Master Thesis

A Spatial Analysis on Tipping Points and Physical Disorder Reports in Eindhoven

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Abstract

This thesis examines the relationship between socioeconomic tipping points and reports of physical disorder in Eindhoven from 2015 to 2020. By analyzing 500x500 meter socioeconomic data using linear and segmented regressions, the study explores how income levels interact with disorder reports.

No significant income-based tipping points were found at the 500x500 meter scale or in larger areas of 1000x1000 or 2500x2500 meters. However, segmented regressions identified significant breakpoints in disorder reports at specific income thresholds, highlighting complex community responses. A positive association was found between the percentage of low-income residents and disorder reports per inhabitant, indicating that lower-income areas report more disorder, potentially due to higher actual disorder or greater reliance on municipal services. Significant breakpoints were identified at 49.2% and 60.5% for low-income households, suggesting critical ranges where community efforts to address disorder differentiate. Reports from low-income areas are processed slightly faster than those from higher-income areas, with a further significant decrease in processing in areas with 49.2% to 60.5% lower-income households. This indicates a concentrated municipal effort to maintain neighborhood quality in these areas. Fixed effect first-difference regressions showed that the influence of reports on income levels is nearly equal to the influence of income levels on reports, suggesting no clear causal relationship. While the number of reports is higher in low-income areas, it does not significantly drive socioeconomic changes.

The findings highlight the need for further research on the relationship between physical disorder and socioeconomic status. Municipalities should focus on community engagement in lower-income areas to foster collective efforts in maintaining neighborhood quality. Targeted policies should address areas with 49.2% to 60.5% lower-income households to prevent them from tipping into severe disorder. Understanding the dynamics of physical disorder reporting can help policymakers improve urban living conditions and prevent neighborhood decline.

Keywords: socioeconomic tipping points, broken windows theory, physical disorder, gentrification, urban policy, segmented regression analysis

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1. Introduction

1.1 Background

Urban areas are vibrant places which are always changing. Such change can be socioeconomic, and entails the changing composition of inhabitants of a neighborhood, which can even lead to displacement. This phenomenon can also be identified as gentrification (Smith, 1996). One factor in the decision to move is that of the reputation of the neighborhood, of which cleanliness can be an aspect (Permentier, 2009). The cleanliness of a neighborhood has a value to its residents and influences their opinion on the neighborhood. It has been found that physical disorder (such as litter in the streets, vandalism and noise) can contribute to residential mobility because it reduces residential satisfaction (Parkes et. al, 2002). Furthermore, there are negative health effects in areas with a high amount of physical disorder (e.g. Quinn et al., 2014). When this is combined with the 'broken windows' theory, which states that a certain amount of physical disorder (like a broken window) will lead to more physical disorder (Kelling & Wilson, 1982), the social importance of researching this subject becomes more clear.

It is assumed that when the social and physical disorder reaches a certain height, residents who can afford to leave these aeras, will leave these areas (Pinkster et. al, 2014). In line with the broken windows theory, this departure can result in a continued decline of the neighborhood. However, residents within the same neighborhood do have diverging perceptions of neighborhood quality and disorder, depending on their own residential history, age, and employment situation (Kleinhans, 2009). So, residents who can afford to will not necessarily leave these areas but may not value physical disorder as highly, or instead intend to change the physical disorder while staying in the area. Lower-income may not have these exit opportunities, which increases their dependency on the neighborhood.

In the Netherlands, people can file a complaint about public space (*'melding openbare ruimte'*) to notify their municipality about something wrong in the public space. Depending on the system being used, people can report on a category, or fill in their complaint after which the system is trained to categorize. These reports can be done online, using an app, or by calling (Melding Openbare Ruimte, 2024). Possible reports include fly tipping, broken public lighting or anything wrong with the roads. The municipality can act on reports filed by the residents. Thus, they help in keeping their neighborhood clean and organized through these reports.

Residents have to know that their reports have an effect. If no effect is felt, there is less incentive to report again in a following instance of physical disorder. A low processing period is important to ensure that the effect of the specific report of a resident is felt, and there is trust in the responsibility of the government to take on such tasks. In turn, this leads to residents reporting again in the following instance of physical disorder. Ultimately, by reporting on physical disorder, the residents can assist decreasing the prevalence of physical disorder, thus potentially improving the socioeconomic status of the neighborhood.

1.2 Scope and aim of the research

The main focus of this thesis is on physical disorder and socioeconomic change. To measure socioeconomic change, data of income percentages will be used. With that data, it is possible to find whether tipping points exist in socioeconomic change. This is based on the tipping point research from the United States which is often about ethnic changes in the neighborhood where a minority grows bigger than a certain threshold from which the minority is supposed to 'take over' as other minorities leave the neighborhood (Grodzins, 1958; Wolfe, 1963). Research has identified these tipping points for income levels as well, but that research has of yet mainly been done in the United States (Malone, 2020), and not in the Netherlands. Therefore, this thesis seeks to work on this research gap to understand more about these effects for the Netherlands.

As for reports on physical disorder, the city of Eindhoven is used based on the period of 2015-2020, for which data is available. The choice for Eindhoven is simply because of the availability of data, which is a lot better than in other major Dutch cities. There are other methods for measuring physical disorder, such as audits or virtual research, but this thesis will be on reports. This will omit the residents who do not report, but give extra focus to residents who feel a sufficient responsibility or aggravation to report. Furthermore, the exact amount of physical disorder cannot be taken into account for this thesis, because this information is not available. But the assumption that there is a direct relationship between the amount of reports and the actual physical disorder can be made. So if we understand more about the reports on physical disorder, it can also give us a better understanding of physical disorder itself.

It is important to research physical disorder because it is a form of disturbance that can have negative health impacts, among other negative outcomes(Quinn et al., 2014). There is a role and responsibility for the government to tackle physical disorder. They can do so through regular activities such as waste treatment. By reporting on physical disorder people can help their municipality when the regular visits are not enough. However, this can also be evidence of areas with a higher prevalence of physical disorder or a lack of focus of the municipality on such an area. To find out how the municipality reacts to the reports, the processing period can be viewed. It is necessary for the municipality to react on reports, so that people keep on filing reports and identifying physical disorder. Due to the negative effects of physical disorder and the potential outcomes of the broken window effect, it is therefore necessary for policy implication for the municipality to have a good understanding of the reports and their effects on the neighborhood.

This thesis will be looking at changes in urban areas and the reports that are done. If there is indeed an influence of reports on socioeconomic change, that can tell us a lot about the workings behind neighborhood change. This leads to the following research question: *How does the relationship between the socioeconomic status of an area and physical disorder work?*

This thesis will look into reports on physical disorder to understand more about that relationship. By answering this research question, we will be able to better understand the socioeconomic changes of an area and the effects of reports on public space. To answer this question, the sub questions are as followed:

- *Is it possible to identify a tipping point in CBS-square data of 500 by 500 meters, 1000 by 1000 meters, or 2500 by 2500 meters?*

- *How does the relationship between the socioeconomic status of an area and the number of reports per inhabitant on physical disorder work?*
- *How does the processing period of reports relate to the socioeconomic status of an area?*

2. Literature review

2.1 Tipping points

When it comes to socioeconomic change, a major focus of research over the last decades has been on gentrification. A commonly used definition of gentrification is that of Smith (1996) which explains gentrification as the process by which higher income households displace lower income residents of a neighborhood, changing the essential character and flavor of that neighborhood. An aspect of gentrification can be the displacement of lower-income residents, although gentrification can also happen without physical displacement. Gentrification entails a change in the public structure of a neighborhood (shops and meeting places) and these transformations in public facilities cause a loss of sense of place even without physical displacement (Shaw & Hagemans, 2015). This cultural erosion is one of the main negative effects of gentrification (Cole et al., 2024). However, gentrification can also create a social mix that revitalizes the economy and incentivizes a new creative culture (Shaw & Hagemans, 2015; Gainza, 2017). Furthermore, findings suggest that gentrification can lead to lower crime rates as neighborhoods become more affluent and better policed (Cole et al., 2021). The debate on the positive and negative aspects of gentrification is still ongoing. The importance of gentrification as a research subject is clear however, which is why this thesis will entail the socioeconomic change as well, of which gentrification is a well-known phenomenon.

To know more about the socioeconomic change in Eindhoven, this thesis will focus on tipping points. Research in tipping point originates from the United States where during the middle of the 20th century the original description of the tipping-point hypothesis was formulated. This was based on the aspect of 'white flight', when the percentage of blacks in a neighborhood reached a certain threshold (Grodzins, 1958; Wolfe, 1963). These articles are now severely outdated, but the hypothesis of a tipping point in neighborhoods has been the origin of many papers. The definition of a tipping point was broadened by Schelling (1971: 181) to the point where 'a recognizable new minority enters a neighborhood in sufficient numbers to cause the earlier residents to begin evacuating'. For a long time, research on the tipping-point hypothesis was kept to the racial aspect of neighborhood change in the segregated areas of the United States. Recently however, research in the subject has crossed the pond and been picked up in Western Europe due to the rising migrant population (Rathelot and Safi, 2014; Aldén et al., 2015). As such, tipping point has stayed as a relevant research subject.

But the research into tipping has also broadened into other aspects than racial or ethnic change. Goering (1978) established that racial proportions would be only one element in determining population turnover, but more research was necessary to pinpoint what these other elements could be. An example of this is a study by Malone (2020) on whether tipping exists amongst income groups in the neighborhood. He relates back to research by Coulson & Bond (1990) and Glaeser et al., (2008) who found that an influx of poor people can cause tipping behavior amongst the rich so long as rich people gain more utility from living with other rich people than they do from living with poor people. However, Malone (2020) uses the research methods from tipping-point research on race to try and identify the threshold percentile that is the tipping point. He identifies this tipping point to range from 7 to 12%, although for a point it is not clear as it varies a lot, and has thus many other factors that influence the tipping point. But it is at this range where the people in the neighborhood who are below the 10^{th} percentile of income in their city exceed the tipping point. That relates to the findings by Quercia and Galster (2000) that there is no definitive single value for the tipping point; it all depends on the particular neighborhood and metropolitan-wide contexts.

Malone (2020) only researched a tipping point of the lowest 10^{th} percentile of income, and related this to a corresponding outflow of inhabitants in the highest 10^{th} percentile of income. Thus, it only sought to find a tipping point based on an outflow of high income inhabitants, and not the other way around. This is a valid way of researching such a tipping point. Because as found in research by Permentier et al. (2007), due to the higher spatial residential mobility, high income inhabitants would be more able to move when a certain factor reaches a level where a move is desired. Furthermore, there are anecdotal examples of residents objecting housing for low income inhabitants due to the belief that this would lead to a drop in house values, increases in crime, and decreases in the quality of local schools (Tighe, 2010).

However, a tipping point due to an outflow of low income inhabitants could also be possible.

Along with finding a tipping point, another important finding relates to the policy implications of income tipping. The findings by Malone (2020: 26-27) suggest that '*policies that provide low-income people with the means to enter more affluent neighborhoods (e.g. housing vouchers) may be self-ameliorating in that they could cause the composition of the neighborhood to change if they bring it past its tipping point.'.* Ultimately, Malone (2020) acknowledges that the tipping point when it comes to income is not very clear, and there are other elements that influence the processes, similar to the findings of Goering (1978). Furthermore, by bringing income and ethnic segregation together in a study on neighborhood change processes and tipping points, Malmberg & Clark (2019) argue that ethnic segregation and income segregation are linked processes that interact with each other. Due to the complexity, they argue that segregation is not as simple as a threshold model as introduced by Schelling (1971) and suggested by the tipping point theory. But still, Malmberg & Clark (2019) conclude that tipping points may exist. This shows the intricate and complex processes that inhibit neighborhood change.

Finally, there is one more article to discuss which relates back to the original racial aspect, as it researched the ethnic composition, but of Dutch neighborhoods. In his 2016 article, Ong examined how the neighborhood composition changes over time, and whether neighborhoods 'tip' towards becoming highly segregated neighborhoods. Ong uses the models of Schelling (1971) which conclude that neighborhood transitions will lead to a segregated society. However, Ong (2016) is unable to find such a tipping point dynamic in three major Dutch metropolitan areas. However, he was able to identify native Dutch or Western minority households that fled or avoided neighborhoods with non-western minorities. This mention of avoiding neighborhoods relates to 'white avoidance' (Ellen, 2000) with native Dutch households being less likely, compared with Turkish and Moroccan households, to move from a 'non-concentrated' to a 'concentrated' non-Western neighbourhood (Bolt et al., 2008). While there is evidence of white avoidance, the findings of Ong (2016) do not suggest that there is a significant tipping point after which the neighborhoods change into segregated enclaves.

So now it's interesting to understand why this does not happen in the Netherlands, although there is much more evidence of it happening in the United States. The explanations for this are threefold (Ong, 2016);

1. a large social housing sector which supports socially integrated neighborhoods,
2. centralized tax and redistributive regime and local amenities being almost universally funded by the central government,
3. the strong regulatory role of the state in housing and urban planning which may have even reversed the ripping tendency of at-risk neighborhoods

Further on in this literature review we will get back to the exact policies of the Dutch government that has influenced this conclusion. For this thesis, it is important to note that in his paper, Ong (2016) conducted research on finding a tipping point for three different metropolitan areas. As he concluded himself, there might be the possibility for multiple tipping points in such a large area, so that a tipping point might be found on a smaller scale. It is this research gap identified by Ong identifies that this thesis will try to fill.

2.2 Dutch spatial planning

Before getting to the results about the possible tipping points in income in areas in Eindhoven, we must first understand the layout of Dutch neighborhoods. Dutch neighborhoods are significantly different from the more segregated American neighborhoods that were the subject of most current research in tipping points. This has mainly to do with policies of the Dutch government since after the second World War, which will be further delved into.

After the second World War, the Netherlands had to be rebuilt and due to the baby boom there was a necessity for many new homes. This was done through a hierarchical top-down structure with heavy regulation (Modai-Snir & van Ham, 2018; Tisma & Mijer, 2018). Functionality was key, as planning was institutionalized in governmental structure where regulations and zoning plans had generic conditions that could be used throughout the country (Gerrits et al., 2012). One of the regulations that was rather exemplary for the Netherlands and impacts this thesis, as well as it impacted the results of Ong (2016), is the high percentage of social housing in Dutch cities. This ensured affordability of housing within city boundaries, and for low-income households in the Netherlands to be less likely to be priced out of cities (Modai-Snir & van Ham, 2018). Furthermore, it created a stable housing market for low income inhabitants, that could be used to create a 'social mix' by diversifying tenure compositions in neighborhoods (Boterman & van Gent, 2014). Housing policies are also structured in a way where tenants in the Netherlands have rental protection which protects them from the displacement that is central in gentrification theory. In this sense the Dutch housing market regime '*functions as a buffer to changing socio-spatial structures'* (Modai-Snir & van Ham, 2018: 1677). As such, it was able to moderate gentrification and displacement processes (van Gent, 2013), which corresponds with the findings of Ong (2016) and can explain why he was unable to identify significant tipping points. This is the situation as it was until the 1990s, when a distinctive change came in Dutch spatial planning.

The top-down approach and the idea that planners could mold society came under intense pressure, and an approach based on area-specific policies became complementary to the traditional coordinative and procedural approach (Gerrits et al., 2012). To summarize, 'government' changed to 'governance' and from centralized top-down to decentralized network governance (Tisma & Mijer, 2018).

Along with this change, also came a deregulation of the Dutch housing market. The privatization and liberalization spurred gentrification, displacement and the strengthening of urban divisions (Boterman & van Gent, 2014). This also led to a slow positional downgrade of neighborhoods with a large share of social housing. The aforementioned 'social mix' that was the goal of urban regeneration policies intended to target these 'problematic' neighborhoods (Boterman & van Gent, 2014; Kleinhans, 2004). During this time, it was concluded that inequality between neighborhoods between 1971 and 2000 had grown. The relative income difference between the poorest and richest neighborhoods had risen sharply (van de Ven, 2003). The mixing of tenure compositions to create mixed socioeconomic neighborhoods had not worked, as there were no absolutely mixed neighborhoods and neighborhoods were much more segregated than was expected (de Vries, 2005).

This leads to one of the major Dutch housing policies to be discussed for this thesis; the 'Vogelaarwijken' that were introduced by minister Ella Vogelaar in 2007. This was a list of Dutch neighborhoods that scored worse on 18 indicators that were divided on deprivation indicators and socioeconomic indicators. The list immediately became a hot topic of discussion, and received a lot of criticism, especially on the indicators that were used. These indicators were of utmost importance, because being included on the list meant a large grant of money from the government. This included criticism that the indicators were not as 'objective' as announced, that indicators were included which should have no influence, and that the ultimate selection had a political component based on consultations with municipalities (van Gent et al., 2009). As mentioned before, there was an incentive to get a neighborhood on this list, and this political component contradicts the former claim of 'objective' selection. Other criticism came from the idea that came with this list that these were highly segregated 'probleemwijken', neighborhoods with lots of problems. When in reality, segregation levels in social and ethnic terms were moderate compared to other European cities, and not increasing (Musterd, 2005; Musterd & Ostendorf, 2007). In discussing this, van Gent et al. (2009) again mention the social mix in Dutch neighborhoods.

This social mix is an explicit aim of the regeneration policy for neighborhoods to create more cohesive societies as it is supposed to be good for increasing mutual tolerance between groups and for enhancing livability in the neighborhood (Dekker & Varady, 2011). Research in Rotterdam has shown that social cohesion is a big influence on fly tipping, referred to as 'naastplaatsingen' (de Vries, 2021). To achieve the social mix, the policy looked mainly into types of housing, as some of the housing for lower-income households were being replaced by owner-occupied homes, which bring in middle-class households (Dekker & Varady, 2011). Although it is argued by van Wilsem et al. (2006) that community cohesion is seen to be low not only in disadvantaged neighborhoods, but also in areas characterized by strong social heterogeneity and instability. Another factor in this are the middle-class enclaves that were found by Kleinhans (2009). Even though a neighborhood might seem to have a lot of social mixing going on, on a smaller scale, separated communities could be discovered based on the socioeconomic status of residents. This creates a situation where the diversification of housing has not resulted in social cohesion, but enclaves where residents interact solely with fellow residents with similar social positions.

2.3 Physical disorder

Along with socioeconomic change, a focus of this thesis is on physical disorder. Physical disorder can be explained as visual cues of disorder such as litter, broken windows, or the deterioration of urban environments (Anderson, 2008; Hur & Nasar, 2014; Quinn et al., 2014). Physical disorder can have several effects, and relates to the 'broken windows theory'. This theory, posed by Wilson and Kelling (1982), explains that just as a broken window invites greater damage, minor offenses, when left unchecked, can lead to violent crimes and urban decay. When disorderly behavior goes unchallenged, that signal implies that no one cares (Weiss, 2010). In this sense, it relates to the necessity of the use of voice of residents. Furthermore, residents need to feel a responsibility for the status of their neighborhood. The broken windows theory has a criminological background, but can be applied to other fields as well. The idea of community policing that is central to the theory, where members of the community work together to maintain public order and safety (Weiss, 2010), can also be applied to physical disorder. As found in Rotterdam, a higher social cohesion relates to fewer reports of physical disorder (de Vries, 2021). Similarly, Weiss (2010) found in a research on success in implementing community policing, that citizen participation has the greatest importance.

Physical disorder has several negative outcomes, including a negative impact on mental and physical health (Quinn et al., 2014), substance abuse (Latkin et al., 2007; O'Brien et al., 2019), and perceived safety (Miles, 2008; Ndjila et al., 2019).

By doing audits in neighborhoods of different income levels, Taylor et al., (2012) found that physical disorder is significantly more prevalent in lower-income neighborhoods. These findings correspond to research done in Amsterdam and Rotterdam (de Vries, 2021; O&S, 2022). This is further supported by Kelly et al. (2007) who also found a similar relationship between predominantly African-

American neighborhoods with greater physical disorder than primarily white neighborhoods, which corresponds with the aforementioned findings due to the neighborhood composition in many American neighborhoods.

Wilson and Kelling (1982) posed that there are three types of neighborhoods (from serene, to tipping, to crime-ridden). Steenbeek and Kreis (2015) tried to find whether there are neighborhoods in Amsterdam that are 'tipping' in physical disorder. Because there is a policy implication, as these would be areas of importance to policy makers to keep these areas from becoming crime-ridden. However, Steenbeek and Kreis were unable to find definitive areas that were tipping in Amsterdam. But while their empirical research method was unable to find tipping areas, they conclude that further research is necessary with other methods of data collection.

Research on physical disorder has traditionally been done by doing in-person audits (e.g. Tayler et al., 2012; Steenbeek & Kreis, 2015). However, recent new research methods have been found in virtual audits such as Google Street View or unmanned aerial systems (UAV) for example that have led to new outcomes (Quinn et al., 2014; Grubesic et al., 2018; Chen et al., 2022). This gives the opportunity to conduct research on a much larger scale. Still, there will be a discrepancy between the physical disorder that can thus be identified and the physical disorder that is noted by residents. These may indicate physical disorder that is more irritating, or has more necessity to be fixed as soon as possible, but will also relate to the willingness to report, as was found in Amsterdam (O&S, 2022). By using the reports, we hope to be better able to identify changes over time, and to relate this to changes in urban areas.

2.4 Reports on physical disorder

Lower-income households are more dependent on the neighborhood because they have limited exit opportunities. Thus, they are more inclined to use their voice to set change in motion. The reports that people can file are a way to 'voice' their complaints with the municipality. Using Hirschman's (1970) 'exit, voice and loyalty' framework, Permentier et al. (2007) found how residents respond to poor neighborhood reputations. The exit option is to move out of the neighborhood. Voice is the expression of dissatisfaction which can be directed to the municipality. Reports on physical disorder are a method for residents to do this. The method of choice (exit or voice) is based on the dependency on their area of residence.

However, it is important for the municipality to react adequately to this (e.g. Ross et al., 2001). Because lower-income households have no choice but to use their voice, or accept the situation of physical disorder, it is an important aspect of research to understand more about the reports.

People can report on problems in public space at their municipalities. While it has been a method of reporting for a long time, not much research has been done on the subject. Research has been conducted by the municipalities of Amsterdam (O&S, 2022) and Rotterdam (de Vries, 2021) about why and who do these reports at the municipalities. In Amsterdam, it was found that a higher population density relates to less reports per inhabitant, while a higher percentage of higher educated inhabitants relates to more reports per inhabitant. The average income does not play a big part, although there is a small negative relationship; a higher average income relates to some less reports. Furthermore, the researchers found that inhabitants who have more trust in public services such as police are more inclined to report, along with inhabitants who feel a duty and are motivated in improving their environment. And when residents trust that their reports of physical disorder, such as vandalism or poor infrastructure, will be effectively addressed, they are more likely to report subsequent issues and engage in community improvement efforts. Ross et al. (2001) established that people who live in disadvantages neighborhoods are more mistrusting and often feel powerless. Therein lies a responsibility for the municipality to work on the reports to combat mistrust in public services and the feeling of powerlessness. While the Amsterdam research looked into the motivations for people to report on public space, the Rotterdam research focused on the 'origin' of those reports such as fly tipping.

The Rotterdam research looked into explanations for fly tipping The main explanations for this behavior is complacency, impatience, aversion to touch containers, copying behavior, and a lack of knowledge about the rules. One of the main findings was that 'naastplaatsingen' happen most often in areas of a low social cohesion. Furthermore, they are most apparent in areas of a lower socioeconomic position. This might relate to the findings in Amsterdam, where more reports were registered in such areas. But it must be noted, for these researches and this thesis, that we are only able to register the reports, and the ‘naastplaatsingen’ or other problems themselves are not registered. So this will always give an unfulfilled understanding of the exact relation between physical disorder and reports.

3. Methodology

3.1 Methods

For this thesis we will try to find tipping points in the city of Eindhoven. This will be done by doing a segmented regression on income percentages. To get a better understanding of the research method, we have made examples of a linear regression, a segmented regression and an example of a tipping point indicated by the R^2. These can be seen in Figures 1-3. These examples do not correspond to any actual geographic area or real-world data; instead, it is designed to demonstrate the methodology in a controlled and simplified context.

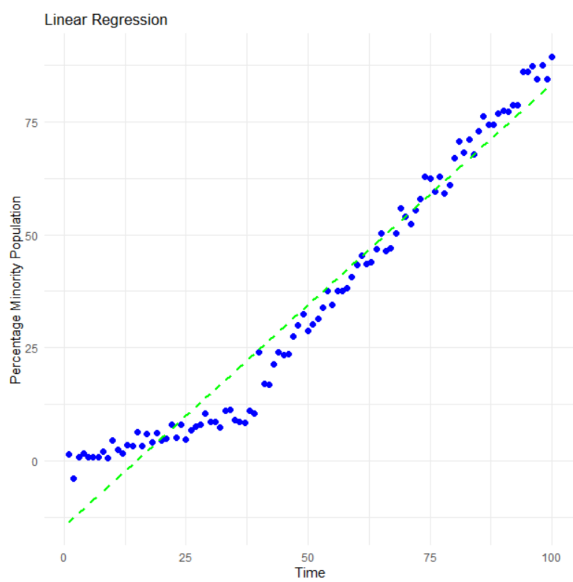

Figure 1: Example of linear regression

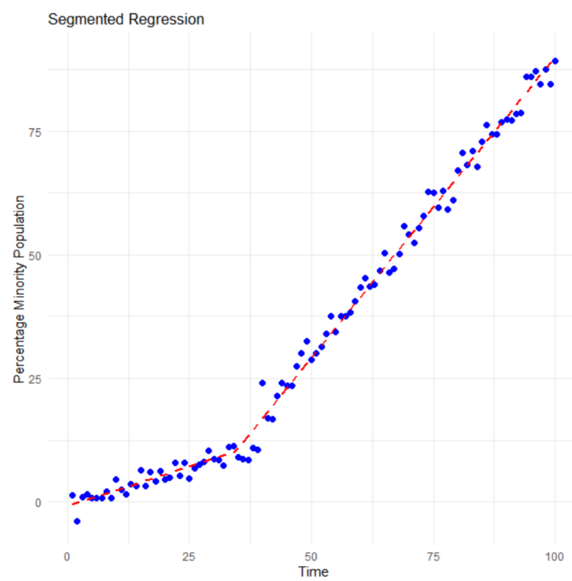

Figure 2: Example of segmented regression

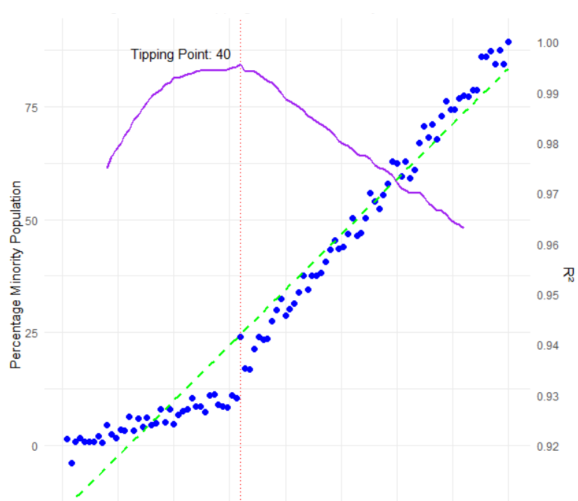

Figure 3: Example of tipping point indicated by R^2

As can be seen in Figures 1-3, the example data indicates an area where a minority population increases at a certain tempo, until a tipping point after which the increase is more rapid. The linear regression that can be seen in Figure 1 (yellow line) is a way to get an understanding of the relationship between, in this case, time and the percentage of a minority population for an area. By doing a segmented regression, as seen in Figure 2, we can get a better understanding of the exact relation that is more detailed than the linear regression. While both regressions indicate the increasing minority population, it is the segmented regression that tells us more about changes in that increase. In this example, the data is very clear and a quick look would already indicate where the tipping point is. But with larger datasets with more variance, that will not be possible and doing such a segmented regression is necessary. In Figure 3, the R^2 (coefficient of determination) is also visualized. We visualize the R^2 to evaluate how well the segmented regression model fits the data at different potential tipping points. The R^2 value indicates the proportion of variance explained by the model. Although the examples do not show this, it is possible to find more than one tipping point.

For finding the tipping point in income level in Eindhoven, the segmented regressions will be done using R. For the relation between the income level and number of reports per inhabitant a linear regression will be done. But again, to get a more detailed understanding, a segmented regression will be done as well. The results of both segmented regressions can lead to further research. This will entail research on the influence of reports on the socioeconomic status of an area, which will be discussed later on. Another aspect is that of the processing period. As explained in the introduction, the processing period can give a better understanding of the current focus of the municipality on physical disorder. By doing linear regressions, it can become clear whether a difference in income percentages leads to a different processing period. Based on these results, and the results of the segmented regression, that can lead to further research on processing period. If there are tipping points, a Welch two-sample t-test can give information on the before-and-after processing periods.

Again using R, it is possible to do first-difference fixed effect regressions to understand the causal relationship between the amount of reports per inhabitant and the income level. First-difference fixed effect regressions entail a regression which looks at changes in income level from year to year within each area. So instead of focusing on the absolute numbers, we focus on how much the percentages increase or decrease each year. Similarly, this is done for the number of reports per inhabitant per area. This transforms the data, for which we can perform a regression analysis. Then we can analyze how much more (or fewer) reports are made each year based on the changing income distribution, and thus identify the importance and influence of reports on socioeconomic status of the area. The first-difference fixed effect regressions were done on the scale of 500 by 500 meters squares with three different income percentages (low, middle and high). Furthermore, if tipping points are found in one or more squares, it is possible using the identified breakpoints of those squares to indicate what the influence of reports on this is, and whether there is perhaps a relative increase in reports before or after this breakpoint. If there are significant results, these can be used for discontinuity graphs to get a clearer understanding of the relationship. This is in accordance with Álden et al. (2015) who used regression discontinuity methods to understand more about ethnic segregation and tipping behavior.

3.2 Data gathering

Our first aim is to identify potential tipping points in income at different measures of areas. We use the Statistics Netherlands (CBS) raster data at the 500 by 500 meter resolution. Raster data is available from the CBS at 100 by 100 meters as well. However, because a larger share of these grid-cells cover too few households to be reported (for purposes of anonymity), we elect to use the 500 meter data. Furthermore, the four-digit postal code data neighborhood data were found to be too large, spatially and population wise (Ong, 2016). These were therefore rejected as alternatives. The CBS has gathered data based on squares of 500 by 500 meters in the Netherlands over several years with many different indicators. The important indicators for this thesis are the coding, amount of residents, and the percentage of low and high income residents. Coding is based on the geographical area of the square, which is important for making spatially-weighted statistics and being able to relate these later on to physical disorder reports. For privacy reasons, the CBS only includes data when there is a minimum of 100 households in the area. Areas in Eindhoven with less than 100 households were thus omitted for this thesis, as well as the reports filed in these areas. At last, the income statistics are based on the disposable income of private households (excluding students). As for the low income percentages, this is based on the private households that are in the 40% lowest disposable incomes. The highest income percentages are based on the private households that are in the top 20% highest disposable incomes. This leads us to conclude that there is a middle income percentage based on the private households that are in the 40-80 percentile of disposable incomes. This data was not provided by the CBS, but could simply be calculated by extracting the percentages of low and high income from 100. Data on income is only available for the period of 2015-2020, which is therefore the period of this thesis.

As explained, the method for finding tipping points will be through segmented regressions. There are two main issues with this identification of tipping points. First, the results may be susceptible to changes in the definition of what is a low income. To address this issue, we estimate regressions for the share of low income, middle income, and high income in a neighborhood. As such, we are able to assess potential changes across the income distribution, meaning if our definition of low income is too narrow our robustness checks will reveal this. Unfortunately, there is no alternative available for when our definition of low incomes is too wide, however, we would expect to pick up on any effect that happens at categories smaller than we defined as part of the overall effect for the larger category.

Next, we estimate our regressions for different sized neighborhoods. While there is no uniform definition of a functional neighborhood or experienced neighborhood, and no direct information based on the literature of the appropriate size of the neighborhood, we operate under a smaller is better assumption. However, to ensure that we will pick up on larger scale effects, we also incorporate analyses with aggregated neighborhood cells, at 1000x1000 and 2500x2500 meters.

As for the second sub-question, data of reports on physical disorder had to be gathered. To get a coherent and large enough database, the focus was on the largest cities in the Netherlands. As mentioned before, income data of the CBS in squares was only available for 2015-2020. The period in which municipalities gathered reports on physical disorder that were available were very different from municipality to municipality, and none of them before 2013. Only Eindhoven was able to provide data for the complete period of 2015-2020, as its total period was from 2013 to 2024. Thus, the decision for which area to research was rather simple. Other municipalities had often had a system change, which led to data that was deleted or data that was not compatible with earlier data.

Using GIS, it was possible to use the geographical location of the reports to spatially join them with the aforementioned CBS squares of 500x500 meters and within the municipality of Eindhoven. All reports outside these squares and timeframe were excluded. This led to a dataset with 366883 reports within 188 squares. To be able to do the necessary statistical tests, the reports per inhabitant were calculated by dividing the total number of reports for a certain square for a year with the population of that square for that year. A combined dataset of income percentages data and the number of reports per inhabitant makes it possible to conduct linear and segmented regressions.

The data from Eindhoven details the exact date and time of the report, the type of report and the geographical location. The types of reports can be seen in Table 2 (p. 27). Along with the exact data and time of the report, the data also includes a column named "gewijzigd", or "altered". After inquiry at the municipality, it became clear that the altered column is the last date on which the report was altered. This can be the date that the report was completed, or it could indicate additions. As we work with data from 2015 to 2020, it could relatively safely be assumed that the final altered date would be the one on which the report was completed. The processing period of the reports can be calculated by comparing the two dates. Thus, a column containing the days it took to process a report will be added to the dataset. This data will then be used for a linear regression analyses based on percentages of the income levels. Doing so, this will result in findings on whether the processing period varies among areas based on income levels. Furthermore, the processing period can be used in analyses after results on tipping points have been found to get a better understanding of the before and after.

3.3 Ethics

As for the ethical considerations in this study, there is the necessity of the anonymization of data. This is already done by the CBS. As explained, when there are too few inhabitants for an area, the data is hidden from the public. This data could therefore also not be used for this thesis. As for the reports, these also do not include any personal information that could be traced back to the person filing the report. Furthermore, the data has been grouped together in their respective areas for statistical analyses, which further ensures anonymity. This thesis intends to keep an open view when it comes to the socioeconomic status of areas, with the ultimate goal of improving the public space of residents by getting a better understanding of socioeconomic changes.

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4. Results

4.1 Descriptive statistics

	2015	2016	2017	2018	2019	2020
Population	223220	224788	226921	229136	231633	234401
Number of reports	42853	52551	52800	67403	83997	95152
Number of reports per inhabitant	0.1920	0.2339	0.2326	0.2942	0.3626	0.4059

Table 1: Table with population statistics and reports on physical disorder in Eindhoven for 2015-2020 (*Eindhoven in Cijfers,* 2021; *Meldingen Openbare Ruimte,* 2024)

Due to the availability of data, the scale and area of this study is Eindhoven in the period of 2015 to 2020. To get a better understanding of the kind of data that is being used, this section of the results will first entail the descriptives. In Table 1, the statistics on population and reports in Eindhoven can be seen. These indicate an increase in the number of reports per inhabitant. This increase was also detected in Amsterdam, where the sudden rise in 2019 and 2020 is explained by the COVID pandemic (O&S, 2022). However, for Eindhoven the number of reports keep rising to a total of 114.669 reports in 2023 (*Meldingen Openbare Ruimte,* 2024). This indicates that while COVID may help explain the sudden rise in 2019, it does not explain the sustained increase after 2021. The increase might indicate a higher prevalence of physical disorder or better knowledge of the possibility to file a complaint.

For more detailed information, the next page entails a visualization of the relevant statistics and research area of this thesis. As explained in the methodology, a selection of squares was made. The 188 squares that resulted in this selection can be seen in Figure 4, placed over the city of Eindhoven. For these 188 squares, the average number of residents over the study period are visualized in Figure 5. When compared with the average income level percentages, a relationship between a high percentage of higher-income households and low number of residents and vice-versa becomes apparent. Similarly, the number of residents is usually higher in areas with a higher percentage of lower-income households.

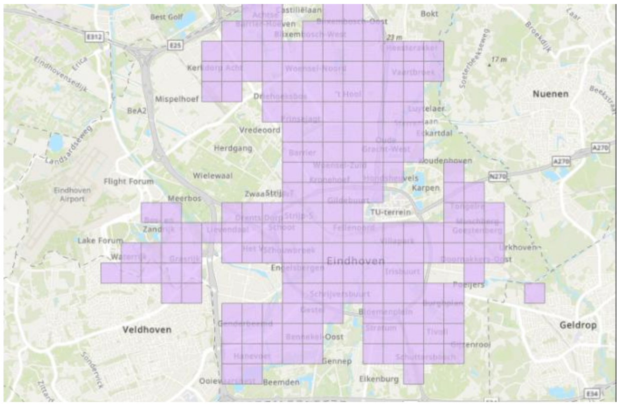

Figure 4: Eindhoven and areas of this study

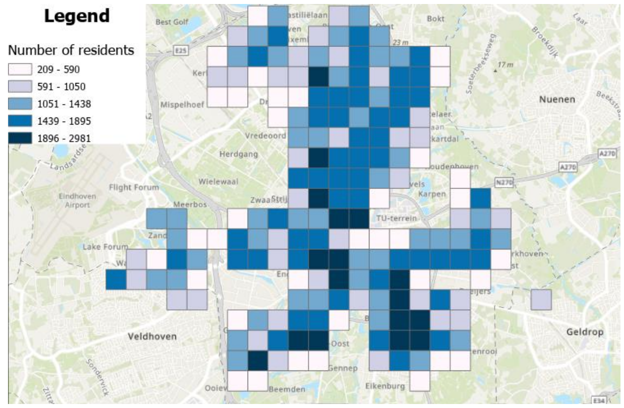

Figure 5: Average number of inhabitants per square 2015-2020

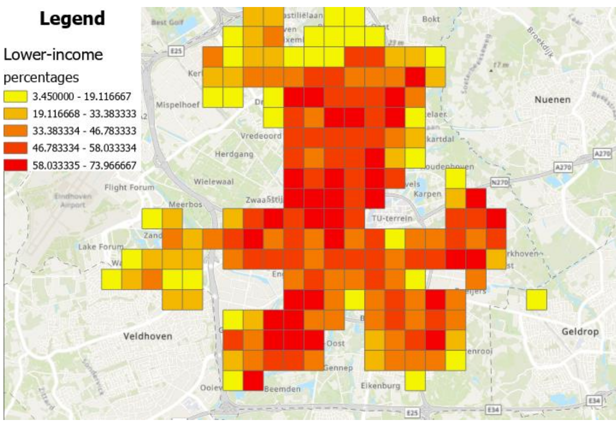

Figure 6: Average percentage of lower-income households per square 2015-2020

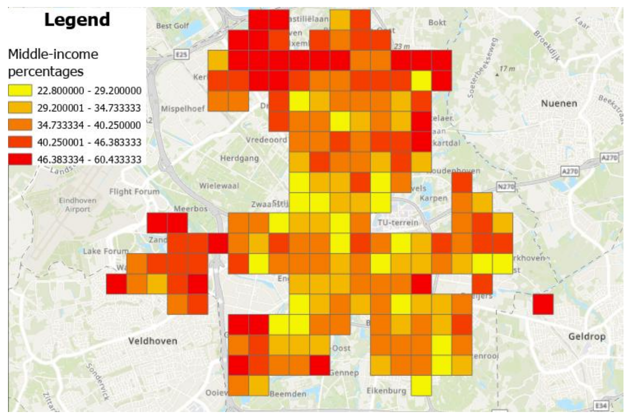

Figure 7: Average percentage of middle-income households per square 2015-2020

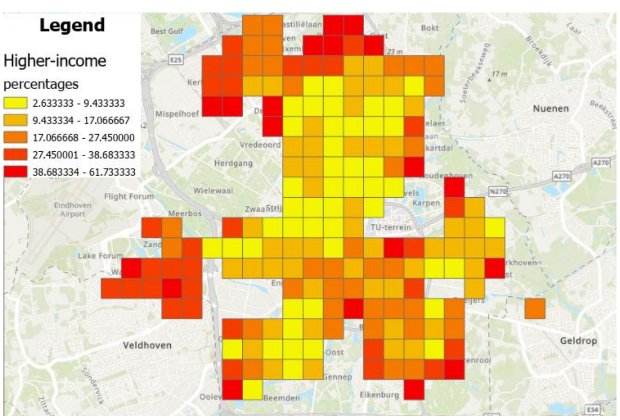

Figure 8: Average percentage of higher-income households per square 2015-2020

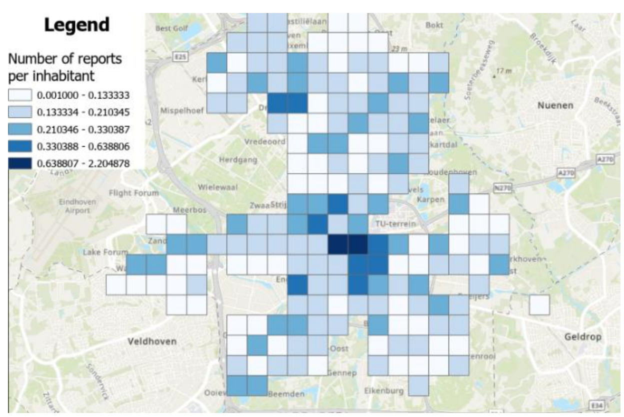

Figure 9: Average number of reports per inhabitant per square 2015-2020

To get an idea of the composition of the urban areas in Eindhoven, Figures have been made on income and population using data from the CBS, and GIS has been used for the visualization. In Figures 6-8 the average income percentages per square over the period 2015-2020 in Eindhoven can be seen for the areas that are being used for this thesis. These indicate a prevalence of lower-income households in the center of the city, whereas the higher-income households are situated more in the outskirts of Eindhoven. At first view this would indicate that the city of Eindhoven is more segregated than the social mix that we know from Dutch urban planning literature. However, with 74 and 62 percent as the highest percentages for lower- and higher-income households respectively, there is no extreme segregation of more than 90% in any of the areas. Looking at Figure 9, the findings of the municipality of Amsterdam about the relation between population density and number of reports do not seem to hold for Eindhoven (O&S, 2022). The visualization does indicate a higher prevalence of reports in the center. The other research methods of this thesis will tell us more about the different influences on the number of reports per inhabitant.

For this study, 366883 reports were used. These are divided into 14 head categories which are then subdivided into 102 sub-categories. Table 2 shows all the different types of reports that people can file, and the number of reports per type within the period of 2015-2020. This shows that the utmost number of reports are on illegal dumping. Other notable types with a high number of reports are the underground waste container, tiles and pavers, parking nuisance, trees, and street lighting.

Subject	**Number**	**Subject**	**Number**	**Subject**	**Number**
1.1 Waste bin	4,195	14.1 Asphalt	3,175	7.1 Parking nuisance	12,732
1.2 Old paper	3,227	14.2 Tiles and pavers	34,823	7.10 Environmental offense	216
1.3 Underground waste container	15,726	14.3 Road markings	1,289	7.11 Permits	578
1.4 Underground glass container	275	14.4 Speed bumps	375	7.12 Other	7,155

1.5 Aboveground glass container	251	14.5 Disabled ramp	214	7.13 Fireworks nuisance	4,867
1.6 Plastic container	1,758	14.6 Unsafe traffic situation	1,957	7.14 Shared mobility	164
1.7 Clothing container	317	14.7 Other	1,690	7.2 Trailers or caravans	2,815
1.8 Mini container (wheelie bin)	2,649	14.8 Bicycle paths inspection round	906	7.3 Dog nuisance	2,493
1.9 Other	902	2.1 Trees	26,071	7.4 Youth nuisance	969
10.1 Sewerage	8,129	2.2 Green spaces	5,159	7.5 Noise nuisance	3,689
10.2 Drains or gullies	7,500	2.3 Grass	1,053	7.6 Odor nuisance	1,058
10.3 Canals	92	2.4 Other	1,373	7.7 Room rental nuisance	232
10.4 Ponds and water features	630	3.1 Stray cats	406	7.8 Illegally occupied municipal land	1,785
10.5 Blue algae	37	3.2 Dead animals	2,550	7.9 Mini containers left on the street too long	1,565
10.6 Groundwater	199	3.3 Rats	3,037	8.1 Projects	1,184
10.7 Groundwater	4	3.4 Wasps or bees	560	8.2 Municipal buildings	201
10.7 Other	704	3.5 Oak processionary caterpillar	2,213	8.3 Vacant lots	81
11.1 Play equipment	1,614	3.6 Other	1,178	8.4 Other	1,235
11.2 Surfaces	267	4.1 Ice within the gritting route	71	8.5 Sports facilities	2,462
11.3 Fences	125	4.2 Ice outside the gritting route	65	9.1 Weed control	6,033
11.4 Street furniture	25	4.2-Broken fixtures/collision damage (public lighting)	101	9.10 Knotweed	338
11.5 Other	132	4.3 Ice due to other cause	95	9.11 Bamboo	16

12.1 Traffic sign	8,388	4.3-Broken lamps (public lighting and traffic lights)	570	9.2 Mowing management	1,492
12.10 Billboard or column	383	4.4 Other	47	9.3 Litter	11,644
12.11 Other	4,541	5.1 Graffiti on municipal property	710	9.4 Paint and oil	720
12.2 Street name sign	1,112	5.2 Graffiti on private property	560	9.5 Leaf waste	3,965
12.3 Signposting	684	5.3 Racist slogans and/or symbols	95	9.6 Street sweeping	4,023
12.4 Posts	5,085	5.4 Illegal posters on municipal property	469	9.7 Other	1,247
12.5 Waste bins	4,175	5.5 Illegal posters on private property	37	9.8 Road surface cleaning	669
12.6 Benches	1,890	5.6 Other	144	9.9 Giant hogweed	259
12.7 Fences	2,834	6.1 Illegal dumping	93,669		
12.8 Bus shelter	1,034	6.3 Hazardous substances	168		
12.9 Mailbox	13	6.4 (Moped) bike wreck	8,083		
13.1 Street lighting	39,205	6.5 Car wreck	1,102		
13.2 Traffic lights	2,911	6.6 Caravan or trailer wreck	147		
13.3 Other	410	6.7 Other	195		

Table 2: types of reports and number of reports per type

4.2 Regimes or tipping points in disorder and income levels

Following the order of the sub-questions, the next part of the results will start with the segmented regressions on income with the goal of finding tipping points. There were no significant tipping points found for any of the income levels at 500 by 500 meters (Table 19). Although a high R^2 could often be found, the results indicated no significant breakpoint in any of the 188 squares for any of the income percentages for a 95% significance. As for the larger areas of 1000x1000 and 2500x2500 meters, these also did not result in any significant breakpoints. The resulting data can be read in appendix A at the end of this thesis. They are not included here immediately for readability purposes. The square code that is used in the 1000x1000 groups is the first square to which three surrounding squares were combined. Out of 188 single squares, there were 119 instances where there was surrounding data in squares to combine them for a 1000x1000 square. 9 groups could be made of 2500x2500 meters squares, for which the results can be read in Table 21. To answer the sub-question; for the period and spatial area of this study, there were no tipping points.

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	3.88E-01	5.78E-04	671.3	<2e-16
Percentage of low incomes	-4.53E-06	3.54E-08	-127.9	<2e-16
	Residual standard error: 0.3451 on 366882 degrees of freedom			
	Multiple R-squared: 0.0427	Adjusted R-squared: 0.0427	F-statistic: 1.637e+04 on 1 and 366882 DF	p-value: < 2.2e-16

Table 3: results of linear regression of relationship between percentage of low income residents and reports per inhabitant

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.379E-01	05.787E-04	670.3	<2e-16
Percentage of middle incomes	2.268E-06	1.772E-08	128.0	<2e-16
	Residual standard error: 0.3451 on 366882 degrees of freedom			
	Multiple R-squared: 0.04274	Adjusted R-squared: 0.04274	F-statistic: 1.638E+04 on 1 and 366882 DF	p-value: < 2.2e-16

Table 4: results of linear regression of relationship between percentage of middle income residents and reports per inhabitant

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.3881E-01	5.785E-04	670.9	<2e-16
Percentage of high incomes	-4.538E-06	3.5433E-08	-128.0	<2e-16
	Residual standard error: 0.3451 on 336882 degrees of freedom			
	Multiple R-squared: 0.04277	Adjusted R-squared: 0.04277	F-statistic: 1.639e+04 on 1 and 366882 DF	p-value: < 2.2e-16

Table 5: results of linear regression of relationship between percentage of high income residents and reports per inhabitant

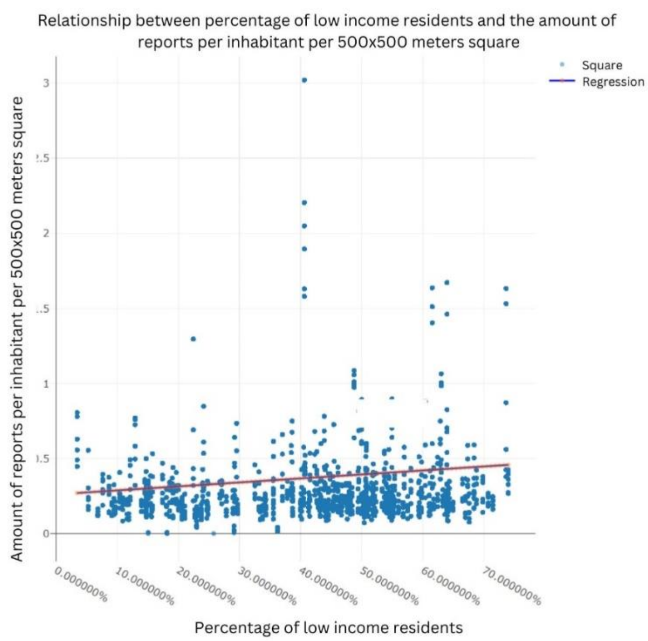

Figure 10: results of linear regression of lower income residents per square and reports per inhabitant

The second aspect of this thesis is to get a better understanding of the reports on physical disorder that are being done. As explained in the methodology, this is done first through conducting linear regressions on the CBS data on income and reports on physical disorder for Eindhoven. The results can be seen in Figures 10-12 and indicate something that is expected from the research that was done in Amsterdam as well on this sort of reports (O&S, 2022). Figure 10 shows the result of the linear regression for the percentage of lower income residents (0-40% income). These results indicate a positive relationship between the amount of reports per inhabitant and percentage of lower income residents. So when that percentage in a certain square is higher, that often leads to more reports per inhabitant as well. This is in contrast to the results of middle- and higher income residents (Figures 11 and 12) which show a negative relationship between the amount of reports per inhabitant and percentage of middle- and higher income residents. More detailed information on the exact relationship can be seen in

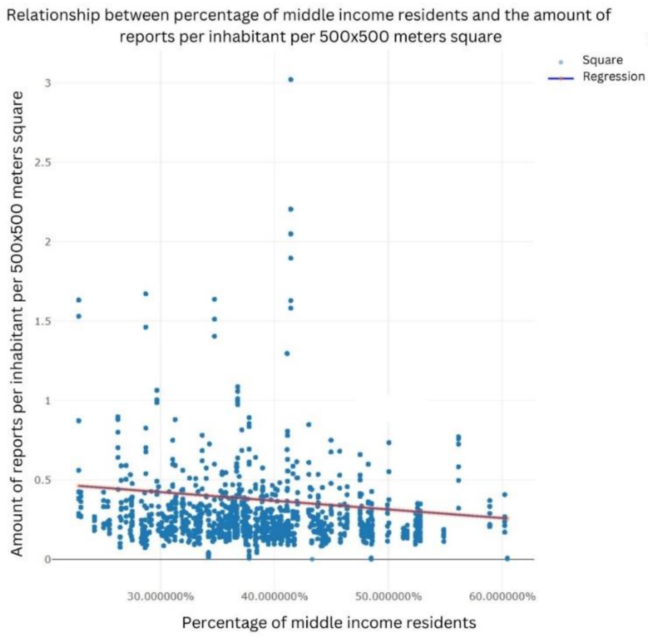

Figure 11: results of linear regression of percentage of middle income residents per square and reports per inhabitant

Tables 3-5. They show that the hypothesis that lower income areas have more reports can thus be accepted. The implications of these findings will be discussed further on.

Another way to understand more about the relationship between the amount of reports and income level is to do a segmented regression, instead of a linear regression. This brings up more subtle differences, as it looks for breakpoints in the data that indicate a significant distraction from the straight line of the linear regression. The segmented regressions were also done using R, and can be seen in Figures 13-15 (page 33). These Figures visualize the relationship between lower-, middle- and higher-income households respectively. The results show a significant (>95% confidence) breakpoint for all income levels, and for lower-income households even two breakpoints. The exact results can be seen in Table 6, 7, and 8(on the next page). These show the two significant breakpoints at 49.2% and 60.5% for lower-income households. For the areas between these breakpoints, an increase in percentage of lower-income households actually leads to a decrease in number of reports per inhabitant. This goes against the trend which was indicated by the linear regression. For middle- and higher-income households the breakpoint is at 30.2% and 8.6%

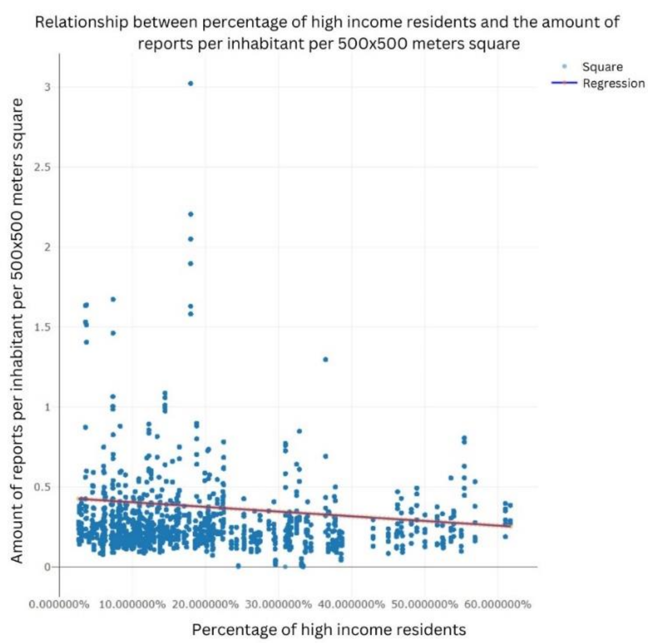

Figure 12: results of linear regression of percentage of high income residents per square and reports per inhabitant

respectively. The segmented regression line as shown in Figures 14 and 15 can thus not be taken at hand, as the second breakpoint is not significant.

$breakpoints			
	Initial	Est.	St.Err
psi1.Lower.income	NA	49.18511	2.331263
psi2.Lower.income	NA	60.4698	1.822965
$significant			
U1.Lower.income	U2.Lower.income		
TRUE	TRUE		

Table 6: results of segmented regression of amount of reports per inhabitant and lower-income households

$breakpoints			
	Initial	Est.	St.Err
psi1.Middle.income	NA	30.18264	0.7213859
psi2.Middle.income	NA	34.6917	1.5385492
$significant			
U1.Middle.income	U2.Middle.income		
TRUE	FALSE		

Table 7: results of segmented regression of amount of reports per inhabitant and middle-income households

$breakpoints			
	Initial	Est.	St.Err
psi1.high_income	NA	8.621228	0.77881
psi2.high_income	NA	12.62336	1.442581
$significant			
U1.high_income	U2.high_income		
TRUE	FALSE		

Table 8: results of segmented regression of amount of reports per inhabitant and higher-income households

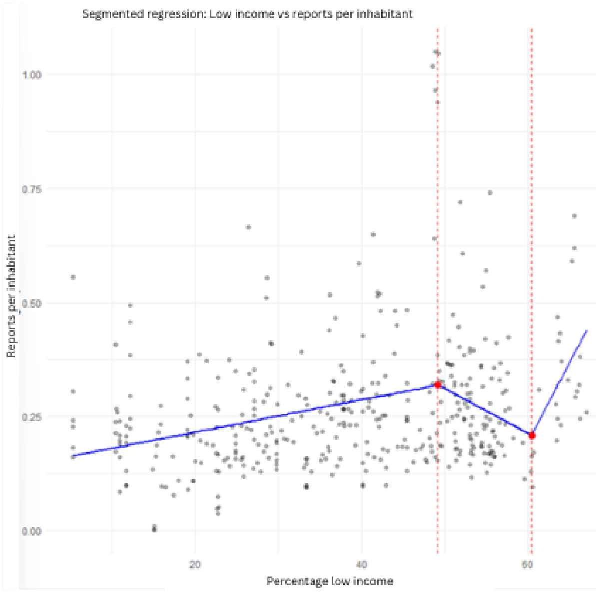

Figure 13: Segmented regression of lower-income households percentage and number of reports per inhabitant

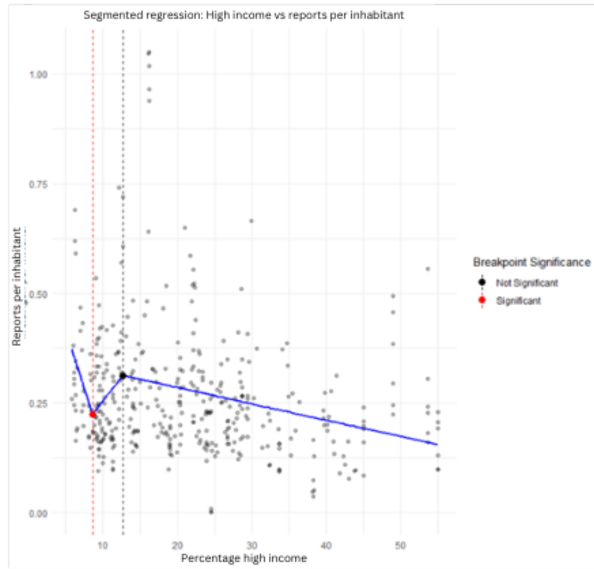

Figure 14: Segmented regression of middle-income households percentage and number of reports per inhabitant

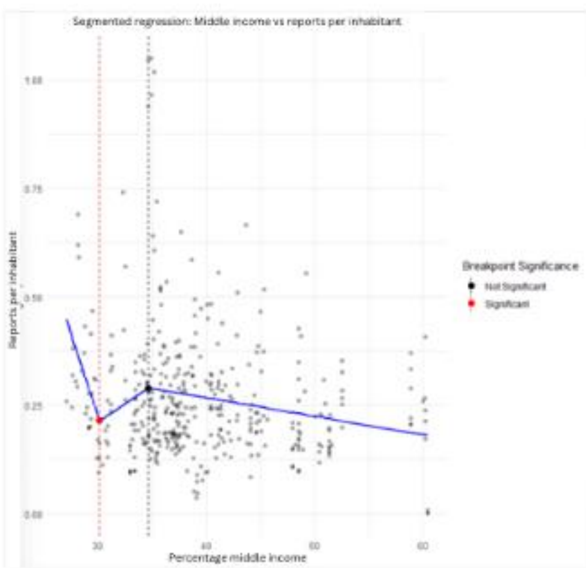

Figure 15: Segmented regression of higher-income households percentage and number of reports per inhabitant

4.3 Response time and disorder

After understanding more about the relationship between the socioeconomic status of an area and the number of reports, the next section of this thesis is on the processing period of reports. At first, a linear regression has been done on lower-, middle- and higher-income percentages and the processing period. As mentioned in the methodology, the processing period is based on a number of days for every report. The results of the linear regression can be seen in Tables 9-11. All three linear regressions have a significant result. What these results show, is that there is actually a negative relationship between low income areas and the processing period which indicates that reports in an area with a high percentage of low income residents are processed a bit quicker. However, looking at the very low R^2 it becomes clear that this effect is very small, and there are other aspects that have a larger influence on the processing period. From these results it is possible to conclude that the processing period is not an explanation for a higher amount of reports.

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	10.20291	0.014867	686.29	<2e-16 ***
Percentage of low incomes	-0.00912	0.000382	-23.86	<2e-16 ***
	Residual standard error: 15.66 on 3922237 degrees of freedom			
	Multiple R-squared: 0.0001451	Adjusted R-squared: 0.0001448	F-statistic: 569.1 on 1 and 3922237 DF	p-value: < 2.2e-16

Table 9: results of linear regression of relationship between percentage of low income residents and processing period

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	6.052166	6.052166	111.08	<2e-16 ***
Percentage of low incomes	0.104306	0.001448	72.04	<2e-16 ***
	Residual standard error: 15.64 on 2139026 degrees of freedom			
	Multiple R-squared: 0.00242	Adjusted R-squared: 0.00242	F-statistic: 5189 on 1 and 2139026 DF	p-value: < 2.2e-16

Table 10: results of linear regression of relationship between percentages of middle income residents and processing period

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	8.675962	0.018438	470.55	<2e-16 ***
Percentage of low incomes	0.07435	0.07435	81.52	<2e-16 ***
	Residual standard error: 15.63 on 2138987 degrees of freedom			
	Multiple R-squared: 0.003097	Adjusted R-squared: 0.003096	F-statistic: 6645 on 1 and 2138987 DF	p-value: < 2.2e-16

Table 11: results of linear regression of relationship between percentages of high income residents and processing period

The processing period has also been used in relation to the aforementioned 49.2-60.5 percent range of lower-income households where the amount of reports per inhabitant suddenly drops. A two sample t-test has been done to research whether there is a significantly shorter or longer processing period for the reports in this range. The results can be seen in Table 12 which indicate that, for areas with a mean percentage of 49.2-60.5 of lower-income households during the 2015-2020 period, the processing period is significantly lower. However, the absolute difference of the means is only less than a day. When combined with the knowledge that the processing period has many other influences that give more weight than income level, the importance of this outcome should not be overstated. Along with the two sample t-test on processing period, a similar test was done using a chi-square test to compare the types of reports that are most common for areas inside and outside of the 49.2-60.5 range (Table 13). The results indicate that there is a significant difference, although this is not very surprising as there are 103 different types of reports (Table 2). More significant could be looking at the exact percentages of the different types, but this did not show any severe outliers. The top 6 different types can be seen in Table 14 and 15. So although both tests are significant, they are unable to explain more about the 49.2-60.5 range. It would be up to other variables or research methods to give a better understanding.

Welch Two Sample t-test	
T	-15.502
Degrees of Freedom (df)	204764
p-value	<2.2E-16
Alternative Hypothesis	True difference in means is not equal to 0
95% Confidence Interval	-0.9805545 to -0.7604325
Sample estimates	
Mean of x (49.2-60.5 squares)	9.348338
Mean of y (!49.2-60.5 squares)	10.218831

Table 12: Results of Two Sample T-test on the processing period between areas inside and outside of 49.2-60.5% range of lower-income households

Data	matrix(c(combined_Table$n.x, combined_Table$n.y), ncol = 2)
X-squared	3407
Degrees of Freedom (df)	102
p-value	<2.2e-16

Table 13: Results of chi-square test of frequency of types of reports between areas inside and outside 49.2-60.5% range of lower-income households

Type of report	n	Percentage
6.1 Illegal dumping	29771	28.0
14.2 Tiles and paving stones	8949	8.41
13.1 Street lighting	8462	7.95
2.1 Trees	5818	5.47
1.3 Underground waste container	5415	5.09
7.1 Parking nuisance	3747	3.52

Table 14: Top 6 type of reports of physical disorder for areas of 49.2-60.5% low-income households

Type of report	n	Percentage
6.1 Illegal dumping	58395	22.4
13.1 Street lighting	26694	10.2
14.2 Tiles and paving stones	24455	9.39
2.1 Trees	18148	6.97
1.3 Underground waste container	10119	3.88
7.1 Parking nuisance	8380	3.22

Table 15: Top 6 type of reports of physical disorder for areas outside of 49.2-60.5% low-income households

4.4 Influence of reports on the socioeconomic status of an area

To answer the main research question, fixed effect first-difference regressions were processed in R. The results of the fixed effect first-difference regressions can be seen in Tables 16-18. The results show again the low income percentages having distinctively different results than middle and high income percentages. However, the most important result is that the influence of reports on income percentages is almost equal to the influence of income percentages on reports. Consequently, there is no clear causal relationship where one variable would significantly influence change in the other variable.

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.03980350	0.00348879	11.4090	<2e-16 ***
Lower-income households	0.00022819	0.00162709	0.1402	0.8805
	R-squared: 2.1239E-05	Adjusted R-squared: -0.0010587	F-statistic: 0.0196682 on 1 and 926 DF	0.885
T test of coefficients				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.03980350	0.00274466	14.5022	<2e-16
Lower-income households	0.00022819	0.00342821	0.066	0.9469

Table 16: results of fixed effect First-Difference model of lower-income households percentage and reports per inhabitant

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0. 0398149	0.0034862	11.4209	<2e-16 ***
Middle-income households	-0.0010483	0.0014574	-0.7193	0.4721
	R-squared: 0.00055844	Adjusted R-squared: -0.0052087	F-statistic: 0.517406 on 1 and 926 DF	p-value: 0.47213
T test of coefficients				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.0398149	0.0026737	15.0034	<2e-16
Middle-income households	-0.0010483	0.0011903	-0.8807	0.3787

Table 17: results of fixed effect First-Difference model of middle-income households percentage and reports per inhabitant

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0. 0397153	0.0034868	11.3901	<2e-16 ***
High-income households	0.0016100	0.0019879	0.8099	0.4182
	R-squared: 0.00070779	Adjusted R-squared: -0.00037136	F-statistic: 0.655878 on 1 and 926 DF	p-value: 0.41823
T test of coefficients				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.0397153	0.0026936	14.744	<2e-16
High-income households	0.0016100	0.0041248	0.3903	0.6964

Table 18: results of fixed effect First-Difference model of high-income households percentage and reports per inhabitant

5. Discussion

5.1 Regimes or tipping points in disorder and income levels

Following the methodology, this discussion will start with the results of the segmented regressions that were done on income differences in the CBS squares. An explanation for these results are the relatively short period that is being researched. Due to limitations of the available data, the period is 2015 to 2020. Any tipping points within this period should still surface however. After more detailed inspection of the results per square, it became clear that differences in income level percentages of a square were often very small. Furthermore, in those differences that could be identified, it was very hard to identify a clear trend. What often happened, is that a certain income level percentage would rise for a certain year, to decrease in the next year, and later maybe go up again. Any differences here would often be 1-2 percentage points or less. Another reason for this might be the relatively small area of data per square. This is in line with the expectation based on the Dutch neighborhood composition as was explained in the literature review. Even at the smaller scale, no tipping points could be found. The small scale did bring the potential problem that small changes in the population can have a relatively big impact on the data. However, considering these results, we can conclude that for the period of 2015-2020 no significant tipping points can be identified in Eindhoven based on income level for areas of 500 by 500 meters.

Because of the limitations of the small area described above, the aim of this thesis is also to research whether a tipping point could be identified on larger areas of 1000 by 1000 meters and 2500 by 2500 meters. However, again no significant breakpoints could be identified in any of the squares in Eindhoven over the period of 2015 to 2020. This leads us to conclude that tipping points as exist in the United States are not apparent in the Netherlands based on this research. An explanation for this is the social mixing of the Dutch neighborhood, which also comes out using this research method and reduces gentrification forces. Because it was not possible to find any tipping points, it is also not possible to make discontinuity graphs as a breakpoint needs to be identified to do such regressions.

In accordance with the findings of Ong (2016), the main explanation for these results is also the setup of Dutch neighborhoods. As explained in the literature review, Dutch neighborhoods have had a policy of social mixing for the last decades. This lead to neighborhoods that were more resilient to effects such as gentrification than their American counterparts. Because of this understanding of Dutch neighborhoods, this thesis tried to find a tipping point on a smaller scale. A longer period could potentially give other results, but other explanations are more at hand. Kleinhans (2009) showed that middle-class residents in disadvantages neighborhoods lived in enclaves. Thus, neighborhood change does not happen often due to social mixing policies, and when for example middle-class residents take up residence in disadvantaged neighborhoods it is in enclaves that would be harder to identify. Living in such enclaves would not give the benefits to social cohesion that social mixing is expected to encourage. However, these results do give us a further understanding to the workings of the social mixing policies which do seem to be working. More research would be needed on a longer period to establish whether trends and tipping points could then be identified.

5.2 Reports on physical disorder per inhabitant

The second aspect of this thesis is to get a better understanding of the reports on physical disorder that are being filed. As explained in the methodology, this is done through conducting linear regressions on the CBS data on income and reports on physical disorder for Eindhoven. These results indicate a positive relationship between the amount of reports per inhabitant and percentage of lower income residents (Figure 10). When that percentage in a certain square is higher, it often leads to more reports per inhabitant as well. This is in contrast to the results of middle- and higher income residents (Figures 11 and 12) which show a negative relationship between the amount of reports per inhabitant and percentage of middle- and higher income residents. The hypothesis that lower income areas have more reports can thus be accepted, which is in line with the findings in Amsterdam (O&S, 2022). Although the results are significant, the R^2 is very low. Only a very small portion of the effect can be explained by the reports. Although these results do not measure the actual prevalence of physical disorder, the careful assumption can be made that for neighborhoods with a high number of reports, the prevalence of physical disorder is also high. That is because of the correlation of these findings and those of Taylor et al. (2012) which indicated the higher prevalence of physical disorder in neighborhoods with a low socioeconomic status. However, further research would be needed to be able to conclude such a hypothesis.

To get a better understanding of the relationship between the amount of reports and income level, a segmented regression was done to identify breakpoints. The results showed two significant (>95% confidence) for lower-income households percentages. The exact results can be seen in Tables 6, 7 and 8**.** To delve further into this, what stands out most about the middle- and higher-income results is the immediate drastic decline at the lower percentages. However, due to the relatively low amount of cases at these percentages and the insignificant second breakpoint, we have to be careful to think too much about this. The breakpoint at ~8% of higher-income households and the visualization do seem to indicate that perhaps at this range there is large enough presence of higher-income households to significantly reduce physical disorder. It might also be that at this range, the 'social mixing' and consequent social cohesion is of a level where there is less of a necessity to individually voice physical disorder reports. People might be more inclined to speak to each other, or to work together in keeping the urban area clean and organized. But this is guess work, yet could be interesting for future research. With lower-income households and its two significant breakpoints there's more to say, which brings some very interesting findings.

The results indicate two significant breakpoints, at 49.2% and at 60.5% (Table 6). At this range, the number of reports per inhabitant suddenly drops, for then to rise again very steeply. This gives the idea of something like a 'last effort' by the community to decrease physical disorder with each other. After the threshold of 60.5%, the community seems to have given up and physical disorder rises and people just individually report at the municipality. This might indicate an occurrence of the 'broken windows' theory, where carelessness has taken over. As mentioned before, Wilson and Kelling propose three types of neighborhoods (serene, to tipping, to crime-ridden). These results might indicate a range based on percentage of lower-income households at 49.2% to 60.5% in which the area might be tipping. The importance of identifying tipping areas was emphasized by Wilson and Kelling as these are the areas “where the public order is deteriorating but not unreclaimable, where the streets are used frequently but by apprehensive people, where a window is likely to be broken at any time, and must quickly be fixed if all are not to be shattered” (Wilson and Kelling 1982:38). Of course, these results are all based on the assumption that the amount of reports equal the amount of physical disorder. Yet it is not known whether that is true. However, this range could be a very interesting case for municipalities to dive deeper into. If this is indeed something like a ‘last effort’, there is role to play for the municipality to learn more and try to keep areas from moving over the threshold of 60.5%. If there is more of a community responsibility in this range, the municipality can focus on facilitating clean-up groups for example. This could be expanded to the fringes of the range as well to fuel more community responsibility as well. By increasing this range, and keeping areas from going over the threshold, the municipality can reduce major costs that are induced via physical disorder and improve public space.

5.3 Response time and disorder

As explained in the introduction there is a responsibility for the municipality to act on disorder, and not let it take too long. Furthermore, there is the broken windows effect, which further exemplifies the need to act on disorder. For those reasons, this thesis has also looked into response time and disorder. Reporting on physical disorder is a way for inhabitants to individually voice the necessity of municipal actions and dissatisfaction about the current situation (Permentier et al., 2007). Linear regressions have been done to get an understanding of the relationship between the socioeconomic status and processing period. The idea that the municipality would somewhat ignore the voice of residents in lower income neighborhoods is not supported, and the contrary seems to be more the case. This relates to an explanation posed in Rotterdam, where garbage trucks go more often and with more trucks to neighborhoods where more ‘naastplaatsingen’ are known, which is often in neighborhoods of low socioeconomic status (de Vries, 2021). Furthermore, this strengthens the indication that the amount of reports would be higher because of a higher prevalence of physical disorder. Looking at the very low R^2, however, it becomes clear that this effect is very small, and there are other aspects that have a larger influence on the processing period.

The processing period has also been used in relation to the aforementioned 49.2-60.5 percent range of lower-income households where the amount of reports per inhabitant suddenly drops. The results indicate that, for areas with a mean percentage of 49.2-60.5 of lower-income households during the 2015-2020 period, the processing period is significantly lower. It may indicate that there could be some kind of focus of the municipality to help in the 'cleaning-up' of the neighborhood to the effect that was earlier stated which could be as a last resort. But this definitely needs further research before such statements can truly be made. Along with the two sample t-test on processing period, a similar test was done using a chi-square test to compare the types of reports that are most common for areas inside and outside of the 49.2-60.5 range. The results indicate that there is a significant difference, although this is not very surprising as there are 103 different types of reports (Table 2). More significant could be looking at the exact percentages of the different types, but this did not show any severe outliers. However, these results did not differ very much. The conclusion here is that the types of report are roughly the same, and the explanation for the lower processing period should be found elsewhere.

5.4 Influence of reports on the socioeconomic status of an area

At last, the influence of reports on the socioeconomic status of an area needs to be discussed; the main research question. The idea of this research question was based on the assumption that tipping points would have been found, with which discontinuity graphs could be made. However, no tipping points were found and as such no discontinuity graphs have been made. This makes it more challenging to establish a 'before and after'. However, it is still possible to understand more about the influence of the amount of reports per inhabitant on changes in income level over an area and vice-versa. Using R, and the complete dataset, fixed effect first-difference regressions have been made that give information about the influence of reports on income percentages. As discussed, these did not indicate a clear causal relationship where one variable significantly influences change in another variable. Although inhabitants can and do often report on physical disorder in neighborhoods of low socioeconomic status, and municipalities process these reports faster than in other neighborhoods, the results indicate that this does not have the effect that it initiates a rise in population of middle to high income inhabitants. The very low R^2 again shows that the relationship between reports and income is rather small, and there are other variants that have a bigger influence. It must therefore be concluded that reports on physical disorder do not significantly influence socioeconomic change.

There are various limitations to these findings that are necessary to be discussed. One of these has been mentioned in the literature review, as it is also discussed by Epskamp and de Vries (2021), and is about the people who don't report. This is a very important group of people, of which we know (almost) nothing. There are incentives to report which relate to trust in the public services, a feeling of duty, and feeling of importance of improving the public space (O&S, 2021). Thus, further research could be done on the reasoning behind not reporting and about the absolute amount of physical disorder in areas. For this research, it is only possible to look at reports which can give an indication of the amount of physical disorder in the area, but it is not possible to know how the amount of reports relate to the amount of physical disorder. As such, it is not possible to conclude from these results that lower income residents would have a higher tendency to report, or that these areas have a higher amount of physical disorder. As for that last part however, there is evidence that this is the case for low-income neighborhoods (Kelly et al., 2007; Taylor et al., 2012).

Another limitation lies in that we know when and where the reports were filed, but there is no data about who does the report. Concluding that the amount of reports per inhabitant is higher in areas with a higher percentage of lower income inhabitants does not necessarily mean that a reasoning for this could be that there is a higher tendency to report with low-income inhabitants. It is not necessary to be a resident of the area to do the report. People with a high sense of duty of reporting could also feel this sense when traversing through a different area than where they live, and thus influence the amount of reports per inhabitant, no matter their own income level. By doing so, they influence the results of this thesis. However, it is impossible to determine how big this influence is.

6. Conclusion

Since the Second World War, Dutch spatial planning has gone through several phases. This has ultimately resulted in an urban composition that is rather exclusive to the Netherlands, with a high percentage of social housing placed throughout urban areas, aiming for social mixing. After it was found that the methods devised in the second half of the 20th century didn't work due to segregation and gentrification resulting from the liberalization of the Dutch housing market, a diversification based on housing type was devised to combat this movement (Boterman & van Gent, 2014; Modai-Snir & van Ham, 2018). However, there are still clear disadvantaged neighborhoods in the Netherlands, and it is important to understand these as best as we can. One way in which the inhabitants of such neighborhoods can voice dissatisfaction about aspects of their neighborhoods is through reports on physical disorder. It has been found that physical disorder is more prevalent in neighborhoods of low socioeconomic status (Taylor et al., 2012; de Vries, 2021). This thesis is about the impact that such reports can possibly have on socioeconomic change.

To answer the main research question, at first research was conducted on the changes in income level on different scales in Eindhoven for the period 2015-2020. No significant breakpoints were found. This suggests that the concept of tipping points, as observed in other contexts like the United States, may not be as applicable to Dutch urban areas. The results show that the social mixing that has been a focus in Dutch policymaking has appeared to have made the urban areas less susceptible to rapid gentrification, corresponding with the findings of Modai-Snir & van Ham (2018) on the Dutch housing market regime working as a buffer.

In order to answer the main research question, it was also important to get a better understanding of the reports on physical disorder. The linear regression for every lower-income level showed a positive relationship between that percentage and the number of reports per inhabitant. For the middle- and higher-income percentages, the relationship was negative. These results concluded that there is a significant distribution of a high number of reports in areas with a high percentage of lower-income households, which corresponds with the literature (de Vries, 2021;

O&S, 2022). Although it cannot be said with certainty, these results indicate a higher actual prevalence of physical disorder in lower-income areas. It might also indicate a greater reliance on municipal intervention to address these issues.

Furthermore, this thesis gives more support to the findings in Rotterdam about the higher prevalence of physical disorder in such neighborhoods, although 'on the ground' or virtual research would have to be done to be able to absolutely state such a conclusion. Another research aspect missing in this thesis and the research in Rotterdam is the consideration of people who do not report. The reports on physical disorder give an interesting look into the physical disorder in different urban areas, but their influence on the bigger picture is rather marginal.

To get a more detailed understanding of this relationship, segmented regressions were performed to find breakpoints. Two significant thresholds were found at 49.2% and 60.5% of low-income households, between which the number of reports declined. After the threshold of 60.5%, the number of reports increases severely. These findings may represent the broken window theory and indicate the tipping point after which the neighborhood experiences a carelessness and big increase in physical disorder, as proposed by Wilson and Kelling (1982). For the range in between the two thresholds, this might indicate a ‘clean-up’ where physical disorder is less abundant or cleaned by the community. It must be noted, however, that the number of areas with a higher percentage than 60.5% of lower-income households is rather small, and that reports on physical disorder do not necessarily represent actual physical disorder. More research could give answers to the many questions that can be posed from these results.

Considering the importance and responsibility of the municipality to process the reports, and the potential higher reliance in lower-income neighborhoods, the processing times of the reports were also explored. These showed that the municipality does seem to have a focus on lower-income neighborhoods, although it must be noted that the variance explained by the report processing period was very small. To combine this with the earlier results of the segmented regression, the processing period was also analyzed for differences between the two groups inside and outside of the 49.2% and 60.5% thresholds. The conducted t-test indicates that the processing period is lower in the areas within the thresholds, thus further supporting the idea of a 'clean up'. However, as the variance of the processing period on all reports was very low, and the difference is less than a day, it's not possible to make conclusive remarks about this.

Because no tipping points were found in any of the squares in Eindhoven, it was inconvenient for further statistical tests based on a before and after. Therefore, fixed effect first-difference regressions were done to still get a better understanding of the relationship between reports on physical disorder and income level change in the neighborhood. Consistent with the other results of this thesis, it was found that the variance of the influence that can be explained by reports was very small. Furthermore, the influence was found to be both ways. The regressions showed that the influence of reports on income levels is almost equal to the influence of income levels on reports, with no clear causal relationship dominating. These results show that not too much weight must be given on the effect of physical disorder reports on neighborhood change. Socioeconomic changes in the urban area are not significantly driven by reports on physical disorder. Other studies might find different results when compared to other variables, such as the ethnic composition, but similar results are likely.

For future research, exploring additional information such as the relationship between reports on physical disorder and actual physical disorder, and understanding the motivations behind non-reporting could provide deeper insights into neighborhood dynamics. Policy implications include the need for enhanced community engagement in lower-income areas and the potential for targeted policies based on the identified critical thresholds to maintain neighborhood quality and stability. Overall, this thesis underscores the complexity of urban dynamics and the multifaceted nature of variables influencing socioeconomic neighborhood change. While the direct impact of disorder reports on socioeconomic changes appears limited, these reports offer valuable data for policymakers aiming to foster resilient and vibrant urban communities and improve public spaces.

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8. Appendix A

Square	Significant	Breakpoint lower income	R^2 lower income	Breakpoint middle income	R^2 middle income	Breakpoint high income	R^2 high income
E1545N3825	FALSE	2017.05556	0.66982711	2017.24876	0.99756586	2017.35659	0.84744935
E1550N3825	FALSE	2017.99999	0.92514794	2018.00004	0.79535317	2016.36044	0.94718829
E1555N3825	FALSE	2016.37458	0.92507114	2018.63494	0.83477527	2018.63142	0.90811725
E1555N3830	FALSE	2016.40382	0.23276819	2017.33333	0.38461538	2016.36177	0.7307306
E1560N3840	FALSE	2018.61474	0.96616175	2018.59772	0.03795206	2017.78261	0.96385542
E1560N3830	FALSE	2018.58347	0.3560744	2016.38091	0.52559476	2016.0216	0.89794501
E1560N3825	FALSE	2016.37875	0.81563085	2017.48551	0.98979592	2018.00008	0.88148358
E1565N3825	FALSE	2018.79452	0.96050296	2016.99998	0.96179484	2017.58503	0.99199813
E1565N3840	FALSE	2016.39811	0.63952539	2016.39469	0.8315172	2018.65517	0.92236795
E1565N3830	FALSE	2016.40426	0.84808563	2018	0.83180059	2016.38165	0.77044706
E1565N3820	FALSE	2018.63283	0.57219042	2018.61634	0.57481946	2016.99992	0.72136527
E1565N3835	FALSE	2018.60334	0.36816717	2017.00001	0.96119914	2018	0.32354568
E1570N3825	FALSE	2017	0.68088044	2017.25926	0.65465253	2018.00007	0.92149562
E1570N3820	FALSE	2016.40946	0.40823846	2018.52756	0.89159624	2016.52511	0.86401977
E1570N3830	FALSE	2016.99993	0.90592601	2018.65818	0.52975463	2018.60485	0.67413969
E1570N3835	FALSE	2016.40716	0.84614953	2018.59793	0.23655107	2016.99237	0.1304761
E1575N3880	FALSE	2018.59499	0.83393988	2018.5943	0.73499682	2018.21615	0.97663262
E1575N3835	FALSE	2017.10256	0.71908263	2018.61693	0.93882899	2017.85535	0.94428808
E1575N3870	FALSE	2016.76531	0.82404965	2018.0087	0.37195536	2017.71429	0.92004164
E1575N3875	FALSE	2018.7699	0.80632124	2017.09677	0.13596939	2018.00001	0.51395736
E1580N3800	FALSE	2018.60169	0.95116163	2017.46032	0.5814439	2017.5474	0.96563929
E1580N3885	FALSE	2016.38171	0.41470839	2017.68333	0.80343143	2016.29535	0.95401262
E1580N3830	FALSE	2017.27556	0.97685385	2017.66061	0.96880615	2017.65686	0.94236396
E1580N3805	FALSE	2018.00003	0.7907208	2018.62006	0.96469681	2017.44253	0.9193353
E1580N3835	FALSE	2017.59524	0.90917311	2017.62903	0.73394821	2017.95455	0.88149351
E1580N3810	FALSE	2018.60827	0.45367464	2018.27778	0.95696721	2016.41347	0.87207115
E1580N3880	FALSE	2016.9908	0.46055233	2016.38922	0.51737956	2016.29545	0.86154195
E1580N3815	FALSE	2017.58772	0.72646389	2016.39076	0.12097739	2018.60607	0.68812442
E1580N3840	FALSE	2018.00934	0.85288981	2018.61827	0.79571683	2016.34737	0.47665811
E1580N3870	FALSE	2018.59204	0.21328786	2016.625	0.60424364	2016.40683	0.28669857
E1580N3875	FALSE	2017	0.84176476	2017.05	0.90691902	2018.62259	0.03798229
E1585N3885	FALSE	2018.00003	0.77562413	2017.11111	0.21250699	2016.14563	0.99437424
E1585N3880	FALSE	2016.41392	0.14435486	2016.46512	0.64870968	2016.99998	0.97189188
E1585N3810	FALSE	2016.38721	0.76478153	2016.37572	0.85850914	2016.15528	0.96842105
E1585N3830	FALSE	2016.37276	0.66928314	2016.39493	0.56894796	2018.60929	0.92083828
E1585N3805	FALSE	2018.9115	0.73890646	2018.97549	0.88451883	2017.04167	0.87846378

E1585N3840	FALSE	2018.60013	0.66757874	2018.92489	0.74630225	2016.22222	0.87263078
E1585N3800	FALSE	2017.9999	0.71992464	2016.38548	0.52839415	2017.99993	0.80067358
E1585N3890	FALSE	2016.83691	0.86444228	2018.60424	0.39220423	2018	0.7136083
E1585N3815	FALSE	2016.11364	0.57879342	2017.07937	0.82971539	2018.30233	0.451
E1585N3875	FALSE	2016.3968	0.59824132	2016.39155	0.63534511	2017.30909	0.40998496
E1585N3835	FALSE	2016.40847	0.81645109	2018.60849	0.50807392	2016.40595	0.24385522
E1590N3830	FALSE	2017.20635	0.48444444	2018.78795	0.69240343	2017.99989	0.98051812
E1590N3835	FALSE	2016.38941	0.54551476	2016.39267	0.01045221	2016.9	0.94993046
E1590N3885	FALSE	2018.4898	0.90194903	2018.97812	0.92528653	2016.38959	0.93644879
E1590N3865	FALSE	2016.99997	0.34461656	2016.99994	0.59274136	2018.00001	0.87280863
E1590N3810	FALSE	2018.61847	0.67880656	2018.58883	0.42365766	2017.63158	0.87020785
E1590N3840	FALSE	2018.60523	0.19960471	2016.39339	0.35073754	2016.39953	0.86641802
E1590N3880	FALSE	2017.99991	0.62558898	2017.99998	0.73432276	2016.37391	0.77207716
E1590N3805	FALSE	2016.1581	0.86499198	2018.61168	0.14133904	2018.84568	0.62619954
E1590N3870	FALSE	2016.54585	0.32888257	2016.58219	0.47434326	2018.59679	0.5272802
E1590N3815	FALSE	2016.38473	0.27749394	2016.38683	0.63928102	2017.10256	0.38333333
E1590N3875	FALSE	2017.17021	0.83850538	2017.09402	0.9209746	2018.6081	0.23628507
E1590N3890	FALSE	2017.32836	0.99815398	2017.20833	0.79370274	2018.59212	0.22224533
E1595N3805	FALSE	2016.08639	0.78413643	2016.25243	0.93056669	2016.38801	0.99985055
E1595N3860	FALSE	2018.62523	0.80903094	2018.612	0.36482481	2016.58824	0.94726644
E1595N3810	FALSE	2016.39143	0.88879077	2017.99998	0.98583618	2016.38871	0.90107984
E1595N3855	FALSE	2016.99993	0.8764373	2017.00001	0.83745822	2016.35877	0.89439373
E1595N3845	FALSE	2018.00002	0.72395435	2018.61883	0.32842745	2016.53571	0.84050633
E1595N3850	FALSE	2016.40236	0.84371313	2016.25641	0.80996462	2016.99999	0.8044849
E1595N3835	FALSE	2018.62906	0.44407601	2016.68702	0.60334896	2018.59716	0.75964467
E1595N3815	FALSE	2016.3667	0.44720267	2018.63224	0.30449036	2018	0.73083226
E1595N3865	FALSE	2017.17007	0.98245192	2017.70588	0.98255814	2018.00006	0.63744025
E1595N3880	FALSE	2016.4058	0.97673103	2016.63291	0.92516741	2018.60429	0.52957115
E1595N3840	FALSE	2018.59721	0.71774989	2018.89826	0.97887355	2016.39671	0.4130893
E1595N3825	FALSE	2018.60113	0.77074909	2018.60583	0.93685138	2018.61265	0.40180398
E1595N3870	FALSE	2017.69444	0.82337662	2017.2	0.864	2018.59104	0.28605244
E1595N3875	FALSE	2018.7005	0.87043601	2017.85294	0.82082452	2017	0.23119435
E1595N3830	FALSE	2018.61173	0.99158038	2017.60784	0.89183354	2018.00939	0.13379831
E1595N3820	FALSE	2018.60771	0.34383024	2018.59701	0.95679264	2018.61173	0.10322198
E1600N3835	FALSE	2018.00001	0.56943383	2016.30201	0.72977718	2016.06925	0.9958172
E1600N3875	FALSE	2017.33333	0.61135371	2017.00002	0.77506831	2016.39415	0.91298348
E1600N3885	FALSE	2018.69599	0.82197329	2018.61082	0.77333967	2016.41591	0.88992984
E1600N3860	FALSE	2016.55118	0.95116704	2018.60392	0.90834284	2018.92788	0.88216153
E1600N3810	FALSE	2018.60143	0.68388054	2016.2924	0.75879912	2016.03012	0.84351585
E1600N3850	FALSE	2017.19608	0.98798654	2016.39243	0.92332935	2016.22167	0.81107766
E1600N3805	FALSE	2016.08013	0.92954492	2016.40262	0.66017543	2017.99998	0.78982042
E1600N3815	FALSE	2018.6056	0.89901016	2018.64946	0.81864085	2018	0.6969847
E1600N3820	FALSE	2017.65	0.77129338	2017.25	0.67062044	2016.5316	0.57198929
E1600N3855	FALSE	2018.00021	0.42580832	2017.45614	0.54498927	2017.14815	0.5518617
E1600N3865	FALSE	2018.5679	0.87111965	2018.59342	0.40445887	2018.59153	0.49635933

E1600N3840	FALSE	2017	0.95802562	2017.51923	0.97115002	2016.99109	0.45292099
E1600N3825	FALSE	2016.35973	0.28825415	2016.36051	0.37091895	2016.36185	0.31216997
E1600N3830	FALSE	2016.35466	0.56335644	2018.65415	0.79165218	2017.08333	0.29824561
E1600N3870	FALSE	2016.39162	0.35125685	2016.40809	0.70969925	2016.37977	0.28894951
E1600N3845	FALSE	2017.99999	0.70029	2018.00009	0.57792625	2016.99997	0.24811985
E1600N3880	FALSE	2016.32303	0.77503831	2017.88095	0.99961759	2016.39806	0.1044053
E1605N3885	FALSE	2016.99966	0.72768049	2016.99997	0.92728609	2018.23729	0.96098266
E1605N3815	FALSE	2018.87832	0.95169013	2017.13021	0.85012195	2017.99999	0.95768632
E1605N3875	FALSE	2018.59957	0.68343328	2018.58334	0.91981123	2017.30952	0.91211147
E1605N3830	FALSE	2017.43137	0.96746218	2016.36283	0.58215319	2017.39785	0.88658632
E1605N3860	FALSE	2016.71429	0.29300061	2016.40054	0.7552878	2018.00025	0.87570021
E1605N3855	FALSE	2018.60803	0.82338201	2018.59464	0.84137754	2016.99993	0.81824637
E1605N3870	FALSE	2018.61659	0.82165472	2016.37821	0.51947461	2018.62656	0.81055858
E1605N3845	FALSE	2018.00908	0.17046173	2016.36421	0.13224776	2016.39586	0.76734108
E1605N3880	FALSE	2016.38889	0.32177074	2016.40663	0.8444154	2018.00003	0.65786157
E1605N3890	FALSE	2016.99999	0.53929405	2016.99998	0.32756277	2018.12791	0.65395748
E1605N3835	FALSE	2018.62294	0.71024853	2018.60506	0.52690505	2018.62347	0.65188211
E1605N3850	FALSE	2017.06061	0.50820051	2018.59615	0.68674642	2016.35079	0.55583522
E1605N3840	FALSE	2016.37295	0.69645274	2017.73958	0.82025547	2016.36251	0.549524
E1605N3820	FALSE	2016.99997	0.86339485	2017.83333	0.88617818	2016.99993	0.43487925
E1605N3865	FALSE	2016.75556	0.96447824	2018	0.85401063	2018.59337	0.27115373
E1605N3825	FALSE	2017.99996	0.54718066	2018.60434	0.79455667	2016.3927	0.09744621
E1610N3870	FALSE	2017.00003	0.99440281	2018.86842	0.60516129	2016.37736	0.99210526
E1610N3825	FALSE	2018.21569	0.26779449	2017.69048	0.9495088	2016.08065	0.99065004
E1610N3830	FALSE	2018.60135	0.66730248	2016.41361	0.32343976	2017.79259	0.97937394
E1610N3890	FALSE	2018.37653	0.94660239	2017.07966	0.99214673	2017.99145	0.94777003
E1610N3860	FALSE	2018.00028	0.66861921	2016.99997	0.7130399	2016.05181	0.94520857
E1610N3840	FALSE	2016.40004	0.40058498	2016.394	0.9299416	2016.99993	0.93553529
E1610N3845	FALSE	2018.64096	0.80660438	2018.6614	0.95362505	2016.33959	0.88382646
E1610N3865	FALSE	2018.60772	0.57578682	2017.15315	0.38690395	2017.91667	0.87952788
E1610N3835	FALSE	2018.79075	0.90696083	2018.83918	0.86528014	2018.80189	0.75745079
E1610N3850	FALSE	2018.60864	0.93891217	2018.96667	0.98629374	2016.3681	0.68801976
E1610N3875	FALSE	2018.61837	0.3200677	2018.96296	0.54000894	2016.2069	0.61961274
E1610N3820	FALSE	2018.74249	0.93228054	2017.00001	0.93556479	2016.99044	0.5722853
E1610N3885	FALSE	2018.61477	0.72273445	2018.60461	0.94263018	2016.99999	0.51055188
E1610N3880	FALSE	2016.3125	0.84196018	2016.99179	0.36222642	2018.6092	0.40877099
E1610N3855	FALSE	2016.39913	0.8454355	2018.00001	0.96548073	2018.59549	0.2222266
E1615N3835	FALSE	2018.60737	0.86638464	2018.77591	0.96908004	2017.36905	0.99246126
E1615N3810	FALSE	2018.00903	0.33496909	2018.00001	0.52674937	2018.00002	0.94494231
E1615N3825	FALSE	2017.39506	0.66892118	2017.00001	0.72876836	2018	0.93706409
E1615N3870	FALSE	2016.74713	0.9150748	2017.02516	0.8	2017.00002	0.89833255
E1615N3830	FALSE	2016.02959	0.98869505	2016.39325	0.75188806	2018.03346	0.89295011
E1615N3880	FALSE	2017.68283	0.89724727	2017.48378	0.87507889	2016.99101	0.82951602
E1615N3805	FALSE	2018.29286	0.93961503	2018.62382	0.75865269	2016.73171	0.77850266
E1615N3865	FALSE	2018.93261	0.96047428	2017.69663	0.8792548	2016.3621	0.73251577

E1615N3855	FALSE	2018.59938	0.45298925	2016.39407	0.76205444	2018.59566	0.72035555
E1615N3860	FALSE	2016.72581	0.96526253	2016.69876	0.90661999	2016.37868	0.53127202
E1615N3815	FALSE	2016.29891	0.92706682	2016.07102	0.77344235	2016.41466	0.45790183
E1615N3875	FALSE	2018.73757	0.95970149	2018.8262	0.99664	2018.59981	0.44952235
E1615N3820	FALSE	2018.59281	0.71705729	2018.63636	0.86240892	2018.80337	0.42464619
E1615N3885	FALSE	2018.62141	0.76670172	2016.39146	0.95350189	2016.61611	0.41548541
E1615N3850	FALSE	2018.58985	0.69713731	2018.62125	0.3687712	2016.99999	0.27935168
E1615N3845	FALSE	2017.99999	0.91291547	2016.29289	0.45506387	2018.588	0.07849412
E1620N3880	FALSE	2016.35505	0.57143325	2016.39216	0.6882615	2016.66667	1
E1620N3870	FALSE	2018.13043	0.64214976	2016.40416	0.80576006	2017.23333	0.98428677
E1620N3875	FALSE	2016.36316	0.3484182	2018.6085	0.923802	2016.39968	0.92162109
E1620N3865	FALSE	2018.00002	0.68894379	2017.99999	0.72639872	2017.92157	0.91697248
E1620N3830	FALSE	2017.99998	0.7844535	2018.75	0.54988914	2018.63188	0.91260053
E1620N3860	FALSE	2018.59709	0.63094485	2016.39705	0.58262635	2016.48649	0.89811784
E1620N3815	FALSE	2016.45611	0.8157458	2017.80952	0.85289116	2016.3888	0.87127591
E1620N3805	FALSE	2017.61765	0.97330402	2016.625	0.84108199	2017.55556	0.79455165
E1620N3825	FALSE	2016.3929	0.81885433	2016.179	0.99618764	2016.99989	0.76009047
E1620N3835	FALSE	2016.4082	0.52118521	2016.38281	0.35276379	2016.10078	0.7575012
E1620N3850	FALSE	2016.99994	0.46148453	2018.00834	0.56035752	2016.1625	0.68276024
E1620N3810	FALSE	2016.99994	0.15774806	2017	0.63302471	2016.67251	0.65201049
E1620N3820	FALSE	2018.00913	0.61948715	2017.92	0.53932584	2018.00007	0.56732814
E1620N3855	FALSE	2016.36626	0.75672525	2016.99058	0.92014379	2018.61964	0.38207906
E1625N3805	FALSE	2018.26667	0.53347037	2018.63034	0.52170583	2016.39182	0.96551419
E1625N3880	FALSE	2016.1711	0.827275	2017.61111	0.51966964	2016.1506	0.94523577
E1625N3825	FALSE	2018	0.89740391	2017.88021	0.88819154	2016.51145	0.93095168
E1625N3875	FALSE	2018.56989	0.32972743	2016.40536	0.77464985	2016.38822	0.86992848
E1625N3865	FALSE	2018.61823	0.62337031	2018.37861	0.73821891	2018.63496	0.84216922
E1625N3810	FALSE	2017.43333	0.35207254	2018.60746	0.40258291	2016.03906	0.78135593
E1625N3835	FALSE	2018.0002	0.45291111	2016.40891	0.18590505	2017.51587	0.75488044
E1625N3820	FALSE	2016.39863	0.16991734	2018.31641	0.99015796	2016.33333	0.73795181
E1625N3855	FALSE	2016.38864	0.76684148	2018.84241	0.58497788	2018.63295	0.69857806
E1625N3860	FALSE	2016.64833	0.80651183	2017.45098	0.96387283	2016.48159	0.68824933
E1625N3800	FALSE	2016.51282	0.97611374	2018.59329	0.38034893	2016.30238	0.64773039
E1625N3815	FALSE	2018.54918	0.74602888	2018.00029	0.39420069	2016.39011	0.60686907
E1625N3830	FALSE	2017.30952	0.50986842	2016.17986	0.72536765	2018.0002	0.35931913
E1625N3870	FALSE	2018.62486	0.03430943	2016.39781	0.82788604	2016.99975	0.06119493
E1630N3835	FALSE	2018.5868	0.96921981	2016.40046	0.59290964	2016.42339	0.97617504
E1630N3805	FALSE	2016.36496	0.6741131	2016.99047	0.53161425	2016.40847	0.97158227
E1630N3810	FALSE	2016.38868	0.54639991	2016.37988	0.1568696	2016.38011	0.88941695
E1630N3820	FALSE	2018.61536	0.33542887	2016.38914	0.67067186	2016.02183	0.88068768
E1630N3815	FALSE	2016.65079	0.94692938	2016.4607	0.92841116	2018.60153	0.7235736
E1630N3875	FALSE	2018.61017	0.78616879	2018.62477	0.43880819	2018.00934	0.72288784
E1630N3880	FALSE	2016.9908	0.21970765	2016.99999	0.7242907	2016.39978	0.342187
E1630N3830	FALSE	2018.59955	0.88762083	2016.39279	0.14907811	2018.60592	0.22577112
E1635N3810	FALSE	2017.13924	0.84603263	2017.54825	0.54638619	2018.6875	0.81973748

E1635N3830	FALSE	2018.61328	0.65988346	2018.61141	0.01925952	2018.00944	0.76988499
E1635N3845	FALSE	2018.84733	0.95531335	2017.56757	0.94545455	2018	0.74232782
E1635N3815	FALSE	2016.39771	0.85495022	2016.41057	0.65192326	2016.18182	0.67263427
E1635N3850	FALSE	2018.58599	0.81777119	2018.6022	0.59706112	2016.36025	0.64120944
E1635N3840	FALSE	2017.06522	0.92965779	2017	0.71534153	2016.17621	0.58015642
E1635N3835	FALSE	2017.98333	0.68011782	2018	0.61959824	2016.99997	0.53568402
E1635N3820	FALSE	2016.39091	0.80011453	2016.35199	0.53001176	2017.99997	0.34068735
E1635N3805	FALSE	2016.40847	0.57770626	2016.75	0.66694387	2016.37913	0.275965
E1640N3825	FALSE	2017.9422	0.94465897	2018.00001	0.76344691	2016.99994	0.92073554
E1640N3830	FALSE	2016.63636	0.98311445	2018.00024	0.95686413	2018	0.91277245
E1640N3840	FALSE	2018.46602	0.90794342	2017.5303	0.57526502	2018.63045	0.88422638
E1640N3835	FALSE	2017	0.97099166	2016.99986	0.90505799	2017.45679	0.62014438
E1640N3845	FALSE	2016.66406	0.99094719	2016.37118	0.59743499	2018.60335	0.11801165
E1645N3830	FALSE	2016.41103	0.88194412	2017.59074	0.68347467	2018.31222	0.93813098
E1645N3835	FALSE	2016.99993	0.61786797	2017.2381	0.98187686	2017.57778	0.87223587
E1645N3840	FALSE	2017.16931	0.82964779	2017.45238	0.7412191	2016.81967	0.71571313
E1655N3820	FALSE	2018.60714	0.85249916	2016.36203	0.29754212	2016.34315	0.28212882

Table 19: Results of segmented regression on income percentage on 500x500 meters squares

Square	Significant	Breakpoints lower income	R^2 lower income	Breakpoints middle income	R^2 middle income	Breakpoints high income	R^2 high income
E1555N3825	FALSE	2016.4126	0.907563989	2016.398132	0.79085978	2018.61716	0.88712639
E1560N3825	FALSE	2018.991984	0.929386859	2016.352561	0.642038475	2016.158948	0.992658282
E1565N3820	FALSE	2018.773637	0.376010438	2016.383657	0.485323026	2018.878171	0.99730409
E1565N3825	FALSE	2018	0.809141597	2016.402069	0.564981575	2016.258926	0.947841809
E1565N3830	FALSE	2016.864806	0.78295827	2016.357175	0.222446402	2016.413829	0.844201914
E1575N3870	FALSE	2018.009029	0.323045582	2018.009531	0.201245751	2016.392934	0.258649563
E1575N3875	FALSE	2017.869091	0.667090722	2016.999976	0.9544948	2016.374524	0.872849016
E1580N3800	FALSE	2018.874398	0.681596227	2016.999985	0.831899828	2017.297448	0.927095701
E1580N3805	FALSE	2016.49998	0.967651813	2017.027594	0.941380628	2016.39544	0.278128241
E1580N3810	FALSE	2017.635045	0.973769531	2016.386729	0.651785806	2016.077512	0.895082542
E1580N3830	FALSE	2018.000001	0.909210487	2018.000105	0.486476395	2016.392654	0.891333915
E1580N3835	FALSE	2018.633418	0.659579534	2018.609876	0.325644984	2016.984674	0.799531089
E1580N3875	FALSE	2018.996298	0.396306967	2018.000041	0.74269008	2018.000039	0.445412435
E1580N3880	FALSE	2018.000002	0.924614665	2018.000002	0.661148438	2016.361532	0.813588017
E1585N3805	FALSE	2016.397768	0.140671862	2018.871057	0.555201292	2018.710674	0.868135743
E1585N3810	FALSE	2018.000045	0.780888481	2016.469635	0.276273854	2016.855058	0.959769779

E1585N3830	FALSE	2018.632977	0.694721233	2018.587131	0.946011173	2017.000011	0.310570972
E1585N3835	FALSE	2018.590526	0.392519112	2018.621419	0.664192173	2017.069109	0.887698534
E1585N3875	FALSE	2018.588024	0.20445228	2016.602541	0.992228251	2017.000006	0.67465585
E1585N3880	FALSE	2017.125904	0.827950832	2017.000001	0.950194327	2016.999871	0.932354023
E1585N3885	FALSE	2017.178777	0.836278543	2017.000017	0.696288802	2018.00001	0.929735091
E1590N3805	FALSE	2018.606558	0.36306287	2016.910028	0.847383684	2018.2526	0.942477048
E1590N3810	FALSE	2018.799105	0.986934065	2018.924604	0.956144136	2016.385606	0.913711439
E1590N3830	FALSE	2017.03905	0.56459261	2018.8078	0.836950066	2017.360518	0.936354685
E1590N3835	FALSE	2016.394474	0.823450096	2018.590323	0.089569211	2017.000003	0.929995008
E1590N3865	FALSE	2018.669352	0.69875875	2017.999992	0.825371128	2018.619092	0.015727914
E1590N3870	FALSE	2018.601232	0.796603837	2016.999945	0.937927207	2018.036237	0.577417045
E1590N3875	FALSE	2018.586543	0.640082032	2018.008931	0.930701291	2018.759777	0.487553652
E1595N3805	FALSE	2018.588442	0.659950259	2016.393875	0.196195309	2018.48721	0.93408836
E1595N3810	FALSE	2018.700954	0.932825096	2016.999915	0.364501079	2017.999981	0.910655037
E1595N3815	FALSE	2018.722703	0.726397587	2018.621912	0.596817056	2017.99999	0.727806526
E1595N3820	FALSE	2016.999986	0.944598779	2018.000155	0.892837116	2018.666783	0.221606451
E1595N3825	FALSE	2016.737399	0.975561038	2016.39785	0.644450231	2018	0.250087953
E1595N3830	FALSE	2017.350453	0.965456405	2016.390826	0.348149369	2017.410853	0.98983952
E1595N3835	FALSE	2018.956507	0.877826425	2018.606635	0.491632805	2016.835692	0.940646997
E1595N3840	FALSE	2018.632637	0.767223158	2018.617929	0.527588384	2016.983168	0.487548986
E1595N3845	FALSE	2016.404815	0.764073988	2016.385627	0.722799908	2016.221595	0.905659976
E1595N3850	FALSE	2018.009051	0.655803135	2016.412293	0.357007923	2016.154967	0.871212918
E1595N3855	FALSE	2018.611989	0.644190684	2017.156453	0.906266725	2017.468459	0.993413943
E1595N3860	FALSE	2018.762876	0.516817925	2017.019406	0.72395758	2016.242548	0.946858683
E1595N3865	FALSE	2016.380759	0.10088911	2018.620305	0.229887271	2018.656282	0.226031095
E1595N3870	FALSE	2016.373839	0.574243393	2016.386286	0.758597785	2018.614099	0.70948563
E1595N3875	FALSE	2018.000064	0.645778573	2018.000063	0.83766663	2016.39199	0.70024188
E1600N3815	FALSE	2018.000025	0.946437308	2016.999964	0.999480474	2017.999991	0.684516782
E1600N3820	FALSE	2018.605533	0.870415354	2018.812225	0.952049379	2018.008764	0.316335952
E1600N3825	FALSE	2017.000003	0.935871277	2018.502977	0.96817484	2016.991385	0.839726846
E1600N3830	FALSE	2018.586869	0.938407306	2016.376833	0.607045723	2016.379089	0.896440758
E1600N3835	FALSE	2016.400531	0.545542429	2018.000157	0.402529233	2016.318162	0.857986382
E1600N3840	FALSE	2016.999858	0.533463813	2016.990701	0.293344529	2018.636909	0.339801561
E1600N3845	FALSE	2018.633585	0.472931618	2016.380383	0.145838016	2016.390558	0.524218264
E1600N3850	FALSE	2018.009188	0.336777316	2018.000141	0.439802719	2016.384396	0.331405275
E1600N3855	FALSE	2016.392778	0.116697949	2016.48657	0.962226702	2017.213333	0.867434219
E1600N3860	FALSE	2016.39354	0.880522379	2016.389569	0.7875085	2016.392867	0.321575284

E1600N3865	FALSE	2016.393762	0.812664425	2016.39126	0.607553395	2018.000045	0.513659438
E1600N3870	FALSE	2018.709249	0.596970416	2018.000004	0.896828768	2018.000018	0.954636143
E1600N3875	FALSE	2017.999998	0.826044403	2018.000027	0.836401833	2016.269945	0.990951673
E1600N3880	FALSE	2016.370357	0.095304507	2017.99998	0.793846817	2018.688458	0.813278978
E1605N3820	FALSE	2018.630373	0.828315091	2017.06573	0.754635686	2016.557279	0.800350685
E1605N3825	FALSE	2018.821247	0.842139316	2018.884642	0.839153762	2017.700555	0.850608067
E1605N3830	FALSE	2018.87623	0.957816009	2018.633767	0.645039785	2017.824213	0.935489363
E1605N3835	FALSE	2018.613709	0.838513693	2018.634913	0.504228111	2016.366724	0.899238023
E1605N3840	FALSE	2018.60089	0.522107957	2018.612772	0.132650608	2018.607953	0.7405769
E1605N3845	FALSE	2018.607911	0.347116069	2016.329674	0.645558892	2016.414597	0.700532976
E1605N3850	FALSE	2016.381091	0.786703803	2018.000003	0.956081695	2016.389904	0.542850602
E1605N3855	FALSE	2018.599628	0.78331669	2018.592092	0.837144474	2018.587919	0.368933229
E1605N3860	FALSE	2018.836566	0.802477999	2018.000046	0.545624704	2016.391472	0.406822559
E1605N3865	FALSE	2016.991386	0.668894468	2016.658417	0.749284201	2017.999965	0.79436785
E1605N3870	FALSE	2016.407889	0.214015195	2018.194832	0.756366673	2017.707118	0.966907573
E1605N3875	FALSE	2017.716187	0.854164343	2017.60104	0.940864423	2017.394782	0.86427873
E1605N3880	FALSE	2018.603451	0.885323498	2018.009624	0.335555629	2018.029426	0.469386263
E1605N3885	FALSE	2017.625701	0.970453625	2018.000022	0.738927098	2018.000001	0.574381355
E1610N3820	FALSE	2016.378939	0.816423033	2016.37392	0.168209013	2017.000008	0.943271108
E1610N3825	FALSE	2018.000006	0.523600981	2018.000002	0.660097128	2018.000004	0.969148581
E1610N3830	FALSE	2017.681118	0.94049003	2017.416068	0.91623172	2018.120659	0.973589693
E1610N3845	FALSE	2018.977782	0.990572997	2018.528606	0.957129926	2016.999971	0.586119527
E1610N3850	FALSE	2018.000024	0.665476258	2016.152779	0.889808162	2016.137187	0.584492063
E1610N3855	FALSE	2018.611288	0.733130399	2016.398197	0.554964808	2016.394124	0.489901301
E1610N3860	FALSE	2018.942252	0.999537032	2018.943374	0.835068038	2016.366222	0.506535101
E1610N3865	FALSE	2016.37889	0.59158966	2018.868334	0.839593758	2016.3776	0.57033914
E1610N3870	FALSE	2018.587184	0.941379316	2016.407297	0.950263999	#N/B	#N/B
E1610N3875	FALSE	2018.927325	0.818542886	2018.752953	0.560867607	2016.999848	0.878910379
E1610N3880	FALSE	2016.002916	0.669305813	2018.475717	0.967241502	#N/B	#N/B
E1615N3805	FALSE	2018.000257	0.193936453	2016.460493	0.661191245	2016.713693	0.800002101
E1615N3810	FALSE	2018.64846	0.170635839	2018.000016	0.91122656	2017.000286	0.816266867
E1615N3815	FALSE	2018.204351	0.967299975	2018.57632	0.959771404	2016.410442	0.61621166
E1615N3820	FALSE	2016.352515	0.054675648	2016.388956	0.004160389	2016.991248	0.310626617
E1615N3825	FALSE	2016.99147	0.309496327	2016.990846	0.501472463	2018.615963	0.977351177
E1615N3830	FALSE	2017.707793	0.686586609	2017.33775	0.863186295	2018.000219	0.626035912
E1615N3850	FALSE	2018.942126	0.997875544	2016.574767	0.994225191	2016.378761	0.567023396
E1615N3855	FALSE	2016.521067	0.613573041	2016.169864	0.581781276	2018.000053	0.753227036

E1615N3860	FALSE	2018.592787	0.404143461	2018.605867	0.410138104	2016.04057	0.89769319
E1615N3865	FALSE	2018.940245	0.978892727	2018.624744	0.435418519	2017.593085	0.975695303
E1615N3870	FALSE	2017.834497	0.468447582	2017.082242	0.793103035	2016.999999	0.745917653
E1615N3875	FALSE	2018.653419	0.133541536	2016.305709	0.779319026	2016.156253	0.944485853
E1620N3805	FALSE	2016.030826	0.872031531	2016.2697	0.762176339	2016.702545	0.823225772
E1620N3810	FALSE	2018.292949	0.579510687	2016.310579	0.769345289	2016.516002	0.672741623
E1620N3815	FALSE	2018.037137	0.785237277	2018.000004	0.977433962	2018.71821	0.666725379
E1620N3820	FALSE	2017.99908	0.767301859	2017.335161	0.538246877	2018.99009	0.885518565
E1620N3825	FALSE	2018.430827	0.769240124	2018.585481	0.698622297	2018.008829	0.34229825
E1620N3830	FALSE	2018.726204	0.985887972	2017.452565	0.695896508	2017.792517	0.957323616
E1620N3855	FALSE	2018.000024	0.767407243	2018.000011	0.89745177	2018.634089	0.868553593
E1620N3860	FALSE	2016.413152	0.093957062	2018.607002	0.292081626	2018.60644	0.681485151
E1620N3865	FALSE	2018.602431	0.299832837	2016.999903	0.782264289	2016.999887	0.941826905
E1620N3870	FALSE	2018.613265	0.551082462	2016.990751	0.495500424	2018.615021	0.347133393
E1620N3875	FALSE	2018.596148	0.602662979	2018.000166	0.879861016	2018.60808	0.995949413
E1625N3805	FALSE	2018	0.859639748	2018.000005	0.598105928	2018.591284	0.991142293
E1625N3810	FALSE	2018.000004	0.650273552	2017.999981	0.67366749	2016.494909	0.975459582
E1625N3815	FALSE	2018.072821	0.476077731	2018.209784	0.318573404	2016.362411	0.932572842
E1625N3830	FALSE	2016.31556	0.787722064	2018.309148	0.970615234	2018.009523	0.636567442
E1625N3875	FALSE	2017.000044	0.32744916	2016.409463	0.669767709	2016.415089	0.919102003
E1630N3805	FALSE	2018.633806	0.718316434	2016.991393	0.259294878	2018.495153	0.82490179
E1630N3810	FALSE	2018.966993	0.860232473	2018.651939	0.629068445	2016.496588	0.998323226
E1630N3815	FALSE	2018.000006	0.881606798	2016.391961	0.522109668	2016.367109	0.518841687
E1630N3830	FALSE	2016.406436	0.89048141	2016.375109	0.655953887	2016.999975	0.698856428
E1635N3830	FALSE	2017.28606	0.77822602	2016.999979	0.458799094	2018.60671	0.674145057
E1635N3835	FALSE	2017.97518	0.721597419	2018.139544	0.632846823	2018.80581	0.536699984
E1635N3840	FALSE	2018.000086	0.664031815	2018.98286	0.33933071	2018.625831	0.115994487
E1640N3830	FALSE	2017.00001	0.777661632	2017.188128	0.808812434	2018.647532	0.860021426
E1640N3835	FALSE	2017.705679	0.937071881	2017.720186	0.886968354	2017.729551	0.894195887

Table 20: Results of segmented regression on income percentages on squares of 1000x1000 meters

Group	Breakpoint lower income	Significance lower income	R^2 lower income	Breakpoint middle income	Significance middle income	R^2 middle income	Breakpoint higher income	Significance higher income	R^2 higher income
1	2018.344	0.142	0.7881	2018.165	0.061	0.8897	2018	0.112	0.9371
2	2018.826	0.524	0.6611	2018.64	0.469	0.5034	2016	0.788	0.2228

3	2019	0.434	0.7777	2018.673	0.631	0.5737	2018	0.999	0.3944
4	2019	0.122	0.8727	2018.605	0.0259	0.9678	2017.959	0.218	0.8838
5	2019	0.519	0.6952	2018.861	0.258	0.6387	2018	0.255	0.7362
6	2019	0.376	0.7336	2018.711	0.234	0.6845	2018	0.296	0.5164
7	2016.894	0.972	0.7005	2016.026	0.866	0.8927	2016	0.863	0.8101
8	2016.252	0.517	0.3434	2016	0.351	0.6194	2016	0.341	0.7673
9	2016	0.333	0.7213	2016	0.296	0.6755	2016	0.47	0.914

Table 21: results of segmented regression on income percentages on squares of 2500x2500 meters