Spatial Okun's Law for a Set of Islands? The Case of Indonesia

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Abstract This paper estimates the Okun's law using a spatial panel approach for Indonesian's districts over the period 2009-2020. Given the geography of the archipelago, we deviate from the traditional definitions of neighbors and use instead a Thiessen polygons structure to capture the spillovers from neighboring regions. Our results show that the Okun's Law relies heavily on the regional economic and industrial structure, revealing a differentiated Okun's coefficient for eastern (agrarian) and western (industrialized) provinces. The magnitude of the spillovers support the appropriateness of using the Thiessen polygons structure to build the weight matrix.

Keywords Okun's law · Spatial econometrics · Unemployment · GDP growth · Indonesia

JEL Classifications C21 · E23 · E24 · R11

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1 Introduction

Few statistical relationships have been as popular among academics and policy makers alike as the Okun's law. Named after Arthur Okun (1963), this statistical relationship links the change in unemployment rate to GDP growth showing that on average a 2% to 3% of GDP growth decreases unemployment by one percentage point. The parsimony, simplicity and empirical regularity of the Okun's law are very appealing for policy makers and academics (Smith 1974; Freeman 2000), making it one of the pillars of mainstream economics as pointed by Blinder (1997).

The aim of this paper is to estimate the Okun's coefficient for Indonesia at the district level using a spatial panel data approach. The use of spatial econometric techniques to compute the Okun's law allows to calculate the regional spillovers in the labor and goods markets, and has became a popular alternative to the more traditional time series, showing that the interaction with neighbors in the form of trade, migration and commuting in a well integrated market is very important to determine the Okun's coefficient (Montero Kuscevic 2014; Villaverde and Maza 2021). However, Indonesia's regions pose a particular challenge in the definition of neighbors. With more than 15,000 island, the country is the largest archipelago in the world, having regions that do not share physical borders among them, and are completely surrounded by water. This singular geography raises questions about the labor and goods market spillovers, as well as the regional integration within the boundaries of the country.

This paper makes two contributions to the existing Okun's literature. First, it uses a novel approach to define neighboring regions in the Okun's law context. Traditionally, neighbors have been defined as regions that share a common physical border such as states in mainland USA. However, for regions that do not have contiguous borders (for instance metropolitan areas) the definition of neighbor becomes less clear, and researches have to resort to other methods like k-nearest neighbors within an arbitrary threshold or inverse distance as a proxy for closeness among regions. In this paper we use a different approach and create artificial boundaries based on Thiessen polygons. While our results are country specific, we believe that our methodology opens a new avenue of research within the Okun's tradition and could be very useful within certain type of spatial units such as cities.

Second, to the best of our knowledge, there is no spatial estimation of the Okun's coefficient for Indonesia at the district level. Moreover, we divide our data into sub-samples for the east and west to account for the existing industrial differences. Our results show the importance of this division for policy purposes as it shows that the sensitivity of the unemployment rate relies on the type of predominant industry.

The remainder of this paper is organized as follows. The next section features a literature review highlighting the most relevant findings and specification on the Okun's law. Sections 3 and 4 make an exploratory analysis of our data and a detailed description of the methodology, section 5 presents the results while the last section concludes.

2 Related literature

The existing literature in the Okun's law is vast and diverse, encompassing different approaches, data sets, countries, and econometric techniques. In his original paper Okun (1963) estimated the empirical relationship between the change in unemployment rate and the percentage change in output using quarterly data for the US over the period 1947-1960. He observed that "For each extra one per cent of GNP, unemployment is 0.3 points lower" evidencing the existence of a three to one trade-off between these variables. Initially, the studies of the Okun's law circumscribed to time series analysis of an entire country; but, new developments in the econometric theory as well as longer data sets enabled researches to estimate this relationship in a variety of alternative specifications most notably panel, spatial, and time-varying coefficients (Kim et al 2021; Elhorst and Emili 2022). In this section we will categorize the most important findings from an empirical perspective that are relevant to our research[1].

The first category are those studies that follow the original "Okun's tradition", that is, a time series analysis on a single country. It is important to mention that initially, the focus was on the value of the coefficient and the strength of the relationship (see Tatom (1981); Friedman and Wachter (1974); Bishop and Haveman (1979)). Eventually, the analysis included the stability and asymmetries of the relationship especially during periods of boom and bust. For instance Knotek (2007); Gordon (2010); Lee (2000); Huang and

[1] For a more theoretical approach see Prachowny (1993) and Attfield and Silverstone (1997).

Chang (2005) noted that the state of the business cycle, the structural changes and the model specification determine how stable are the coefficients. Other studies integrated new developments in time series to perform time-varying and non-linear estimations that generated similar results (Kim et al (2021); Wang and Huang (2017); Cuaresma (2003). On the other hand we have those authors who argue in favor of a robust and stable relationship, although they acknowledge that there might be short-run deviations in the coefficients, they conclude that there is no structural change in the relationship Sögner (2001); Ball et al (2013); Economou and Psarianos (2016); Michail (2019).

A subdivision in this time series category is the use of multiple countries to analyze and compare the responsiveness of unemployment to changes in GDP among different spatial units. Kaufman (1988); Moosa (1997); Goto and Bürgi (2021) are good examples of this type of research. In general, their conclusions are similar in that the unemployment rate in countries with flexible labor markets and higher productivity are more responsive to changes in GDP. Finally, the collection of regional data allowed the analysis of the Okun's coefficient for regions within a country. The advantage of using variables at this level of aggregation is that the institutional differences are minimized, as regions share a common monetary system, legal framework and even cultural aspects; hence, it is easier to focus on other things such as productivity. Blackley (1991); Adanu (2005); Villaverde and Maza (2009); Yazgan and Yilmazkuday (2009); Christopoulos (2004); Kosfeld and Dreger (2006) are all examples of studies at the regional level. Despite the heterogeneity in their samples (different countries, time periods and specifications) most of them pointed at the level of industrialization, local tax policies, and demographics of the labor force as the main reasons for the observed difference in the regional Okun's coefficient.

The second category is panel data which has a few advantages over time series, namely the increase in the degrees of freedom, the efficiency gains from pooling, and the possibility to control for omitted variables at the country (regional) level Baltagi and Griffin (1997); Baltagi et al (2000). In general, the findings are not substantially different to those found under the time series methodology. If anything, these studies confirm the existence of a robust negative relationship between unemployment and GDP, both in the short run, and the long run (Freeman (2001); Huang and Yeh (2013); de Mendonça and de Oliveira (2019); Palombi et al (2015); Furceri et al (2020); Boďa and Považanová (2020))

The third and last category is the spatial modeling of the Okun's law. By explicitly adding spatially weighted variables these studies challenged the reliability and unbiasness of the Okun's coefficient when mechanically applied to regions within a country[2]. The intuition behind the spatial setup is simple, in a well integrated labor market, urban unemployment should be highly dependent on neighboring GDP and unemployment conditions (Montero Kuscevic (2014)); however, as it is well known, the traditional Okun's regression does not consider the effects of spillovers from nearby regions; therefore, while the Okun's equation might be appropriate at the country level, it might not necessarily capture the underlying data generating process at a regional level. In fact, another reason to explicitly model for neighbors' conditions is that failing to do so might result in biased ordinary least squares coefficients as shown by LeSage and Pace (2009).

Most of these studies that fall under the spatial econometric approach coincide in at least two findings. First, the existence of a positive and statistically significant spatial correlation coefficient on the unemployment rate; meaning that, the increase in unemployment in one region is associated with an increase in unemployment in neighboring regions. Second, the Okun's coefficient drops substantially when neighboring GDP is included in the econometric modeling. Actually, the marginal effect of neighbors' GDP is as high (and sometimes even higher) as self GDP on the unemployment rate. These results provide a new perspective of the relationship between GDP and unemployment at a regional level (see Azorín et al (2017); Elhorst and Emili (2022); Villaverde and Maza (2021); Almeida et al (2020)).

As shown by Basistha and Kuscevic (2017); Pereira (2014); Palombi et al (2017) these results are driven by commuting, migration, employment changes and integration in the market for goods and services[3]. From a policy perspective these results show the importance of policy coordination among geographically close regions.

To summarize, there is a consensus about the importance of the specification to determine the Okun's coefficient; furthermore, a rapidly growing literature reveals the problems of using the traditional Okun's approach for the regional analysis, as it omits neighbor's spillovers and interaction, this

[2] Or even to countries with free labor mobility that are part of a monetary union.

[3] There might be other reasons as well. Leguizamon and Montero Kuscevic (2019) show that regional fiscal policy in the US is influenced by neighbor's fiscal policies. This might add another channel of interaction between.

is especially important in markets with high labor mobility and low cultural differences. There are certainly many other research avenues to explore in this relationship, but we will not discuss them due to space limitations[4].

3 Data

3.1 Descriptive statistics

Our original dataset consists of the annual unemployment rate and Gross Regional Domestic Product (GRDP) for 514 districts (kabupaten and kota) in Indonesia over the period of 2008-2020. The unemployment rate is measured as the percentage of unemployment to the number of labor force, while GRDP is measured in constant price of 2010. We compute the change in unemployment rate and GRDP growth for estimating the non-spatial and spatial Okun's law. As a result, our final dataset covers the 2009-2020 for the two variables across 514 Indonesian districts and thus forms a panel of 6168 observations. We use this dataset to estimate Okun's law for the total districts. Then, we subset the dataset into two groups: the west and the east regions. We follow Hill et al (2008) in defining regions for the west and east. The dataset for the west regions covers 282 districts and makes a panel of 3384 observations. On the other hand, 232 districts are included in the dataset for the east and constitute 2784 observations in a panel form. Both data of unemployment rate and GRDP are collected from the Central Bureau of Statistics of Indonesia (BPS in Indonesian acronym).

Table 1 presents the summary statistics of our variables. To closely capture the dynamics of unemployment-output relationship, we divide the descriptive statistics into three different periods: the entire period (2009-2020), pre-crisis of COVID-19 pandemic (2009-2019) and crisis period due to the pandemic (2019-2020). There are a few points worth mentioning. First, a quick glance at the table provides an initial conclusion about Okun's law at the country and regional levels, that is, the existence of of a negative relationship between the changes of unemployment rate and output growth. For example, during the pre-pandemic period, the average unemployment rate of total districts declined by 0.25% per year and output grew by 5.83%; while in con-

[4] For instance, Marconi et al (2016); Hutengs and Stadtmann (2013); Zanin (2014); Montero Kuscevic (2020) emphasize the existence of different Okun's coefficients depending on gender or age groups

trast, the average unemployment rate surged by 1.16% and output dropped by 1.06% per year during the pandemic period. Second, as discussed in the introduction, there are noticeable distinction between the west and east regions. For instance, the average unemployment rate is considerably lower in the east (4.79%) compared that in the west (5.82%). At the same time, the average GRDP growth of the eastern regions is substantially higher than the growth rate in the west (5.86% *vis-à-vis* 4.75%). This regional comparison signifies the standard theoretical concept: unemployment is lower in places where GRDP grows faster. Third, still on the west-east difference, the negative impacts of the COVID-19 pandemic seem to be more prevalent in the west than in the east. Unemployment rate increased by 1.48% on average in the west, while the increment was 0.77% in the east, almost a half of the unemployment rate upswing in the west. Similarly, the deterioration in output was about three times larger in the west (-1.51% per year) *vis-à-vis* in the east (-0.52%). Interestingly, the standard deviation of the output growth in the west is significantly lower (2.13%) than that in the east (4.11%) during the same period. These results might be a signal of discrepancies in economic structures across districts − that shape the dispersed regional impacts of national shocks − have been greater in the eastern region.

Table 1: Summary statistics

Variable	Period	Total		West		East	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
U, %	2009-2020	5.36	3.04	5.82	3.03	4.79	2.96
	2009-2019	5.34	3.07	5.78	3.05	4.80	2.99
	2019-2020	5.55	2.74	6.27	2.76	4.68	2.45
ΔU, % *pt*	2009-2020	-0.13	1.76	-0.13	1.73	-0.14	1.80
	2009-2019	-0.25	1.75	-0.28	1.68	-0.22	1.84
	2019-2020	1.16	1.26	1.48	1.40	0.77	0.94
ΔGRDP, %	2009-2020	5.25	4.07	4.75	2.87	5.86	5.09
	2009-2019	5.83	3.63	5.32	2.19	6.44	4.76
	2019-2020	-1.06	3.21	-1.51	2.13	-0.52	4.11
Observations	2009-2020	6168		3384		2784	

Notes: U and GRDP refer to the unemployment rate and GRDP (output),respectively.
Source: Authors' calculation.

We also offer preliminary results from an analysis of Okun's law, as illustrated in Fig 1. Overall, the scatter plots show evidence of the Okun's law relationship in Indonesia; changes in the unemployment rate are negatively connected with changes in output growth. The link applies to all districts, as well as the western and eastern regions separately. Remarkably, these visualizations reinforce the west vs. east distinction: the slope of the Okun is flatter in eastern regions. More comments will be provided in Section 5 based on the econometric results.

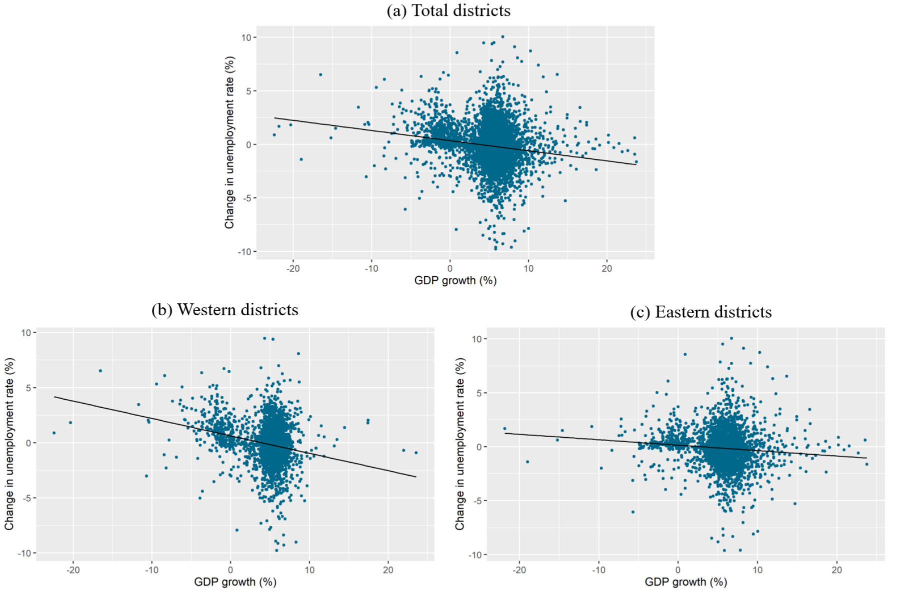
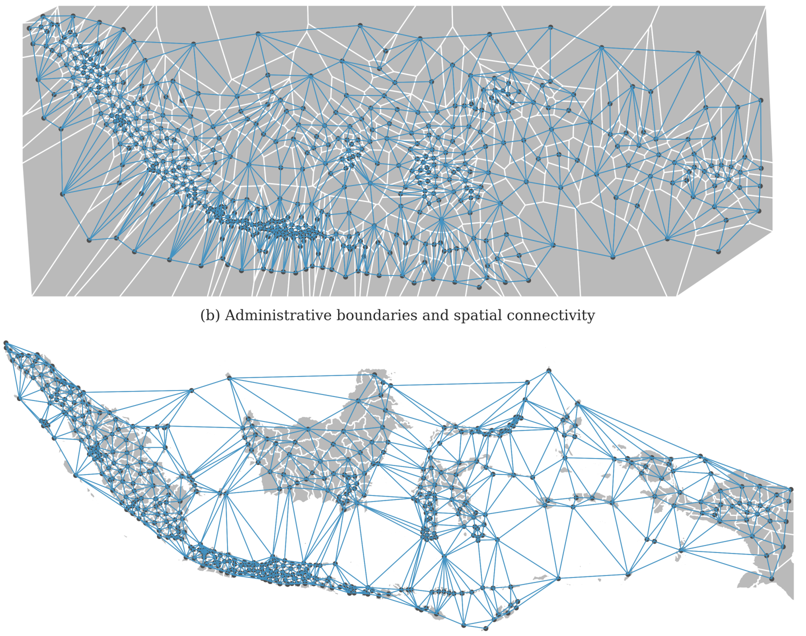


Fig. 1: Non-spatial Okun's law.

3.2 Spatial connectivity structure

We first need to define a spatial connectivity structure across Indonesia's districts to conduct both spatial dependence and spatial regression analyses. This structure, known in the spatial analysis literature as the spatial weight matrix, defines a neighborhood for each region. For this purpose, different criteria are available. Geographical contiguity, distance thresholds, inverse distance, and k-nearest neighbors are among the most commonly used. The archipelago composition of Indonesia, however, constraints the usage of some of these criteria. In particular, the geographical contiguity criteria cannot be directly applied. Consistent with the most recent literature about spatial analysis in Indonesia (Aginta et al 2021; Miranti and Mendez 2022; Santos-Marquez et al 2021), we apply a Thiessen polygon structure to identify each district's neighbors. This criterion has the advantage that incorporates both distance and contiguity to identify the neighbors of each region.



(a) Thiessen polygons and spatial connectivity

(b) Administrative boundaries and spatial connectivity

Fig. 2: Identification of spatial connectivity in Indonesia

Figure 2 shows how the spatial connective structure (panel b) has been defined from the boundaries of a Thiessen polygon (panel a). The dots in the panels indicate the centroids of each of the 514 districts of Indonesia. Administrative boundaries (panel b) in Indonesia are not entirely contiguous due to the presence of islands. Consequently, the Queen contiguity criterion, which is the most common method for determining geographical neighbors, is not directly applicable. Using the computational geometry approach described in Brassel and Reif (1979) and Aurenhammer (1991), it is possible to generate a completely contiguous new polygon structure (panel a) from the original administrative boundary centroids. These polygons are created by computing perpendicular bisectors between every pair of adjacent points. The recent literature on spatial analysis refers to this connected structure and its construction framework as the Thiessen polygon approach (Anselin 2020). In the context of this (derived) polygon structure, it is now possible to identify the neighbors of each region as those who share a common border or a corner. Figure 3 also applies the Thiessen polygon approach to identify the spatial connectivity structure of eastern and western regions separately.

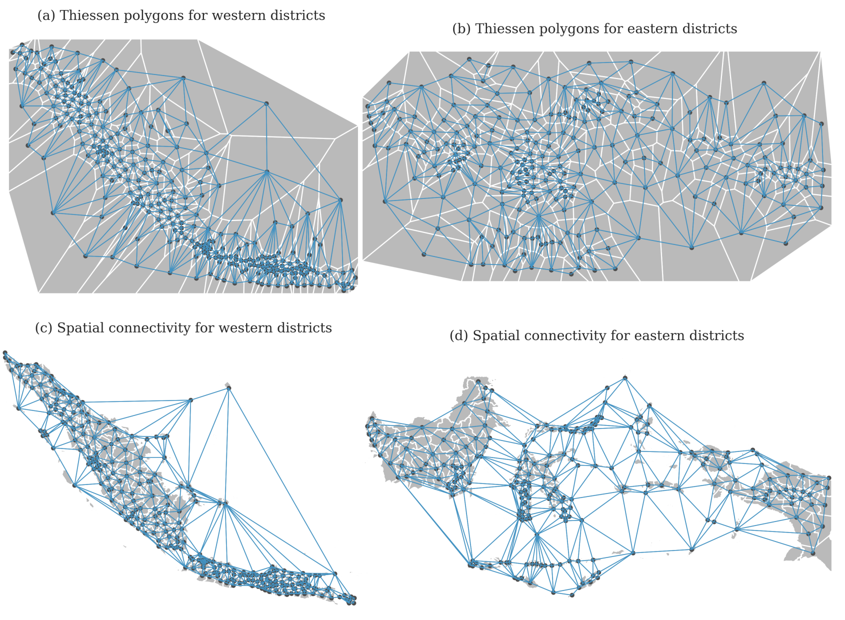


Fig. 3: Identification of spatial connectivity in east and west Indonesia

Notes: The identification of east and west Indonesia is based on the national plan.

4 Methods

4.1 Exploratory spatial data analysis (ESDA)

An ESDA is commonly employed in various spatial analyses to offer an initial assessment of the nature of spatial dependence observed in the data. In short, the spatial dependence analysis combines the concept of attribute similarity with the concept of locational similarity; that is, assessing how similar or dissimilar the neighbors of a location are in the attribute being investigated. The global spatial autocorrelation metric summarizes the degree of attribute and location similarity or dissimilarity, which is evaluated against the null hypothesis of a random location. The rejection of this null hypothesis indicates a spatial pattern or spatial structure, which provides further information about the subject under investigation. Moran's I statistic is arguably the most widely used measure of global spatial autocorrelation (Cliff et al 1981). This statistic is essentially a cross product correlation between a variable and its spatial lag. The spatial lag is computed by means of a spatial weights matrix W. Therefore, Moran's I statistic captures the magnitude of linear association of the value of a variable at one location with the spatially lagged values, i.e., spatially weighted average of values at neighboring locations (Anselin 1995). The Moran's I statistic at a year or point of time t is given by

$$I_t = \frac{N}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \left[\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(X_i - \bar{X}\right)\left(X_j - \bar{X}\right)}{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2} \right] \tag{1}$$

where w_{ij} is an element of spatial weight matrix, which contains the information about the neighborhood structure between the states i and j. w_{ij} is based on binary relationship; it equals one if i and j are neighbors and zero otherwise.

4.2 Spatial regression analysis

As previously mentioned, the ESDA is a good starting point to evaluate the observed spatial dependence in the variables of interest; however, we are usually looking for a more in-depth understanding of the data generating process. On this regard, the spatial regression analysis becomes very helpful and allow us to further scrutinize the spatial interaction observed in the data. Moreover, it also deals with two types of bias estimates, those associated with Ordinary Least Squares and those that derive from ignoring the spatial component of the true data generating process (i.e. omitted variable bias).

While there are many advantages of the spatial regression analysis, there are however some caveats that we need to keep in mind, especially when interpreting the estimated coefficients. Let's take as an example the panel setup for a standard Okun's regression:

$$\Delta U_{i,t} = \beta_1 + \beta_2 \Delta gdp_{i,t} + \epsilon_{i,t} \tag{2}$$

Where $U_{i,t}$ is unemployment rate in province i and period t, gdp is the log of real gross domestic product, and $\epsilon_{i,t}$ is a well-behaved error term. The "Okun's" coefficient in equation 2 has the standard interpretation. But, in a well-integrated labor market with low frictions and only marginal mobility costs, it would be reasonable to expect some sort of regional interaction in the unemployment rate due to commuting and/or labor migration, generating a linear relationship of the form:

$$\Delta U_{i,t} = \rho W \Delta U_{j,t} + \beta_2 \Delta gdp + \epsilon_{i,t} \tag{3}$$

The model in equation 3 is known as the Spatial Autoregressive Model (SAR). It has two main differences compared to the model in equation 2, namely the coefficient rho -bounded in the $(-1, 1)$ interval- that captures the direction and strength of spatial correlation in the dependent variable; and the N $\times$ N row-normalized W weight matrix, usually though not always based on contiguity. The weight matrix is used to construct the vector $W\Delta U$ which consist of the neighbors' weighted average change in unemployment for each region in a given period of time.

There are, however, two potential problems with equation 3. The first and most evident is that OLS estimation will generate biased coefficients due to the simultaneity in the dependent variable; but, this could be solved by the use of maximum likelihood estimators. The second problem is the omission of exogenous spatially autocorrelated variables that could bias our estimates. In our case, the omission of the spatial interaction in the goods market among regions could lead to potential bias of the coefficients[5]. To overcome this problem LeSage and Pace (2009) suggest the use of a Spatial Durbin Model, which differs from the SAR model in the inclusion of spatially weighted exogenous variables and has the following form:

$$\Delta U_{i,t} = \rho W \Delta U_{j,t} + \beta_2 \Delta gdp + \theta W \Delta gdp_{j,t} + \epsilon_{i,t} \tag{4}$$

Finally, while the β coefficient resemble those found in a typical OLS regression, its interpretation is completely different. In fact, it would be meaningless to interpret the coefficients as they are, and it is needed a further decomposition to disentangle the direct and indirect effects.

[5] These interactions could be due to trade, migration or commuting

4.2.1 Direct and indirect effect

To understand the interpretation of the spatial coefficients let us rewrite equation 4 in matrix form and including region and time fixed effects:

$$\Delta U = \rho W_T \Delta U + \beta \Delta gdp + \theta W_T \Delta gdp + \Gamma_t + \lambda_i + \epsilon \tag{5}$$

where $W_T = I_T \bigotimes W$, and $\Gamma and \lambda$ are region and time fixed effect vectors. It is easy to see in equation 5 that the variable ΔU is on both side of the equation, hence, the interpretation of the estimated coefficient in terms of marginal effects become meaningless. However, we can rewrite 5 to obtain the DGP:

$$\Delta U = Z^{-1} \left(\beta \Delta gdp + \theta W_T \Delta gdp + \Gamma_t + \lambda_i + \epsilon \right) \tag{6}$$

The last paragraph is of paramount importance to understand the interpretation of the coefficients in a spatial setup. We can now define the direct effect as the average of the main diagonal elements of $(I_N - \rho W)^{-1} (I_N \beta + \theta W)$, or the change in unemployment rate in a region i given by the change in the GDP in the same region. By contrast, the indirect effect also known as the spatial spillovers is the cumulative effect of the change in GDP in region i on other states. It could be measured by subtracting the direct effect from the total effect, that is by subtracting the average of the main diagonal elements from average sum of the rows of $(I_N - \rho W)^{-1} (I_N \beta + \theta W)$.

5 Results

5.1 Exploratory spatial data analysis

In this sub-section we show and discuss our results from ESDA. We first document the spatial distribution of unemployment rate and GDP in 2020 as seen in Fig 4. It is important to note that the division of districts is generated based on a natural breaks map that groups data using a nonlinear algorithm to maximize within-group homogeneity, as pioneered by Fisher (1958) and Jenks (1977). Essentially, this is a one-dimensional clustering algorithm that determines the break points that produce clusters with the highest within-group similarity.

Generally speaking, we see a spatial clustering pattern unemployment rate and GDP at district level; that is, districts that belong to the same group are neighbors geographically. For instance, the neighbors of districts with low unemployment rates generally also have low rate of unemployment. Similarly, districts with high level of GDP tend to cluster mostly in the more industrialised-western regions. All of these indicate that spatial dependence involves in the data generating process of unemployment and GDP across Indonesian districts.

As mentioned previously, the magnitude of spatial dependence is generally implied by the Moran's I statistic. Therefore, we compute Moran's I for unemployment and GDP for each year from 2008 to 2020 using eq. 1. We further document the evolution of spatial dependence overtime in Fig 5.

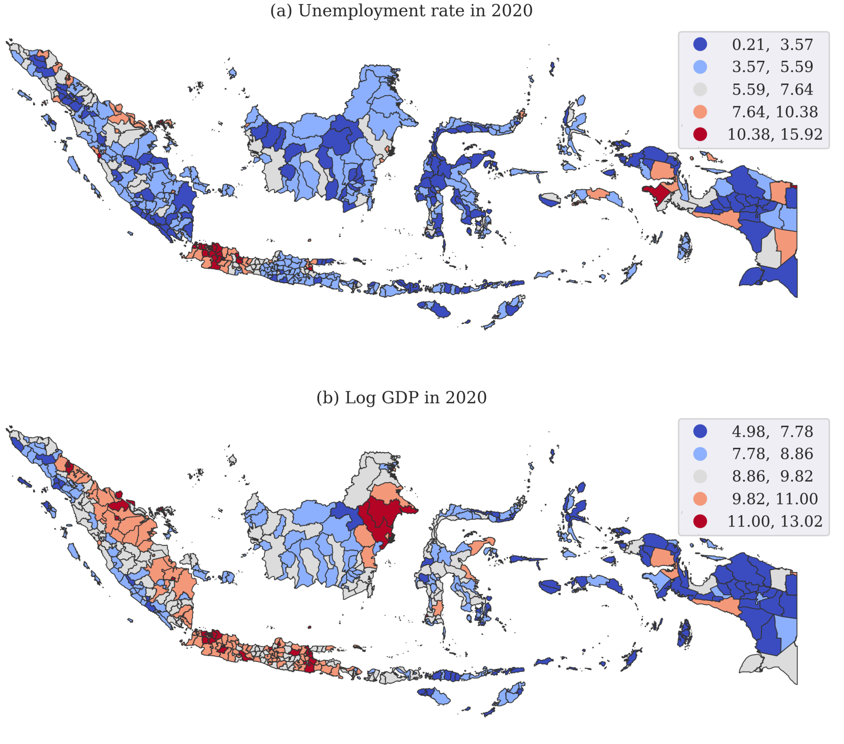


Fig. 4: Spatial distribution of unemployment and GDP

Notes: ADDyourNotesHERE

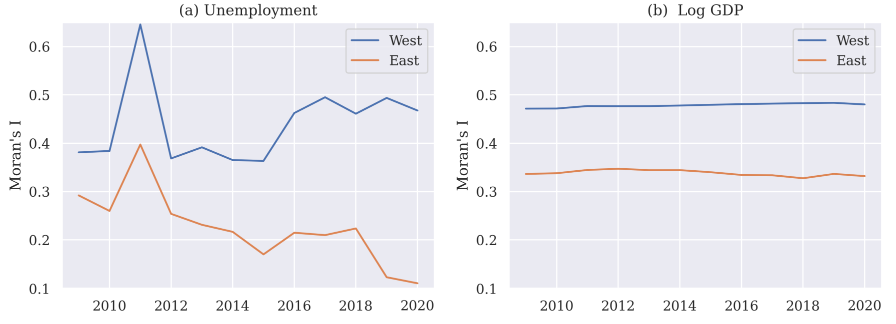


Fig. 5: Evolution of spatial dependence

Notes: ADDyourNotesHERE

5.2 Spatial regression analysis

Table 2 presents the results of estimating equation 2 for all the 514 Indonesian districts, and show evidence of the the existence of an Okun's law, that is, a negative and statistically significant relationship between GDP growth and the change in unemployment rate. However, the estimated values are lower than what is usually found for other countries\regions in the empirical literature; in fact, these results are rather unusual if we consider that the Okun's coefficient is in absolute terms around 0.3, hence we need to delve deeper into the data and explore the reasons behind this low sensitivity of unemployment to changes in GDP.

Table 2: Okun's law estimates: Non-spatial panel for all districts

Variables	Pooled OLS	District FE	Time FE	District and time FE
GDP growth (%, yoy)	-0.044***	-0.057***	0.003	0.002
	(0.005)	(0.006)	(0.006)	(0.007)
Constant	0.098***	0.164***	-0.317***	-0.312***
	(0.036)	(0.041)	(0.083)	(0.088)
Observations	6,168	6,168	6,168	6,168
Number of districts	514	514	514	514
R-squared	0.010	0.014	0.078	0.079

Notes: The dependent variable is the annual change in the unemployment rate of 514 districts during 2009-2020 period. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1. Source: Authors' estimates.

As previously mentioned, there is a clear difference in per capita GDP between eastern and western Indonesian regions, besides, the productive structures are also different, with the East being more rural and agricultural, while the West being more industrialized and technological-oriented. This is not a minor issue, because as many authors have shown[6], the industrial structure might affect the coefficient, therefore, we divide our data into these two regions with distinct industrial structure and and re-estimate equation two.

Table 3 presents the estimation of the Okun's coefficient using only the eastern (mostly agricultural) districts. While results show a negative relationship between the variables, the coefficients are even lower than before, more precisely, they are only one third of the coefficients estimated for all the districts (see Table 2). Interestingly, when we use data for the western districts the outcome is completely different. Table 4 shows that the estimated coefficients for the West are as much as three times higher than the estimates for all the 512 districts and around eight times higher than those found for the eastern provinces and reported in Table 3. These results show that the relatively low Okun's coefficients obtained in Table 2 are mostly driven by the eastern provinces.

Table 3: Okun's law estimates: Non-spatial panel for East districts

Variables	Pooled OLS	District FE	Time FE	District and time FE
GDP growth (%, yoy)	-0.015**	-0.020***	0.007	0.008
	(0.007)	(0.008)	(0.007)	(0.008)
Constant	-0.045	-0.018	-0.195	-0.200
	(0.052)	(0.058)	(0.124)	(0.132)
Observations	2,784	2,784	2,784	2,784
Number of districts	232	232	232	232
R-squared	0.002	0.003	0.060	0.061

Notes: The dependent variable is the annual change in the unemployment rate of 232 districts in the east during 2009-2020 period. Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Authors' estimates.

The unresponsiveness of unemployment to GDP growth in the East can be explained by the inelastic labor supply. As pointed by Jayachandran (2006) agricultural economies with workers close to subsistence tend to have a more inelastic labor supply; furthermore, for the specific case of Indonesia, Franken-

[6] See Blackley (1991); Adanu (2005) among others

berg et al (2003) presented evidence of an inelastic individual labor supply, supporting the low coefficients previously reported for the East. Additinally, agricultural employment as a share of total employment in Indonesia has been steadily decreasing due to the mechanization of the agricultural fields from 55% of total employment in the early nineties to 30% three decades later. Finally, we are not taking into account the possible existence of spillovers from/to neighboring districts in both the labor and the goods markets. Estimating these spillovers with the appropriate spatial models explained in the previous section could give us a better understanding of the response of unemployment to GDP growth.

Table 4: Okun's law estimates: Non-spatial panel for West districts

Variables	Pooled OLS	District FE	Time FE	District and time FE
GDP growth (%, yoy)	-0.121***	-0.148***	-0.019	-0.032**
	(0.010)	(0.011)	(0.013)	(0.016)
Constant	0.441***	0.569***	-0.329***	-0.259**
	(0.056)	(0.062)	(0.118)	(0.130)
Observations	3,384	3,384	3,384	3,384
Number of districts	282	282	282	282
R-squared	0.041	0.051	0.112	0.114

Notes: The dependent variable is the annual change in the unemployment rate of 282 districts in the west during 2009-2020 period. Standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Authors' estimates.

Results in Table five show the estimation of a Spatial Durbin Model (equation 3) for all the 512 districts. The SDM reveals very interesting features of the data that are worth mentioning. First, the spatial correlation coefficient ρ is always positive and statistically significant meaning that regions with a high unemployment rate are -in average- surrounded by other regions with a high unemployment rate and vice versa, signaling the importance of the spatial modeling in a well integrated labor market. Second, the direct effect is negative and statistically significant showing that -as expected- an increase in GDP in a given region is followed by a decrease in the unemployment rate in the same region. Third, the indirect effect is also negative and statistically significant implying that for any given district, an increase in the neighbors' average GDP is associated with a decrease in unemployment rate in the said district. Finally, the total effect, which for our purposes is the real Okun's coefficient, is also negative and statistically significant, but more importantly, it is at least twice the size of the coefficient found in table two.

Table 5: Okun's law estimates: Panel Spatial Durbin Model for total districts

Variables	No FE	District FE	District and time FE
GDP growth (%, yoy)	-0.009	-0.011	0.003
*W*GDP growth (%, yoy)	-0.068***	-0.089***	-0.008
ρ	0.241***	0.226***	0.142***
Direct effect	-0.012**	-0.015**	0.003
Indirect effect	-0.090***	-0.115***	-0.009
Total effect	-0.102***	-0.130***	-0.006

Notes: The dependent variable is the annual change in the unemployment rate of 514 districts during 2009-2020 period. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1. Source: Authors' estimates.

Tables 6 and 7 show the results of estimating an SDM for the eastern and western districts respectively. Just as with table five, the ρ coefficient is positive and statistically significant, however the spatial dependence is higher in the West indicating more integrated markets than the eastern districts, a result that confirms our results in the exploratory data analysis and summarized in figure 5. The total effect is also higher in the western districts corroborating our previous findings that unemployment is more responsive in the West than in the East. It is remarkable that the Okun's coefficient for the West under the SDM is now closer to what is usually found in the literature.

Table 6: Okun's law estimates: Panel Spatial Durbin Model for East districts

Variables	No FE	District FE	District and time FE
GDP growth (%, yoy)	-0.004	-0.005	0.007
*W*GDP growth (%, yoy)	-0.039***	-0.050***	0.013
ρ	0.157***	0.148***	0.035
Direct effect	-0.005	-0.007	0.007
Indirect effect	-0.046***	-0.058***	0.014
Total effect	-0.051***	-0.064***	0.021

Notes: The dependent variable is the annual change in the unemployment rate of 232 districts in the east during 2009-2020 period. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1. Source: Authors' estimates.

A common result in our estimations is the large size of the indirect effect, which in fact is always larger -in absolute terms- than the direct effect. This apparently odd result is quite common in the spatial Okun's specifications and is explained by the systematic interconnection in the labor and goods markets. In other words, our results indicate that the unemployment rate in any given district is heavily dependent on the national labor market conditions as well as on the national business cycle.

Table 7: Okun's law estimates: Panel Spatial Durbin Model for West districts

Variables	No FE	District FE	District and time FE
GDP growth (%, yoy)	-0.013	-0.01	-0.003
WGDP growth (%, yoy)	-0.120***	-0.145***	-0.068**
ρ	0.273***	0.256***	0.179***
Direct effect	-0.019	-0.018	-0.005
Indirect effect	-0.163***	-0.191***	-0.081**
Total effect	-0.182***	-0.209***	-0.086***

Notes: The dependent variable is the annual change in the unemployment rate of 282 districts in the west during 2009-2020 period. Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1. Source: Authors' estimates.

6 Concluding remarks

In this study we estimated the Okun's Law for Indonesian districts over the period 2009-2020. Given the geographical isolation of the spatial units in the archipelago, we defined the relevant neighbors using Thiessen polygons instead of the more popular inverse distance. This novelty in an Okun's setup allow the use of spatial units that do not necessarily share a common geographical border such as cities or metropolitan areas.

Overall, our results reveal the existence of an Okun's relationship in Indonesian districts. However, when the data is split into eastern and western districts, the Okun's coefficient appear to be considerably higher in the more industrialized western districts than in the more agricultural eastern regions, providing support to the the hypothesis that agricultural economies have a more inelastic labor supply.

Additionally, our results using Spatial Durbin Models detected the presence of a positive spatial correlation in unemployment and a high dependence of unemployment to neighboring conditions. These results have important policy relevance as they imply the need for policy coordination among districts.

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