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Article

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Estimating Crowd: Electoral Adjustment and Spatial Effects of Turnout During Covid-19 Pandemic

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Abstract: While extensive scholarship has examined determinants of voter turnout, spatial dimensions of turnout – particularly during crises – remain understudied. This article investigates the rise in voter turnout during the 2020 mayoral election in Surabaya, Indonesia, one of the largest elections held amid the peak periods of Covid-19 infection. Utilizing spatial econometric models, it analyzes how geographical proximity to Covid-19 cases and electoral adjustments to reduce polling station crowding shaped voter behavior. The findings indicate that spatial effects, approximated via spatial autoregressive models, contributed to higher turnout during the pandemic. Moreover, electoral adjustments – specifically reductions in polling site population size – significantly influenced turnout. Although spatial effects were also observed in pre-pandemic elections, their magnitude increased during the pandemic. These results suggest that simple administrative interventions can reshape voters' calculus during a public health crisis, offering insight into how turnout may evolve under exceptional circumstances.

Keywords: turnout; voting; spatial effect; Covid-19 pandemic; electoral adjustment

1 Introduction

A substantial body of research on voter turnout focuses on individual-level behavior and system-level factors (for comprehensive overviews, see Geys 2006; Smets and Van Ham 2013). While most of these studies examine turnout in the context of routine electoral cycles, some elections have occurred during periods of severe public health crises. In such exceptional circumstances, electoral adjustments and special voting

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arrangements – such as early voting, postal voting, proxy voting, home-based voting, and modifications to polling stations – are often implemented to mitigate risk, as documented by Asplund et al. (2021). However, in some settings, including the one examined in this study, such accommodations were largely absent. Under a voluntary voting system, why did some individuals choose to vote while others abstained during a life-threatening pandemic? Specifically, does proximity to the crisis affect voter turnout during an infectious disease outbreak? Alternatively, do administrative features – such as how the election is managed and whether adjustments are made – better explain voters' decisions? To explore these questions in the context of the Covid-19 pandemic, this paper investigates the extent to which spatial factors influence voter turnout during a public health crisis.

By incorporating spatial econometric techniques (Anselin 2007) into the model specifications, this article seeks to examine how geographic location and spatial context influence voter behavior. Empirically, the study focuses on the 2020 mayoral election in Surabaya, Indonesia, held in December of that year. While voter turnout was relatively low in previous elections – 51 % in 2015 and 44 % in 2010 – the 2020 election saw an increase to 53 %, despite the widespread threat posed by a highly infectious virus. Notably, in several other countries that held elections during the Covid-19 pandemic – such as Mexico, Iceland, and Nicaragua – turnout was even higher than in comparable pre-pandemic elections.[1] In a crisis, a high percentage of electoral participation in a voluntarily voting system is counterintuitive.

However, the proximity of physical spaces and locations – approximating the extent of social interactions – may help explain such political behavior. The findings indicate that electoral participation can be "infectious," even when compared to Covid-19 case levels during the pandemic-era elections. Notably, based on spatial autoregressive models, this paper argues that turnout contagion during a crisis is largely attributable to neighboring effects. The imitation or diffusion theory underlying these neighboring effects offers a compelling explanation for the counterintuitive rise in turnout observed in Surabaya and other locations, where participation increased during the pandemic compared to previous, non-crisis elections. Specifically, electoral adjustments designed to reduce crowding and limit excessive physical interactions on election day are found to have a statistically significant impact on turnout.

This study contributes to two broader scholarly debates. First, it underscores the importance of analyzing voter turnout within the context of a public health crisis. One productive approach is to incorporate new explanatory variables – absent from conventional elections – such as crisis proximity and administrative adjustments,

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1 See International IDEA turnout database. Data section below provides elaborative exploration of turnout during the pandemic across countries.

which may significantly influence participation under exogenous conditions. Second, it advances the study of turnout by explicitly incorporating spatial dimensions into the modeling strategy, thereby revealing neighboring effects that are particularly salient when physical contact is a concern.

The structure of the paper is as follows. The first section reviews key theories on the influence of institutional arrangements on turnout, evaluating their relevance during the pandemic. The subsequent section presents models that are likely to capture turnout behavior under crisis conditions. A third section introduces the spatial approach as a framework to explain increased turnout during the pandemic. This is followed by a description of the empirical strategy and presentation of the results, with concluding discussion thereafter.

2 Institutional Arrangement and Turnout

Literature on voter turnout suggests several drivers and perspectives that explain voter turnout's macro and micro-foundations. In the macro-level theories, system-level variables and institutionalist 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 et al 2008; Aldrich et al 2011; Dinas 2017), obviously explain voter turnout but they are not directly connected with the effect of institutional arrangements.

Institutional arrangement or administration are one of the other oceanic literatures 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) are applied. 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 between the PR system and turnout. 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 candidates increase turnout (for initial study, see Blais and Carty 1990).

However, such system-level variables are impossible to be adjusted in a crisis due to the political costs and time constraints. 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 mainly addresses voting engineering in the forms of voting by mail, early voting, or absentee ballot voting. For instance, Gerber et al (2013) provide evidence that all-mail elections improve turnout by about 2–4 percentage points. Gronke and Miller (2012) even find that the increase in turnout by mail is about 10 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 et al 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 the geographical proximity of 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, such as the measures and parameters, in their model specification.

3 Turnout in a Time of Crisis

Electoral adjustment is only feasible in a crisis 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 distance voting, such as e-voting and voting by mail (postal voting), can be regarded as politically feasible. Yet, such ballot-delivery adjustments require extensive resources, ranging from infrastructure, staffing, security issues, and cost. In archipelagic countries, moreover, it will be extremely difficult to address postal voting during a pandemic as a prolonged crisis.

Because of the constant mode of in-person voting, the electoral battle remains on the ground during voting day. At the same time, voters are haunted by the Covid-19 proximity in their neighborhood by keeping an eye on 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.

3.1 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 in a polling station arguably pre-empts the overcrowding of voters on election day as a 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 a population that generates a 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, and people are cautious when an overcrowded 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 hypothesizes that:

H1: "The larger size the polling site's voter population, the lower the turnout."

3.2 The 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) arguably affects political participation. This mechanism is similar to the population size model. As pioneered by Downs (1957), the rational-choice model has been employed extensively to explain the behavioral premises of voter turnout. This model, nevertheless, is hardly ever linked 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 of 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 health risks, we may propose a pandemic model of turnout as follows.

H2: "The higher the infection, the lower the turnout."

3.3 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, the political mobilization model may give us an enduring theory of voter turnout, either in normal or crisis circumstances. 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 mainly by a small vote margin, the likelihood the voters cast their votes is higher than in 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 boosts 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) to increase turnout (Gerber and Green 2000, 2005).[2] As a close (or competitive) election indicates the extent to which the candidates mobilize voters, this article hypothesizes that:

H3: "A competitive electoral district has a higher turnout than that of a non-competitive electoral constituency."

Lastly, demographic characteristics have been crucial variables that possibly confound those models. Demographic characteristics, such as gender, age, 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). Additionally, age potentially plays critically in a time of pandemic where elder voters are susceptible to such a circumstance. In short, we also need to control for these variables should we examine those three models.

4 Contagious Turnout: a Spatial Model

The cross-sectional models elaborated earlier, nevertheless, are contingent on the context where social interactions occur. Therefore, this article proposes an alternative theory that explains turnout beyond a time of pandemic: contagious turnout. As turnout is contagious, we may expect that turnout is spatially clustered or

2 Though they find a null finding on phone-call, Imai (2005), based on replication of Gerber and Green's field experiment data, maintains that phone-call positively affects turnout.

structured, e.g., there will be a high turnout pattern in one geographic area and a low turnout pattern 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 to such forces, including political mobilization and group responses.

Thus, the decision-making of turnout implies either 1) a product of turnout in the neighboring areas or 2) other unobserved variables that situate turnout decisions 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 – the Method section elaborates on the econometrics behind these models later. Therefore, hypothesis of these two spatial models of turnout are as follows:

H4: "Turnout in an electoral constituency is spatially correlated with either turnout in its neighboring areas or other unobserved variables."

Regarding the imitation mechanism, e.g., a high turnout in one electoral area is due to a high turnout in its neighboring areas, explicit and implicit interactions operate in electoral participation. Explicit (direct) interactions lead to information distribution that affects turnout (Feddersen and Pesendorfer (1999) spatially. 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 the 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 observing people coming to polling sites reduces such safety precautions, driving voters under such interactions to turn out to vote. 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 remote 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 a spatial effect occurs.

Related to the second mechanism, e.g., a high turnout in an electoral area is due to unobserved variables that spatially affect turnout in the electoral area, the spatial structure of turnout can be driven by various forces, but political forces and group response are potential major forces. In terms of political mobilization, candidates will strategically target specific areas where a large number of 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 prospectively 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 spatial clustering in the context of contagious turnout.

Taken together, 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 during the time of the pandemic, the next section elaborates on data and methods.

5 Data and Method

5.1 Data

This study examines data from the Surabaya mayoral election in Indonesia, held on December 9, 2020. Turnout in previous elections – 51 % in 2015, 44 % in 2010, and 48 % in 2005 – was consistently lower than in the 2020 pandemic election, which reached 53 %. This increase is counterintuitive given the global health context: the World

Health Organization (WHO) declared a Covid-19 outbreak on January 30, 2020, and officially categorized it as a global pandemic on March 11, 2020. Covid-19 vaccines were not available until late 2020 and were distributed globally only in 2021. Therefore, elections conducted between March 2020 and early 2021 occurred during the peak of the global crisis – a critical period of the Covid-19 pandemic.

Analyzing turnout in elections held during this critical period allows the study to contextualize the 2020 Surabaya mayoral election. Examining turnout trends across countries provides empirical insights into global patterns of electoral participation during the pandemic and positions Surabaya's case as distinctive. To that end, this study utilizes turnout data from 2,390 national elections compiled by International IDEA. Among these, 24 countries held elections between March 2020 and January 2021. With the exceptions of Romania and Anguilla, most of these elections were held on or after January 1, 2021 – having been postponed from earlier dates that would have coincided with the pandemic's most critical period. It is important to note that International IDEA records only national-level elections; local elections, such as the one held in Surabaya, are not included.

Drawing from these "pandemic elections," the study compares turnout in two electoral cycles for each of the 24 countries: one held during the critical period of the Covid-19 pandemic and one just prior to it. As shown in the boxplot in Figure 1, the global average turnout during the pandemic period was lower than in the immediately preceding elections. This makes the increased turnout in Surabaya particularly noteworthy. The accompanying dot plot illustrates that the number of countries

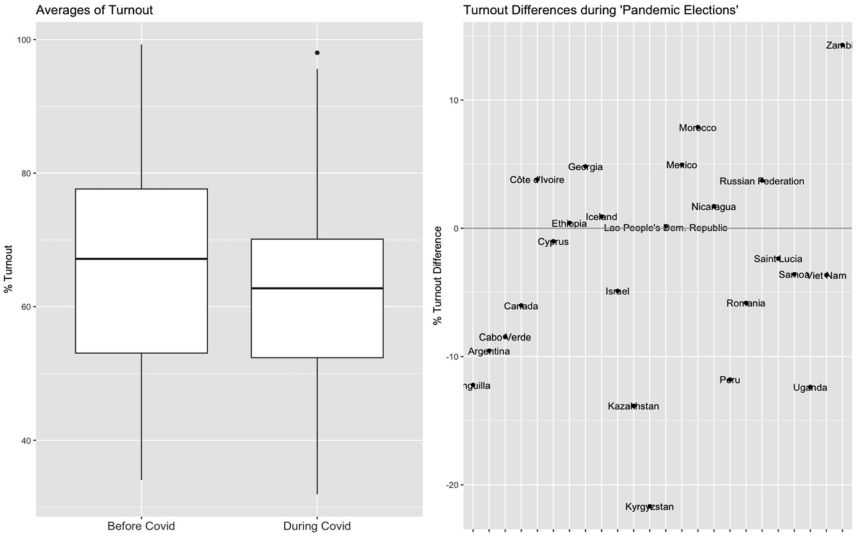

Figure 1: Differences of turnout across elections held before and during the critical period of Covid-19 pandemic.

experiencing a decline in turnout (i.e. percentage differences below the zero line), such as Canada, Israel, Peru, Argentina, and Uganda, significantly exceeds the number of countries – such as Mexico, Morocco, Iceland, and Nicaragua – where turnout during the pandemic exceeded pre-pandemic levels (i.e. percentage differences above the zero line).

Therefore, investigating an increase of turnout in 2020 Surabaya municipal election provides an exemplary notion on how we explain an increase of turnout during a time of crisis. In this regard, the election was contested by two candidates who, to some extent, made the case suitable to examine the models. Furthermore, credited as the second largest city after Indonesian capital Jakarta and as the capital of the second largest province East Jawa in Indonesia, Surabaya is a melting-pot megapolitan inhabited by more than three million people. With Indonesian threshold of poverty rate ($2 USD per day income), only about 4–5% Surabaya households that are at poverty level in 2020 based on Indonesian Statistics Bureau. This figure is considerably low relative to other cities or global poverty (about 9 % or more). In addition to unavailable village-level economic data, this low economic disparity helps anticipate empirical examinations from economic confounders.

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 complement the two key datasets. As this research also fielded data collection on the ground by visiting mayoral and sub-district offices for village-level data and validation, these are the most updated data in 2020 and 2021.

In addition, in the case of urban villages as aggregate-level units, an urban village (*kelurahan*) is a small unit of electoral constituencies that may uncover such spatial patterning of social-political interactions. It is because neighborhood politics and social interactions occur among voters at the village level where polling sites are administered, Covid-19 infection cases are registered and reported, and the votes are contested.

Figure 2 shows the maps of the spatial distribution of Covid-19 infection cases on the right-hand side and turnout on the left-hand side. 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 10 or more minor cases, in the region. At a glance, these maps give us a sense that the relationship between turnout and the Covid-19 pandemic is negatively associated spatially. As this interpretation might be premature, we need to investigate further the spatial models examining the distribution of Covid-19 and turnout elaborated later.

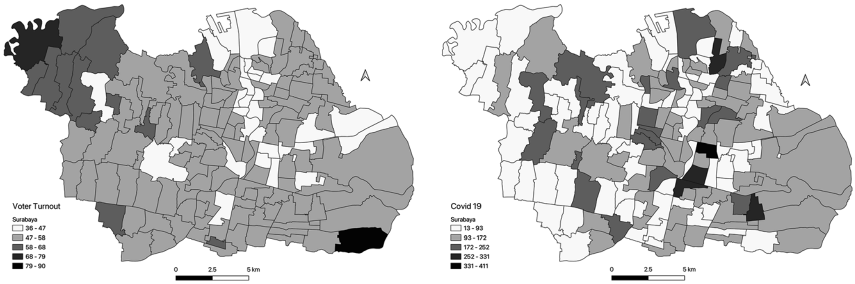

Figure 2: Voting during the Covid-19 pandemic in 2020 Surabaya mayoral election.

5.2 Variables

Voter turnout, the dependent variable, is defined as the percentage of total votes cast relative to the number of registered voters. While some scholars use the voting-age population as the denominator, the available village-level data include only official records of registered voters. Moreover, the number of registered voters is presumed to closely approximate the voting-age population at the village level.[3]

To examine the cross-sectional models, several explanatory variables are developed. The first explanatory variable – the average number of voters per polling station – captures the relationship between the total number of polling sites and the total number of registered voters. This variable is central for approximating the electoral adjustment made in response to the Covid-19 pandemic. In the Indonesian context, the maximum number of voters per polling station was reduced from 800 in pre-pandemic elections to 500 stations during the pandemic, reflecting an institutional effort to reduce crowding on election day.

For the political mobilization thesis, approximated by close election (competitiveness), 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. Relatedly, the proximity of Covid-19 refers to the rise of the number of infection cases one week before the election. The increase in infection cases sets the alarm to the voters not to take their health risks by attending polling sites.

3 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.

The analysis includes several control variables that may confound the relationship between explanatory factors and voter turnout. The age composition of each administrative unit is considered, as villages with a higher proportion of older residents – who are more vulnerable to Covid-19 – may exhibit lower turnout rates compared to those with a younger demographic profile. Specifically, the proportion of inhabitants aged 50 and above is calculated for each village.

Gender composition is also included as a control variable, measured by the ratio of males to females. Villages with a greater proportion of male residents are theoretically expected to exhibit higher turnout. Additionally, educational attainment is accounted for, drawing on the resource model of political participation, which posits that individuals with higher levels of education are more likely to vote. The variable is operationalized as the proportion of residents in each village who have attended higher education.

Finally, the number of religious places of worship is included, with mosques being the predominant type across villages. These institutions often function as centers of political socialization and community engagement, which can facilitate political mobilization and increase voter turnout. Descriptive statistics for all control variables are presented in Table A1 of Appendix A.[4]

5.3 Methods

My empirical strategy heavily employs spatial econometrics by addressing data on hundreds of urban village-level units in Surabaya. The underlying assumption of spatial econometrics is that the units are not independent as social interactions are inevitable (see Anselin 2007; Anselin and Florax 1995). 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 type of data set of 154 village-level units that share their borders for relatively short distances situates this paper to apply first-order contiguity rather than second-order contiguity. Moreover, queen contiguity here is aimed to have all the surrounding village neighbors, even those that share a small magnitude of borderlines.[5]

4 The author is aware that micro-level geolocational variable (i.e., coordinate) is a reliable spatial measure but no data on voter's or polling locations is available and feasible to be constructed. Yet, this paper also reports geographically weighted regression results based on computed centroids stemming from the given shape file of Surabaya city.

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

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, and otherwise. Global Moran's I Statistics is computed as follows.

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

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 the turnout, and μ is the average turnout percentage 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) is able to show the spatial clustering of turnout between the neighboring units. This test statistic is computed as follows.

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

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

Once we find a positive and significant result in Moran's I statistics, i.e. an indication of spatial patterning of voter turnout, we need to specify the spatial autoregressive models. The models estimate the spatial effects of the variable of interest or the error relating to any omitted (unobserved) variables that are spatially correlated with voter turnout. As I theoretically suggest that turnout effects are local rather than global, i.e. turnout in an urban village affects more its neighboring villages rather than all villages in Surabaya, Spatial Durbni Error Model (SDEM) is pursued through the following equations.[6]

6 Though we may investigate spatial effect through spatial lag dependence or spatial error models followed by Lagrange Multiplier to test the proper model, I jump to the nested spatial regression model where local effects are theoretically reliable for turnout. Yet, I tested the spatial Durbin error model (SDEM) for restriction to the simpler models (SLX and SEM) where the result suggests remaining in SDEM. Appendix provides the statistical tests on this model selection.

$$y = X\beta + WX\theta + u \tag{3}$$

and

$$u = \lambda Wu + \varepsilon \tag{4}$$

where y is a vector that represents the dependent variable of voter turnout, W is an $n \times n$ spatial weights matrix, 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. λ is the spatial lag parameter to be estimated. Note that a likelihood ratio test has been conducted to investigate whether SDEM should be restricted to a simpler model, e.g., Spatial Error Model (SEM). Appendix provides the test result of the model selection.

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). In addition, I at first draw Ordinary Least Squares and counterfactual models based on the observed variables to show how spatial models differ from the "regular models" when we specify spatial weighted matrix into our model specifications. Note that this article also reports results from geographical weighted regression (GWR) beneficial to statistically explore the tests. Though geolocational variables specifying longitudes and latitudes (coordinates), either voter's or polling site's locations, that are necessary for GWR are not available, centroids (the middle points of an area, i.e. each urban village based on its border line) are able to be computed.[7] Given the nature of the spatial analyses and the geospatial data, I employ a series of data processing in R, GeoDa, and QGIS software.

6 Results

6.1 Contagious Turnout

Figure 3 shows that turnout in the election during the pandemic (2020) and the one before the pandemic (2015) are significantly spatially correlated ($p < 0.05$). Note that both autocorrelations are approximated by the percentage of voter turnout where some squared dots in both plots indicate neighboring correlations of turnout between the neighboring villages. This means that the plots clearly show that a high turnout in one village has a link with a high turnout in the neighboring villages and

7 Different from GWR that requires coordinates as the basis for spatial weighting, spatial models – including various autoregressive models and autocorrelations – do not necessarily require geolocational data such as coordinates.

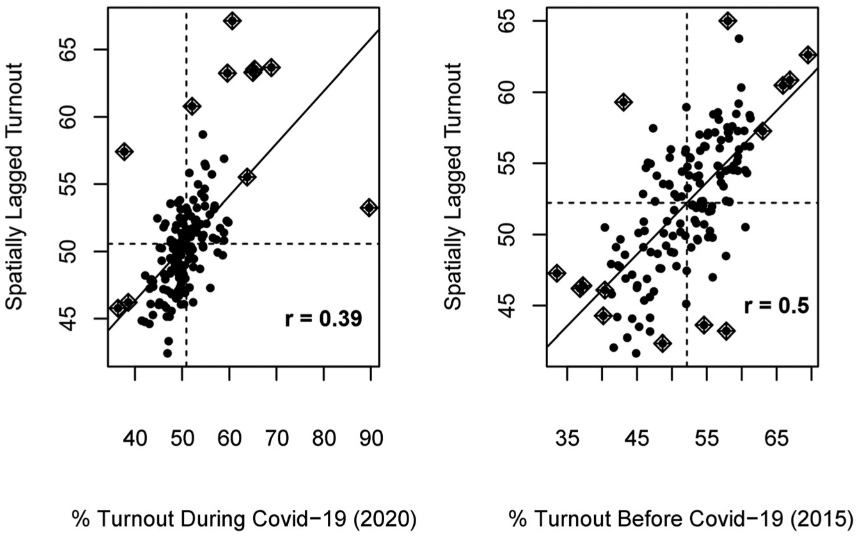

Figure 3: Global Moran's I statistics of voter turnout in the pandemic election (December 2020) and the pra-pandemic election (2015).

vice versa. The quadratic plots of autocorrelations in Figure 2 show four relationships between turnouts of neighboring villages, i.e. high-high turnouts on the upper-right, low-low turnouts on the lower-left, high-low turnouts on the upper-left, and low-high turnout on the lower-right areas. In other words, turnout is not spatially random as the Moran I's statistics indicate the presence of spatial patterning indicated by their positive coefficients (direction of the autocorrelation).

However, a closer look shows that the autocorrelation coefficient of turnout during a pandemic ($r = 0.390$) is lower than that in the 2015 mayoral election indicated by $r = 0.50$. These Moran's I statistics suggest that turnout has been already contagious, and even at a higher level, before the pandemic. People in regular elections before a pandemic have no constraints to have encountered, and political mobilizations on the ground are arguably more massive than those during pandemic elections. In order to clarify this possible explanation, Local Moran's I, also known as local indicators of spatial autocorrelation, abbreviated as LISA, gives us a more detailed picture of how the spatial patterning of turnout occurred between the 2020 and 2015 elections.

First of all, the maps in Figure 4 show a similar spatial clustering of voter turnout between the 2020 and 2015 mayoral elections, indicated by think-colored neighboring villages having spatially significant autocorrelation at a significant level at $\alpha = 0.05$ and those with a significant level at $\alpha = 0.1$ in thin-colored neighboring villages. With

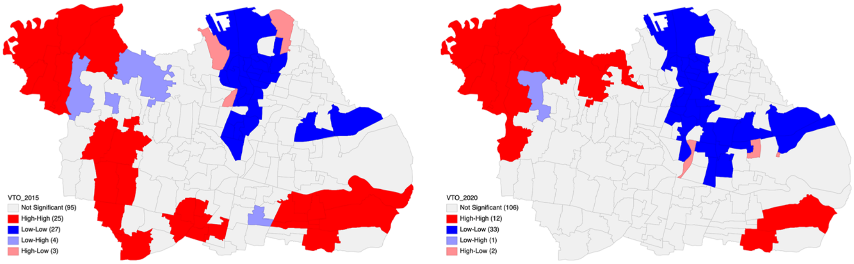

Figure 4: Local Moran's I statistics of turnouts in 2015 and 2020 elections.

significantly high-high (dark red) and low-low (soft red) 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, in 2020 election. This cluster of villages in 2020 also occurred 2015 election with an addition in the southwest part of the city. In short, these comparisons of LISA between the two periods of elections suggest that the contagious turnout during a pandemic is not new and the spatial patterning of turnout might have some geographical strongholds.

Furthermore, suppose we return to the left-hand map of Figure 2. 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 in 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 turnouts. 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.

Moreover, such electoral participation is even more "infectious" than the virus shown on the right plot. This comparison is not intended to test the theory I proposed earlier. Rather, a comparison between turnout and Covid-19 spatial autocorrelations is to demonstrate the extent to which turnout is contagious. The spatial patterning, or spatial clustering, becomes more evident when we see the spatial mapping of the local Moran's statistics.

In contrast, as shown in Figures A1 and A2 of Appendix B, the Covid-19 infections before the mayoral election are not spatially clustered clearly with a very low autocorrelation coefficient *r* (0.004). In other words, conditions in one village are not strongly associated with infections in other villages. Though this is a surprising finding, some suggest that family-based clusters of infections massively took place throughout Indonesia in 2020, including Surabaya city (see Soedarsono 2020). Evidently, as depicted in Figure 6 of the same Appendix, we do not find spatial patterning of the Covid-19 infection across villages as massive as those in turnout.

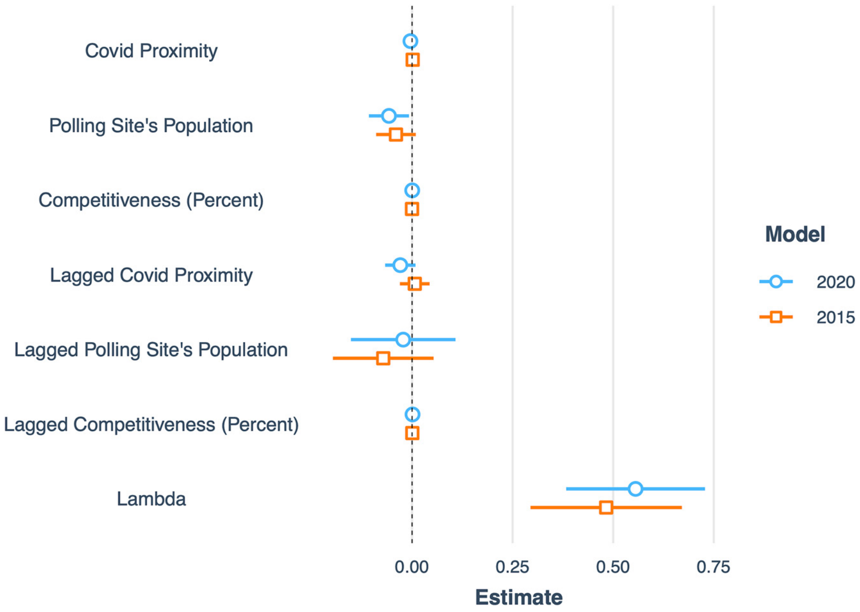

Figure 5: Spatial durbin error models for turnouts between 2020 and 2015 Surabaya municipal elections.

Thus, it is more critical to investigate how 'traditional' and new pandemic-related variables, juxtaposed with the spatial effects, affect turnout during the pandemic rather than merely to seek how Covid-19 virus affect turnout.

Yet, in what mechanisms the turnout in both elections is spatially structured, and what are the drivers that situate voters to eagerly turn out to vote in a time of such a crisis? The following results elaborate on these questions.

6.2 Spatial Models of Turnout

As mentioned earlier, I theoretically propose that spatial effects of turnouts are local. This means that turnouts in one spatial unit (i.e. an urban village in Surabaya) affects turnout in its neighboring villages, rather than globally affecting all urban villages across in the city. Thus, modeling the effect through Spatial Durbin Error Model (SDEM) is theoretically reasonable. Additionally, the likelihood test between SDEM and Spatial Error Model (SEM), reported in Appendix, also provides statistical reason to maintain SDEM though I did cross-sectional examinations through multiple models, as reported in Appendix, before jumping to examine spatial dimensions in the model specifications.[8]

Following on the theoretical proposition and the statistical test, Figure 5 displays how SDEM-based spatial effects of turnouts occur in 2015 before-pandemic and 2020 during-pandemic elections. In this regard, I apply variables generated in the 2020 election for 2015 turnout as counterfactual models, i.e. how such variables, especially the Covid-19 pandemic and electoral adjustment, occurred in the 2015 election, which in fact did not occur.

Lambda in Figure 5 highlights the extent to which local spatial effects occurred in before and during pandemic election. Its statistical significances at $p < 0.05$ suggest that turnouts are spatially correlated in both elections, which is consistent with H4

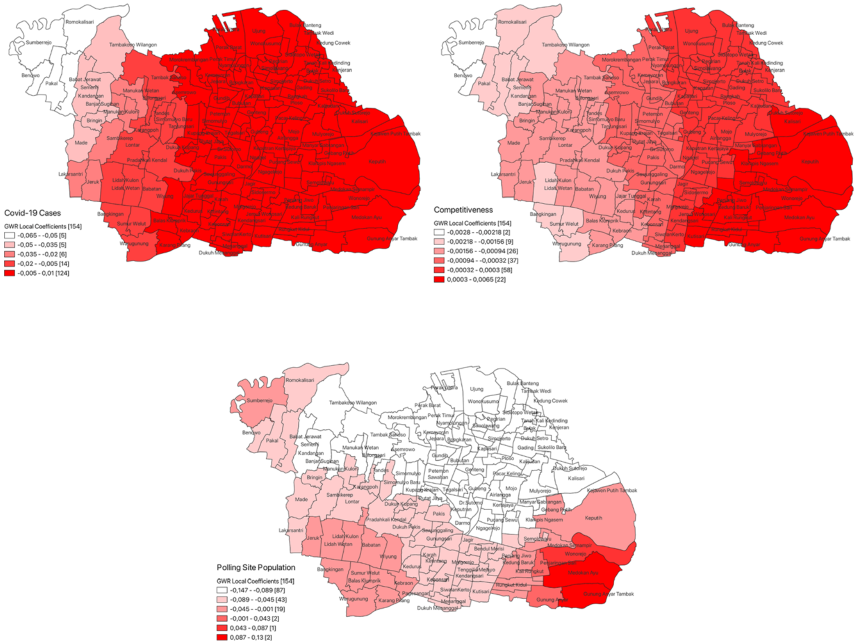

Figure 6: Spatial classification of local coefficients of geographically weighted regression of the effects of Covid-19 cases, competitiveness, and polling population on turnout in 2020 Surabaya election.

8 Table A2 in Appendix shows that models 1–4 and models 5–6 report turnout models in the 2015 and 2020 mayoral elections, respectively. Note that I also run restricted spatial models where the Lagrange Multiplier diagnostics drive us to conclude that spatial lag dependence approximates the spatial effects of turnout rather than a spatial error.

on spatial effects of turnout. This means that turnouts as a proxy of electoral participation in one village are spatially correlated with turnouts in neighboring villages. A closer look, however, signifies that the spatial magnitude is higher during 2020 pandemic election (0.56) than before pandemic in 2015 election (0.48), suggesting that local neighboring effects of turnout is higher during the pandemic. In other words, turnout is more "contagious" during pandemic than in 2015.

If we break the models down into the specifications of the variables, population size at the polling sites in the election during a pandemic convincingly explains the voter turnout ($p < 0.05$). We are nevertheless uncertain in 2015 if the pandemic occurred though the estimates show the same direction as in 2020. Its negative coefficients, especially in 2020 models, meet our theoretical expectation that turnout in a large polling site's population size is low when the population size at the polling site is relatively large. An increase in population size at the polling site contributes to a decrease in turnout, all else equal, since people are cautious when overcrowded is expected as the result of their neighboring interactions. Note that the tests do not find such significant effects of the electoral adjustments in the 2015 models, which makes a lot of sense if we refer to our theoretical expectation of the cost of voting during a pandemic: the importance of assessing physical contacts and overcrowded in a polling site during the pandemic.

Meanwhile, Covid-19 proximity in the counterfactual election in 2015 and pandemic election in 2020 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. Thus, we are not sure whether voters follow such a theoretical direction. Accordingly, 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 given the contradictory directions of its coefficients across the two elections and its non-significant results at $\alpha = 0.05$. These results suggest that pandemic proximity and political variable do not explain why voters vote (or not) during the pandemic.

Different from the two focal variables, the proportion of males and the proportion of people who attend higher education in each village are statistically significant across models. These variables signify that they explain turnout in both electoral circumstances. Their positive coefficients confirm the resource model of turnout, where men and people with higher education are more likely to vote. Importantly, people who are 50 years old and older are only statistically significant in the 2020 models, which makes more sense in a time of the pandemic. Their negative coefficients maintain that villages with a higher proportion of elders tend to have lower turnout during the pandemic. Nevertheless, these cross-section models may be necessary to elucidate turnout during a pandemic, but they are not sufficient to explain the rise of turnout during the pandemic. Thus, we need to look at how spatial effects might operate in a turnout along with the observed variables.

Table 1 reports how spatial effects of turnout in 2020 election occur across modeling strategies though this article theoretically proposes and tests the significance of the Spatial Durbin Error Model (SDEM).[9] Overall, the statistical significances, the point estimates, and standard errors differ (reduced or corrected) across the models are "corrected" from the one to another models when we specify weighted spatial matrix into the model specifications. Male proportion is no longer consistently significant across the models, and most of the estimates of the variables are reduced. Other than the proportion of voters who attend higher education, the result highlights that the electoral adjustment during the pandemic, approximated by the reduction of the polling site's allocated population size, remains statistically significant. But again, they are corrected to be smaller effect sizes.

As an exploratory analysis, Figure 6 presents maps of the local coefficients for three key explanatory variables – Covid-19 cases, electoral competitiveness, and polling site population – estimated using Geographically Weighted Regression (GWR). The model specification follows a multiple linear regression framework, consistent with the SDM and SDEM models reported in Table 1. The bandwidth for geographic weighting was determined through cross-validation, and the spatial coordinates used were centroids derived from the Surabaya city shapefile.

The results reveal a diverse spatial pattern in the relationship between the three focal variables and voter turnout. Figure 6 depicts the spatial distribution and directionality of these local relationships using a graduated red color scale, where deeper opacity indicates stronger and typically more positive associations. In line with our theoretical expectations, negative relationships are anticipated: lower Covid-19 case counts, smaller voter populations at polling sites, and greater electoral competitiveness (i.e. narrower margins between candidates) are expected to correspond with higher turnout.

A closer inspection of the maps indicates that the spatial variation in the coefficients for Covid-19 cases is relatively limited, whereas the relationship between polling site population and turnout exhibits the highest degree of spatial dispersion. This wide variation underscores the localized effect of polling site population on turnout, a finding consistent with the SDEM model results.

Furthermore, to follow up on the Spatial Durbin Error Model on Table 1, Table 2 shows whether the spatial effects of the variables of interest are statistically significant in terms of their direct and indirect impacts. It shows that we do not have evidence on indirect impacts across the variables since their p-values of SDEM's

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

Table 1: Spatial models of turnout in 2020 Surabaya election.

	Outcome: Turnouts (%) in 2020[a]			
	SLG	**SDM**	**SER**	**SDEM**
Covid-19 Proximity	−0.003	−0.001	−0.001	−0.004
	(0.006)	(0.006)	(0.006)	(0.007)
Polling Site's Population	−0.061**	−0.061*	−0.065**	−0.057**
	(0.024)	(0.024)	(0.025)	(0.025)
Competitiveness (Percent)	0.0003	0.0003	0.0003	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Gender (Male-Female Ratio)	1.093	0.768	0.750	0.797
	(0.900)	(0.947)	(0.947)	(0.972)
50 years old and older (%)	−0.295**	−0.276*	−0.301**	−0.309**
	(0.140)	(0.147)	(0.148)	(0.146)
Higher Education (Percent)	0.168***	0.217***	0.210***	0.205***
	(0.063)	(0.080)	(0.078)	(0.076)
Worship Buildings	−0.017	−0.025	−0.015	−0.019
	(0.030)	(0.031)	(0.031)	(0.033)
Lagged Covid-19 Proximity		−0.017		−0.029
		(0.016)		(0.019)
Lagged Polling Site's Population		−0.019		−0.022
		(0.051)		(0.066)
Lagged Competitiveness (%)		0.0005		0.001
		(0.001)		(0.001)
Lagged Gender (M-F Ratio)		1.892		0.348
		(1.816)		(2.351)
Lagged 50+ years old (%)		−0.087		−0.615
		(0.323)		(0.397)
Lagged Higher Education (%)		−0.059		−0.083
		(0.114)		(0.151)
Lagged Worship Buildings		−0.001		0.012
		(0.073)		(0.084)
Constant	−0.458	−64.107	41.197	47.803
	(48.845)	(98.974)	(51.686)	(151.712)
N	154	154	154	154
Log Likelihood	−460.094	−456.144	−461.861	−455.554
Wald Test (df = 1)	36.899***	22.133***	42.629***	39.860***
LR Test (df = 1)	31.167***	17.531***	27.632***	18.712***
AIC	940.187	946.289	943.721	945.108

***p < 0.01; **p < 0.05; *p < 0.1. [a]Observations are village-level units. Models 1–4 are Spatial Lag Dependence (SLG), Spatial Durbin (SDM), Spatial Error (SER), and Spatial Durbin Error (SDEM) Models, respectively.

impact measures are above 0.1. Yet, the explanatory variable of interest of polling population (0.024 of p-value), along with age and education level, has statistically significant direct impact in terms of the local spatial effects, estimated through

Table 2: p-values of SDEM's Impact Measures.

Variable	Direct	Indirect	Total
Covid proximity	0.556	0.129	0.156
Polling Site's population	0.024	0.740	0.312
Competitiveness (percent)	0.363	0.245	0.181
Gender (male-female ratio)	0.412	0.882	0.682
50 years old and older (percent)	0.034	0.121	0.037
Higher education (percent)	0.007	0.584	0.462
Worship buildings	0.568	0.884	0.949

SDEM. This means that effects of estimating crowd in the polling site is spatially direct among voters who turned out to vote during the heyday of the pandemic.

Empirically, turnout – driven by how voters estimate the crowds based on polling site population in one village – is a function of turnout in neighboring villages (as computed by the queen contagion weighted matrix) along with their observed variables. In other words, as this result rejects the null of the spatial autoregressive models, turnout is spatially an outcome of both the neighboring observed variable of interest (turnouts) and unobserved variables that might also bear spatial effects since the outcome of turnout is a function of the weighted measure of neighboring turnouts. However, our main takeaway is that the significant result conforms to the theory of contagious turnout. Turnout is a result of neighboring effects where the effects are a spatial outcome of explicit/implicit social interactions of the diffusion theory. In the absence of convenient voting, people who turn out 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. However, I acknowledge that these models are at the village-level unit and do not reach observations of the individual voters, as many other studies apply spatial econometrics. Yet, the significant results of the spatial autoregressive models detect and indicate individual behavior at the aggregate level since spatial models assume that observations are not independent as the interactions occur between units due to their spatial dimensions.

7 Conclusions

This study demonstrates that electoral participation is not randomly distributed; rather, the process by which individuals decide to vote at polling sites is spatially structured. This clustering implies that turnout is, to some extent, contagious. Based on estimates from the Spatial Durbin Error Model (SDEM), this contagious turnout appears to result from neighboring effects, where social interactions and group responses occur due to the inherently multidimensional and multidirectional nature of spatial influences. Although counterfactual models using 2015 election data suggest that contagious turnout is not a unique feature of pandemic-era elections, the spatial effects documented help explain the counterintuitive rise in turnout in Surabaya and other areas during the Covid-19 crisis.

Building on the theoretical premise of neighboring effects, voters may influence one another through spatial proximity, reinforcing perceptions that voting is safe. Empirically, the unique circumstances of the pandemic may have amplified this phenomenon: after prolonged isolation, an election provided a legally sanctioned opportunity for citizens to leave their homes, potentially increasing participation.

While the findings are based on cross-sectional models, they also reveal that electoral adjustments implemented during the pandemic – most notably, the reduction in the number of voters per polling station – were significantly associated with turnout. In contrast, other factors such as the intensity of political competition and proximity to Covid-19 infection clusters did not show a meaningful impact on electoral behavior. These results suggest that even minimal but targeted administrative adjustments in electoral management during a crisis can alter the cost-benefit calculus of voting. Specifically, voter sensitivity to the potential for overcrowding appears to play a critical role in shaping turnout decisions. In contexts lacking alternative voting mechanisms – such as early voting, proxy voting, postal ballots, or home-based voting – individuals are more likely to abstain when they anticipate crowding at polling sites, but more inclined to participate when assigned to a less populated station.

These findings carry important policy implications for understanding how electoral adjustments and spatial dynamics interact to influence voter turnout during a crisis. However, further research is needed. First, while the study uses village-level data to approximate social interactions – the central assumption of spatial econometric models – more granular units of analysis could offer deeper insight. Finer-scale analyses, such as at the neighborhood or block level (e.g., *Rukun Warga*or RW units in Indonesian cities), would allow for a more precise identification of spatial effects. Many polling sites in Indonesia serve multiple administrative blocks, meaning that intra-village clustering likely reflects real patterns of social interaction. Moreover, working with a larger number of observations from lower-level units could improve statistical precision through the law of large numbers.

Second, although the models employed control for observed covariates, they cannot account for all possible confounders – a limitation inherent in observational research. Future studies should explore how spatial effects and crisis-related variables, particularly electoral adjustments, operate in rural areas. As the present analysis focuses on an urban setting, it may overlook social and communal dynamics that are more prominent in rural environments and potentially magnify spatial influences and political mobilization.

Finally, the study acknowledges that additional variables – such as actual distance to polling stations, incumbency advantage, or voters' economic profiles – could further inform analyses of turnout during a pandemic. While these factors were not feasible to include in the present study, a sensitivity analysis (Appendix D) indicates modest robustness of the findings. Ultimately, the Covid-19 pandemic presents a rare opportunity for researchers to examine electoral behavior under extraordinary conditions, including the role of previously unobservable variables and crisis-induced voter decision-making processes.

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Appendix A

Table A1: Descriptive statistics of the variables.

Statistic	N[a]	Mean	St. Dev.	Min	Max
2020 turnout (percent)	154	50.90	5.93	36.41	89.63
2015 turnout (percent)	154	52.15	6.38	33.53	69.50
Polling site's population size (N-voters)	154	402.73	16.00	339.00	442.48
Covid-19 proximity (N-cases)	154	110.24	65.96	13	411
Competitiveness (N-votes)	154	1,210.36	965.07	10	4,607
Gender (percent of male)	154	49.59	0.62	48.00	51.74
50 years old and older (percent)	154	22.91	3.86	8.48	36.17
Higher education population (percent)	154	13.47	7.30	2.30	33.24
Public buildings (religious houses)	154	24.45	13.63	1	73

[a]Observations are village-level units.

Appendix B: Covid-19 Spatial Analysis

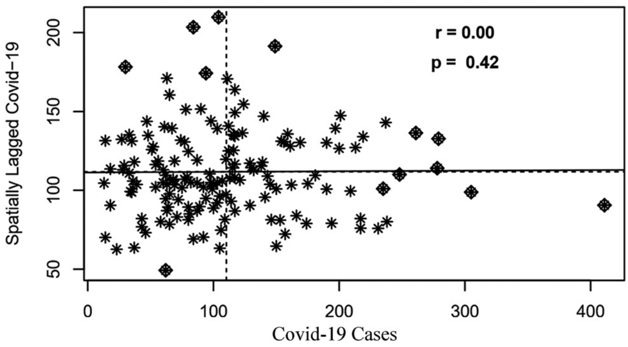

Figure A1: Spatial autocorrelation: global Moran's I statistics statistics of the covid-19 infection cases a week prior to the voting day.

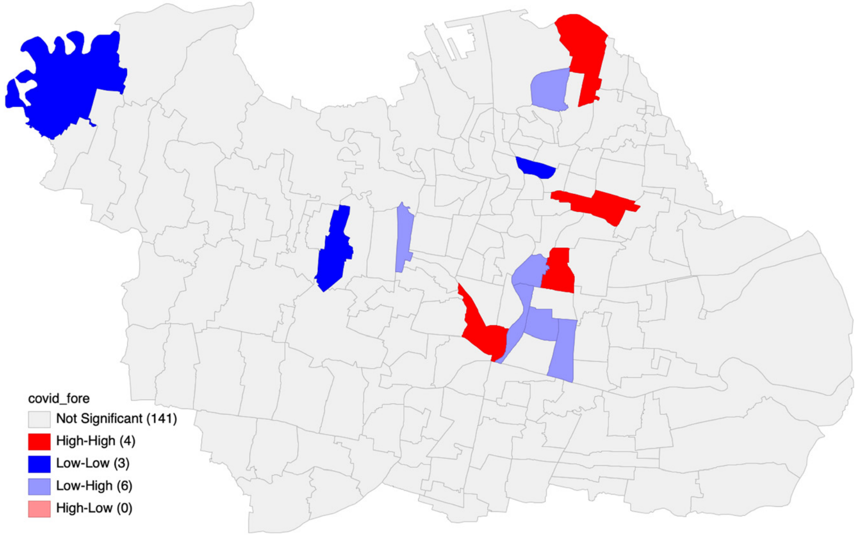

Figure A2: Spatial autocorrelation: local Moran's I statistics of the covid-19 infection cases a week prior to the voting day.

Table A2: Spatial autoregressive models of voter turnout[a]

	Turnout 2015				Turnout 2020			
	1	2	3	4	5	6	7	8
Covid-19 proximity	0.001	0.001			−0.003	−0.001		
	(0.006)	(0.006)			(0.006)	(0.006)		
Polling site's population	−0.020			−0.020	−0.061**			−0.060**
	(0.024)			(0.024)	(0.024)			(0.024)
Competitiveness (percent)	−0.0003		−0.0003		0.0003		0.0002	
	(0.0004)		(0.0004)		(0.0004)		(0.0004)	
Gender (male percent)	1.365	1.522*	1.477	1.416	1.093	1.351	1.387	1.044
	(0.907)	(0.899)	(0.901)	(0.905)	(0.900)	(0.908)	(0.910)	(0.898)
50 years old and older (percent)	−0.159	−0.147	−0.146	−0.154	−0.295**	−0.274*	−0.275*	−0.304**
	(0.141)	(0.141)	(0.140)	(0.140)	(0.140)	(0.143)	(0.142)	(0.140)
Higher education (percent)	0.138**	0.137**	0.138**	0.137**	0.168***	0.167**	0.165**	0.169***
	(0.063)	(0.064)	(0.064)	(0.063)	(0.063)	(0.065)	(0.065)	(0.063)
Worship buildings	0.037	0.036	0.040	0.036	−0.017	−0.014	−0.018	−0.020
	(0.031)	(0.031)	(0.029)	(0.028)	(0.030)	(0.031)	(0.029)	(0.028)
Constant	−39.188	−55.500	−52.917	−41.760	−0.458	−38.236	−40.459	1.918
	(49.162)	(46.439)	(46.562)	(49.089)	(48.845)	(46.946)	(47.060)	(48.793)
Spatial lag[b]	0.627***	0.626***	0.625***	0.626***	0.524***	0.526***	0.530***	0.523***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.086)	(0.087)	(0.086)	(0.086)
N	154	154	154	154	154	154	154	154
Log likelihood	−463.490	−464.073	−463.871	−463.727	−460.094	−463.435	−463.283	−460.402
Wald test (df = 1)	67.476***	67.224***	67.265***	67.217***	36.899***	36.939***	37.694***	36.721***
LR test (df = 1)	50.238***	49.959***	49.978***	50.148***	31.167***	30.737***	31.232***	31.151***
AIC	946.979	944.146	943.742	943.454	940.187	942.870	942.566	936.803

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. [a]Observations are village-level units. [b]All estimates of the spatial lag parameter are statistically significant ($p < 0.05$).

Appendix C: Tests of Spatial Model Selections

Below are R outputs of the likelihood ratio tests for Spatial Durbin Error Model (SDEM) and Lagrange Multiplier diagnostics for spatial dependence from one to another model specifications. In this regard, SDEM is tested against restricted Spatial Error Model (SEM). As the p-value (0.0821) is not statistically significant at $p < 0.05$, the likelihood ration test suggests that we should maintain SDEM.

Likelihood ratio for spatial linear models

data:

Likelihood ratio = 12.614, df = 7, p-value = 0.0821 sample estimates: Log likelihood of sesdm2 Log likelihood of ser2 -455.5538 -461.8607

Rao's score (a.k.a Lagrange multiplier) diagnostics for spatial dependence

The Lagrange Multiplier (LM) diagnostics show that both LM for error (LMerr) and lag dependence (LMlag) models are statistically distinguishable from zero at $\alpha = 0.05$. However, robust LM diagnostics suggest that the robust spatial error model (RLMerr) (p = 0.189) while the robust spatial lag model (RLMlag) is statistically significant ($p < 0.01$).

data:

model: lm(formula = VTO_2020 ~ covid_fore + compttvnes + voterbytps + gndr_mlPrc + u_Old_0Prc + p_hig_rPrc + b_worships, data = dat) test weights: listw

RSerr = 28.148, df = 1, p-value = 1.124e-07

Rao's score (a.k.a Lagrange multiplier) diagnostics for spatial dependence

data:

model: lm(formula = VTO_2020 ~ covid_fore + compttvnes + voterbytps + gndr_mlPrc + u_Old_0Prc + p_hig_rPrc + b_worships, data = dat) test weights: listw

adjRSerr = 2.2493, df = 1, p-value = 0.1337

Rao's score (a.k.a Lagrange multiplier) diagnostics for spatial dependence

data:

model:

lm(formula = VTO_2020 ~ covid_fore + compttvnes + voterbytps + gndr_mlPrc + u_Old_0Prc + p_hig_rPrc + b_worships, data = dat) test weights: listw

RSlag = 40.121, df = 1, p-value = 2.387e-10

Rao's score (a.k.a Lagrange multiplier) diagnostics for spatial dependence

data:

model:

lm(formula = VTO_2020 ~ covid_fore + compttvnes + voterbytps + gndr_mlPrc + u_Old_0Prc + p_hig_rPrc + b_worships, data = dat) test weights: listw

adjRSlag = 14.222, df = 1, p-value = 0.0001624

Appendix D: Sensitivity Analysis

Figure A3 below reports results of an extreme confounder sensitivity analysis developed by Cinelli and Hazlett (2020) based on omitted variable bias framework. The analysis draws on level of education as an extreme confounder for simulation, polling station population as the treatment, and turnout as the outcome. Both left--hand contour graph and right-hand smoothed line graph show a modest robustness that small to moderate unobserved confounding could potentially overturn the result. The benchmark covariate (*p_hig_rPrc* as coded education level) is almost strong enough to explain away the result if it were unobserved instead of included.

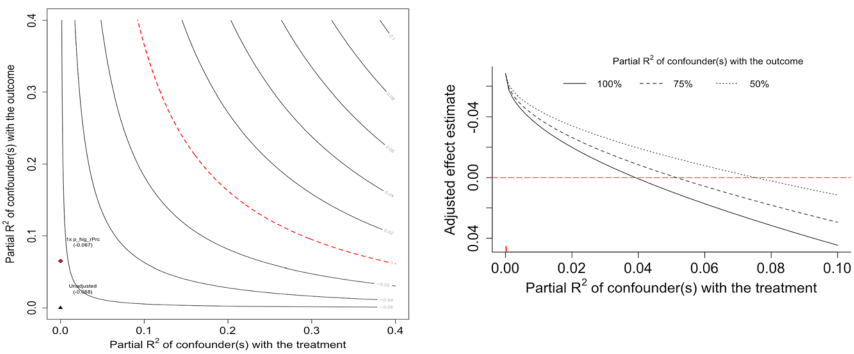

Figure A3: Visual results of extreme confounder sensitivity analysis based on Cinelli and Hazlett's (2020) omitted variable bias framework.

Beyond the graphs, this analysis reveals that the robustness value of this specification is 0.1823 which means that unobserved confounders, orthogonal to the covariates, would need to explain at least 18.23 % of the residual variance in both the treatment (polling population size) and the outcome (turnout) to nullify the result – i.e., to bring the point estimates to zero, which is a bias of 100 % of the original estimate.

References

Aldrich, John H., M. Montgomery Jacob, and Wendy Wood. 2011. "Turnout as a Habit." *Political Behavior* 33 (4): 535–63.

Aldrich, John H., and Libby M. Jenke. 2017. *Turnout and the Calculus of Voting: Recent Advances and Prospects for Integration with Theories of Campaigns and Elections*, 83–95. The Routledge Handbook of Elections, Voting Behaviorand Public Opinion.

Anselin, Luc. 2007. “Spatial Econometrics.” In *A Companion to Theoretical Econometrics*, 310–30. Wiley.

Anselin, Luc, and Raymond J. G. M. Florax. 1995. “New Directions in Spatial Econometrics: Introduction.” In *New Directions in Spatial Econometrics*, 3–18. Springer.

Asplund, Lars, Fakiha Ahmed Erik, Bor Stevense, Sulemana Umar, Toby James, and Alistair Clark, et al. 2021. “Elections and Covid-19: How Special Voting Arrangements Were Expanded in 2020.” *International IDEA*, https://www.idea.int/news/elections-and-covid-19.

Baller, Robert D., and Kelly K. Richardson. 2002. “Social Integration, Imitation, and the Geographic Patterning of Suicide.” *American Sociological Review* 67 (6): 873–88.

Blais, André. 2000. *To Vote or Not to Vote? The Merits and Limits of Rational Choice Theory*. University of Pittsburgh Pre.

Blais, André, and R. Kenneth Carty. 1990. “Does Proportional Representation Foster Voter Turnout?” *European Journal of Political Research* 18 (2): 167–81.

Bormann, Nils-Christian, and Matt Golder. 2013. “Democratic Electoral Systems Around the World, 1946–2011.” *Electoral Studies* 32 (2): 360–9.

Brady, Henry E., and John E. McNulty. 2011. “Turning Out to Vote: The Costs of Finding and Getting to the Polling Place.” *American Political Science Review* 105 (1): 115–34.

Cann, Damon M., and Jeffrey Bryan Cole. 2011. “Strategic Campaigning, Closeness, and Voter Mobilization in US Presidential Elections.” *Electoral Studies* 30 (2): 344–52.

Cantoni, Enrico. 2020. “A Precinct Too Far: Turnout and Voting Costs.” *American Economic Journal: Applied Economics* 12 (1): 61–85.

Cebula, Richard J., Garey C. Durden, and Patricia E. Gaynor. 2008. “The Impact of the Repeat-Voting-Habit Persistence Phenomenon on the Probability of Voting in Presidential Elections.” *Southern Economic Journal* 75 (2): 429–40.

Cho, Wendy K. Tam. 2003. “Contagion Effects and Ethnic Contribution Networks.” *American Journal of Political Science* 47 (2): 368–87.

Cho, Wendy K. Tam, and Neil Baer. 2011. “Environmental Determinants of Racial Attitudes Redux: The Critical Decisions Related to Operationalizing Context.” *American Politics Research* 39 (2): 414–36.

Cho, Wendy K. Tam, and James G. Gimpel. 2010. “Rough Terrain: Spatial Variation in Campaign Contributing and Volunteerism.” *American Journal of Political Science* 54 (1): 74–89.

Cho, Wendy K. Tam, and Thomas J. Rudolph. 2008. “Emanating Political Participation: Untangling the Spatial Structure behind Participation.” *British Journal of Political Science* 38 (2): 273–89.

Cinelli, Carlos, and Chad Hazlett. 2020. “Making Sense of Sensitivity: Extending Omitted Variable Bias.” *Journal of the Royal Statistical Society - Series B: Statistical Methodology* 82 (1): 39–67.

Dinas, Elias. 2017. “The Acquisition of Voting Habits.” In *The Routledge Handbook of Elections, Voting Behaviorand Public Opinion*, 108–20. Routledge.

Diwakar, Rekha. 2008. “Voter Turnout in the Indian States: An Empirical Analysis.” *Journal of Elections, Public Opinion and Parties* 18 (1): 75–100.

Downs, Anthony. 1957. “An Economic Theory of Political Action in a Democracy.” *The Journal of Political Economy* 65 (2): 135–50.

Dyck, Joshua J., and James G. Gimpel. 2005. “Distance, Turnout, and the Convenience of Voting.” *Social Science Quarterly* 86 (3): 531–48.

Feddersen, Timothy J., and Wolfgang Pesendorfer. 1999. “Abstention in Elections with Asymmetric Information and Diverse Preferences.” *American Political Science Review* 93 (2): 381–98.

Franklin, Mark N. 1999. “Electoral Engineering and Cross-National Turnout Differences: What Role for Compulsory Voting?” *British Journal of Political Science* 29 (1): 205–16.

Gerber, Alan S., and Donald P. Green. 2000. “The Effects of Canvassing, Telephone Calls, and Direct Mail on Voter Turnout: A Field Experiment.” *American Political Science Review* 94 (3): 653–63.

Gerber, Alan S., and Donald P. Green. 2005. “Correction to Gerber and Green (2000), Replication of Disputed Findings, and Reply to Imai (2005).” *American Political Science Review* 99 (2): 301–13.
Gerber, Alan S., Gregory A. Huber, and Seth J. Hill. 2013. “Identifying the Effect of All-Mail Elections on Turnout: Staggered Reform in the Evergreen State.” *Political Science Research and Methods* 1 (1): 91–116.
Geys, Benny. 2006. “Explaining Voter Turnout: A Review of Aggregate-Level Research.” *Electoral Studies* 25 (4): 637–63.
Green, Donald P., and Alan S. Gerber. 2019. *Get Out the Vote: How to Increase Voter Turnout*. Brookings Institution Press.
Grofman, Bernard. 1995. *Information, Participation, and Choice: An Economic Theory of Democracy in Perspective*. University of Michigan Press.
Gronke, Paul, and Peter Miller. 2012. “Voting by Mail and Turnout in Oregon: Revisiting Southwell and Burchett.” *American Politics Research* 40 (6): 976–97.
Haute, Tristan, Camille Kelbel, François Briatte, and Giulia Sandri. 2021. “Down with Covid: Patterns of Electoral Turnout in the 2020 French Local Elections.” *Journal of Elections, Public Opinion and Parties* 31 (sup 1): 69–81.
Imai, Kosuke. 2005. “Do Get-Out-The-Vote Calls Reduce Turnout? the Importance of Statistical Methods for Field Experiments.” *American Political Science Review* 99 (2): 283–300.
Indridason, Indridi H. 2008. “Competition & Turnout: The Majority Run-Off as a Natural Experiment.” *Electoral Studies* 27 (4): 699–710.
Karp, Jeffrey A., and Susan A. Banducci. 2000. “Going Postal: How All-Mail Elections Influence Turnout.” *Political Behavior* 22 (3): 223–39.
Kostadinova, Tatiana, and Timothy J. Power. 2007. “Does Democratization Depress Participation? Voter Turnout in the Latin American and Eastern European Transitional Democracies.” *Political Research Quarterly* 60 (3): 363–77.
Merkley, Eric, Thomas Bergeron, Peter John Loewen, Angelo Elias, and Miriam Lapp. 2022. “Communicating Safety Precautions Can Help Maintain In-Person Voter Turnout during a Pandemic.” *Electoral Studies* 75: 102421.
Morton, Rebecca B., Daniel Muller, Lionel Page, and Benno Torgler. 2015. “Exit Polls, Turnout, and Bandwagon Voting: Evidence from a Natural Experiment.” *European Economic Review* 77: 65–81.
Noury, Abdul, François Abel, Olivier Gergaud, and Alexandre Garel. 2021. “How Does COVID-19 Affect Electoral Participation? Evidence from the French Municipal Elections.” *PloS One* 16 (2): e0247026.
Nwankwo, Cletus Famous. 2021. “COVID-19 Pandemic and Political Participation in Lagos, Nigeria.” *SN Social Sciences* 1 (6): 1–23.
Orford, Scott, Colin Railings, Michael Thrasher, and Galina Borisyuk. 2011. “Changes in the Probability of Voter Turnout when Resiting Polling Stations: A Case Study in Brent, UK.” *Environment and Planning C: Government and Policy* 29 (1): 149–69.
Pettigrew, Stephen. 2021. “The Downstream Consequences of Long Waits: How Lines at the Precinct Depress Future Turnout.” *Electoral Studies* 71: 102188.
Plutzer, Eric. 2017. “Demographics and the Social Bases of Voter Turnout.” In *The Routledge Handbook of Elections, Voting Behaviorand Public Opinion*, 69–82. Routledge.
Richey, Sean. 2008. “Voting by Mail: Turnout and Institutional Reform in Oregon.” *Social Science Quarterly* 89 (4): 902–15.
Rosenstone, Steven J., and John Mark Hansen. 1993. *Mobilization, Participation, and Democracy in America*. Longman Publishing Group.
Schur, Lisa, Ameri Mason, and Meera Adya. 2017. “Disability, Voter Turnout, and Polling Place Accessibility.” *Social Science Quarterly* 98 (5): 1374–90.

Simonovits, Gábor. 2012. “Competition and Turnout Revisited: The Importance of Measuring Expected Closeness Accurately.” *Electoral Studies* 31 (2): 364–71.
Smets, Kaat, and Carolien Van Ham. 2013. “The Embarrassment of Riches? A MetaAnalysis of Individual-Level Research on Voter Turnout.” *Electoral Studies* 32 (2): 344–59.
Soedarsono, Soedarsono. 2020. “A Family Cluster of Coronavirus Disease (COVID-19) Infection with Different Clinical Manifestations.” *Acta Medica Indonesiana* 52 (2): 155–62.
Southwell, Priscilla L., and Justin I. Burchett. 2000. “The Effect of All-Mail Elections on Voter Turnout.” *American Politics Quarterly* 28 (1): 72–9.
Stockemer, Daniel. 2017. “What Affects Voter Turnout? A Review Article/MetaAnalysis of Aggregate Research.” *Government and Opposition* 52 (4): 698–722.
Voss, Paul R., David D. Long, Roger B. Hammer, and Samantha Friedman. 2006. “County Child Poverty Rates in the US: A Spatial Regression Approach.” *Population Research and Policy Review* 25 (4): 369–91.
Vowles, Jack. 2017. “The Big Picture: Turnout at the Macro-Level.” In *The Routledge Handbook of Elections, Voting Behaviorand Public Opinion*, 57–68. Routledge.