The impact of urban green spaces on the probability of urban crime in Indonesia

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ABSTRACT
Does the presence of green spaces in urban environments reduce the probability of crime? This paper applies the difference-in-differences approach to quantify the impact of urban green spaces on the probability of crime occurrence using data from the three largest metropolitan areas in Indonesia. Specifically, the study employs urban wards level data from the Village Potential Census (PODES) of 2014 and 2018 collected by Indonesia Statistics. Estimation results indicate a negative and significant impact of new urban green spaces on the probability of crime occurrence at the urban wards level. Results are reversed for those urban wards that lost green spaces, indicating an increase in the probability of crime when green spaces decrease. Results remain qualitatively unchanged with the inclusion of regional dummies and other control variables to control for regional differences, which indicates the robustness of our findings. By providing evidence that access to nature has a mitigating impact on crime in urban settings, city governments and communities are empowered to support these interventions.

1. Introduction
As cities develop, conflicts arise regarding the optimal development of urban spaces. Environmental planning, when integrated into urban spatial planning, can facilitate more sustainable city development by balancing land development with environmental preservation. Development of urban green spaces is one of the most common strategies in environmental planning to maintain environmental quality in urban areas (Knox and Pinch 2009). In addition to the environmental benefits, other direct benefits of urban green spaces include improving the cities’ aesthetics, providing places for physical exercise, and facilitating social interactions (Pradipta 2020; Rasidi, Jamirsah, and Said 2012). Furthermore, other indirect benefits of urban green space have been identified, including the reduction of crime in cities in the developed world (Bogar and Beyer 2016; McCord and Houser 2017).

Urban spaces generally have higher rates of crime than non-urban areas (Knox and Pinch 2009). Therefore, it has become a common perception that urban areas, including urban open green spaces, are prone to high rates of crime. However, this perception that urban green spaces are associated with increased crime is contested by evidence from recent studies. Recent multidisciplinary research investigating the connections between urban green space and crime has shown that urban green spaces are facilitators for the prevention of crime and violence, often through the same mechanisms that explain other health benefits of green space (Branas et al. 2011; Brown 2018; Kuo and Sullivan 2001a, 2001b; Nitkowski 2017). However, these studies are mostly carried out in the developed world, so the effect of urban green space on crime in cities in the developing world remains largely unexplored. This may hinder the momentum of greening interventions that could bring various direct and indirect benefits to the urban inhabitants in the developing world (Cho et al. 2008; Emery and Flora, 2006).

This study examines the role of open green spaces on the reduction of crime occurrence in urban areas. Specifically, this paper will focus on crime occurrence in cities in the developing world. We employ data from urban wards (i.e. villages within urban areas) from three main cities in Indonesia: Jakarta, Medan, and Surabaya. These three cities are the capitals of the three provinces with the highest crime rates in Indonesia. The Indonesian Statistics/Badan Pusat Statistik (BPS 2020) reported that in 2019, Metro Jaya (Jakarta) Regional Police recorded the highest number of crimes in Indonesia with 31,934 incidents, followed by the Sumatera Utara Regional Police (headquartered in Medan) who...
recorded 30,831 incidents, and the Jawa Timur Regional Police (headquarter in Surabaya) who recorded 26,985 incidents.

This paper applies the difference-in-differences approach to quantify the impact of urban green space on the probability of crime occurrence in the three largest metropolitan areas in Indonesia between 2014 and 2018 using data from the Village Potential Censuses (PODES) of 2014 and 2018. The results show that urban green space significantly reduced the probability of crime occurrence in these three cities. An introduction of one green space area is found to significantly reduce the crime rate by about 13.4%.

2. Urban open green space and crime

The theoretical link between urban green space, the environment, and crime occurrence has been discussed in the Broken Windows Theory (BWT) and in Crime Prevention Through Environmental Design (CPTED) (Bogar and Beyer 2016). The BWT is a criminology theory supported by empirical evidence in several cities and countries. This theory states that any visible signs of crime in a densely populated, lower income, urban area will encourage additional criminal activity, and will lead to minor forms of public or social disorder which may in turn lead to severe crimes (Meinen 2014). Signs of public disorder include fights, disturbances among neighbors, and loitering while drinking alcohol, which can lead to a sense of danger (Ross and Mirowsky 1999). Vandalism and graffiti in a neighborhood are often followed by broken street furniture, destruction of bus stop signs, and damage to abandoned buildings (Ross and Mirowsky 1999; Meinen 2014). BWT is supported by empirical evidence and is discussed extensively by Bogar and Beyer (2016). They tabulated ten major studies in several cities in America, utilizing BWT and other theories, including attention and restoration theory, social cohesion, and Jacob’s eyes on the street theory. Bogar and Beyer (2016) find that in selected cities of America, greening city policy was followed by significant reductions in reported crimes in the subsequent year.

Branas et al. (2011) and Wolfe and Mennis (2012) carry out a study in Philadelphia, PA, using attention and restoration theory. They investigate the utilization of vacant lots through the planting of trees and grass or installation of ground coverings and canopies. Branas et al. (2011) report that greening interventions indeed lowered the vandalism rate; however, they discovered an increase in disorderly conduct such as littering. Meanwhile, Wolfe and Mennis (2012) claim that increases in vegetation resulted in decreased occurrence of burglaries and aggravated assault in the greened neighborhoods. Overall, the ten studies discussed in Bogar and Beyer (2016) report a decrease in crime rate and violence in cities that actively promoted green space.

The concept of CPTED pairs open space with dense residential housing as part of its method to prevent crime. The hope is for the community to foster a sense of positive regard for the neighborhood. Felson (2006) and Fennelly (2015) consider one aspect of CPTED to be the relationship between human and environment, which allows changes to the environment to be used to affect human behavior. The CPTED employs various methods to limit the opportunity for crime. For example, in a city center, suspicious areas should have more ample lighting, blind spots should be reduced, and legitimate businesses, as well as open parks, should be placed in areas that were formerly used for criminal activity.

Shepley et al. (2019) examine whether the existence of nature in urban areas decreases the occurrence of crime. Their research indicates that, in numerous settings, green spaces that include trees, parks, and other natural features, do have a relieving effect. Several researchers have investigated the relationship between nature and urban crime, revealing that crime rates decreased and community cohesion increased following the greening of community spaces (Blair 2014; Bogar and Beyer 2016). By demonstrating that the existence of nature contributes to the reduction of crimes in urban settings, city governments and communities will have stronger reasons to develop urban green spaces (Brown 2018).

The impact of green spaces on the reduction of crime occurrence is attributable to the co-presence of multiple influences which can be categorized into physical features and qualities (Shepley et al. 2019). The physical features of green spaces include parks, which enable community interaction and can be used as places for exercise. Several studies suggest a link between health outcomes and green space (Cummins and Fagg 2011; Gomez et al. 2010; Mytton et al. 2012). This positive association is due to increased levels of physical activity among individuals who live in areas with more green space. Green space qualities include biophilic support, territorial definition, community enfranchisement, and climate moderation. Biophilic building construction enables relaxation and a sense of calm. Biophilic support is provided by nature, including parks, which have a calming impact on human psychological and emotional state and improve cognitive functioning (Lin, Egerer, and Ossola 2018; Roe et al. 2013). According to Lin, Egerer, and Ossola (2018), urban gardens are not only important for modern cities and towns, but are also
likely to play an important role for cities extending well into the future. Urban gardens can help conserve a positive and genuine biophilic drive for future generations who are likely to live even further distanced from the natural world.

Recent studies that have investigated the relationship between parks and crime occurrence have arrived at different conclusions. Brown (2018) and Nitkowski (2017) find that the presence of parks is related to reductions in crime occurrence. They conclude that the more parks were utilized by residents for socializing, the less likely it was for violence and crime to occur throughout the day. Garvin, Cannuscio, and Branas (2013) carry out a randomized controlled trial of vacant lot greening to test the impact on reported crimes and residents’ perceptions of safety and disorder. While the decrease in the number of reported crimes was not statistically significant, they found a significant increase in the residents’ perceptions of safety.

On the other hand, studies by Donovan and Prestemon (2010), Gorham et al. (2009), Mc Cord and Kimberly (2018), Kim and Hipp (2018) and Abu-Lughod (2006) find that as the number of urban parks increased, the number of crimes also increased. Meanwhile, McCord and Houser (2017) and Kim and Hipp (2018) show that areas surrounding urban parks are prone to crimes and disorder. Other studies, such as the study by Lee (2013) and Blair (2014), find no significant relationship between parks and crimes.

Our study contributes to this area of research by providing empirical evidence, specifically in the case of cities in developing countries, that increased urban green open space reduces the occurrence of crime.

### 2.1. Urban green open space in the context of Indonesia

In Indonesia, according to Act Number 26 of 2007, each city should have at least 30% of its total area dedicated to green open spaces. Unfortunately, the existence of green open space in the cities in Indonesia is still below this stipulated figure. Jakarta, for example, has an area of 661.5 square kilometers; according to this law it should have at least 200 square kilometers of green open space. However, due to the use of available land for other infrastructure such as buildings and modern shopping centers, less than 99 square kilometers were dedicated to open green space in the city by 2019 (BPS 2020). In the nation of Indonesia as a whole, the existence of green areas has decreased over the past 30 years due to the massive infrastructure development, which is not environmentally sound. According to data from the Ministry of Public Works and Public Housing as of mid-2019, only 13 out of 174 cities in Indonesia emphasized the importance of green open space for regional development.

### 2.2. Crime rates in Indonesia

A sense of security is one of the most important human needs. Indicators generally used to measure security are total crime and the crime rate per 100,000 population. Table 1 presents the statistics of the Total Crime and Crime Rate per 100,000 population in Indonesia from 2012 to 2019 (BPS 2014, 2016, 2020). The total crime figures fluctuate within that period, increasing from 2012 to 2013 and from 2014 through 2016. Fortunately, the overall trend from 2012 to 2019 indicates decreasing total crime. In line with the trend in total crime, the number of crime incidents, or criminal acts, per 100,000 population also shows a declining trend from 2012 to 2019. A higher crime rate shows a higher level of vulnerability to crime in certain regions, and vice versa. Table 1 shows that the level of risk of being exposed to crime, for every 100,000 population, decreases from 134 in 2012–103 in 2019.

Most of the crimes occur in urban areas with high population density. While the crime rate statistics indicate a declining trend, urban security remains one of the main concerns of city governments and the Indonesian police. Personal safety and security issues have become associated with urban life, and personal quality of life and exposure to crime has become an important benchmark for the overall quality of life of a community (England and Simon 2010; Tretter 2013). Hence, reducing crime occurrence is highly relevant to improving the quality of life in urban areas.

### 3. Data and methodology

This study utilizes urban wards level data from the Village Potential Census (PODES) of 2014 and 2018 to analyse the impact of open green spaces on the probability of crime occurrence. Only data from the PODES in 2014 and 2018 are included, as these are the only

| Year | Total crime | Crime rate (Per 100,000 population) |
|------|-------------|-------------------------------------|
| 2012 | 341,159     | 134                                 |
| 2013 | 342,084     | 140                                 |
| 2014 | 325,317     | 131                                 |
| 2015 | 352,936     | 140                                 |
| 2016 | 357,197     | 140                                 |
| 2017 | 336,652     | 129                                 |
| 2018 | 294,281     | 113                                 |
| 2019 | 269,324     | 103                                 |

Source: Indonesia Statistics (BPS), 2014, 2016, 2020.
two censuses in which the questions on crimes consistently appeared in the questionnaire. The data, which are available from Indonesia Statistics (BPS), consist of detailed micro level information on villages and urban wards in Indonesia. From this database, we limit the data to the urban wards within the areas of Jakarta, Medan and Surabaya, which represent the three main cities in Indonesia. Jakarta is the capital of Indonesia, and the largest city with more than 9.6 million inhabitants. Surabaya is the second largest city in Indonesia with more than 3.1 million inhabitants, while Medan is the largest city in Sumatra Island with approximately 2.9 million inhabitants. These three cities are the capitals of the three provinces with the highest crime rates in Indonesia. Overall, the data consist of more than 250 urban wards from the three cities Figure 1.

One of the most popular approaches in impact assessment studies is the difference-in-differences method (DID). This approach has an intuitive appeal and has been widely used in economics, public policy, health research, management, and other fields. The DID approach incorporates insights from cross-sectional treatment-control comparisons and before-after studies. Assuming there is a difference in outcomes, DID compares the results in the treatment group to a control group, with data from after the policy implementation, to estimate the impact of a policy or ‘treatment’ (Fredriksson and de Oliveira 2019).

Difference-in-differences (DID) is designed to imitate an experimental research design using data from an observational study by studying the differential effect of treatment on a treatment group versus a control group in a natural experiment. DID calculates the effect of treatment (namely, the explanatory variable or independent variable) on an outcome (i.e. the response variable or dependent variable) by comparing the average difference over time in the outcome variable for the treatment group compared with the average difference over time for the control group. The objective is to reduce extraneous factors and selection bias (Angrist and Pischke 2008).

The data in a simple DID study come from two groups and two time periods, and are usually at the individual level, which is a lower level than the treatment intervention itself. Repeated cross-sectional samples of the population (ideally random draws) or a panel of data may be used. In the case of two groups and two time periods, the DID estimate of policy impact can be written as follows:

\[ \text{DID} = (\bar{y}_{g=Treatment,t=After} - \bar{y}_{g=Treatment,t=Before}) - (\bar{y}_{g=Control,t=After} - \bar{y}_{g=Control,t=Before}) \]  

(1)

where \( y \) is the outcome variable, the bar represents the average value (averaged over individuals, typically indexed by \( i \)), the group is indexed by \( g \), and \( t \) represents time. With before and after data for treatment and control, the data are thus divided into the four groups and the above double difference is calculated.

In order to identify the significance level of the DID, regression analysis is used. In an OLS regression framework, the estimation model is written as:

\[ y_{igt} = A_g + B_t + \beta D_{gt} + \epsilon_{igt} \]  

(2)

Figure 1. The locations of the cities under study: Medan, Jakarta and Surabaya.
where $A_g$ are treatment/control group fixed effects, $B_{it}$ before/after fixed effects, $D_{gij}$ is a dummy variable that equals 1 for treatment group in the after period and zero otherwise, and $\epsilon_{igt}$ is the error term. In this regard, the $\beta$-coefficient provides the DID estimate.

DID estimation is a simple way to eliminate variation which may have resulted due to factors influencing both control and treatment groups (Wooldridge 2013). In our model, data from the pre- and post-treatment groups are applied. We identify a control and a treatment group based on the existence of the open green space in particular urban ward. Between 2014 and 2018, the urban wards which changed from not having open green space to having a green space are defined as the treatment group. Those urban wards that remained without open green space between 2014 and 2018 are referred to as the control group. The econometric model specifications are presented below. The subscript $t$ refers to both the 2014 and the 2018 surveys. In this study we are using a panel dataset.

$$\text{crime}_{it} = \beta_0 + \beta_1 \text{ward}_i + \text{post}_t + \delta \text{ward}_i \times \text{post}_t + \delta X_{it} + \epsilon_{it}$$  \hspace{1cm} (3)

$\text{crime}_{it}$: 1 if there is occurrence of crime in the urban ward, and 0 if none; $\text{ward}_i$: 1 if the urban ward is in the treatment group, and 0 if the control group; $\text{post}_t$: 0 for pre-treatment and 1 for post-treatment; $\text{ward}_i \times \text{post}_t$: interaction between treatment and post; $X_{it}$: vector of explanatory variables describing urban ward.

Regarding the measurement of crime, the crime data in PODES comes from the question: ‘Does – specific type of crime – ever happen in this village?’ The answer is ‘yes’, or ‘never’. In this case, there are 6 types of crimes asked about in the questionnaire: theft, robbery, homicide, harassment, rape, and drug use. In this case, we construct a dummy variable where 1 indicates the crime occurrence (regardless the type), and 0 means no crime occurrence of any type.

In addition to the probability of overall crime occurrence, we also estimate the effect of open green space establishment on the probability of robbery, where the variable for robbery is coded 1 if there is occurrence of robbery in the urban ward, and 0 if none.

### 4. Results and discussion

Table 2 describes the statistics descriptive of the main variables used in this study, which include overall crime occurrence and robbery. Robbery occurred in 20% of all urban wards, while crime in general occurred in almost all urban wards (82.2%). Open green space is available in 54% of all urban wards in the sample, with about 33% new open green space established during the period of observation. Unfortunately, 22% of the urban wards in the data set lost their open green spaces during the same period. This is probably due to real estate development and other form of urban development which convert open green spaces into built areas. This loss of open green spaces provides an opportunity to empirically explore whether the establishment of open green spaces can have the reverse effect on urban wards where the establishment of open green spaces may paradoxically lead to the later demolition of open green spaces.

Meanwhile, the descriptive statistics of other variables, which are included as control variables in the econometric model, are presented in Table 3. The control variables include the change of the religious building (mosque, church, temple, etc.), school buildings, and the community library. The religious building is a proxy for the religiosity of the population in each urban ward. The current general conclusion of various studies is that religiosity is negatively associated with criminal offenses and that the deterrent effect of religion is stronger for non-violent offenses and drug use (Baier and Bradley 2001; Baur 2018; Johnson 2011; Johnson and Jang 2011). According to Baur (2018), outdoor recreation in natural settings can reduce stress, enable better concentration, improve mood, and generally promote a more positive mental state.

Meanwhile, schools and public libraries are generally active and regularly maintained and thus may have had

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**Table 2. Descriptive statistics of main variables.**

| Variable          | Obs. | Mean | SD  | Min. | Max. |
|-------------------|------|------|-----|------|------|
| Robbery           | 1,086| 0.209| 0.407| 0    | 1    |
| Crime (overall)   | 1,086| 0.822| 0.382| 0    | 1    |
| Open green space  | 1,086| 0.542| 0.498| 0    | 1    |
| New open green space | 520  | 0.335| 0.472| 0    | 1    |
| Loss open green space | 566  | 0.226| 0.419| 0    | 1    |

**Table 3. Descriptive statistics of control variables.**

| Variables            | Obs. | Mean and proportion | SD   | Min. | Max. |
|----------------------|------|----------------------|------|------|------|
| Mosque               | 1,086| 10.00                | 6.840| 0    | 89   |
| Islamic prayer house | 1,086| 15.72                | 14.44| 0    | 99   |
| Protestant church    | 1,086| 3.153                | 4.285| 0    | 63   |
| Catholic church      | 1,086| 0.530                | 1.061| 0    | 10   |
| Hindu Temple         | 1,086| 0.0691               | 0.285| 0    | 2    |
| Buddhist Temple      | 1,086| 0.793                | 1.932| 0    | 18   |
| Kindergarten         | 1,086| 6.830                | 6.157| 0    | 92   |
| Elementary school    | 1,086| 8.634                | 6.485| 0    | 41   |
| Junior high school   | 1,086| 3.358                | 2.755| 0    | 16   |
| Senior high school   | 1,086| 3.096                | 3.027| 0    | 18   |
| University           | 1,086| 0.826                | 1.232| 0    | 9    |
| Playgroup            | 1,086| 2.118                | 2.829| 0    | 8    |
| Childcare            | 1,086| 1.031                | 0.872| 0    | 2    |
| Community library    | 1,086| 1.400                | 1.373| 0    | 4    |
a deterrent effect on crime occurrence (Booth 1981; Brown 2018).

Next, we consider the estimation results of the impact of the establishment of open green spaces on crime in Tables 4 and 5. Each of these two models is estimated four times: with no control, with regional dummy, with control variables, and mixed (both regional dummy and control variables). The control variables include the indicators in Table 2. The open green space effect is separated across all models with the main variable of interest, Ward_new x Post, illustrating the impact of establishment of open green space on crime in Table 4 and 5, both of which utilize the DID approach.

The open green space effect is the focus of our study. Table 4 shows the estimation results on the probability of crime occurrence. Columns (1), (3), (5) and (7) of Table 4 show the estimation results, where the treatment group consists of the urban wards which did not have open green spaces in 2014 and had open green spaces in 2018 (referred to as ‘increased’ in Tables 4 and 5). The control groups are the urban wards which did not have any green space both in 2014 and 2018. The estimation result in column (1), without any control variables, shows that the coefficient of the interaction variable is negative and statistically significant at 5%. This suggests that the establishment of the open green spaces reduces the probability of crime occurrence. Furthermore, the establishment of open green space leads to a 13.9% reduction in crime occurrence, as indicated by the coefficient of the interaction variable. The negative and significant effects remain consistent both when the regional dummy is added into the estimation, column (3), and when the control variables are included into the estimation, column (5). While the negative effect remains consistent, the effect decreases slightly as the regional dummy and the control variables are included in the estimation. In this case, the establishment of new open green spaces reduces the probability of crime occurrence by 13.4%.

In order to check the robustness, we estimate whether the destruction of open green spaces would have the reverse effect of the establishment of open green spaces on the probability of crime occurrence. Columns (2), (4), (6), and (8) of Table 4 show the estimation results for the treatment group consisting of the urban wards reporting that they initially had open green spaces in 2014 and no longer had open green spaces in 2018 (referred to as ‘decreased’ in Tables 4 and 5). In this regard, the control group consists of the urban wards which reported that they have green spaces both in 2014 and 2018. Interestingly, the results are the opposite of the previous model; the destruction of the open green spaces leads to an increase in crime occurrence probability. Without any control variables, the crime occurrence probability increased by 11%, shown by the coefficient of the interaction variable in column (2). Including both regional dummy and control variables in the estimation slightly increases the crime occurrence probability to 11.8%. Although both are not statistically significant, the positive sign indicates that decreased open green spaces have the opposite effect of increased open green spaces on the probability of crime occurrence.

Table 5 shows the estimation results on the probability of robbery in the urban wards. Similarly to Table 4, columns (1), (3), (5) and (7) of Table 5 show the estimation results where the treatment group consists of the urban wards that did not have open green spaces in 2014 and have open green spaces in 2018 (referred to as ‘increased’ in Table 5). The control group is the urban wards which did not have any green spaces both in 2014 and 2018. Column (1) of Table 5 shows the estimation result without any control variables. In this case, the coefficient of the interaction variable is

| Table 4. The regression results of the DID estimation on overall crime. |
|-----------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|------------------------------|
| Variables                   | No control                  | Region                       | Control                      | Control and region            |
|                             | (1) increased | decreased | (2) increased | decreased | (3) increased | decreased | (4) increased | decreased | (5) increased | decreased | (6) increased | decreased | (7) increased | decreased | (8) increased | decreased |
| Constant                    | 0.803*** (0.0303)          | 0.872*** (0.0226)          | 0.766*** (0.0730)          | 0.998*** (0.0349)          | 0.656*** (0.215)          | 0.0579 (0.238)          | 0.498*** (0.230)         | 0.0943 (0.246)         |
| Ward (new green space = 1)  | 0.0356 (0.0498)           | 0.0498 (0.0562)           | 0.116*** (0.0368)         | −0.142*** (0.0377)        | 0.116*** (0.0366)        | −0.142*** (0.0372)       | 0.0887 (0.127)          | −0.188 (0.241)          | 0.0814 (0.128)         | −0.126 (0.246)         |
| Post (D2018 = 1)            | 0.116*** (0.0682)         | −0.139*** (0.0674)        | 0.116*** (0.0674)         | −0.139*** (0.0674)        | −0.148*** (0.0746)       | −0.134* (0.0736)         | 0.0670 (0.0559)         | 0.0066 (0.0595)         | 0.0381 (0.059)          | −0.126 (0.246)         |
| Ward_new x Post             | −0.0753 (0.0553)          | 0.0610 (0.0824)           | 0.0110 (0.0557)           | 0.0808 (0.0824)           | 0.110 (0.0821)           | 0.124 (0.0839)           | 0.118 (0.0823)          | 0.076 (0.111)           | 0.166 (0.211)          | 0.111 (0.211)          |
| Observations                | 520                       | 566                        | 520                        | 566                        | 520                        | 566                        | 520                        | 566                        | 520                        | 566                        |
| R-squared                   | 0.020                     | 0.025                      | 0.046                      | 0.061                      | 0.055                      | 0.077                      | 0.076                      | 0.111                     | 0.020                     | 0.025                     |

Robust standard errors in parentheses.  
*** p < 0.01, ** p < 0.05, * p < 0.1.
negative and statistically significant at a 5% level of significance. The coefficient $-0.173$ suggests that the establishment of open green spaces reduces the probability of robbery occurrence by 17.3%. The negative and significant effects remain consistent both when the regional dummy is added into the estimation, column (3), and when the control variables are included in the estimation, column (5). Including both the regional dummy and the control variables slightly decreases the negative effect of open green space on the probability of robbery to 16.7%.

As a robustness check, we estimate the impact of the destruction of open green space on the probability of robbery in the urban wards. In this regard, columns (2), (4), (6), and (8) of Table 5 show the estimation results where the treatment group consists of the urban wards reporting a loss of open green spaces, as indicated by the existence of open green spaces in 2014 and reporting no open green spaces in 2018. In this estimation, the control group consists of the urban wards which reported having green spaces both in 2014 and 2018. Similarly to Table 4, the results in Table 5 also contrast the previous model, where the control group is the urban wards with increased open green spaces. Column (2) of Table 5 shows that, without any control variables, the destruction of the open green spaces leads to a 15.3% increase of robbery probability in the urban wards. Including both regional dummy and control variables in the estimation slightly reduces positive effect to 14.6%. Both are statistically significant at 5% significance.

As illustrated in Tables 4 and 5, all of the models show that open green space has a statistically significant impact on reducing crime. The estimation in columns 7 and 8 is the most robust, as it controls for all variables. Ultimately, the DID results in columns 7 and 8 of both tables indicate that the new establishment of open green spaces leads to a 13.4% decrease in overall crime and a 16% decrease in robbery. For robustness, the Tables 4 and 5 also measure the treatment effect of the decrease or loss of open green space. The results are consistent: All the DID coefficients for wards

| Table 5. The regression results of the DID estimation on robbery. |
|---------------------------------------------------------------|
| **Variables** | **No Control** | | | **Region** | | | | **Control** | | | | **Control and Region** |
| | (1) increased | (2) decreased | **(3) increased** | **(4) decreased** | **(5) increased** | **(6) decreased** | **(7) increased** | **(8) decreased** |
| Constant | 0.139*** | 0.311*** | 0.107* | 0.348*** | −0.416*** | 0.446 | −0.538*** | 0.321 |
| Ward (new greenspace = 1) | 0.0797 | (0.0517) | 0.0728 | (0.0523) | 0.0846 | (0.0538) | 0.0818 | (0.0561) |
| Post (D2018 = 1) | 0.139*** | −0.169*** | 0.139*** | −0.169*** | 0.289*** | −0.466* | 0.286*** | −0.386 |
| Ward_new x Post (1.new#1.D2018) | −0.173** | (0.0747) | −0.173* | (0.0739) | −0.180** | (0.0773) | −0.167** | (0.0763) |
| Ward (loss greenspace = 1) | −0.139*** | (0.0568) | −0.137** | (0.0577) | −0.116** | (0.0582) | −0.106* | (0.0576) |
| Ward_loss x Post (1.Loss#1.D2018) | 0.153*** | (0.0765) | 0.153*** | (0.0757) | 0.148* | (0.0758) | 0.146** | (0.0734) |
| Observations | 520 | 566 | 520 | 566 | 497 | 561 | 497 | 561 |
| R-squared | 0.020 | 0.037 | 0.037 | 0.064 | 0.097 | 0.079 | 0.116 | 0.128 |

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$. 

| Table 6. Mean Difference test of 2014 and 2018 control variables for increased open green space. |
|---------------------------------------------------------------|
| **Variables** | **Treatment** | | | **Control** | | | |
| | Mean-Diff | $p$-value | | Mean-Diff | $p$-value |
| Mosque | −1,141 | 0.324 | −0.509 | 0.374 |
| Islamic prayer house | −0.839 | 0.748 | −0.578 | 0.562 |
| Protestant church | 0.023 | 0.967 | −0.110 | 0.805 |
| Catholic church | 0.034 | 0.850 | −0.058 | 0.549 |
| Hindu Temple | −0.023 | 0.648 | −0.023 | 0.442 |
| Buddhist Temple | −0.069 | 0.791 | −0.046 | 0.847 |
| Kindergarten | −0.506 | 0.632 | −0.064 | 0.924 |
| Elementary school | 0.977 | 0.375 | −0.289 | 0.519 |
| Junior high school | −0.207 | 0.619 | −0.098 | 0.621 |
| Senior high school | −0.218 | 0.639 | 0.000 | 1.000 |
| University | −0.069 | 0.669 | −0.092 | 0.339 |
| Playgroup | 2,149 | 0.000*** | 4.329 | 0.000*** |
| Childcare | 1,471 | 0.000*** | 1.676 | 0.000*** |
| Community library | 1,333 | 0.000*** | 2.266 | 0.000*** |

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

| Table 7. Mean difference test of 2014 and 2018 control variables for decreased open green space. |
|---------------------------------------------------------------|
| **Variables** | **Treatment** | | | **Control** | | | |
| | Mean-Diff | $p$-value | | Mean-Diff | $p$-value |
| Mosque | −0.891 | 0.318 | −0.416 | 0.488 |
| Islamic prayer house | −1.313 | 0.597 | 0.863 | 0.545 |
| Protestant church | 0.656 | 0.452 | −0.087 | 0.838 |
| Catholic church | −0.016 | 0.939 | 0.000 | 1.000 |
| Hindu Temple | −0.016 | 0.563 | 0.046 | 1.085 |
| Buddhist Temple | −0.047 | 0.856 | −0.027 | 0.877 |
| Kindergarten | −0.766 | 0.380 | −0.269 | 0.617 |
| Elementary school | 0.719 | 0.426 | 1.142 | 0.0842* |
| Junior high school | 0.141 | 0.714 | 0.233 | 0.444 |
| Senior high school | 0.016 | 0.972 | 0.137 | 0.671 |
| University | 0.016 | 0.950 | −0.046 | 0.734 |
| Playgroup | 2,500 | 0.000*** | 2.301 | 0.000*** |
| Childcare | 1,422 | 0.000*** | 1.447 | 0.000*** |
| Community library | 1,453 | 0.000*** | 1.329 | 0.000*** |

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

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with a decrease in open green space have the reverse sign with almost the same magnitude as for the wards with an increase in open green space.

An important identifying assumption of the DID estimation method is the parallel trend assumption. It is not feasible to test the parallel trend assumption in our study since we only have two data points across time. However, although a formal parallel test is not plausible, we conducted a mean difference test of the wards’ characteristics before and after the intervention (green space increased or decreased) for both treated (wards with increased or decreased green space) and control wards. The results are summarized in Tables 6 and 7. In general, both tables demonstrate that most of the urban wards’ characteristics that went unchanged (not statistically significance mean difference) and that changed (statistically significance mean difference) are the same for both treated and control wards. This indicates that the dynamic of characteristics of the wards are the same for both treated and untreated wards, which then informally supports the argument of parallel trend assumption.

In general, these findings extend the literature on the importance of green spaces within urban settings, specifically by providing empirical evidence on the lessening effect of open green spaces on crime and robbery incidents in Indonesia. The effect of establishing open green spaces on the reduction of crime and robbery may not be direct; establishing open green space in urban areas provides places for community interaction, places for exercise (Shepley et al. 2019), biophilic support (Roe et al. 2013), and the reduction of vacant places prone to crime incidents (Garvin, Cannuscio, and Branas 2013), all of which may then contribute to decreasing crime and robbery incidents in the urban setting.

5. Conclusion

Despite the common perception that urban green spaces are prone to violence and crime, recent findings contest these perceptions. Innovative and multidisciplinary research which specifically examines the relationships between urban green space and crime has recently indicated that urban green spaces facilitate the reduction of crime and violence, often through the same mechanisms as the other health benefits of green space (Bogar and Beyer 2016). Given these divergent notions of the interrelationships between urban green spaces and crime, and the potential for greening strategies to improve a wider range of public health issues including crime and violence, a deeper understanding of the current evidence is required. In particular, the direction of the relationship between urban green spaces and crime, the quantitative meaning of this relationship, and the causal processes that promote the relationship between urban green space and crime should be systematically determined. This study contributes to this body of literature by establishing empirical evidence for the causal inference on the impact of establishment and removal of open green spaces in an urban area within context of the developing world.

Using the urban wards data level from three of the largest cities in Indonesia, which are also the capitals of the three provinces with the highest crime rates in Indonesia, we estimated the impact of the increase of urban green space on the crime occurrence and robbery. Results of the estimation suggest that the development of new urban green spaces have a negative and substantial effect of on the occurrence of crime at the level of urban wards. Furthermore, the loss of urban green spaces has the reverse effect by increasing crime occurrence. These results remain significant with the inclusion of regional dummies as well as other control variables, which indicates the robustness of the results in controlling for regional differences. This evidence may serve as a rationale for city governments and residents to embrace these measures as access to nature is shown to have a mitigating effect on crime in urban settings.

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