Contagious Turnout during Infectious Pandemic: A Spatial Analysis

DRAFT

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Election bears spatial dimension when it meets infectious pandemic. General public suspects that the rise of infections after the election might relate to how the election was conducted. But, how about if this "cliche suspicion" does not happen, i.e., electoral participation does not contribute to the rise of Covid-19 infections. There are cases when an election is held during a heyday of life-threatening health risks. Still, electoral adjustments and special voting arrangements, including early voting, postal voting, proxy voting, home voting, and polling station arrangements, as documented by Asplund et al. (2021) and colleagues, are absent. In a setting of a voluntary voting system, why did some voters vote and others did not during the pandemic? While a large number of scholarships on voter turnout address individual-level behavior and system-level factors, does space and location matter in explaining the turnout in a time of crisis? Thus, this paper addresses the effect of Covid-19 on electoral participation rather than the reverse.

By incorporating spatial econometrics Anselin (2007) into the model specifications, this paper tries to uncover how location and space affect human behavior in voter turnout. As a pilot project, this research examines the mayoral election in Surabaya city, Indonesia, held in December 2020. While turnout in 2015 (51%) and 2010 (44%) were also relatively low, more people in 2020 (53%) came to polling stations when infectious viruses threatened the whole population. In a crisis, a high percentage of electoral participation in a voluntarily voting system seems counterintuitive.

Yet, the proximity of spaces and locations that approximate the extent to which social interactions occur might explain such a political behavior. The findings suggest that electoral participation is "infectious," relative to the Covid-19 virus when elections were held during the pandemic. This paper argues that the contagion of turnout in such a time of crisis is arguably a result of neighboring effects. The imitation/diffusion theory of the neighboring effect explains the counterintuitive case in Surabaya and other places where turnout is higher in times of crises than that in a regular election before the pandemic.

This paper will be delivered as follows. The first section surveys central premises about the effects of institutional arrangement on turnout that may and may not work in a time of the pandemic. The following section provides some possible models that arguably work for turnout theory. Third, I propose the spatial approach of turnout that may explain an increase in turnout during the pandemic. Then, I elaborate on the data and method outlining my empirical strategy on spatial econometrics. Lastly, I report the results, followed by a discussion.

1 Institutional Arrangement and Turnout

Literature on voter turnout suggests several drivers and perspectives that explain the macro and microfoundation of voter turnout. At the macro-level theories, system-level variables and institutionalist's points of view are the central premises. Some models of the micro-level models, including scholarships from utility maximization of a rational actor and political mobilization models, are linked to the macro-level variables. Other individual-level models, such as habitual, motivational, and citizen-duty variables (see Cebula, Durden, and Gaynor 2008; Aldrich, Montgomery, and Wood 2011; Dinas 2017), obviously explain voter turnout but they are not directly connected with the effect of institutional arrangements.

Institutional arrangement and administration are some of the other oceanic literature on turnout. As the "big picture of electoral turnout" (Vowles (2017)), many authors in this area suggest that electoral system affect turnout where proportional representation electoral system (hereafter, PR system) (Bormann and Golder 2013) and compulsory voting (Blais 2000; Franklin 1999; Geys 2006). Geys (2006) argue that the effect of compulsory voting on turnout is one of the robust findings. A meta-analysis by Stockemer (2017, 705) nevertheless finds that some studies do not support the positive relationship of PR system. Yet, proponents of the PR effect argue that districts are more competitive due to the nature of multimember districts. Large campaigns and political mobilization from a large number of the candidates increase turnout (for initial study, see Blais and Carty 1990).

However, such system-level variables are impossible to adjustment in a crisis. Instead, administrative arrangements are plausible in a time of crisis. In this regard, we deal with electoral management and administration of voting and polling station as the driver of turnout. Comparative electoral administration addresses a voting engineering mainly in the forms of voting by mail and early or absentee ballot voting. For instance, Gerber, Huber, and Hill (2013) provide evidence that all-mail elections improve turnout by about 2-4 percentage points. Gronke and Miller (2012) even find that the increase of turnout by mail is about ten percentage points (for a similar case, see also Richey 2008; Southwell and Burchett 2000; Karp and Banducci 2000).

Meanwhile, the distance of polling stations has been vastly examined across elections and countries (see Cantoni 2020; Dyck and Gimpel 2005). Others find that accessibility and location of polling stations also convey a significant relationship (Schur, Ameri, and Adya 2017; Brady and McNulty 2011; Orford et al. 2011). The significant association of distance and location of the polling station with turnout suggests that the spatial dimension of electoral management matters in turnout.

These studies, nevertheless, do not address how such administrative arrangements of voting and polling sites operate in the context of pandemics or crises. Furthermore, some studies have documented the adverse effects of Covid-19 on turnout (see, for instance, Haute et al. 2021; Noury et al. 2021; Nwankwo 2021). Nonetheless, they are not sensitive to how electoral administrative arrangements and electoral politics intersect with the nature of infectious pandemics where geographical proximity of the virus affects political participation. Moreover, studies investigating the effect of the institutional properties of election during the pandemic (see Pettigrew 2021), especially polling sites, do not specify spatial components (measures and parameters) into their model specification.

2 Turnout in A Time of Crisis

In a crisis, electoral adjustment is only feasible when it is politically and logistically gratuitous. Changing electoral systems and the related properties, such as ballot structure and electoral formula, is politically costly as the change will directly affect the electoral gains. Shifting an in-person ballot to other types of a distance voting, such as e-voting and voting by mail (postal voting), can be regarded as politically feasible. Yet, such special adjustments of voting require extensive resources, ranging from infrastructure, staffing, security issues and cost. An archipelagic country such as Indonesia will be extremely difficult to address postal voting during a pandemic as a prolonged crisis.

Because of the constant mode of in-person voting, electoral battle remains on the ground during the voting day. At the same time, voters are haunted by the Covid-19 proximity in their neighborhood by keeping an eye how a crowd may occur in the polling sites. Thus, we have three possible cross-sectional models that relate to voter turnout during the pandemic: administrative adjustment, political mobilization, and proximity of crisis.

2.1 Administrative Adjustment: Polling Site's Population Size

Under the absence of convenient (or distance voting), engineering polling stations by enlarging their number, so lowering the size of voters in each polling site than usual elections, is a plausible electoral adjustment. Though it looks simple, reducing population size is arguably pre-empt the overcrowding of voters on election day; the crowd is a critical issue during the infectious pandemic. Though most studies agree with the negative effect of population size on turnout (Geys 2006, 642), the competing debate remains in the homogeneity thesis. They argue that a smaller size of population that generates homogeneous society increases turnout as group solidarity and feasible linkage between politicians (or political leaders) and voters foster people to vote (Kostadinova and Power 2007). However, in a time of crisis, population size relates to the extent to which voters expect their health risk. People are cautious when overcrowded in the polling site is expected. All these institutional arrangements and adjustments return to the theoretical premise of the cost of voting. Drawing on this notion, this model argues that the larger size the polling site's voter population, the lower the turnout.

2.2 Proximity of Crisis: Covid-19 Infections

Following Downsian rational-choice model, the proximity of crisis (i.e., the extent to which Covid-19 infections occur in the neighboring area) affects political participation. This mechanism is similar to the population size model. As pioneered by Downs (1957), rational-choice model has been employed extensively to explain behavioral premises of voter turnout. This model, nevertheless, is hardly ever to link with institutional factors such as administrative arrangements of how an election is held. It primarily suggests the idea of the cost of voting or "calculus of voting" derived from the utility function from rational-choice theory (see Aldrich and Jenke (2017)). In addition, the role of information distribution is also under this model (Feddersen and Pesendorfer (1999)). For instance, though Morton et al. (2015) estimate the effect of exit poll information on the decreasing turnout, they suggest that exit poll information also increases bandwagon voting. Similarly, in the case of the Covid-19 pandemic, a voter is expected to stay at home when any type of distance voting is absent, as people hesitate when surroundings are infectious. Based on the cost of voting related to helth risks, this model suggests that the higher the infection, then the lower turnout.

2.3 Close Election: Political mobilization

An election is somehow a political contest among candidates (or parties) that situate them to compete by mobilizing voters to vote for their electoral gain. Other than pandemic-related arguments, thus, political mobilization model may give us an enduring theory of voter turnout, either in normal or crisis circumstance. Political mobilization theory relates to the idea of a close election. By close election, it means that when there are two competing candidates who contest competitively, indicated mostly by a small vote margin, the likelihood the voters cast their votes is higher than an election under uncontested candidates or non-competitive race (Cann and Cole 2011; Grofman 1995; Indridason 2008; Simonovits 2012). Close election situates candidates to mobilize voters and media to report more coverage regarding the contesting candidates, which boost people to vote. Based on their massive field experiment, Green and Gerber (2019) documented several campaign approaches of get-out-the-vote techniques that foster turnout, including mail, postcard, and in-person visit (canvassing) increase turnout (Gerber and Green 2000, 2005). Though they find null finding on phone-call, Imai (2005), based on replication of Gerber and Green's field experiment data, maintain that phone-call does positively affect on turnout. As a close (or competitive) election indicates the extent to which the candidates mobilize voters, this model suggests that a competitive electoral district has a higher turnout than that of non-competitive electoral constituency.

Lastly, demographic characteristics have been crucial variables that possibly confound those models. Demographic characteristics, such as income and education, have always been inevitable variables in explaining voter turnout (Plutzer 2017). For instance, a high level of education and literacy rate is linked with electoral participation Diwakar (2008). In short, we need to control for these variables should we examine those three models.

3 Contagious Turnout: A Spatial Model

The cross-sectional models elaborated earlier, nevertheless, are contingent on the context where social interactions occur. Therefore I propose an alternative theory that explains turnout beyond a time of pandemic: contagious turnout. This theory potentially addresses a set of questions posed earlier, based on the counterintuitive case: why turnout in a time of crisis increases. I contend that the decision-making of turnout is 1) a product of turnout in the neighboring areas or 2) other unobserved variables that situate turnout decision due to the variables' spatial dimension. In spatial econometrics (Anselin and Florax 1995; Anselin 2007), the former mechanism refers to a spatial lag dependence model and the latter constitutes a spatial error model; that I will elaborate on the econometrics behind these models later. For now, I focus on substantive premises that explain the contagious turnout.

As turnout is contagious, we may expect that turnout is spatially clustered or structured, e.g., there will be a high turnout in one geographic area and a low turnout in another region. Though the school of thought in spatial analysis provides several mechanisms that explain spatial patterning (see, for instance, Voss et al. 2006; Cho and Rudolph 2008), I contend that the contagious nature of turnout is more driven by two mechanisms. . First, it is an imitation/diffusion mechanism that emphasizes multi-directional interactions. The second mechanism relates to an external-force mechanism that situates turnout as a response for such forces, including political mobilization and group responses.

Regarding the imitation mechanism, explicit and implicit interactions operate in electoral participation. Explicit (direct) interactions lead to information distribution that affects turnout (Feddersen and Pesendorfer (1999)). In terms of implicit interaction, low-intensity interaction where political participation is a result of casual observations of the surroundings, such as yard signs, stickers, or flags (Cho and Rudolph 2008). In the case of turnout during pandemic, people are prone to perceive that the risks are minimal when they see voting goers crossing their neighborhood area. Merkley et al. (2022) suggest that safety precautions explain in-person turnout during the pandemic. Nevertheless, because of spatial proximity, explicit interaction (e.g., verbal conversation) or implicit causal observation by seeing people come to polling sites reduces such safety precautions, driving voters under such interactions turnout. This is why this mechanism is also referred to as neighboring effects.

One may suspect that today's digital environment challenges the spatial clustering of such political interactions due to distance interactions. Yet, in cases where voters must attend polling sites due to the absence of distance voting administration, information and interactions that operate either offline or online most likely concern the risk of attending polling sites during the infectious pandemic. Attending polling sites resembles imitation and diffusion of neighboring effects as people get out to vote as their neighbors do so. Once voter turnout is spatially clustered and structured, we conclude that this spatial effect occurs.

Related to the second mechanism, spatial structure of turnout can be driven by various forces, but political forces and group response are potential major forces. In terms of f political mobilization, candidates will strategically target specific areas where large number indifferent (swing) voters are expected and "social networks may develop in response to mobilization" (Cho 2003, 370). Accordingly, political interactions occurring between candidates (or the campaign team) and potential voters potentially generate spatial structure. As an elite-driven process of social interaction, political mobilization at the battlegrounds where a close (competitive) election is likely to occur is expected to drive geographical clusters of interactions (see Rosenstone and Hansen 1993; Cho and Rudolph 2008).

Furthermore, the external-force mechanism is also a product of group responses (Voss et al. 2006) and inter-group interaction (Cho and Baer 2011). At the micro-level view, individuals living in the same area share common attributes or characteristics, such as geographical conditions, labor practices, or industrial structures, where these characteristics situate people to "respond similarly to external forces" (Voss et al. 2006, [376]). Meanwhile, social organizations and informal commonality at the neighborhood level may also generate a uniform response (in an aggregate measure) in the way how people participate in an election. Individual interactions, in turn, create a group response at the space dimension, which produces a spatial clustering in the context of contagious turnout.

Putting all these altogether, once we find a conclusive spatial pattern of turnout, that indicates that contagious turnout operates during the pandemic. It also means that the three cross-sectional models may not be supportive enough to explain the rise of turnout in a time of crisis. In order to prove whether cross-sectional or contagious theories operate in the time of pandemic, the next section elaborates on data and method.

4 Data and Method

4.1 Data

This study examines data based on Surabaya Mayoral Election, Indonesia, held in 2020. To be sure, the election was contested by two candidates who, to some extent, made the case suitable to examine the models. Other than data availability and research feasibility, the municipal administration provides Covid-19 aggregate data on a daily basis regarding its 154 village-level units. This data juxtaposes with mayoral-election data provided by Indonesian General Election Commission which is also at village-level units. The third data set on demographic characteristics (education and income), i.e., a 2000-respondent exit poll data set from my previous project (see Budi 2021), complement the two key datasets.[1]

In addition, in the case of aggregate-level studies, a small unit of electoral constituencies, such as the village-level unit, may uncover such spatial patterning of social-political interactions. It is because neighborhood politics and social interactions occur among

[1] The exit poll project covers all 152 villages proportionally with minimal 10 respondents. Therefore, two villages are not covered in the exit poll project due to its very small size of the voter population. As my village-level aggregation of this data may embody a statistical artifact, I am still trying to seek village-level demographic profiles that might be provided by a Statistics Bureau.

voters at the village level where polling sites are administered, Covid-19 infection cases are registered and reported, and the votes are contested.

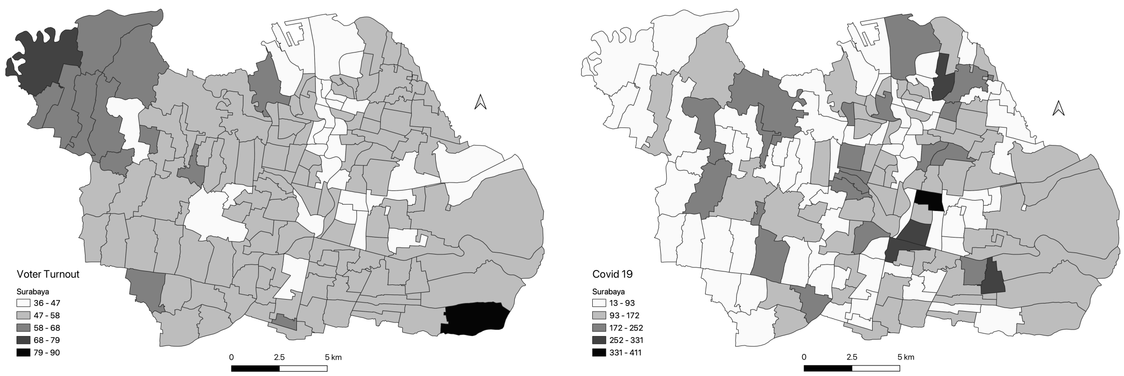

Figure 1: Voting during Covid-19 Pandemic in 2020 Surabaya Mayoral Election

Figure 1 shows the spatial distribution of Covid-19 infection cases in the left-side map and electoral participation in the right-side map. We see that the voter turnout is relatively high, indicated by 50% or more turnout, in the northwestern villages, while the distribution of Covid-19 infection cases is also relatively low, marked by ten or more minor cases, in the region. At a glance, these maps give us a sense that the relationship between turnout and Covid-19 pandemic is negatively associated. Though this interpretation is premature as we need to investigate further the spatial models, the distribution of Covid-19 and turnout relates to the results and analyses elaborated later.

4.2 Variables

I define voter turnout, the dependent variable, as a percentage of the number of total votes by total registered voters. I acknowledge that other authors employ voting age population as the denominator, rather than the registered voters. Yet, the village-level data only provide an official record of the registered voters. Besides, the number of the registered voters is presumably slightly the same as that of the voting-age population.[2]

To examine the cross-sectional models, I develop several explanatory variables. The first explanatory variable, i.e., the average voter population size in each polling site, deals with the number of polling stations and the total number of voters. I expect that higher turnout occurs in villages with smaller polling sites' population sizes. For the political mobilization thesis, approximated by close election, the other independent variable addresses the difference between the number of voters gained by the two candidates. Thus, the smaller the contrast of the votes indicates a high level of competitiveness, approximating extensive mobilization in the given village. Lastly, the

[2]There is a procedure where individuals who are able to prove their state ID are eligible to vote even though they are not registered in the electoral data base. In addition, the Indonesian General Commission have validated their data in several ways before the voting day to make sure all the eligible residents are registered.

proximity of Covid-19 refers to the rise of the infection cases one week before the election. The rise of infection cases sets the alarm to the voters not to take their health risk by attending polling sites. I also control for demographic profiles, especially education and income, though this paper's data on demographic covariates are subject to change. I report these variables in Table 1.

Table 1: Descriptive Statistics of the Variables

Statistic	N	Mean	St. Dev.	Min	Max
Voter Turnout	154	50.90	5.93	36.41	89.63
Polling Site's Population Size	154	402.70	16.00	339.00	442.50
Covid-19 Proximity	154	3.46	3.30	0	17
Competitiveness	154	1210.00	965.10	10	4607
Income (Aggregate)	152	0.26	0.18	0.00	0.75
Education (Aggregate)	152	0.19	0.18	0.00	0.88

$*$ Obervations are village-level units

4.3 Method

My empirical strategy heavily employs spatial econometrics (see Anselin 1995, 2006, 2013) by addressing data on hundreds of village-level units in Surabaya. The underlying assumption is that the units are not independent since social interactions are inevitable. Thus, spatial approximation, known as spatial weight matrix, is necessary to measure the extent to which the interactions occur and affect the resulting behavior of voter turnout. In this regard, I employ first-order queen contiguity for the spatial weight matrix (W). The relatively small data set of 154 villages situates this paper to apply first-order contiguity rather than second-order contiguity. Moreover, queen contiguity here aims to have all the surrounding village neighbors, even those that share a small magnitude of borderlines.[3]

Based on that basic logic, assessing the randomness of the observations scattered across spaces and locations is imperative. In many instances, the spatial patterning is a result of demographic groups living in the nearby area (see Cho and Gimpel 2010). Autocorrelation, computed mostly through Moran's I statistics, is a stochastic method that gauges the spatial randomness of observations, i.e., whether the units' variable of interest is spatially clustered/structured or random. In other words, once we find a significant positive coefficient of the Moran's I statistics, we may *temporarily* conclude that voter turnout is spatially correlated (clustered), i.e., a high (or low) turnout in one village is associated with a high (or low) turnout in its surrounding villages. Global Moran's I Statistics is computed as follows.

[3] Results from rook contiguity also generates similar coefficient of the global Moran's I test statistics as the difference is about 0.001.

$$I = \left(\frac{n}{\sum_i \sum_j w_{ij}} \right) \left(\frac{\sum_i \sum_j w_{ij}(x_i - \mu)}{\sum_i (x_i - \mu)^2} \right) \tag{1}$$

where i and j index the spatial units of which there are n, w_{ij} is an element of a row-standardized spatial weights matrix, x is the percent of turnout, and μ is the average percentage of turnout in the sample.

While we are equipped with the statistics to assess spatial patterning across all the village-level units, the Local Moran's I, or local indicators of spatial autocorrelation (LISA), are able to show the spatial clustering of turnout between the neighboring units. This test statistic is computed as follows.

$$I_i = \left(\frac{z_i}{\sum_i z_i^2} \right) \left(\sum_j w_{ij} z_j \right) \tag{2}$$

where z is the mean-deviated form of the percent of turnout in particular villages.

Once we find a positive and significant result in the Moran's I statistics, i.e., an indication of spatial patterning of voter turnout, we need to specify the spatial autoregressive models. The models, primarily investigated through spatial lag dependence or spatial error models, estimate the spatial effects of the variable of interests or the error relating to any omitted (unobserved) variables that are spatially correlated on voter turnout. The spatial lag dependence model is computed as follows.

$$y = \rho W y \ + \ X\beta \ + \varepsilon \tag{3}$$

where y is a vector that represents the dependent variable of voter turnout, W is an n $\times$ n spatial weights matrix, ρ is the spatial autoregressive constant to be estimated, X is the explanatory variables with β as the coefficients, and ε is the error term. Meanwhile, we seek whether there is an error that relates to spatial attributes of any omitted variables through the following spatial error equation.

$$y = \ X\beta \ + \epsilon \tag{4}$$

and

$$\epsilon = \lambda W \epsilon + \varepsilon \tag{5}$$

where λ is the spatial lag parameter to be estimated and the other terms are similar to the equation (3). As we are not sure whether spatial lag or spatial error models explain the spatial patterning of turnout regarding our variables of interest, Lagrange Multiplier (LM) test statistics are employed to determine the model that generates a significant result.

The spatial autocorrelation and autoregressive statistics have been applied across disciplines that take spatial effects into account (see, for instance, Baller and Richardson 2002; Voss et al. 2006). Given the nature of the spatial analyses and the geospatial data, I employ a series of data processing in R, GeoDa, and QGIS software.

5 Results

5.1 Contagious Turnout: A Comparison

Figure 2 shows that the electoral participation (the left plot), approximated by the percentage of voter turnout, is even more "infectious" than the virus shown on the right plot. This comparison is not intended to test the theory I have proposed earlier. Rather, a comparison between turnout and Covid-19 spatial autocorrelations is to demonstrate the extent to which turnout is contagious. As displayed on the left-hand side of Figure 2, the turnout is significantly spatially associated ($p < .05$). Though the autocorrelation coefficient r (.390) is not high, indicated when $r > .50$, the plot clearly shows that high turnout in one village has a link with a high turnout of the neighboring villages, and vice versa. In other words, turnout is not spatially random as the Moran I's statistics indicate the presence of spatial patterning.

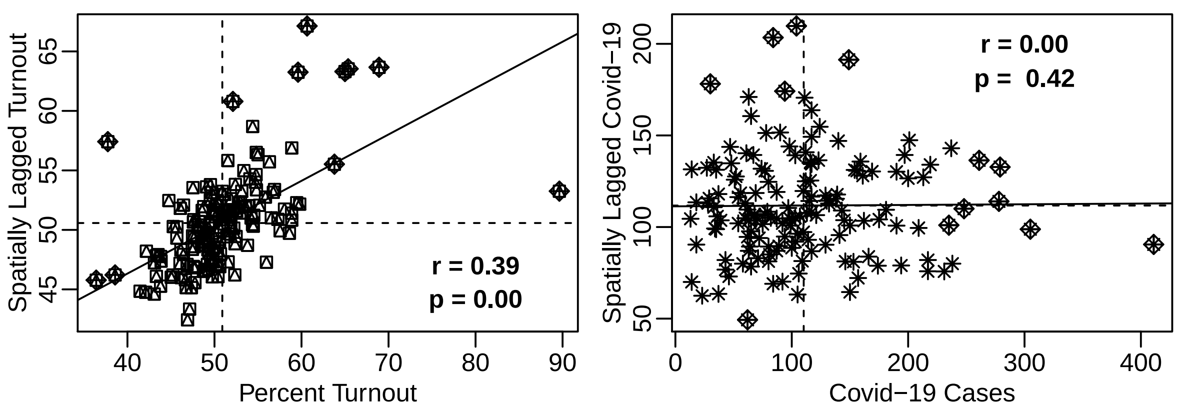

Figure 2: Global Moran's I Statistics of Voter Turnout Percentage and the Covid-19 Infection Cases A Week before Voting Day

In contrast, the Covid-19 infections before the mayoral election are not strongly spatially clustered with a very low autocorrelation coefficient r (.004). In other words, infections in one village are not strongly associated with infections in other villages. The insignificant result of the Covid-19 cases is a surprising finding. But, epidemiologists, including the Indonesian government, suggest that family-based cluster of infections have massively taken place in 2020 (see Soedarsono 2020). This result of autocorrelation of the Covid-19 infections seems to confirm such claims. The spatial patterning, or spatial clustering, becomes more evident when we see the spatial mapping of the local Moran's statistics.

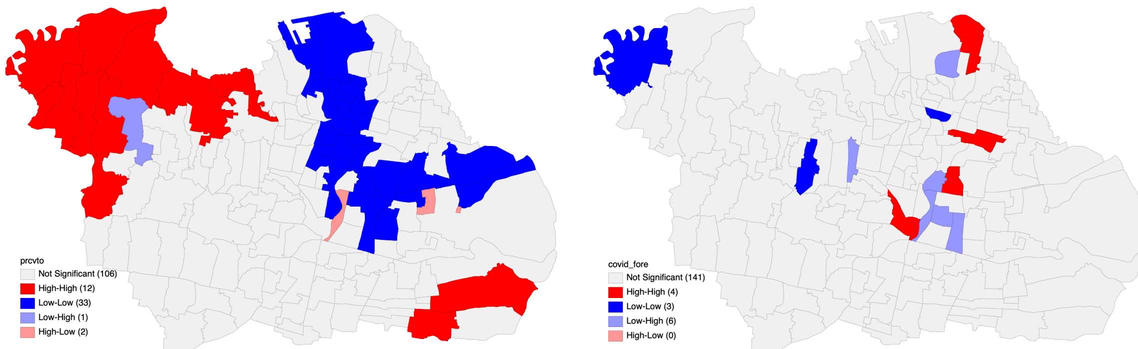

Figure 3: Local Moran's I Statistics of Electoral Participation and Covid-19 Infection Case

The maps in Figure 3 show an apparent spatial clustering of voter turnout in the left-hand map, relative to the cases of Covid-19 infections. With significantly high-high and low-low autocorrelations, the high voter turnout of 12 villages and the low voter turnout of 33 villages are clustered in the west and in the middle north-east part of the city, respectively. On the contrary, we do not find spatial patterning of the Covid-19 infection as massive as that of the electoral participation.

Furthermore, suppose we return to the left-hand map of Figure 1. In that case, the clustering of the high turnout in the western part of the city seems to fit the epidemiologist's expectation of the low infection of the western region, relative to the low turnout in the southern part of the city. However, the low turnout in the middle north-eastern part does not meet our low infection expectations. Villages with a low infection rate are expected to have a cluster of high turnout. This spatial patterning of turnout leads us to investigate further possible factors, including proximity of Covid-19 infections, that situate people to come to polling stations.

5.2 Spatial Models of Turnout

Table 2 reports spatial autoregressive (spatial lag dependence) models in columns 1-3.[4]. It also reports the standard regression (Ordinary Least Square) model in model columns 4-6 to examine the cross-sectional models of turnout. As attached in Appendix A, theThe Lagrange Multiplier (LM) diagnostics, as attached in Appendix A, show that both LM for error and lag dependence models are significant with p-value<.05. However, robust LM diagnostics display that spatial lag model is more statistically significance (p-value = .1) than the spatial error model (p-value = .5). I report all the regression statistics for the sake of transparency and clarification.

Though the statistical significance across the models is the same as those in the standard regression models, the point estimates and standard errors differ (reduced or

[4]The spatial models are computed in R where GeoDa also reports exactly the same results.

corrected) when we specify spatial parameters into the model. Spatial models assume that observations are not independent as the interactions occur between units due to their spatial dimensions. In the models, they are defined as a spatial weight matrix, i.e., a measure for spatial closeness estimated by sharing borders.

The spatial parameters (ρ) shown in the Spatial Lag row clearly suggest that spatial lag dependence occurs in turnout. Across the three models, the coefficients of the spatial lag are significant ($p < 0.05$) with 0.6065, 0.6098, 0.6003 for the first (crisis proximity), second (close election), and third (administrative adjustment) models, respectively. The significant result of the spatial lag dependence model conforms to the theory of contagious turnout. Turnout is a result of neighboring effects where effects are a product of either explicit/implicit social interactions of the diffusion theory or by external-force mechanisms of the group response theory. Under the absence of convenient (distance) voting, people who come to vote at the polling sites are mainly driven by turnout decisions among their neighbors. This mechanism conforms to the two-dimensional and multi-directional nature of spatial autocorrelation. Diffusion occurs when the resulting interactions affect each other across multiple neighbors.

In terms of the cross-sectional OSL models, the results suggest that Covid-19 proximity in Model 1-2 shows negative coefficients. This result at a glance follows the theoretical expectation that turnout decreases when the number of infection cases in the neighborhood is high. Nevertheless, these estimates are not statistically indistinguishable, so we are not sure whether voters follow such a theoretical direction. Political mobilization, approximated by the level of competitiveness (close election or the margin of votes between candidates), even does not show any sign of our expectation. This result suggests that pandemic proximity and political variable do not explain why voters vote (or not) during the pandemic.

More importantly, population size at the polling sites in Model 5-6 clearly explains the voter turnout ($p < .05$). Its negative coefficients in both the original and lagged variables (-0.060) meet the theoretical expectation that turnout in a large polling site's population size is low when the population size at the polling site contributes is relatively large. An increase in population size at the polling site contributes to a decrease in turnout since people are cautious when an overcrowded is expected as the result of their neighboring interactions. But again, this cross-section model is not sufficient to explain the rise of turnout during the pandemic.

Table 2: Spatial Autoregressive Models of Voter Turnout∗

	Voter Turnout					
	spatial autoregressive			**OLS**		
	1	**2**	**3**	**4**	**5**	**6**
Covid-19 Proximity	−0.092			−0.117		
	(0.123)			(0.145)		
Competitiveness		0.0002			0.0001	
		(0.0004)			(0.0005)	
Polling Site's Population			-0.060^{**}			-0.061^{*}
			(0.026)			(0.031)
Income	4.678^{*}	4.620^{*}	4.605^{*}	6.884^{**}	6.768^{**}	6.803^{**}
	(2.422)	(2.420)	(2.379)	(2.852)	(2.856)	(2.817)
Education	−2.883	−3.133	−2.943	−3.046	−3.352	−3.171
	(2.470)	(2.449)	(2.410)	(2.907)	(2.889)	(2.854)
Constant	22.090^{***}	21.340^{***}	45.640^{***}	50.050^{***}	49.630^{***}	74.190^{***}
	(4.497)	(4.501)	(11.560)	(0.924)	(1.045)	(12.490)
Spatial Lag	0.6065***	0.6098***	0.6003***			
N	152	152	152	152	152	152
R-squared				0.041	0.037	0.061
Adj. R-squared				0.021	0.017	0.042
Log Likelihood	−463.200	−463.300	−460.900			
Residual Std. Error (df = 148)				5.790	5.802	5.728
F Statistic (df = 3; 148)				2.094	1.878	3.200^{**}
Wald Test (df = 1)	42.640^{***}	43.540^{***}	44.450^{***}			
LR Test (df = 1)	34.710^{***}	35.120^{***}	36.060^{***}			
AIC	938.400	938.700	933.800			

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

∗ Obervations are village-level units

6 Discussion

This paper has shown that electoral participation is not randomly scattered as the way how people come to vote at the polling sites is spatially structured. This clustering suggests that turnout is contagious. Based on the result of the spatial lag model, the contagious turnout stems from the neighboring effects where social interactions and group responses occur due to the nature of multi-dimensional and multi-directional influences of the observations. The result explains the counterintuitive case as shown in Surabaya and other places where voter turnout increases in elections held during the pandemic, relative to those in elections held before the pandemic when convenient voting procedures (e.g., early, electronic, or postal voting) are even absent. Voters potentially imitate and influence each other because of their spatial proximity, reassuring themselves that voting is safe.

Though we cannot rely merely on the cross-section models, this paper also finds that population size is linked to voter turnout at a polling site. However, political mobilization and Covid-19 proximity do not explain the electoral behavior. This result suggests that feasible but simple institutional adjustment of electoral management in a time of crisis is critical. The voters' cautiousness on the polling site's population size predicts turnout during the pandemic, rather than the political competition at the battleground or the proximity of the Covid-19 infection cases.

This study contributes to two broader debates. First, turnout during pandemic needs to be investigated in the context of crisis. One strategy is by specifying spatial dimension into the models in order to seek the neighboring effects on turnout. Distance, location, and other measures of spatial proximity are essential when people are heavily concerned with physical measures of the infectious pandemic. Second, it also contributes to the literature on institutional effects on turnout. Administrative adjustments still matter in explaining turnout in a time of Covid-19, rather than a political and direct measure of pandemic variables. Thus, this study may have policy implications on the way how elections are held during the pandemic.

Nevertheless, it might be premature to suggest that such results are robust for two reasons. First, the village-level unit of analysis may not explain social interactions on the ground, compared with, say, neighboring block-level units (known in Indonesian as *Rukun Warga* or RW). Second, the models only rely on the key variables. Regarding the first concern, narrowing down the unit of analysis may help generate more convincing results due to two reasons. First, a polling site represents a number of RW-level units where the residents are registered to vote. So, the assumption of social interactions among individuals behind the spatial model specifications has an actual basis. Second, narrowing down into neighboring blocks generates much larger observations that may also contribute to the law of large numbers in statistics. RW-level units in Surabaya, for instance, cover more than 1000 blocks where the inhabitants are administratively and spatially clustered. Therefore, we may have more say to draw and explain the spatial analyses.

Related to the second concern, I wonder whether the lack of necessary covariates, specifically demographic profiles, is a critical limitation in this study. Note that the current paper merely employs aggregate demographic data based on the individual-level study of exit poll survey which may convey statistical artifact or ecological fallacy. Demographic variables, or other omitted variables, are most likely to be potential confounders since demographic characteristics have always been inevitable variables in explaining voter turnout (Plutzer 2017). The available data only addresses sub-district demographic profiles, whereas the village-level demographic characteristics are necessary for model specification. For instance, level of education and income may affect the estimates of the effect of the variables of interest. People in villages with a high level of education or income are arguably more hesitant to come to the polling station (low turnout) when the proximity of crisis (Covid-19 infection cases) is high. Thus the next research agenda is to complement these data types with lower-level units and include the relevant variables into the model specifications.

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8 Appendix A: Lagrange Multiplier Diagnostics

Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = prcvto ~ coviddiff + incomepr + edupr, data = dat) weights: datweight

LMerr = 45, df = 1, p-value = 0.00000000002

```
Lagrange multiplier diagnostics for spatial dependence
```

data:
model: lm(formula = prcvto ~ coviddiff + incomepr + edupr, data = dat) weights: datweight

RLMerr = 0.4, df = 1, p-value = 0.5

```
Lagrange multiplier diagnostics for spatial dependence
```

data:
model: lm(formula = prcvto ~ coviddiff + incomepr + edupr, data = dat) weights: datweight

LMlag = 47, df = 1, p-value = 7e-12

```
Lagrange multiplier diagnostics for spatial dependence
```

data:
model: lm(formula = prcvto ~ coviddiff + incomepr + edupr, data = dat) weights: datweight

RLMlag = 2.6, df = 1, p-value = 0.1