;

$$CD = \sqrt{\frac{2T}{N\,(N-1)}}\ \sum_{i=1}^{N-1}\ \sum_{j=i+1}^{N}\ \hat{p}_{ij} \tag{4}$$

$$\hat{p}_{ij} = \hat{p}_{ji} = \frac{\sum_{t=1}^{T}\ e_{it}\,e_{jt}}{(\sum_{t=1}^{T}\ e_{it}^2)^{1/2}\,(\sum_{t=1}^{T}\ e_{jt}^2)^{1/2}} \tag{5}$$

In equation (5), e_{it} are residuals estimated from each unit by the appropriate method. T_{ij} correlation coefficient is the calculated number of observations. Under the H_0 hypothesis, which states that there is no correlation between units, this statistic has a normal distribution if T_{ij}> 3 and N is large enough. This test performs better in small samples under non-stationarity, structural breakage and heterogeneity conditions.

Pesaran, Ullah, and Yamagata (2008) developed the NLM test that is valid when N is small and T is large enough. NLM test statistic is calculated as follows in equation (6);

$$NLM = \sqrt{\frac{1}{N\,(N-1)}}\ \sum_{i=1}^{N-1}\ \sum_{j=i+1}^{N}\ (T\,\hat{p}_{ij}^2\ -\ 1) \tag{6}$$

Since the test loses power when N is large and T is small, mean and mean-variance deviation corrected versions of the test were also obtained. NLM test statistics are as follows in equation (7);

$$NLM^{*}\ =\ \sqrt{\frac{1}{N\,(N-1)}}\ \sum_{i=1}^{N-1}\ \sum_{j=i+1}^{N}\ ((T\ -\ K)\,\hat{p}_{ij}^2\ -\ \mu_{T_{ij}} \tag{7}$$

$$\mu_{T_{ij}} = E\left[(T\ -\ k\,)\hat{p}_{ij}^2\right] = \frac{1}{T-K}\ T_r\left(\,M_i M_j\,\right) \tag{8}$$

$$M_i = I_T - H_i\,H_i = X_i\,(X_{i'}X_i)^{-1}\,X_{i'} \tag{9}$$

The mean of the NLM statistics was found to be exactly zero for all T and N's. Although the increase in N decreases the power of the test, the variance of the test statistic has small sample deviation.

In the study, the presence of cross-sectional dependence was tested by Breusch-Pagan (1980) LM test, Pesaran (2004) CD test, and Pesaran, Ullah, and Yamagata (2008) NLM test. Results regarding the cross-sectional dependence tests are shown in Table 2.

Table 2. Cross-Sectional Dependence Tests Results

Test	Statistics
LM	47.69***
LM adj*	13***
LM CD*	0.3806

Note: *** denotes 1% significance level.

It is appropriate to use Breusch-Pagan LM test when T is big and N is small, Pesaran CD test when N is big, and Pesaran, Ullah and Yamagata NLM test when N and T are big. Since T (20)> N (6) in our analysis, it can be stated that Breusch-Pagan LM test will give more reliable results. When we look at the table, it is seen that H_0 hypothesis is rejected and there is a cross-sectional dependence according to both Breusch-Pagan LM test and Pesaran, Ullah and Yamagata NLM test results.

Cointegration tests to be used in the analysis differ depending on whether the constant and slope parameters are homogeneous or heterogeneous according to the units. Therefore, it is important to test the homogeneity before choosing the method to be used. One can look at the difference between the unit-specific OLS estimators that ignore the panel structure of the data and

the weighted average matrices of WE to test RCM. If there is no statistically significant difference between them, the parameters are homogeneous. The null hypothesis is established as follows;

H_0: $\beta_I = \beta$

The statistic of this test, which is a Hausman type test, is defined as follows in equation 10;

$$\hat{S} = \chi^2_{k\,(N-1)} = \sum_{i=1}^{N} (\hat{\beta}_i - \bar{\beta}^*)' \hat{V}_i^{-1} \hat{\beta}_i - \bar{\beta}^*) \quad (10)$$

Here, OLS estimators obtained from regressions concerning $\hat{\beta}_i$ units, $\bar{\beta}^*$ weighted WE estimator and $\hat{V}_i$ represent the difference between the variances of the two estimators. The test statistic has an χ^2 distribution with K (N-1) degrees of freedom. If the test statistic is greater than the critical value, it is concluded that the parameters are homogeneous. The Swamy S test was used to test the homogeneity and when looking at the results in Table 3, it is understood that the parameters are not homogeneous (Swamy, 1970).

Table 3. Homogeneity Test Results

Statistics	Value
Chi-square (15)	546.10***

Note: *** denotes 1% significance level.

Determining the lag length to be used in the analysis is of great importance for the reliability of the tests to be used in the analysis. In Table 4, R^2, Akaike (AIC) and Bayesian (BIC) information criterion results are given. When the results are analyzed, it is seen that R^2 values are very close to each other at all lag levels and the lag length that minimizes both AIC and BIC model selection criteria is 1. Therefore, the appropriate lag length to be used in the study has been determined as 1.

Table 4. Appropriate Lag Length Test

Lag Length	R^2	AIC	BIC
1	0.999913*	-42.00537*	-117.4018*
2	0.9998924	-40.838	-97.38531
3	0.9998349	-31.44961	-69.14782
4	0.9946537	-16.39175	-35.24085

Panel Unit Root Test

In the study, the stationarity of the series is examined first. Since the series includes cross-sectional dependence, second-generation panel unit root tests that take into account the correlation among units should be applied. Second-generation unit root tests are divided into a) panel unit root tests, which corrects first-generation tests to take into account the correlation among units with various transformations, and b) based on apparently unrelated regression system estimates. In this framework, both Breitung (2000), which is based on the difference of horizontal cross-sectional averages, and MADF panel unit root tests, which were successful in cases where horizontal cross-section covariances are different, and recommended by Taylor and Sarno (1998), were applied.

In order to use standard t statistics in the Breitung panel unit root test, the data are transformed before the regression is estimated. Breitung defined Yit as follows in equation 11;

$$Y_{it} = \mu_i + \beta_i t + X_{it} \quad (11)$$

Here it is generated by the X_{it} autoregressive process;

$$X_{it} = \sum_{k=1}^{p+1} \alpha_{ik} X_{i,t-k} + \varepsilon_{it} \quad (12)$$

$X_{is} = 0$ for $s \leq 0$. e_{it} is assumed to be white noise suitable for the process and is assumed to be independent of e_{js} for all t and s. H_0 hypothesis expresses difference stationary;

$H_0: \rho_1 \equiv \sum_{k=1}^{p+1} \alpha_{ik} - 1 = 0$ (for all i)

Under the alternative hypothesis, the Y_{it} (trend) is stationary. The H_0 hypothesis of the Breitung test is established as "there is a unit root", and the alternative hypothesis is "units are stationary".

Taylor and Sarno proposed the Multivariate Augmented Dickey-Fuller (MADF) unit root test similar to the standard single equation ADF test. The model is set up as follows in equation 13;

$$y_{it} = \mu_1 + \sum_{j=1}^{k} p_{ij}\ y_{it-j} + u_{it}\ \text{i} = 1, \dots, \text{N and t } 1, \dots, \text{T} \quad (13)$$

In the model, the error term is assumed to be an independent normal distribution with a non-scalar covariance matrix;

$u_{it} \sim IN\ (0, \Lambda)$

In the standard single equation ADF unit root test, each unit in the panel data is tested, but the power of the test is weak when there is a cross-sectional dependence. In the estimation of the above equation as a system, the correlation between residues is also taken into account and a test process that covers the whole system is applied. Therefore, the H_0 hypothesis of the MADF panel unit root test is tested as follows;

$$H_0: \sum_{j=1}^{k} p_{ij} - 1 = 0\ \forall \text{I} = 1, \dots, \text{N}$$

$$MADF = \frac{\left(t-\Psi\beta\right)' \widehat{\Psi[Z'(\widehat{\Lambda}^{-1} \otimes I_T)\, Z]^{-1} \Psi'} (t-\Psi\widehat{\beta})\ N\ (T-k-1)}{(Y-Z\widehat{\beta})^{-1} \left(\widehat{\Lambda}^{-1} \otimes I_T\right) (Y-Z\widehat{\beta})} \quad (14)$$

In equation (14) $\widehat{\beta}$ and $\widehat{\Lambda}$ are consistent estimators of β and Λ, respectively. The MADF test statistic has an χ^2 distribution with N degrees of freedom.

Panel Cointegration Test

In the second stage of the analysis, the cointegration relationships among economic growth, trade liberalization, and financial development are investigated. Since there is a cross-sectional dependence in the series, second-generation panel cointegration tests should be applied. For this purpose, the second generation panel cointegration test developed by Gengenbach, Urbain, and Westerlund (2016) was used. Gengenbach, Urbain, and Westerlund panel cointegration test is based on the error correction model using a common factor structure, as seen in equation (15) below.

$$\Delta_{yi} = d\ \delta_{y,x_i} + \alpha_{y_i} y_{i,-1} + \omega_{i,-1} y_i + \upsilon_I \pi_i + \varepsilon_{y,x_i} = \alpha_{y_i} y_{i,-1} + g_i^d \lambda_i + \varepsilon_{y,x_i} \quad (15)$$

In the first phase of the test, OLS estimation of the model is made for the units and the hypothesis H_0: $\alpha_{yi} = 0$ is tested with the t test. (T-1-p) x (T-1-p) dimensional matrix; When $M_A = I_{T-1-p} - A(A'A)A'$, OLS estimator of α_{yi} is;

$\widehat{\alpha}_{yi} = \frac{y'_{i,-1} M_{g_i^d} \Delta y_i}{y'_{i,-1} M g_i^d y_{i,-1}}$, and the variance establishes as;

$\sigma^2_{\widehat{\alpha}_{yi}} = \frac{\sigma^2_{\widehat{\alpha}_{y.xi}}}{y'_{i,-1} M g_i^d y_{i,-1}}$, and the t statistic is defined as follows;

$t_{c_i} = t_{\alpha_{yi}} = \frac{\widehat{\alpha}_{yi}}{\widehat{\sigma}_{\widehat{\alpha}_{yi}}}$. Panel test statistics are the average of unit test statistics;

$\bar{t}_c = \frac{1}{N} \sum_{i=1}^{N} t_{c_i}$

The basic hypothesis of the test is H_0: $\alpha_{yi} = \dots = \dots = \alpha_{yN} = 0$, while the alternative hypothesis is set as H_1: $\alpha_{yi} < 0$.

Long Term Panel Cointegration Test

If there is a cross-sectional dependence in the residuals of the cointegration model, it is appropriate to use second-generation estimators, since the first generation estimators will be deviated. In the study, the Dynamic Ordinary Least Squares Mean Group (DOLSMG) estimator, which is among the second-generation long term panel cointegration tests, was used. In this method, variables are converted by taking the difference from horizontal cross-section averages and estimated by DOLS for units and Pedroni's (2001) DOLSMG for panel.

$$Y_{it} = \mu_i + \beta_I X_{it} + u_{it} \; \mathrm{i} = 1, \ldots, \mathrm{N} \; \mathrm{t} = 1, \ldots, \mathrm{T} \tag{16}$$

By adding the preliminary values and delays of the Xs to the DOLSMG estimator in the above model, the feedback effects and internality problems are eliminated. In the first stage, the model is estimated by dynamic ordinary least squares (DOLS), then the results are combined for the entire panel with the mean group (MG) approach as seen in equation (17).

$$\widehat{\beta}_{DOLSMG} = N^{-1} \left[\sum_{i=1}^{N} \left(\sum_{t=1}^{T} \left(Z_{it} \, Z'_{it}\right)^{-1}\right] \sum_{t=1}^{T} \left(Z_{it} \; \bar{Y}_{it}\right) \right. \tag{17}$$

Z_{it} expresses the vector of explanatory variables in the equation and $\bar{Y}_{it} = Y_{it} - \bar{Y}_i$.

Therefore, the DOLSMG estimator is obtained by taking the mean of the DOLS estimators obtained for each i unit.

$$\widehat{\beta}_{DOLSMG} = N^{-1} \sum_{i=1}^{N} \widehat{\beta}_{DOLS,i} \tag{18}$$

Panel Causality Test

Dumitrescu and Hurlin (2012) stated that an economic event valid for one country will also apply to other countries. Therefore, causality relationships can be tested more effectively in observations in panel data. Dumitrescu-Hurlin panel refers to two stationary processes observed during the X and Y, N units and T time in Granger causality test. And at time t, the following linear model is established for each unit (i);

$$Y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} \; Y_{it-k} + \sum_{k=1}^{K} \beta_i^{(k)} + \varepsilon_{it} \tag{19}$$

In equation (19), the lag length (k) is the same for each unit of the panel and while the panel is balanced, the autoregressive parameter $\gamma_i^{(k)}$ and the slopes $\beta_i^{(k)}$ vary according to units.

The null hypothesis is that "all β_i's are equal to zero" and implies that there is no causality from X to Y for the entire panel, ie no homogeneous panel causality.

$$H_0: \beta_i = 0 \; i = 1, \ldots, N$$

Under the alternative hypothesis, the model is heterogeneous. β_i is valued according to units. The alternative hypothesis is established as "some of the β_i's are different from zero".

$$H_1: \beta_i = 0 \; i = 1, \ldots, N_1$$
$$\beta_i \neq 0 \; i = N_1 + 1, N_2 + 2, \ldots, N$$

The H_0 hypothesis expresses that there is no Granger causality relationship among all examined variables, while the alternative hypothesis expresses that there is a relationship between the variables in one of the units. Although the established model is heterogeneous, the basic hypothesis is homogeneous, while the alternative hypothesis is heterogeneous.

Results and Discussion

In panel data analysis, firstly, panel unit root tests were applied to analyze the stationarity of the series.

Table 5. Panel Unit Root Test Results

Variables	Breitung		MADF			
	Level	First Difference	Level		First Difference	
	Statistics	Critical Value	Statistics	Critical Value	Statistics	Critical Value
EcoGro	1.1937	-1.6386**	26.654	41.700	107.316**	45.195
TraLib	0.9771	-2.1212**	35.475	41.700	90.703**	45.195
FinDev	-0.6075	-5.1930***	25.517	41.700	210.511**	45.195

Note: ** and *** denotes 5% and 1% significance levels, respectively.

Table 5 shows the results of both panel unit root tests. The lag length for the MADF test was chosen as 1. In the Breitung test, a robust estimate was made. For the Breitung panel unit root test, H_0 hypothesis was established as: "units contain unit root" and the alternative hypothesis: "units are stationary". The H_0 hypothesis of the MADF test is established as "the panel's 19 time series are all I (1)". H_0 hypotheses cannot be rejected for both tests at the level of the series. It is understood that all three variables are not stationary for both tests and become stationary when their first order differences are taken.

Spurious regression problem may arise when econometric modeling is performed with panel data that are not stationary at level. The regression established may lead to biased values and misleading R2 values. In this case, it is possible to have a long-term relationship between variables, and the existence of the relationship can be tested using panel co-integration tests.

Table 6. Panel Cointegration Test Results

Coefficient	T-bar	Prob.
-0.894	-3.085	<=0.1

Table 6 shows the results of the Gengenbach, Urbain, and Westerlund panel cointegration test. Lag length was chosen heterogeneously and varies according to units. The test results show that there is insufficient evidence to accept the H_0 hypothesis. Therefore, it is concluded that there is a cointegration relationship among economic growth, trade liberalization, and financial development. The cointegration test results are consistent with the studies of Asghar and Hussain (2014), Erkişi and Ceyhan (2019), and Tufaner (2020).

If non-stationary variables at level are cointegrated in the long run, it is not appropriate to take the differences of these variables. Because taking difference eliminates the common trend that allows variables to move together. Therefore, if a cointegration relationship is found between variables as a result of the cointegration tests, it is necessary to estimate the long term cointegration relationship.

Table 7. Panel Cointegration Test Results

Countries	TraLib (Coefficient)	t-stat	FinDev (Coefficient)	t-stat
Azerbaijan	0.9169**	3.188	-2.171	-0.7264
Kazakhstan	0.261	1.294	2.727**	5.255
Kyrgyzstan	-1.184**	-2.181	2.012**	5.163
Uzbekistan	0.4123	0.9815	1.596	0.774
Turkey	0.4233**	7.758	-5.195**	-14.93
Turkmenistan	0.3487**	11.53	-5.527**	-14.09
PANEL	0.1967**	9.216	-1.093**	-7.578

Note: ** denotes 5% significance level. The lag length is determined as 1. The table value of t is 1.96 for $\alpha = 0.05$.

Table 7 shows the long-term panel cointegration test results based on the DOLSMG estimator. H_0 hypothesis is rejected if the calculated t value is greater than the t table value as an

absolute value; otherwise, it cannot be rejected. The rejection of the H_0 hypothesis indicates that the statistics are significant. The coefficients in the test results show that between trade liberalization and economic growth there is a positive relationship in Azerbaijan, Turkey, and Turkmenistan, there is a negative relationship in Kyrgyzstan, and there is not any significant relationship in Kazakhstan and Uzbekistan. When looking at the relationship between financial development and economic growth it is understood that there is a positive relationship in Kazakhstan and Kyrgyzstan, there is a negative relationship in Turkey and Turkmenistan, and there is not a significant relationship in Azerbaijan and Uzbekistan. For the whole panel, it can be stated that trade liberalization affects economic growth positively as in the study of Erkişi and Ceyhan (2019) and financial development negatively affects economic growth as in the study of Asghar and Hussain (2014). Because trade liberalization increases the efficient distribution of world resources, and weak financial institutions cause the misallocation of resources that support economic growth.

Unidirectional or mutual causality relationship can be seen from one variable to another between economic variables. The existence and direction of causality can be tested with the help of causality tests.

Table 8. Panel Causality Test Results

Null Hypothesis (H_0)	**W-Bar**	**Z-Bar**	**p-value**
TraLib does not Granger cause EcoGro	1.8913	1.5438	0.346
EcoGro does not Granger cause TraLib	0.7570	-0.4209	0.633
FinDev does not Granger cause EcoGro	1.0822	0.1423	0.254
EcoGro does not Granger cause FinDev	1.4189	0.7256	0.196
FinDev does not Granger cause TraLib	0.7064	-0.5086	0.351
TraLib does not Granger cause FinDev	9.0594	4.3815	0.426

Note: The lag length was selected according to the Akaike information criterion.

Table 8 shows the Dumitrescu-Hurlin panel Granger causality test results. Lag length is determined as 4 in the last model according to Akaike (AIC) information criterion and 1 in other models. According to the test results, the H_0 hypotheses could not be rejected. Therefore, there is no causality between trade liberalisation and economic growth, financial development and economic growth, and trade liberalisation and financial development.

When the causality test results are examined, it is understood that, contrary to other studies, all three variables are not Granger causes of each other. Similar to the study of Menyah et al. (2014), it was observed that different findings of studies on trade liberalisation, financial development and economic growth causality in the analysed countries resulted from different country samples. In this context, political instability can delay financial product, and it can lead to a negligible impact on the economic effect on economic growth Gries et al. (2009). Also, according to Çevik, Atukeren, and Korkmaz (2019), the global financial crisis might also have affected the Granger causal relationships between the variables.

Conclusion

After the dissolution of the Soviet Union in 1991, the countries of the Union started the transition period. The Turkic Republics have implemented structural reforms in this process to transition to a planned market economy. Turkey has put into practice structural reforms after experiencing the 2000 and 2001 crises. In this context, it is essential to identify the appropriate trade and financial policies to be implemented to perform sustainable economic growth for the Turkic Republics and Turkey.

This study investigates the impact of trade liberalisation and financial development on economic growth in the 5 Turkic Republics and Turkey. Trade liberalisation and economic growth data were obtained from the World Bank (World Development Indicators) dataset. In contrast, the financial development index was obtained from the International Monetary Fund (Macroeconomic and Financial) dataset. To determine the tests used in the study, cross-sectional dependence and homogeneity tests were conducted. It was understood that there were correlations and

heterogeneity among the units in the series. In the first stage of the analysis, Breitung and MADF panel unit root tests were performed to test the stationary of the series. Then, Gengenbach, Urbain, and Westerlund and DOLSMG panel cointegration tests were used to determine short and long term relationships. Next, the Dumitrescu-Hurlin panel causality test was applied to determine the causality relationship between the variables.

Unit root tests show that the series used in the study were not stationary at the level and became stationary when their first order differences were taken. Empirical findings reveal a strong cointegration relationship between trade liberalisation, financial development, and economic growth. It was understood that trade liberalisation positively affected economic growth, and financial development negatively affected economic growth in the long term for the whole panel. When countries analyse the long-term coefficients, it is observed that there is a positive relationship between trade liberalisation and economic development in Azerbaijan, Turkey, and Turkmenistan, and there is a negative relationship in Kyrgyzstan. At the same time, there is no significant relationship between Kazakhstan and Uzbekistan. It is understood that there is a positive relationship between Kazakhstan and Kyrgyzstan between financial development and economic growth. There is a negative relationship between Turkey and Turkmenistan, and there is no significant relationship between them Azerbaijan and Uzbekistan. Also, according to panel causality test results, it was understood that there was no causal relationship between variables.

For trade liberalisation to positively affect economic growth, it is suggested that Kyrgyzstan reduce the foreign dependency on intermediate material, raw material, and energy imports and reach a level that can compete abroad. However, it is seen that financing the current account deficit with speculative capital inflows led to an economic contraction in Turkey and Turkmenistan. Turkey and Turkmenistan need to increase confidence in their financial markets by increasing financial transparency and accountability. In this context, it is recommended that develop the financial system and improve its functioning in Turkey and Turkmenistan to maintain the desired level of economic growth.

This study has some limitations. The study results cannot be generalised, because different countries have different economic features. The model was specified to test the links among only three variables. So, introducing more variables may provide different results.

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Rage against the machine: A money-burning field experiment

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Abstract

Purpose — This study investigates antisocial behaviour where participants made payoff destruction decisions ("money burning") that are conditional on the co-participant being a human or a computer.

Methods — This study uses the joy-of-destruction minigame experiment with Indonesian citizens living in Australia as the participants. Regression methods are used to observe whether discrimination occurs and to identify factors associated with antisocial behaviour.

Findings — This study finds money burning against the computer to be more prevalent than against humans. There was very limited support that such behaviour was correlated with demographic characteristics or subjective norms, suggesting that the presence of a computer co-participant drives the result.

Implications — The results have a methodological implication for experimental economics where experimenters should anticipate that computer players may have an unforeseen impact on human behaviour. Policy-wise, the study shows a relatively cohesive community which may be driven by the multicultural policy of Australia.

Originality — This is the first antisocial behaviour economics experiment that includes a computer as a potential co-participant.

Keywords — Antisocial behaviour; Other-regarding preferences; Lab-in-the-field experiment; Human-computer interaction.

Introduction

Computers have been included in behavioural economics experiments since the '60s where it was initially used to study interdependence strategies (Messick, 1967). Subsequently, hundreds of studies on computer players have been documented and published. Generally, the inclusion of computer participants in economic experiments was aimed at strengthening the internal validity and can be classified into the following categories (March, 2021): (1) to reduce noise (e.g., by simplifying the strategic environment), (2) to induce types (e.g., by having computers to play games with specific strategies), (3) to remove strategic uncertainties (e.g., the computer is playing equilibrium strategy), (4) to exclude social preferences (e.g., reciprocity should be absent when human plays against computers), and (5) to study human-computer interaction (e.g., how human behaviour changes in the presence of a computer player). These objectives generally conform with most economic theories that assume self-interest.

Despite the wide use of computers in economic experiments, the literature on how computer players may affect *antisocial* behaviour is still very limited, if not non-existent. Out of the five categories above, the inclusion of computer players to exclude social preferences is the most relevant in this study. This is because, by design, a computer receives no utility and is not reciprocal.

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For example, theories on social preferences suggest that a person's utility is affected by their own payoff and the relative payoff share (Bolton & Ockenfels, 2000). This theory was developed following findings from laboratory experiments where *people's* behaviour was sometimes attributed to equity, reciprocity, and competitive motives. We may argue that a person's standing relative to other people is important as jealousy and sympathy are real and may affect the person's behaviour, but what arguments are there that justify that such behaviour will also present when the relative position is against a computer? More importantly, if one's utility u_i is directly influenced by other's utility u_j such that $u_i = x_i - u_j$ (Sadrieh & Schröder, 2016), where x_i is *i*'s payoff and $i \neq j$, it makes no sense to assume that player *j* (the computer) is receiving some kind of utility. Another other-regarding theory focuses on the role of belief, where a person's behaviour is influenced by their belief on the other players intentions (Rabin, 1993). If the computer is programmed to behave randomly, and there is no asymmetric information in the experiment (meaning that human participants know this), then there is no "intention" that any human can observe.

There are no empirical studies in the antisocial behaviour literature on human-computer interaction. However, there are similar studies that may help us in predicting behaviour. First, participants tend to send less money in the trust game—a prosocial behaviour experiment—when paired with computer players (Engelmann et al., 2019). Meanwhile, participants behave more selfishly when they have the opportunity to hide their intentions, as shown in a bargaining experiment (Embrey et al., 2015). Interestingly, in a public-goods game experiment, participants playing against computers behave similarly as those facing human participants (Burton-Chellew et al., 2016). Together, results from these studies suggest that playing against the computer is expected to make people behave more selfishly and that the results can be used to predict behaviour against human participants.

Antisocial behaviour can be categorised as a type of social preference where one's utility is not only negatively affected by other's utility or payoff, but when doing so also does not bring pecuniary benefit to the perpetrator. For example, in the joy-of-destruction (JoD) game, participants have the opportunity to destroy the payoff of other participants without receiving monetary benefit for doing so (Abbink & Herrmann, 2011; Abbink & Sadrieh, 2009). Along with the money-burning (MB) game, the JoD game is one of the most popular games within the payoff-destruction games family. Here we include a game as a payoff-destruction game if it is strategic, allows for antisocial strategy (i.e., the strategy does not bring material benefit to the player), and is not a punishment-type game (such as a public-goods game with punishment). Up to the writing of this article, 36 out of 46 payoff-destruction experiments were using either MB or JoD games. The two games are identical except that the MB game was designed to capture inequity aversion (e.g., by creating unequal initial endowments among the participants), while the JoD game was created to measure pure spite. A range of factors has been found to be associated with antisocial behaviour. For example, the fear of being harmed made 34 per cent of participants in the first-strike game to choose antisocial behaviour (Abbink & de Haan, 2014). Meanwhile, a prosocial act was found to be effective in reducing antisocial behaviour (Diamond & Blackwell, 2017). A combination of anger and exposure to violence is also associated with antisocial behaviour (Zeitzoff, 2014).

In this study, we present our findings on how the inclusion of a computer player changes human behaviour in a lab-in-the-field antisocial experimental game. It is important to state from the beginning that this was not the primary objective of the experiment. Instead, a computer was added to the experimental design following other considerations regarding the implementation of another experiment. To understand this, we need to take a step back and discuss the broader context of the experiment.

The experiment was designed as a pre-test for another experiment conducted in post-conflict Aceh in Indonesia. The Aceh insurgency lasted from 1976 to 2005 where certain ethnic groups, particularly Javanese, were persecuted by the rebels (Schulze, 2004). The region was in relative peace following the peace treaty, but it was unknown whether grievances among different ethnic groups are still lingered. Specifically, it was designed to elicit in-group/out-group biases in a one-shot JoD game with a strategy method, where participants made simultaneous decisions against different types of co-participants identified by their chosen honorific titles (that correspond

to their ethnicity and gender). One of the results from our main study in Aceh is that gender mediates the effect of conflict experience on antisocial behaviour (Chuah et al., 2019). The fieldwork for the study presented in this paper was conducted before the Aceh study, with Indonesian migrants in Melbourne, Australia as the sample. Unlike in Aceh, we expect the population to have a very low conflict experience.

A computerised co-participant was added to the experiment as a means to reduce upset. It was expected that participants would be upset from losing money if they knew that another person was responsible for this event. However, note that participants in the Aceh study were not students, and many experienced the actual conflict. This was considered to have the potential for igniting new conflict if participants knew that another person, possibly coming from a different ethnic group, was behind the antisocial decision. Therefore, in the Melbourne study, a computer was included as a potential co-participant that made random antisocial behaviour decisions. So, in practice, a (human) participant will be randomly matched against either another human co-participant or a computer. However, a computer co-participant was removed from the Aceh study following some of the results from the experiment in Melbourne.

The objective of this study is to observe antisocial behaviour in a conflict-free environment where participants may encounter a computerised co-participant that makes random decisions. Specifically, we want to investigate whether participants discriminate against different types of co-participants and identify factors that might be associated with such decisions. Because of the absence of systematic horizontal conflict among the Indonesian migrant in Melbourne, we hypothesise an indifferent antisocial behaviour by ethnicity or gender (or both). Following findings from other experimental games that use a computer to exclude social preferences, we expect human participants should not do such behaviour when facing a computer player.

Methods

The experiment in this study was conducted using a strategy method (Selten, 1967), which requires participants to reveal all of their strategies given a set of possible choices. Brandts and Charness (2011) noted that experiments with either a strategy method and a direct elicitation approach should not provide different results and empirical irregularities are not systematic (see e.g., Brandts & Charness, 2011; Fischbacher et al., 2012).

Experimental Design

The antisocial behaviour experiment is based on the JoD minigame (Abbink & Herrmann, 2011). Participants could pay to destroy a portion of their co-participant's money in a 1:10 ratio (i.e., paying AUD 1 to destroy AUD 10). We find in the pilot sessions that, relative to lower or higher ratios, antisocial decisions happened quite often but were not so prevalent when this ratio was implemented. The average exchange rate in 2017 (the year this experiment was conducted) was IDR 10,267/AUD.

The strategy method was used by asking participants (of any ethnicity, not limited to Javanese or Acehnese) to make decisions against four types of co-participants (partners), identified by their preferred honorific titles: *Bang* (Acehnese male), *Kak* (Acehnese female), *Mas* (Javanese male), and *Mbak* (Javanese female). We expect such honorifics to be accurate in identifying the participants' gender and ethnicity, especially if one of the ethnic groups is dominant in the sample. It is possible that the titles do not match the actual (preferred) ethnicity and gender, which will be discussed later in the results and discussion section.

The use of honorific titles is necessary for gauging possible group bias while at the same time reducing ethnic salience. Past studies show that the failure to do so would create a demand effect and bias the result (Chuah et al., 2013; Fershtman & Gneezy, 2001). Thus, participants were asked if they were willing to pay to destroy some parts of their partner's money if that person preferred to be called *Bang/Kak/Mas/Mbak*.

The inclusion of a computerised partner aimed to create uncertainty about whether the participant faces humans or computers. Adding the computer as one of the co-participants should

not affect behaviour as it was programmed to make random decisions. Note that the computer partner was not used in the Aceh experiment as we could not find an indication of participants feeling distressed, and they were generally happy to be engaged in such a game.

Lastly, the experiment was designed to observe antisocial behaviour at the lower bound by: (1) only allowing for one decision from one of the participants to be implemented; this was by tossing a coin in one of the locations, (ii) limiting the amount of co-participant's money that could be reduced (40 per cent), and (iii) anonymous decisions. Randomly limiting money-burning was also implemented in Zizzo (2003) and is also expected to remove money-burning decisions that are motivated by their fear of receiving money burning from another participant.

Implementation

There were three phases during each of the sessions.

Phase 1. Participants were asked to choose a seat where the seats were arranged in such a way that it ensured privacy. They were directed to read and sign the consent form and then may start filling in the demographic questionnaire. One of the questions asked about their honorific titles, and once all participants had finished writing the answers to the questionnaire, the experimenter started reading the instruction sheet.

Phase 2. Each participant received AUD 25 and was then asked if they were willing to pay AUD 1 to destroy their partner's money. The decisions needed to be made against human and computer partners. The participants were asked to answer some comprehension questions prior to making the real decisions. Only one randomly chosen decision (using coin toss) from each pair of participants was implemented.

Phase 3. The participants were asked to answer questions on conflict experience, belief (of having their money destroyed), social value orientation (SVO) and personal attitudes. There was a separate payment of AUD 15 for answering the questions. They were then directed to another room for payment and were allowed to leave the session. The applicable decision given the co-participant's actual title was used to determine earnings.

This study was used as a trial for a similar experiment in Aceh, where it was suggested that there would be a potential for tensions to reoccur between the Acehnese and Javanese. Hence, two teams of research assistants (RAs) were assigned to two locations (as far as 37 km), and sessions were held simultaneously. In each location, one RA communicated with the other RA in the other location to (randomly) match the participants while one of the RAs read the instructions.

Posters were publicly advertised around the Indonesian community and also distributed using social media. We did not limit the time for the experiment, although the posters stipulate that each session is expected to last for a couple of hours. Similar to the Aceh experiment, participants must be at least 25 years old. The experiments were conducted in either a community hall (located in the suburbs with prominent Indonesian communities) or a university lecture room.

Graduate students from Indonesia volunteered as RAs. Four pilot sessions were conducted in September 2017. All materials were written in formal Indonesian language and were identical. Lastly, we use pen and paper to run the sessions.

Subject Pool

Based on the Australian Census in 2016, approximately 29 per cent of Indonesian-born residents of Australia were full-time students. This was probably due to the quality of higher education and the two countries' closeness. We could not find evidence of systematic conflicts or social tensions among the Indonesian communities living in Australia, particularly Melbourne.

Around 45 per cent of Indonesian migrants in the larger Melbourne region aged between 30 and 49 years. They are also well educated, with more than half holding higher education degrees. The ethnic composition of the migrants is not known, although Javanese is expected to remain the dominant ethnic group. We also do not expect a significant number of Acehnese in the sample as the ethnic group is just under two per cent of all Indonesians.

Post-experimental Questionnaire

We used several questionnaires to gain some information that might be correlated with money burning behaviour. The main survey was a self-report war victimisation questionnaire, modified from the original questionnaire used in the context of the Tajik Civil War (Cassar et al., 2013), adjusting for some properties that are unique to Aceh. This questionnaire is only required for participants who lived in Aceh during the last five years before the end of the conflict (2000-2005).

The belief question asked if the participants thought their partners would choose the money reduction option. This is an important indicator of antisocial behaviour, as shown in past studies (Abbink & Herrmann, 2011; Prediger et al., 2014). The SVO questionnaire is a series of unincentivized allocation tasks where participants can be categorised as either prosocial, competitive, individualistic or other/unknown (Van Lange, 2000).

This study also utilised questionnaires that measure personal attitudes. The Mach-IV test measures Machiavellianism (Christie et al., 1970). The Buss-Perry Aggression Questionnaire is a well-known survey on self-reported aggression, which consists of four sub-traits (physical aggression, verbal aggression, hostility and anger) (Buss & Perry, 1992). The questionnaire on religiosity consists of a few questions on ritual, consequential, experiential and ideological dimensions (Rohrbaugh & Jessor, 1975). Finally, a set of 12-item questions were used to measure respondents' beliefs about fundamental aspects of their religion (Altemeyer & Hunsberger, 2004).

Results and Discussion

The experimental sessions were held in October 2017, and the complete information of 127 respondents were obtained. Table 1 shows the descriptive statistics where, among other things, ethnic Javanese was the dominant ethnic group.

Table 1. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Burn any types of co-participant money	127	0.26	0.44	0	1
Burn at least one human co-participant's money	127	0.16	0.37	0	1
Burn at least computer co-participant's money	127	0.20	0.40	0	1
Burn only human co-participant's money	127	0.06	0.24	0	1
Burn only computer co-participant's money	127	0.09	0.29	0	1
Count any burning decision	127	0.54	1.10	0	5
Count any burning decision (except computer)	127	0.35	0.88	0	4
Negative belief	127	0.20	0.40	0	1
Female	127	0.46	0.50	0	1
Age	127	31.75	5.91	25	50
Javanese	127	0.50	0.50	0	1
Muslim	127	0.77	0.42	0	1
Married	127	0.63	0.48	0	1
Income > AUD 2,000/month	125	0.53	0.50	0	1

Patterns of Antisocial Behaviour

The results indicated that 26 per cent of the participants chose to destroy their partners' money (Table 1). Moreover, the driver of such behaviour was the money burning decisions against computer co-participant, where 20 per cent of the participants at least chose this option. See Figure 1 for a visual depiction of money burning behaviour.

Using the Mann-Whitney tests we could not find different money burning behaviour by ethnicity or gender (Table 2). As we have very few observations with specific ethnicity-gender combinations (e.g., whether Javanese females are more likely to reduce the money of non-Javanese males), we simplify the categorisation in the following analyses. For example, "female partner" identified decisions against co-participants who preferred female honorifics, the same goes for "Javanese partner". A test of proportions (by gender) provides a p-value of 0.1071, suggesting the slight proneness of male participants to destroy money relative to female participants, but this is

only when we used observations that exclude decisions against computer co-participant. However, using the index of similarity (Sent & van Staveren, 2018), we also find high values (more than 0.9), suggesting that the money burning distributions by gender are overlap.

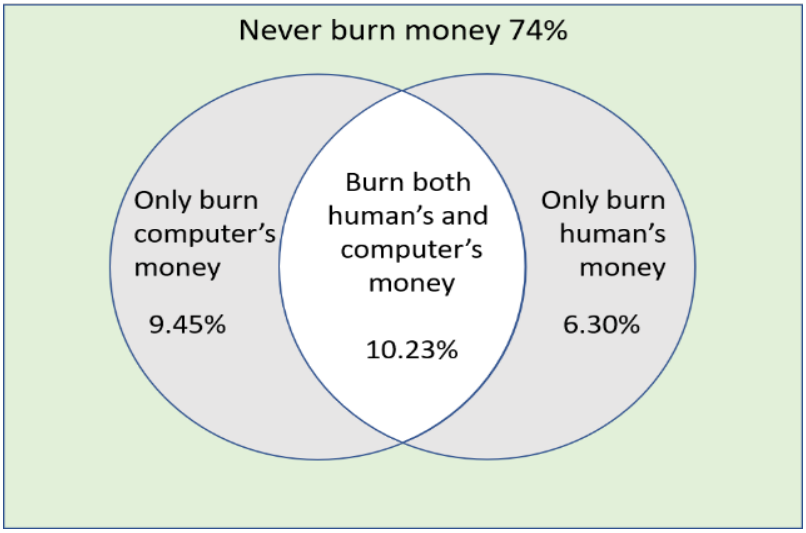

Figure 1. Money burning decisions, human vs computer

Result 1: No differential antisocial behaviour was found by ethnicity or gender.

Table 2. Mean burning decisions by gender and ethnicity

	Gender			Ethnicity		
	Male	Female	p-value	Javanese	Non-Javanese	p-value
Full sample	0.290	0.224	0.402	0.266	0.254	0.881
Excluding computer	0.203	0.121	0.216	0.141	0.190	0.451

Notes: The p-values are from the Mann-Whitney test for difference by gender or ethnicity.

When only considering decisions against human co-participants, the money burning ratio fell to only 16 per cent (including burning both humans' and the computer's money). This rate was higher than the equivalent result from Abbink and Hermann (2011) (10 per cent in the open treatment). The burn rate dropped to six per cent if we only consider decisions against a human partner. But the rate was higher if we only use decisions that were only aimed at the computer partner.

Result 2: Antisocial decisions against the computer were higher than against human co-participant.

The large number of antisocial decisions aimed at the computer was not anticipated. There are some possible explanations for this result. First, it might be the case that the participants failed to comprehend the instructions. However, we conducted a mandatory comprehension quiz prior to the real task. Second, maybe the cost of burning money was too low. This is unlikely as money burning was costless in the original JoD experiment, and we calibrate the cost of burning money during the pilot sessions. Although Javanese tended to burn computer's money more than non-Javanese, but this difference is statistically insignificant as indicated in Table 3. In general, the table suggests demographic characteristics have no explanatory power to explain variations in burning decision that are solely aimed at the computer. It suggests specific experimental design (the option to destroy computer's money) was responsible for the result.

We found that most participants (who burn money) only did it once. The rate is negatively correlated with the number of money burning decisions (Figure 2). Importantly, we could not find differential antisocial behaviour against those with different gender or ethnicity (Figure 3), although Javanese participants tended to destroy non-Javanese co-participants' money a bit more often (Wilcoxon's two-sided p-value = 0.317). This result was expected, as there is no systematic violent conflict among the different Indonesian ethnic groups or gender in Melbourne.

Table 3. Money burning decision against computer by demographic characteristics

		Mean	Difference	p-value
Javanese	Yes	0.12	-0.06	0.24
	No	0.06		
Male	Yes	0.09	-0.02	0.76
	No	0.10		
Married	Yes	0.10	-0.01	0.78
	No	0.08		
Muslim	Yes	0.09	0.01	0.86
	No	0.10		
Student	Yes	0.09	-0.00	0.99
	No	0.09		

Notes: The p-values are from the t-test with unequal variances. Burning decision is equal to 1 if participant only burn computer's money and 0 otherwise. Similar results were obtained when Fisher exact test and Pearson chi-square test are used.

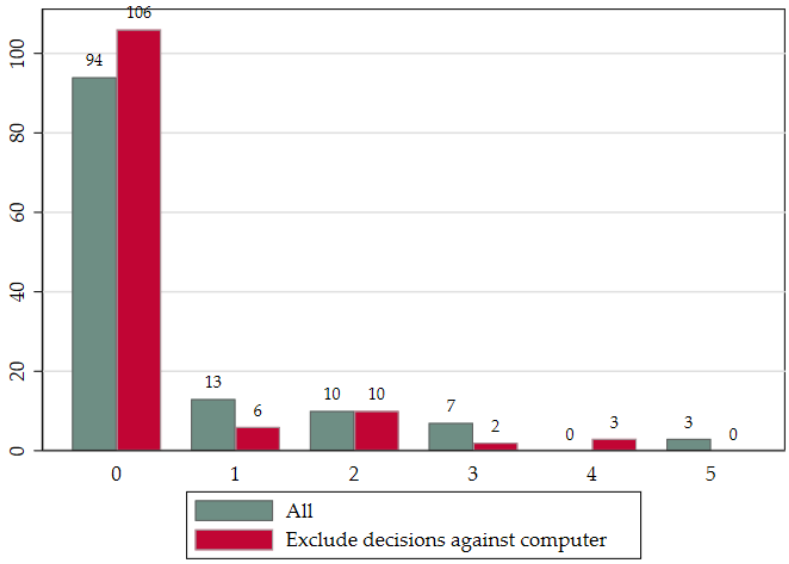

Figure 2. Count burning decisions

Result 3: No discrimination was found by ethnicity or gender.

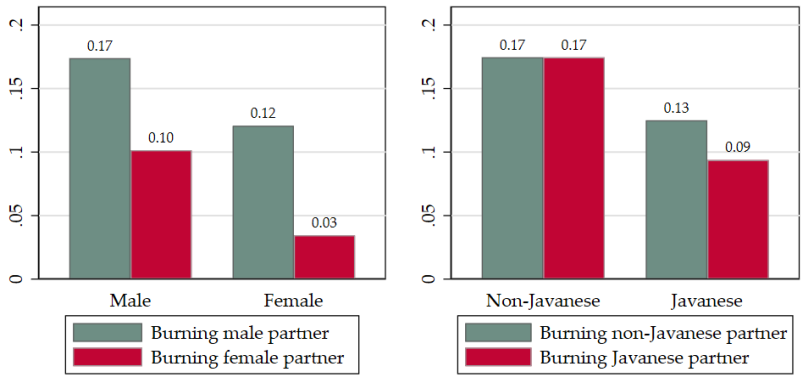

Figure 3. Share of money-burning decisions by ethnicity and gender
Notes: Excluding the computer co-participant.

Males were targeted for money burning significantly more than females, as shown in the left panel of Figure 3. The Wilcoxon test for paired sample gave the p-value of 0.025 (0.096) for differential antisocial decisions among females (males).

Result 4: Females were less likely to have their money destroyed when decisions against the computer co-participant were excluded.

The majority of participants had prosocial tendencies, and their burn rate (destroy the money of the human co-participant) was just 14 per cent—much lower than those in the other categories. However, we only have 16 observations that are not in the prosocial category.

Statistical tests suggested anger has some correlations with money burning behaviour, where, relative to male participants, female participants' average scores for anger are higher.

Result 5: Females that chose to burn tended to have higher scores for anger than did males.

Lastly, negative expectation predicts money burning behaviour where the burn rate for participants who thought that they would receive money burning was 50 per cent—significantly higher than those who did not have such thought (20 per cent). This was confirmed by the Mann-Whitney test, which yielded a p-value < 0.01.

Result 6: Negative belief strongly predicted spiteful behaviour.

Regression Results

Panel data regressions confirmed the results after adding for various controls. Burning decisions were strongly correlated by the types of co-participants (Table 4). When facing the computer (Models 1 to 3), the probability of antisocial decisions was higher than when facing a human (Models 4 and 5). The negative belief was strongly correlated with a higher likelihood of money burning behaviour. We could not find ethnic or gender discrimination (interaction terms were not significant in Models 4 and 5). This finding did not change when subjective norms such as personal attitudes and beliefs were included (results not shown).

Table 4. Panel probit regressions (dependent variable: money burning decision)

	(1)	(2)	(3)	(4)	(5)
Female partner	-1.501***	-1.488***		-0.773*	-0.971**
	(0.310)	(0.307)		(0.453)	(0.401)
Male partner	-0.680**	-0.666**			
	(0.294)	(0.280)			
Javanese partner			-1.009***	-0.130	-0.108
			(0.269)	(0.181)	(0.185)
Non-Javanese partner			-0.921***		
			(0.238)		
Female x Female partner				-0.615	
				(0.825)	
Javanese x Javanese partner					-0.0598
					(0.376)
Negative belief		1.685***	1.588***	2.432***	2.396***
		(0.445)	(0.420)	(0.671)	(0.664)
Student		-1.148***	-1.084***	-1.796***	-1.760***
		(0.427)	(0.404)	(0.654)	(0.646)
Constant	-1.737***	-0.485	-0.494	-1.679	-1.659
	(0.366)	(1.320)	(1.241)	(1.664)	(1.634)
Sample	All	All	All	Exclude computer	Exclude computer
Observations	635	625	625	500	500
Number of id	127	125	125	125	125

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In (1) to (3) partner was relative to computer co-participant. All demographic variables (gender, ethnicity, age, religion, marital status, income) are included in above regressions but their coefficients are not displayed for brevity.

A relatively consistent result is found when the data is simplified to money burning decisions against computers or humans. Although student status negatively predicts money burning decisions against human co-participants, but it is only weakly significant (Table 5).

Table 5. Probit regressions (dependent variable: burning decision)

	Only burn human's money		Only burn computer's money		Any money burning	
	(1)	(2)	(3)	(4)	(5)	(6)
Javanese	-0.217	-0.242	0.721**	0.828**	0.0988	0.192
	(0.444)	(0.449)	(0.355)	(0.387)	(0.293)	(0.305)
Age	0.00624	0.00488	-0.0392	-0.0591	-0.00146	-0.0114
	(0.042)	(0.045)	(0.032)	(0.039)	(0.027)	(0.028)
Muslim	0.399	0.471	-0.398	-0.799*	-0.263	-0.601*
	(0.462)	(0.493)	(0.371)	(0.435)	(0.300)	(0.363)
Married	-0.211	-0.167	0.293	0.232	-0.0838	-0.139
	(0.469)	(0.464)	(0.305)	(0.296)	(0.305)	(0.310)
Income > AUD 2,000	-0.419	-0.445	-0.560*	-0.573**	-0.0265	-0.0367
	(0.399)	(0.416)	(0.293)	(0.263)	(0.274)	(0.275)
Student	-0.788*	-0.734*	0.0784	0.144	-0.592*	-0.628**
	(0.415)	(0.398)	(0.333)	(0.325)	(0.304)	(0.305)
Negative belief	0.577	0.532	-0.308	-0.336	0.852***	0.867***
	(0.385)	(0.395)	(0.417)	(0.418)	(0.295)	(0.297)
Constant	-1.31	1.095	-0.101	-0.401	-0.142	-1.655
	(1.480)	(2.570)	(1.085)	(2.974)	(0.917)	(2.234)
Personal attitudes	No	Yes	No	Yes	No	Yes
Observations	125	125	125	125	125	125

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Personal attitudes: religiosity, religious fundamentalism, Mach-IV and aggression.

Money burning behaviour is positively associated with anger at 5 per cent level (Table 6 Model 1), but this effect is gone once we add an interaction between gender and anger (Model 2). However, this interaction term becomes positively and significantly correlated with money burning behaviour if the sample excludes decisions against the computer (Model 3; see also Figure 4 based on this model). Adding measures of personal attitudes, beliefs, and other sub-traits of aggression to Model 3 did not change the significance of the interaction term. However, bootstrapping reduces the significance of the interaction term, except when Poisson regression with a count of antisocial decisions as the dependent variable is used (results not shown).

Table 6. Panel regression on the role of anger (dependent variable: burning decision)

	(1)	(2)	(3)
Female	-0.581	-2.960*	-6.877***
	(0.362)	(1.782)	(2.514)
Anger	0.0987**	0.0467	0.0333
	(0.0425)	(0.0422)	(0.0564)
Female x Anger		0.138	0.337**
		(0.0979)	(0.136)
Constant	-1.541	-1.087	-2.429
	(1.428)	(1.400)	(1.860)
Sample	All	All	Excluding computer
Observations	625	625	500
Number of id	125	125	125

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Partner ethnic was relative to non-Javanese. Controls: gender, ethnicity, age, marital status, religion, income, belief, student status and types of partners (by ethnicity and gender).

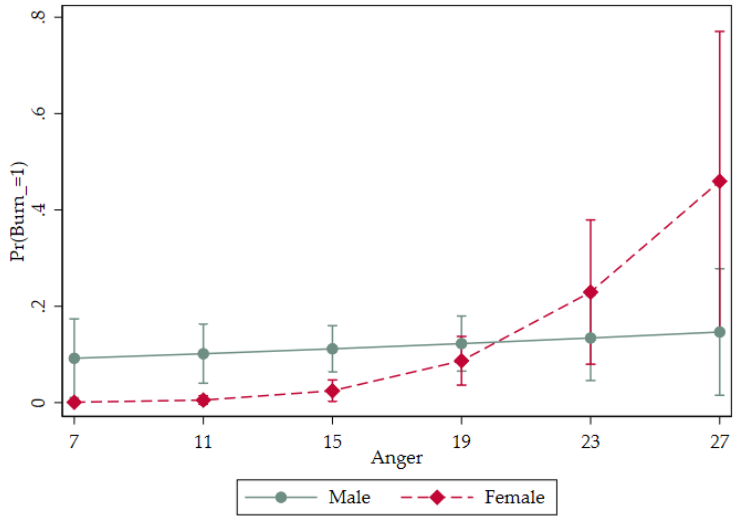

Figure 4. Predicted probability of money burning decision with 95 per cent confidence interval
Notes: The prediction was based on Model 3 in Table 6.

Mismatched Titles and Ethnicity/Gender

While honorific titles that represent ethnicity and gender are common knowledge among the Indonesian population, the accuracy of these titles in predicting the actual ethnicity and gender is subject to population composition. Specifically, the population should be predominantly Acehnese or Javanese for it to be accurate.

The honorifics accurately predicted the ethnicity of all 64 Javanese participants. With the exception of one participant, the Javanese honorifics also correctly predicted gender. However, not all non-Javanese chose *Bang* or *Kak*, and many preferred typical Javanese honorifics. Also, six participants' actual gender identity did not fit with the honorifics they preferred.

Removing observations with mismatched ethnicity and gender did not change the previous results. In particular, result 3 (no discrimination was found by ethnicity or gender), where the Wilcoxon test failed to reject the null of same distribution in money burning decision. The results generally remain the same when participants with mismatched ethnicity or gender were excluded. Those who misreport their honorifics were not different from the rest of the sample regarding to their demographic characteristics based on the Wilcoxon test.

Our data support the absence of discrimination, either by ethnicity or gender. Interestingly, a significant proportion of participants chose antisocial (money burning) decisions, where most were directed toward computer co-participants. We also find that anger, mediated by gender, seem to be correlated with antisocial decisions.

A large number of the participants chose the money burning decision despite the absence of material incentive from doing so. However, once decisions against the computer were excluded, only six per cent of the participants chose money burning. This number is less than the result from a similar experiment (Abbink & Herrmann, 2011). Thus, we concluded that adding the computer affects antisocial behaviour.

The first and third results (indifferent antisocial behaviour against those of different ethnicity or gender) showed unbiased behaviour. It adds to the literature on other-regarding preferences, where the effect of gender was unclear (Croson & Gneezy, 2009; Sent & van Staveren, 2018). These results also confirmed our casual observation that there were no systematic tensions and conflict within the Indonesian community in Melbourne.

The second result—participants were more likely to burn computer's money—was interesting yet unanticipated. This result is likely to be driven by the design of the experiment rather than due to certain individual characteristics of the participants.

The fourth result, where female participants were less likely to have their money destroyed, was new in the literature. This result is similar to the other study that used a dictator game, where women tended to receive more money than men (Dufwenberg & Muren, 2006).

The fifth and sixth results answered the research question on the antecedents of antisocial behaviour. The higher score of anger for female participants who chose to destroy money provides an indication that anger might be perceived differently by gender and that this was reflected in their behavioural decisions. This result was consistent with past studies in psychology, which hypothesises that, in one hand, women view anger as a loss of control (men, on the other hand, view anger as seizing control) (Astin et al., 2003; Litvak et al., 2010). In addition, an antisocial experiment in Israel found that anger had mixed effects on antisocial behaviour and its impact on behaviour was subject to participants' violent experience (Zeitzoff, 2014). The sixth result indicated that negative expectation predicts antisocial behaviour, which was commonly found in the literature (Abbink & Herrmann, 2011; Prediger et al., 2014).

These results were generally unchanged after excluding observations with mismatched gender/ethnicity, using other sub-traits of aggression, an interaction variable between anger and some demographic variables, and personal attitudes variables. However, using standard bootstrap errors weakened some of the results. We also find the average money burning lower in Melbourne compared to the Aceh data, but this location fixed effect diminished when more controls were added.

Conclusions

To conclude, this study complements the Aceh study findings and shows the absence of in-group/out-group discrimination in a community with no experience of extended conflict. Moreover, the surprising finding on antisocial decisions against computer co-participants raises questions regarding motivation, which opens up to future research.

This study has at least two implications. The first is the methodological implication on the method of the experiment where the inclusion of computer players may have an unforeseen impact on participant's behaviour. Second, the relatively small number of antisocial behaviours directed towards human co-participant is relieving, which suggests the relative peace among Indonesian migrants in Melbourne. It is also a reflection, at least partially, of the relative success of the governments—both Australian and Indonesian representatives in Australia—in managing the community. Policy-wise, this could also be the result of the National Agenda for a Multicultural Australia that, among others, is concerned with social justice and cultural identity. Finally, we must also acknowledge the Indonesian community itself for being able to stay cohesive and vibrant despite being far from home.

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