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Household Size and Household Wealth in Indonesia with the Influence of Spatial Aspects

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Abstract

Investigating household wealth should also include spatial analysis to capture the influence of location on the households' net wealth and to avoid underestimation of the effect of the change of variables due to estimation that ignores spatial aspects. This paper examines factors influencing household net wealth in Indonesia with the influence of spatial lag using data from the Indonesian Family Life Survey (IFLS) for 1993–2014. The article relies on the Spatial Durbin Model (SDM) to analyze the data. Results show that household net wealth in Indonesia is spatially related to each other, and the spillover effect makes the change of household net wealth in Indonesia dominated by the change of variables in neighbouring regions. Furthermore, considering the time component, there is a positive effect of households' size on households' net wealth due to the time component concerning the spatial lag of the dependent and independent variables.

Keywords: Spatial Durbin Model; households; wealth; spillover

JEL classifications: C23; I31; J12; J13; R12

1. Introduction

The archipelagic condition of Indonesia, which consists of more than 17,000 islands, challenges the state to distribute economic development to its more than 270 million population. Even though Indonesia has been able to reduce its population growth, from 2.31% in 1971–1980 to 1.98% one decade later, controlling population growth has slowed down. In recent decades, Indonesia has only been able to maintain its population growth of 1.49% in 1990–2000 and 2000–2010 and 1.31% in 2010–2019 (Badan Pusat Statistik 1994–2015).

The economic advantages of having a modest household size should be promoted along with population growth management. Modest family size can help families improve their standard of living, have children of higher quality, and be able to deal with financial shocks, according to scholars such as Hao (1996) and Keister (2004). Moreover, the experience of the crisis shows it increases the risk of food insecurity (Munandar 2020) and child marriage (Rahiem 2021), widens the gender gap (Gani 2021) and puts pressure on accessing primary health care (Kusumaningrum, Siagian & Beazley 2022). Hence, having a small household size will increase the household's ability to deal with the crisis.

Controlling population growth can have positive effects by demonstrating how it affects household wealth, which is a proxy for standard of life. Since households frequently underreport their income or only report regular-base income, evaluating household wealth can be an option to determine a person's living standard (Birdsall 2010; Brown & Gray 2014). Additionally, income is transient, so it is not always indicative of the same circumstances in the future (Oliver & Shapiro 1990). Since families will always have expenses even when they have no income, home wealth can measure the level of living better than expenditures (Friedman 1957). Next, considering the distribution's form, we can see that

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the expense report is typically biased lower at the high and low levels (Ward 2014; Brown & Gray 2014; Clementi et al. 2020).

Another strength of household wealth as the measurement of the standard of living is its ability to reflect purchasing power (Wakita, Fitzsimmons & Liao 2000; Williams & Manning 1972; Fitzsimmons & Leach 1994), which can be inherited (Oliver & Shapiro 1990), and show that people with wealth does not mean they always have more income, e.g., pensioners (Oliver & Shapiro 1990; Filmer & Pritchett 2001; Gibson 2017). Additionally, the inclusion of debt in the wealth assessment allows for a more accurate estimation of the standard of living because it can reduce wealth, give rise to the potential of negative net wealth (defined as debt greater than total wealth), zero net wealth, or positive value (debt lower than total wealth).

Because households in one region may be impacted by the economic actions of households in nearby areas and the same region, it is vital to perform a richer examination of how household size affects household wealth. Ignoring this effect may hide the relationship between variables with the consideration of the spatial aspects. This study investigates the spatial effects of household size on household net wealth in Indonesia. This article contributes by explaining why it is important to consider spatial factors while analysing the household standard of living in low-income countries and during policy-making processes. The literature review in Section 2 follows Section 1 of the introduction. Next, methods and outcomes are covered in Sections 3 and 4. Finally, conclusions are in Section 5.

2. Literature Review

Spatial models enable researchers to capture information related to space that cannot be obtained from the non-spatial model as unobservable variables may be spatially correlated and thereby produce a spatial correlation (Case 1991). When the dependent variable is spatially lagged, the estimation of a standard panel model that does not contain spatial autocorrelation can be modified by inserting lag in the dependent variable, forming a spatial autoregressive model (SAR) model (Anselin 2001; LeSage & Pace 2009):

$$\mathrm{Y} = \rho \mathrm{WY} + \mathrm{X}\beta + \varepsilon \quad (1)$$

where ρ is a spatial autoregressive coefficient, ε is a vector of error terms. WY is the spatial lag for Y at i. While W is a positive $\mathrm{N} \times \mathrm{N}$ spatial weights matrix.

When dependent and independent variables contain spatial lag, the Spatial Durbin Model (SDM) is used (Elhorst 2010; LeSage & Pace 2009):

$$\mathrm{Y} = \rho \mathrm{WY} + \mathrm{X}\beta_1 + \mathrm{WX}\beta_2 + \varepsilon \quad (2)$$

where ρ is a spatial autoregressive coefficient, ε is a vector of error terms. W is a positive $\mathrm{N} \times \mathrm{N}$ spatial weights matrix. WY is the spatial lag for outcome Y, and WX is the spatial lag for explanatory variable X.

Direct, indirect, and cumulative impacts can be separated from spillover effect estimates in geographic models. The immediate effect is described by LeSage & Pace (2009) as a summary measure that averages the effects on dependent variables brought on by changes in the explanatory variable within the same region. The spatial spillover effect, sometimes called the indirect effect, quantifies the influence on the dependent variable in area unit i of changes in the independent variable in all other area units. The k-th explanatory variable is changed by one unit across all observations to calculate the total effect, which accounts for direct and indirect effects and estimates the average cumulative influence on each observation (Table 1).

To control the influence of the time-lagged- and space-time-lagged-dependent variable, the dynamic model is applied:

$$\mathrm{Y_t} = \tau \mathrm{Y_{t-1}} + \psi \mathrm{WY_{t-1}} + \rho \mathrm{WY_t} + \mathrm{X_t}\beta + \mu + \varepsilon_\mathrm{t} \quad (3)$$

where the lagged (in time) dependent variable, in

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Table 1. Direct, Indirect, and Total Effects

	Direct Effect	Indirect Effect
Spatial Autoregressive Model (SAR)		
Static		
Short-term	None	None
Long-term	$\{(I-\rho W)^{-1} \times (\beta_k I)\}^{\bar{d}}$	$\{(I-\rho W)^{-1} \times (\beta_k I)\}^{\overline{rsum}}$
Dynamic		
Short-term	$\{(I-\rho W)^{-1} \times (\beta_k I)\}^{\bar{d}}$	$\{(I-\rho W)^{-1} \times (\beta_k I)\}^{\overline{rsum}}$
Long-term	$\{((1-\tau)I-(\rho+\psi)W)^{-1} \times (\beta_k I)\}^{\bar{d}}$	$\{((1-\tau)I-(\rho+\psi)W)^{-1} \times (\beta_k I)\}^{\overline{rsum}}$
Spatial Durbin Model (SDM)		
Static		
Short-term	none	none
Long-term	$\{(I-\rho W)^{-1} \times (\beta_k I+\theta_k W)\}^{\bar{d}}$	$\{(I-\rho W)^{-1} \times (\beta_k I+\theta_k W)\}^{\overline{rsum}}$
Dynamic		
Short-term	$\{(I-\rho W)^{-1} \times (\beta_k I+\theta_k W)\}^{\bar{d}}$	$\{(I-\rho W)^{-1} \times (\beta_k I+\theta_k W)\}^{\overline{rsum}}$
Long-term	$\{((1-\tau)I-(\rho+\psi)W)^{-1} \times (\beta_k I+\theta_k W)\}^{\bar{d}}$	$\{((1-\tau)I-(\rho+\psi)W)^{-1} \times (\beta_k I+\theta_k W)\}^{\overline{rsum}}$

Source: Belotti, Hughes & Mortari (2017).
Note: The superscript $\bar{d}$ denotes the operator that calculates the mean diagonal element of a matrix, and the superscript $\overline{rsum}$ denotes the operator that calculates the mean row sum of the non-diagonal elements

which $\psi = 0$, or the lagged (in both time and space) dependent variable, in which $\tau = 0$, can be included in the specification.

The spatial weighting matrix, which displays a correlation between regions in an N by N positive and symmetric matrix W and whose neighborhood is set as non-zero elements, is a crucial part of spatial models (Anselin & Bera 1998). The following structure can be applied to the spatial weight matrix:

$$\begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1N} \\ w_{21} & w_{22} & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & W_{NN} \end{bmatrix}$$

More formally, $w_{ij} = 1$ when i and j are neighbours, and $w_{ij} = 0$ otherwise. The weight matrix's diagonal members are set to zero, while its row elements add up to one. Consequently, the value of the row-standardised weights matrix's element is $w^s_{ij} = \frac{w_{ij}}{\sum_j w_{ij}}$. This allows people to interpret operations with the weight matrix as an averaging of nearby values and guarantees that all weights are between 0 and 1.

When two regions, i and j, share a border, the element wij in the contiguity matrix is 1; otherwise, it is 0. The distance-based matrix converts the distance information into a distant decay parameter (Keisuke 2016).

As the contiguity matrix interpret neighbourhood as regions that share the same borders, difficulties may arise for areas that are separated by water boundaries (e.g., sea or lake). If contiguity is used as a measurement, one island may have no neighbours. Therefore, the distance-based matrix type is used to overcome the above drawback. For the archipelagic condition of Indonesia, the distance-based matrix is more suitable to be applied (Vidyattama 2014; Mustajab 2009).

Spatial autocorrelation, or the spatial distribution of the variable of interest that displays a systematic pattern, is the correlation between units concerning spatial characteristics in spatial analysis (Cliff & Ord 1981). Moran's I test, which examines whether attribute values of features cluster or not given their positions to other characteristics, is used to identify the presence of spatial autocorrelation (Anselin 2001). The assumption of the null is that data are distributed randomly (there is no spatial autocorrelation in the model). The assumption of the null is that data are distributed randomly (there is no spatial autocorrelation in the model). The data are more geographically linked, according to the alternative theory. Moran's I values range from -1 to 1, with a positive value indicating that a point is likely to be clustered with nearby points and a negative value the opposite. Values somewhat close to 0 show that the data are dispersed randomly. Moran's I can be converted into z-scores for this statistical hypothesis testing. Positive Z-scores show some kind of spatial clustering of the data. Positive coefficients indicate positive spatial autocorrelation, which means that regions adjacent to the high-value areas also exhibit higher values; zero coefficients indicate no autocorrelation (perfect randomness); and negative coefficients indicate clustering of values with different characteristics (Réquia Jr, Koutrakis & Roig 2015).

Global and local spatial autocorrelation are two different types of spatial autocorrelation. The correlation between data values solely attributable to the relative location and closeness of the objects to which the data pertains is known as global spatial autocorrelation. The estimation of global spatial autocorrelation, on the other hand, offers an average representation of the spatial distribution of the relevant variable and may, thus, obscure intriguing aspects of the phenomenon under investigation. This problem is solved by measuring the local spatial autocorrelation. It has two purposes: Local statistics may be able to identify one or more constrained areas that significantly deviate from spatial randomness when applied to datasets lacking global spatial autocorrelation. Second, local statistics may be used to pinpoint the areas that contribute most to the overall spatial clustering pattern in datasets with global spatial autocorrelation (Sokal, Oden & Thomson 1998).

An analysis of spatial panel models in the form of a space-fixed effect and a time-fixed effect is required to confirm the influence of spatial aspects with respect to space and time. The justification for including time-period fixed effects notes that they control for all time-specific, spatial-invariant variables whose omission could bias the estimates in a typical time-series study. The spatial fixed effect controls all space-specific and time-invariant variables whose omission could prejudice the estimates in a typical cross-sectional study (Baltagi 2008). For geographic interaction effects between the error terms, such as unobserved shocks following a spatial pattern or variables that grow or decrease concurrently in several jurisdictions within the same (business) cycle across time, time-period fixed effects are also accurate (Elhorst 2010). While models without such controls only use the time-series component of the data, models with such controls only use the cross-sectional component (Elhorst & Fréret 2009).

3. Method

This research data from the Indonesian Family Life Survey (IFLS) contains information on the health, demographic, and socio-economic condition of the Indonesian population as well as community attributes and collects data from respondents living in 13 provinces in Indonesia that represents 83 per cent of Indonesia's 1993 population. Information from 7,224 households was gathered in 1993 as part of the IFLS's first wave (IFLS1). 7,698 households were included in the 1997 administration of the IFLS2. In 2000, 10,574 households were surveyed by IFLS3. IFLS4 surveyed 13,995 households in 2007. About 16,931 families were questioned for IFLS5 in 2014 (RAND 2014; Sikoki et al. 2013).

Household net worth is the dependent variable utilized in the analysis. It is calculated as the total value of the household's wealth (the value derived from the market value of assets), less any loans. Since debt can deduct total wealth, there will be three possible values of net wealth that are positive (total wealth higher than debts), zero (total wealth equal to debt), or negative (total wealth lower than debts).

The independent variables are household size and dependency ratio. The main reason for selecting these variables is that they are relatively slow to change; any interventions will take a relatively long time to take effect on those variables. Hence, interventions are urgently needed at the earliest time

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to ensure one can obtain the desired results in the future. Besides, the dynamics of those variables are also influenced not only by personal perception but also by the surrounding environment, e.g., economy, social status in society, and endowment statuses like ethnicity, religion, and social class. Therefore this raises the need to look at the influence from spatial aspects.

The number of people who reside under one roof, including members of core families, extended families, and non-family individuals, is referred to as the household size variable. The dependency ratio variable is needed to measure the non-productive household members (those who are 0–14 and older than 65 years) who each productive household member must support because the variable of household size lacks information regarding financial responsibility owned by the family (aged 15–64). Because there are more non-productive family members whom each productive household member must support, households with greater dependency ratios have higher financial costs overall.

For the dependent variable, data is transformed using the cube root, as Cox (2011) indicated. This transformation is weaker than the logarithm but still handles zero and negative values well. Natural logarithm transformation is used for independent variables because it can make highly skewed distributions less skewed and is only practical for positive values.

Given that the analysis aims to determine how household size affects household net wealth in Indonesia, we must include two types of spatial lag in the analysis: a spatial lag in the dependent variable and a spatial lag in the independent variables. The Spatial Durbin Model is the best model for this analysis (SDM). Also provided are the findings of an estimation of the spatial autocorrelation (SAR) that simply includes the spatial lag of the dependent variable.

Kondo's (2018) estimator is used to find spatial autocorrelation considering a spatiotemporal effect. While estimating spatial autocorrelation for cross-sectional observations, Pisati's (2001) estimator is used. In addition, Pisati's (2001) estimator is used to differentiate the global and local spatial autocorrelation. Finally, using the estimator developed by Belotti, Hughes & Mortari (2017), a quasi-maximum likelihood technique (Yu, De Jong & Lee 2008) is utilized to determine the impact of household size on household net wealth.

4. Results and Analysis

Indonesian household net wealth is spatially connected, albeit this association declined between 1993 and 2014. We can rule out Ho since the estimation of global spatial autocorrelation yields p-values less than 0.05, indicating that the data are spatially correlated. The presence of positive spatial autocorrelation, where regions next to those with high values also exhibit higher values, is shown by positive z-scores. Moran's I has decreased between 1993 and 2014, which suggests that the spatial correlation has decreased (Table 2).

Table 2. Moran's I for Household Net wealth in Indonesia

Year	Moran's I	z	p-value
1993	0.133	8.779	0.000
1997	0.069	4.794	0.000
2000	0.053	3.702	0.000
2007	0.050	3.438	0.001
2014	0.031	2.168	0.030

Global spatial autocorrelation shows a declining Moran's I as the distance between regions is more significant (Figure 1). It indicates households in the neighbouring areas have less impact than households in one region if they are located further than the region.

Local spatial autocorrelation is then estimated to find out the condition of spatial autocorrelation when we isolate the influence of neighbouring regions. Findings show most areas in Indonesia have a decreasing local spatial autocorrelation from 1993 to 2014, except Bali-Nusa Tenggara Barat. The decreasing autocorrelation in areas might be influ-

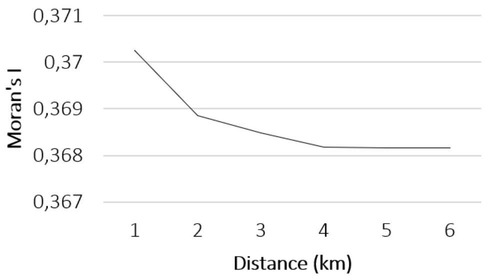

Figure 1. Global Spatial Autocorrelation for Household Net wealth in Indonesia
Source: International Energy Agency (2019)

enced by the increasing role of the regions in the frame of regional autonomy (*otonomi daerah*) that allow higher authority and responsibility for the regions themselves. On the other hand, the increasing autocorrelation in Bali-Nusa Tenggara Barat can be explained by the growing role of non-extraction sectors that are primarily enjoyed by the population in the region and tend to be less connected to other areas due to their island condition.

Estimating the determinants of household net wealth focuses on household size and dependency ratio. Using a standard panel model that ignores spatial aspects shows the reduction in the dependency ratio, which means fewer non-productive-age household members will increase their wealth as it allows families to focus on earning money and reducing expenditure. In contrast, the variable of household size has a positive effect which means the increase in household size increases household net wealth. Hence, any efforts to reduce household size should be relevant to the reduction in the dependency ratio, which is not achieved from this estimation and might be caused by the unobserved aspect that cannot be captured by the standard panel model (Table 4).

A more pertinent discussion of spatial models can be found in the discussion of the spatial lags and the spillovers. The estimation of the Spatial Autocorrelation Model (SAR), which includes spatial lag in the dependent variable, and the Spatial Durbin Model (SDM), which controls spatial lag of dependent and independent variables, is then estimated (LeSage 2008).

Findings from the estimation of SDM show a significant coefficient of spatial lag $\mathrm{p} < 0.01$ for $\rho = 0.666$, $\beta_3 = -98.754$, and $\beta_4 = -1.863$. The value of ρ indicates household net wealth is slightly higher in a region surrounded by regions with high household net wealth, all else the same. While negative coefficient for β_3 and β_4 reflects household net wealth is lower in a region surrounded by regions with high household size and high dependency ratio, all else the same. The first effect may reflect the economic impact that influences one region and other areas, starting from the adjacent regions. The last two effects could result from resource competition, where large households and high dependency ratios lead to higher demand for some goods, such as housing and transportation. Such competition will increase prices, put more strain on other households' finances, and limit their ability to accumulate wealth (Table 5).

Table 3 shows the indirect effect of SDM is more significant than its direct effect, reflecting the change of household net wealth in one region is primarily influenced by the change of variables in the other areas and averaging over all cross-regions combinations. Looking at the variables, the dependency ratio has a negative and significant indirect effect on household net wealth, which means a 1% increase in the dependency ratio variable in neighbouring regions will significantly reduce approximately 5% of household wealth in one region. This implies more non-productive-age household members (relative to productive-age household members) in neighbouring regions will reduce households' wealth in one region.

This circumstance usually occurs in areas with strong economic growth as households prefer to focus on their careers, face significant financial expenses to raise children, and are forced to postpone marriage or opt to have a small household size to obtain a lower dependency ratio. Hence, their high productivity and high economic activities will reduce economic opportunities for households in neighbouring regions, reducing their wealth.

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Table 3. Local Spatial Autocorrelation of Household Net Wealth in Indonesia

Islands	1993		1997		2000		2007		2014	
	Ii	z	Ii	z	Ii	z	Ii	z	Ii	z
Sumatera	0.141	0.705	-0.066	-0.523	-0.070	-0.329	-0.022	-0.003	-0.039	-0.211
Jawa	0.153	1.171	0.125	0.946	0.085	0.625	0.047	0.361	0.021	0.254
Bali-NTB	0.125	0.701	0.041	0.271	0.175	1.126	0.338	2.205	0.383	2.348
Kalimantan	0.012	0.274	0.060	0.537	0.041	0.433	0.040	0.267	-0.103	-0.598
Sulawesi	-0.002	0.035	0.045	0.384	0.025	0.260	-0.030	0.007	0.021	0.252

Table 4. Standard Panel Model

	Fixed Effect	FE with Robust Std. Err.	FE with Robust Clustered Std. Err.
Household size	14.828***	14.828***	14.828**
	(5.495)	(5.495)	(3.050)
Dependency ratio	-28.620***	-28.620***	-28.620***
	(2.255)	(2.255)	(2.554)
Constant	288.682***	288.682***	288.682***
	(7.365)	(7.365)	(3.119)
R-square	0.0171	0.0171	0.0171

Note: ***=p<0.01, **= p<0.05, *= p<0.1.

Table 5. Effect of Household Size on Household Net Wealth

	SAR	SDM
Ln Household size	14.322	-17.164
	(33.64)	(37.221)
Dependency ratio	-0.391	0.034
	(0.265)	(0.33)
W*Ln Household size		-98.754
		(61.055)
W*Dependency ratio		-1.863***
		(0.478)
rho	0.771***	0.666***
	(0.058)	(0.058)
sigma2_e	4337.607***	4283.39***
	(626.506)	(624.864)
Average Impact		
LR Direct		
Ln HH Size	16.236	-19.283
	(35.844)	(38.114)
Dependency ratio	-0.404	-0.026
	(0.268)	(0.32)
LR Indirect		
Ln HH Size	74.811	-315.688*
	(153.514)	(175.206)
Dependency ratio	-1.25	-5.463***
	(0.838)	(1.285)
LR Total		
Ln HH Size	91.047	-334.971*
	(186.333)	(177.821)
Dependency ratio	-1.654	-5.488***
	(1.074)	(1.168)

Note: ***=p<0.01, **= p<0.05, *= p<0.1.

On the other hand, the variable of the household size in the indirect effect shows a negative and less significant impact suggesting an effort to control population growth, shown by the reduction in household size, is beneficial to increasing household standard of living concerning the spillover.

Although the total effect, which combines direct and indirect effects, is higher than the result in the standard panel model in Table 2, which ignores spillovers, it still shows that the influence of the change in variables on household net wealth is greater if spatial aspects are taken into account than if they are not. Additionally, this eliminates the uncertainty about unobserved factors that made Table 2's conclusions unclear.

An analysis of spatial panel models in the form of a space-fixed effect and a time-fixed effect is required to confirm the influence of spatial aspects with respect to space and time. The findings of SDM estimation with the control of individual fixed effects, time fixed effects, and individual and time fixed effects are significant. For example, the change in household net wealth in one location is significantly impacted by the change in household net wealth in other regions, all other things being equal, by controlling those factors (Table 6).

A comparison in Table 4 between estimate that only considers individual fixed effects and SDM that only considers time fixed effects demonstrates the importance of spatial elements in the estimation—the former results in a more significant coefficient of the

Table 6. Estimation of Fixed Effects

	SAR			SDM		
	Individual-fixed-effects	Time-fixed-effects	Individual- and time-fixed-effects	Individual-fixed-effects	Time-fixed-effects	Individual- and time-fixed-effects
Ln HH size	14.3222	-31.399	-4.869	-17.164	-39.031	-4.989
	(33.64)	(25.69)	(33.185)	(37.221)	(27.701)	(34.045)
Dependency ratio	-0.391	-1.379***	-0.113	0.034	-1.192***	0.005
	(0.265)	(0.245)	(0.315)	(0.33)	(0.244)	(0.324)
W*Ln HH size				-98.754	39.054	175.012*
				(61.055)	(77.84)	(99.08)
W*Dependency ratio				-1.863***	-3.57***	-2.771***
				(0.478)	(1.048)	(0.998)
rho	0.771***	0.531***	0.453***	0.666***	0.414***	0.393***
	(0.058)	(0.087)	(0.102)	(0.058)	(0.093)	(0.102)
sigma2_e	4337.607***	8902.579***	4295.181***	4283.39***	8797.288***	4243.607***
	(626.506)	(863.829)	(614.457)	(624.864)	(838.324)	(600.12)

Note: ***=p<0.01, **= p<0.05, *= p<0.1.

spatially lagged dependent variable. Further, the estimation of SDM that controls the individual-fixed effect only gives the negative coefficient of spatial lag of the household size variable. In contrast, the result from SDM that controls time-fixed-effect shows contrary findings, that is, a positive coefficient. It reflects that when time is considered individually, the estimation of spatial lag of household size gives a positive contribution to household net wealth, implying the need to put intervention on this variable only when the model is restricted by time. Elhorst & Fréret (2009) discovered that although models without spatial-fixed-effects produce long-term estimates, those with those effects provide short-term estimations.

A further check is needed to confirm the findings above with the test of the dynamic spatial model that describes the spatiotemporal model's structure, where the specification can include the lagged (in time) dependent variable or the lagged (in both time and space) dependent variable (Belotti, Hughes & Mortari 2017).

$$y_t = \tau y_{t-1} + \psi W y_{t-1} + \rho W y_t + X_t \beta + \mu + y\epsilon_t \quad (4)$$

where dlag(1) refers to the time-lagged dependent variable, in which $\psi = 0$. dlag(2) reflects space-time-lagged dependent variable in which $\tau = 0$. dlag(3) reflects time-lagged and space-time-lagged dependent variables (Table 7).

Table 7 shows that SDM that controls space-time-lagged has a higher coefficient of ρ than the SDM that controls the time-lagged dependent variable. This indicates household net wealth in one region will increase if there is an increasing net wealth of other households in the neighbouring areas, with the space aspect playing a more prominent role than time. These findings support Table 4, which shows spatial aspects have an important contribution in affecting household net wealth, shown from estimates that include spatial aspects with higher results than estimation without considering spatial aspects.

These results have implications for how we think about location and time, which can have differing effects on independent factors' effects on dependent variables. According to LeSage & Pace (2009), using a space-time panel data set may, in practice, result in parameter estimates that show low spatial dependence and high temporal dependence, thus leading one to draw the incorrect conclusion that a pure temporal regression without any spatial component is appropriate. Despite the seeming stark differences between the estimates from these two models, both estimates may be accurate because they are based on separate information sets (LeSage & Pace 2009).

The use of the analysis of spillovers that influences the household standard of living might help Indonesia to redistribute economic activities to re-

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Table 7. Dynamic Spatial Models

	SAR			SDM		
	dlag(1)	dlag(2)	dlag(3)	dlag(1)	dlag(2)	dlag(3)
Cube root NW	0.145***		0.181***	0.164***		0.181***
	(0.027)		(0.03)	(0.026)		(0.029)
W* Cube root NW		0.022	-0.128***		0.031	-0.105*
		(0.044)	(0.048)		(0.051)	(0.056)
Ln HH Size	-175.745***	-133.568***	-160.954***	-155.703***	-131.421***	-156.036***
	(48.762)	(47.732)	(47.285)	(46.891)	(46.918)	(46.439)
Dependency ratio	-0.645**	-0.689**	-0.747***	-0.733**	-0.641*	-0.75**
	(0.265)	(0.276)	(0.277)	(0.354)	(0.351)	(0.354)
W*Ln HH Size				-133.969*	-53.254	-56.284
				(75.928)	(89.266)	(87.201)
W*Dependency ratio				-0.215	-0.376	-0.154
				(0.705)	(0.697)	(0.708)
rho	0.368***	0.355***	0.335***	0.306***	0.343***	0.317***
	(0.111)	(0.113)	(0.114)	(0.119)	(0.118)	(0.119)
sigma2_e	4521.605***	4528.178***	4519.543***	4522.786***	4527.288***	4518.274***
	(598.969)	(601.543)	(600.157)	(604.871)	(604.886)	(604.415)
Average Impact						
SR Direct						
Ln HH Size	-179.13***	-136.467***	-157.378***	-160.326***	-134.934***	-153.37***
	(47.635)	(46.417)	(45.82)	(45.788)	(45.351)	(44.953)
Dependency ratio	-0.635**	-0.676**	-0.742***	-0.718**	-0.626*	-0.743**
	(0.254)	(0.264)	(0.281)	(0.337)	(0.332)	(0.356)
SR Indirect						
Ln HH Size	-105.602**	-75.562*	-82.837*	-269.529**	-154.781	-157.801
	(50.746)	(39.745)	(45.606)	(121.225)	(144.637)	(127.146)
Dependency ratio	-0.37*	-0.372*	-0.387*	-0.707	-0.99	-0.593
	(0.207)	(0.205)	(0.23)	(0.955)	(1.014)	(0.981)
SR Total						
Ln HH Size	-284.732***	-212.028***	-240.215***	-429.855***	-289.715*	-311.171**
	(78.185)	(72.268)	(72.744)	(123.219)	(148.842)	(129.024)
Dependency ratio	-1.004**	-1.048***	-1.129***	-1.425*	-1.616*	-1.337
	(0.405)	(0.409)	(0.432)	(0.858)	(0.927)	(0.846)
LR Direct						
Ln HH Size	-209.938***	-136.56***	-191.792***	-192.619***	-135.146***	-186.839***
	(55.719)	(46.438)	(55.86)	(54.706)	(45.36)	(54.856)
Dependency ratio	-0.744**	-0.677**	-0.905***	-0.861**	-0.627*	-0.906**
	(0.298)	(0.265)	(0.343)	(0.403)	(0.332)	(0.436)
LR Indirect						
Ln HH Size	-165.824*	-83.131*	-70.733	-383.046**	-169.81	-166.243
	(92.549)	(43.074)	(54.286)	(189.283)	(153.534)	(150.215)
Dependency ratio	-0.577	-0.409*	-0.329	-1.053	-1.076	-0.612
	(0.353)	(0.222)	(0.263)	(1.352)	(1.073)	(1.151)
LR Total						
Ln HH Size	-375.762***	-219.691***	-262.525***	-575.665***	-304.955*	-353.082**
	(116.819)	(75.322)	(82.142)	(190.749)	(1580.145)	(150.756)
Dependency ratio	-1.321**	-1.086**	-1.233***	-1.915	-1.703*	-1.518
	(0.559)	(0.425)	(0.48)	(1.243)	(0.989)	(0.979)

Notes: ***=p<0.01, **= p<0.05, *= p<0.1.
dlag(1) = the time-lagged dependent variable, dlag(2) = the space-time-lagged dependent variable, and dlag(3) = time-lagged and space-time-lagged dependent variable.

gions, e.g., in urbanisation form (Mauleny 2016; Haryono 1999), promote infrastructure development (Pramono & Marsisno 2018), and therefore can reduce the gap between regions. One initiative that should be taken is to focus on managing the population growth by creating a small household size. It enables families to enhance their living standards by allocating higher per capita education, nutrition, and housing spending. Hence, families will get many benefits such as higher quality children, less financial expenses, higher wealth levels, and the ability to deal with economic shocks (Hao 1996;

Keister 2003,2004; Soseco 2020,2021).

5. Conclusion

The spatial characteristics of the analysis should be considered when observing the household standard of living from the perspective of net wealth since they have a more significant influence than the results of estimates that do not take them into account. The variable of dependency ratio is the key contributor to the extent to which the spillovers impact household net worth in one region of Indonesia from other households in the neighbouring areas. Therefore, it is crucial to achieving population control measures resulting in smaller households and a more significant proportion of productive household members.

This paper is not without limitations, however. Using a longitudinal and micro-level survey of IFLS may underestimate the value of assets resulting in a skewed calculation. However, it does not drastically change the rankings of households, thereby affecting the results qualitatively. In addition, despite its richness of data, the IFLS lacks information on the regions in eastern Indonesia.

Moving beyond the country level to more in-depth regional analyses is necessary, as this study emphasizes the significance of including spatial features in the analysis of the home standard of living on the national level. Finally, besides the two determinants of household net wealth investigated in this paper, other potential factors also need to be considered, such as the stream of income-which is influenced by, e.g., age, education, type of work, gender, and the expenditure pattern, that influenced by, e.g., location, knowledge.

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