Neighborhood Labeling and Criminal Justice Decisions*

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Abstract

In 2015, the Swedish National Police unexpectedly began publishing their internal list used to identify and monitor "troubled neighborhoods" every other year. This helped establish a public discourse portraying the listed neighborhoods as "no-go zones." The report was not accompanied by any policy response from the criminal justice system or other government agencies. Using multiple data sources, we verify that the (re-)introduction of the list did not lead to significant changes in law enforcement intensity nor to changes in underlying crime. We also show that the report triggered a surge in negative coverage of the listed neighborhoods. We then adopt an RDD approach to estimate the causal effect of neighborhood listing on criminal justice decisions by exploiting the precise timing of the report, comparing defendants who were scheduled for trial with those who had just completed theirs. We find that the sentence length for individuals residing in listed neighborhoods increased by 51.9 percent after the event. The effect is immediate and fades out as media coverage decreases. Courts where relatively few of the judges have personal experience from experience from living in these neighborhoods exhibited the greatest bias. This pattern is consistent with models of decision-making under limited attention, in which courts may overemphasize recent or widely publicized events even when they are unrelated to the case at hand. We also assess potential long-term costs associated with these potentially biased decisions showing that defendants from these neighborhoods experience a 16-percentage-point decline in employment over the three years following their sentence.

Keywords: Neighborhood effects; Stigma; Crime; Sentencing disparities
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1. Introduction

Most major cities around the world have neighborhoods infested by high levels of crime, poverty, and segregation. Because of their structural disadvantages, these neighborhoods tend to acquire negative reputations and are often portrayed unfavorably in the media (Besbris et al., 2015). A longstanding concern is that such place-based stigma affects how residents are treated by public institutions and society at large (e.g., Aaronson et al., 2021,0; Zenou and Boccard, 2000; Yamagishi and Sato, 2025; Wacquant, 2008; Sampson, 2012). Identifying behavioral responses to place-based stigma is, however, empirically difficult. The challenge is to isolate the causal effect of a neighborhood's reputation from the underlying characteristics that generated that reputation. As a result, there is limited causal evidence on whether and how place-based stigma translates into systematic differences in institutional treatment.

This paper examines whether neighborhood reputation affects sentencing decisions in criminal courts—institutions whose judgments shape not only perceptions of fairness but also the behavior of downstream public agencies. Judicial decision-making occurs in settings characterized by substantial information complexity, time pressure, and incomplete case information. Under such conditions, decision-makers may place disproportionate weight on salient or readily observable cues, allowing reputational signals to influence outcomes even when formally irrelevant (Bordalo et al. 2012, 2015). These mechanisms are likely to be particularly consequential for defendants from stigmatized neighborhoods, where entrenched stereotypes and persistent negative media portrayals may magnify the role of such cues (Tversky and Kahneman, 1974). To the extent that judges respond to neighborhood reputation, the resulting patterns may reinforce existing socioeconomic inequalities by generating systematic sentencing disparities, or "excess punishment", that cannot be accounted for by local crime patterns alone.[1] Such disparities may, in turn, contribute to the intergenerational

[1]Large geographic disparities in criminal justice exposure exist even within the same legal system. In Chicago, neighborhood incarceration rates range from under 500 to over 4,000 per 100,000 residents (Sampson and Loeffler, 2010). In Florida, the average felony prison sentence in 2020 was 21 months in Miami-Dade County and 45 months in Okaloosa County (Commission, 2020). Although some variation reflects spatial differences in crime, substantial disparities remain after accounting for crime and case characteristics. In Chicago, some neighborhoods commit residents to prison at more than three times the rate of other neighborhoods with comparable crime levels (Sampson and Loeffler, 2010). Even in Sweden, a comparatively egalitarian context, prison admission rates vary sharply across neighborhoods: areas in the 90th percentile are X times more likely to experience incarceration—a disparity that falls to Y when controlling for local crime and case characteristics.

transmission of economic inequality (Finlay et al., 2023; Chetty and Hendren, 2018).

The context is Sweden where the police in December 2015, unexpectedly started publishing a formerly internal situation report listing so called "troubled neighborhoods" (*utsatta områden* in Swedish).[2] The list of neighborhoods and its publicly available supplement of maps has since been updated biannually on specific dates and without any prenotification of additions to or removals from the report, which originally included 55 neighborhoods. Its release and subsequent amendments have received much public attention, with the included neighborhoods being discussed as "no-go" zones. Yet, unlike most place-based interventions, the situation report was not initially followed up by any immediate policy changes, such as a surge in local policing, modifications to public resources, or action plans to combat organized crime (National Audit Office, 2020). It did not affect moving patterns of residents either. The release of the report can therefore be interpreted as triggering or reinforcing the court's perceptions of the problems associated with these places.

To identify the causal effect of a negative neighborhood stigma shock on sentencing disparities, we implement an RDD approach which exploits the precise timing of the police lists and focuses on defendants who had already been charged and scheduled for trial when the list was released. This design allows us to isolate the behavioral response to the introduction of the list while abstracting from contemporaneous changes in local crime, underlying neighborhood characteristics, or local policy environments. Our analysis uses rich population-based data containing geocoded information on neighborhoods in the police report, defendants' neighborhood of residence. We focus on defendants on trial in a 10 week window around the date of the release or update of the report.

To begin, we document that the release of the situation report produced a negative information shock concerning the listed neighborhoods.[3] To this end, we first classified the universe of media articles written in Swedish mentioning these neighborhoods since February 2015 based on their tone (positive vs. negative) and compare it to a sample of articles of non-listed neighborhoods. We find a significant increase in negative media coverage (both in terms of number of articles and the negativity of their tone) about listed neighborhoods relative to the non-listed control neighborhoods.

[2]The goal in making the list public was to increase transparency in local policing and regain some of the trust that had been lost in 2013 when a media scandal over police ethnic profiling of entire Roma families (including newborns and toddlers) broke out in Sweden (https://www.europarl.europa.eu/doceo/document/E-7-2013-011825_EN.html?)

[3]The listed neighborhoods are clearly disenfranchized in their own right at baseline, as is described more in detailed in Appendix Section 1.1. The negative information shock hence increases public awareness of the existing situation but also generates an artificially discrete categorization of troubled neighborhoods by construction.

This observation aligns with numerous reports affirming that this event played a pivotal role in establishing a narrative of "no-go zones in the Swedish media landscape," potentially contributing to the stigmatization of these places (Backvall, 2019; National Audit Office, 2020). We further demonstrate that the list was compiled based on persistent traits rather than as a reaction to abrupt changes in the social characteristics, that it was not followed up by any policy interventions or changes in neighborhood or family resources, and that it not lead to differential moving patterns. The combination of a negative information shock on listed neighborhoods, the stability of the underlying characteristics, and lack of public interventions lends support to interpreting this event as an exogenous shifter of stigma. We then show that the sentence length for individuals residing in listed neighborhoods increased by more than 60 percent after the event. The effect is immediate and fades out as media coverage decreases. We calculate that about 13 % of the judges in our sample have at some point in their lives resided in a listed neighborhood, and the results show that the increase in sentence length is significantly smaller in courts where a higher share of judges have been exposed to listed neighborhoods. This pattern is consistent with models of decision-making under limited attention, in which courts may overemphasize recent or widely publicized events even when they are unrelated to the case at hand (Bordalo et al., 2015). We also assess potential long-term costs associated with these potentially biased decisions showing that defendants from these neighborhoods experience a 16-percentage-point decline in employment over the three years following their sentence.

The results in this paper contribute to several literatures. First, we add to a large body of work documenting the causal link between neighborhoods and individuals' outcomes, particularly for children. Although this literature has made substantial progress in identifying causal place effects, neighborhood characteristics are deeply intertwined, making it difficult to isolate specific mechanisms even when research designs account for sorting on unobservables (Chetty et al., 2014; Chyn and Katz, 2021; Kling et al., 2007). One mechanism that has received comparatively little attention is place-based stigma. Our results show that stigma constitutes a potentially important, yet previously underappreciated, channel through which neighborhoods shape life outcomes. While some studies have investigated place-based stigma in the context of redlining and credit access (Aaronson et al. 2021, 2023; Fishback et al. 2020), redrawn zoning maps for subsidized neighborhoods (Garrouste

and Lafourcade, 2022), or the depreciation of housing values (Koster and van Ommeren, 2022; Besbris et al., 2015), the policy environment we study operated purely through an informational signal rather than through changes in resources, incentives, or local services.[4]

Second, we contribute to a small but growing literature showing that salient events can influence decision-making within the criminal justice system. Prior studies demonstrate how heightened media attention toward minority groups (Hanemaaijer et al., 2024), intensified terrorism in Israel (Shayo and Zussman, 2011), increased crime salience in France (Philippe and Ouss, 2018), the 9/11 attacks in the United States (McConnell and Rasul 2021a, 2024) , and racially charged political rallies (Grosjean et al., 2023) have shaped judicial or law-enforcement behavior. In contrast to this literature, we highlight the importance of an event that increased the salience of *certain neighborhoods*, rather than the salience of an ethnic or religious minority group. Our results also suggest that neighborhood reputation affects ethnic groups within neighborhoods uniformly.

Third, we contribute to the literature on the consequences of place-based disparities in criminal justice interactions. Such disparities are often interpreted as evidence of "excess punishment," or as a place-specific component of sentencing not fully explained by local crime rates. A central concern is that these differences may reinforce broader economic inequalities (Finlay et al., 2023; Chetty and Hendren, 2018).[5] Because courts adjudicate cases arising from their own jurisdictions, judicial reactions to salient local events risk amplifying pre-existing geographic inequalities. Our findings show that such biases can also intensify the reputational disadvantages faced by residents of stigmatized neighborhoods. Importantly, we show that there is also a long-term penalty from such bias to the labor market.

Lastly, our results also relate more loosely to the literature on racial and ethnic discrimination in the criminal justice system (Arnold et al., 2022; Abrams et al., 2012; Jordan et al., 2023; Hanemaaijer et al., 2024; Tebes and Fagan, 2022; Yang, 2015; Goncalves and Mello, 2021; Ang, 2021; Bindler et al., 2024; Agan, 2024). Because minorities are disproportionately concentrated in certain

[4]Using data from a large Italian bank, and controlling for the non-random selection of firing litigation of employees due to misconduct,Ichino et al. (2003) show that judges are less likely to decide in favor of firms when unemloyment is high

[5]A large literature documents the effects of incarceration on individuals' subsequent outcomes in the United States (Mueller-Smith, 2015; Agan et al., 2023; Garin et al., 2023; Ouss et al., 2023), Norway (Bhuller et al., 2020), and Sweden (Dobbie et al., 2018a; Grenet et al., 2024). Related work using random-judge designs includes Kling (2006) on sentence length, Aizer and Doyle (2015) on juvenile incarceration, and Dobbie et al. (2018b) on pre-trial detention.

neighborhoods, racial and ethnic disparities may generate place-based sentencing differences that cannot be explained by crime levels or case characteristics alone. At the same time, our findings show that place-based stigma operates above and beyond ethnic stigma.[6]

The remainder of the paper is structured as follows. Section 2 provides institutional background for the Swedish context. Section 3 describes the data and empirical strategy. Section 4 presents the estimation results, and Section 5 discusses their implications. Section 6 concludes.

2. Background

This section discusses the introduction of the list of troubled neighborhoods. We present design-based evidence indicating that inclusion on the list is not associated with changes in the characteristics used by the police to identify troubled areas. The section also provides empirical evidence of a substantial surge in media coverage following the publication of the report. Finally, we offer both qualitative and quantitative evidence showing that there was no immediate policy response triggered by the report.

2.1 The Introduction of the Police List

In December 2015, the Swedish police unexpectedly released an internal situation report listing "troubled neighborhoods," which was used to identify and monitor these named neighborhoods. The reason for making the list public seems to have been to enhance transparency regarding police operations, which had been debated since 2013 when a scandal of police ethnic profiling in one Swedish police area broke out.[7]

The list was compiled by combining objective statistics with careful assessment by the local police areas (NOA, 2015). Statistical criteria include poor socioeconomic conditions indicated by high unemployment and poverty (Gerell et al., 2022), but no specific criteria was publicly specified.

[6] As noted by Zenou and Boccard (2000), the "race versus space" debate is central to understanding why minorities face persistent economic disadvantages. Zenou and Boccard present a theoretical model demonstrating that both racial identity and spatial location matter for explaining high unemployment rates among Black workers.

[7] The media revealed that the local police in the county of Skåne had been maintaining an internal database on Roma people that included non-offenders. After the disclosure of this ethnic profiling the police authority of the county of Skåne lost a court case against the Civil Right Defenders (a Swedish extension of the Helsinki committee) in the Stockholm District Court and was heavily criticized by the European Union Comissioner of Human Rights and the Swedish Equality Ombudsman. See https://www.dn.se/nyheter/sverige/detta-har-hant-1/

As shown in Appendix Figure **??**, there is as expected a large and stable gap over time in the socioeconomic characteristics of listed neighborhoods compared to non-listed urban neighborhoods. Importantly, these unadjusted trends display no discernible shifts in the pre-period. This suggests that listing was based on persistent gaps in neighborhood characteristics rather than sudden changes in these. In addition to these social factors, the police authority involved the local police districts in qualitative assessments on whether the neighborhoods had organized crime, parallel social structures, religious radicalization, and residential trust in institutions. The National Operative Unit (NOA) of the police authority then compiled the list into a situation report detailing all identified "troubled neighborhoods." The list has been updated and republished biannually since 2015 (NOA, 2017; NOA, 2019; NOA, 2021; NOA, 2023). A "troubled neighborhood" is then defined as a geographically delimited entity throughout these reports, and supplemental maps are included in the report's appendix (and accompanied by publicly available shapefiles).

The initial round of the list comprised 55 neighborhoods. Table 1 illustrates all the listed neighborhoods and the timing of their inclusion. It is evident that the majority of the neighborhoods initially listed remain on subsequent revisions, with only three neighborhoods removed from the list.[8] Additionally, we observe the inclusion of 9 more neighborhoods in later rounds. Overall, there appears to be only limited changes in the composition of neighborhoods over time. This is again consistent with the list being based on persistent traits of neighborhood disadvantage.

Appendix A provides further details on how these areas compare to other neighborhoods in Sweden, and to other disadvantaged areas in Europe and the US.

2.2 Media Portrayal

The police list, which has been widely debated both in national and international media, has played a crucial role in shaping a media discourse of Swedish so called, "no-go zones."[9] Since its

[8]Based on previous weak evidence of neighborhood stigma reversion once the label is removed (Garrouste and Lafourcade, 2022), in our econometric analysis we consider the neighborhood labeling conferred by the police listing to be an absorbing state that is not reversed during our period of observation.

[9]For instance, in an article entitled "Are There No-Go Zones in Sweden? Police Identify Dozens of 'Vulnerable Areas' Rife With Criminality", Newsweek discusses the Swedish police list of troubled neighborhoods and the reference to Sweden as a hotbed of criminality and radicalization made by President Donald Trump in his alarmist "Look what's happening in Sweden last night...." exclamation (https://www.newsweek.com/sweden-police-vulnerable-areas-no-go-zones-628029). The list has also been highlighted many times in major national media across Europe. See Appendix A.1 for examples of headlines.

introduction, major media outlets have consistently covered the listed neighborhoods, often making them the focal point of news coverage (Backvall, 2019).[10]

Figure 1 shows results of textual analysis of mentions of "troubled" neighborhoods in news articles in Swedish media. The analysis uses data from a media monitoring project called Global Database of Events, Language, and Tone (GDELT), which records instances of events based on articles from a comprehensive, global set of news feeds and is gaining increasing traction in economics (**???**). The content of each article is processed by the GDELT algorithm using text analysis and machine-learning methods to identify salient characteristics, such as event location, date of the event, and the tone-of-content of the article.[11] The data covers all media articles published online since February 2015. It is clear from the figure that the number of articles discussing troubled neighborhoods starts to increase just after the release of the first situation report in December 2015. The release of the report and each subsequent revision (shown in dashed red vertical lines) coincides with clear spikes in media coverage. There is also a spike in June 2018 (shown in dotted red vertical line) when the police called to a press conference to present statistics on the general trends in socioeconomic disadvantage in listed neighborhoods but no list update took place. As a point of reference, the figure also plots the number of articles mentioning "crime." We can see that the spikes in the mentions of troubled areas do not track the trend in articles discussing crime. This suggests that the media interest is not tied to incidences of crime in these neighborhoods.

Appendix Figure A.2 depicts the relative number of Google searches for the terms "troubled neighborhoods." Clear spikes in searches for "troubled neighborhoods" are evident during the months when the list is updated. After these events, the relative number of searches for troubled

[10]The police list and its pertinent dichotomy of neighborhoods into those that are troubled and those that are not has also worked as a convenient instrument for the political discourse of societal problems (**?**). As **?** summarizes her results on the discourse of the Swedish listed neighborhoods, "Politicians have persistently positioned them as perilous places that never joined the present. [...] This history of the recent past focuses on how the "blame" for the problems of modernist urbanism – especially around perceived dangers – has shifted from buildings to people to a politically convenient combination of the two, or what I label "hereafters." I contend that discourses of "unfinished" and "dangerous" places with "criminal" residents have made modernist urbanism a perfect target for xenophobic political discourse, where buildings and landscapes have become scapegoats for less socially acceptable feelings and concerns."

[11]We use GDELT version 2.0 which debuted on February 19, 2015. It collects and translates in real time the content for a massive inventory of global media and decodifies the tone-of-content of each article based on sentiment analysis into a scale from negative to positive. See `www.gdeltproject.org` for a detailed description of the GDELT Project and its methodology.

neighborhoods even exceeds that of very common phrases like "best restaurants."[12] We interpret this as evidence of not only substantial media attention surrounding the report but also significant public interest.

Capitalizing on the fact that GDELT provides for all articles published in online media a measure of tone, Figure 2 plots the average tone of the articles in Swedish media by calendar year and month for neighborhoods included in the Police List in 2015 and a random sample of equal size of non-listed neighborhoods. The algorithm first tallies the number of words with a negative tone and those with a positive tone, then creates an index by weighting each article according to its size and rescale it into an index ranging from -100 to 100. Negative values indicate a more negative tone in the article. To enhance interpretability, we rescale this index by reversing its sign and organizing it into percentiles. Higher values of this so called "negativity index" indicate a more negative tone in the article. Figure 2 reveals that, as expected, listed neighborhoods are portrayed more negatively than non-listed neighborhoods. Furthermore, the gap in negativity between these groups substantially widens following the release of the police reports. In terms of magnitude, by 2019, the average negativity index for non-listed neighborhoods was near the 10th percentile, while for listed neighborhoods, it was close to the 60th percentile. This indicates that the gap in negative portrayal grew from a statistically insignificant 10 percentile difference pre-policy to a 50 percentile difference by the end of 2019.

In summary, the significant public interest in the listed neighborhoods, combined with their negative portrayal in the media, likely contributed to their stigmatization (Backvall 2019; National Audit Office 2020). Such spatial stigmatization may have led to concerns about social image and heightened anticipation or experience of discrimination among their residents (Sampson et al., 2002; Wacquant, 2008).

2.3 (No) Responses to the Introduction of the Police List

i) Police Resources

Qualitative Evidence. Ample evidence from public documents indicates that the police did little to respond to the high-profile report with appropriate interventions or additional resources in

[12]Since Google Trends changed the algorithm in 2015, we are not able to consistently measure searches before 2016.

the listed neighborhoods. An internal report by the police from June 2018 states that "even though the work [by the police] in troubled neighborhoods has high priority, no persistent improvements in manpower is perceived by workers in the field and that no surge [of police presence] has occurred in the troubled neighborhoods" (p. 10) (Hultqvist and Ygge, 2018). Further, the National Audit Office (NAO) reviewed the police work in troubled neighborhoods in 2020 and questioned whether any increases in local patrols had been directed to troubled neighborhoods (National Audit Office, 2020).[13]

Municipalities could address social issues and crime prevention in various ways, for instance by contracting private security firms in certain areas. Our interviews with officers at the Swedish National Council for Crime Prevention (BRÅ) suggest that cooperation between local police and other community actors has improved gradually over the past two decades. However, the list of troubled neighborhoods did not align with any specific programs for increased inter-agency collaboration. According to a BRÅ report (BRÅ, 2018), the Police Authority began providing additional guidance on community policing to local police from 2015 onwards. The report evaluates the implementation of community contracts through four case studies, in which local police, in partnership with other local authorities, commit to a unique set of goals. BRÅ found little to no impact of these community contracts on police practices. The report cites low prioritization of community policing by local police districts and weak collaboration between police and other local actors as key factors behind this limited effect.

Quantitative Evidence. To empirically support the qualitative evidence indicating a lack of significant policy responses, at least during the first three rounds of the report, we utilize matched employer-employee data covering the entire Swedish population.[14] Using this data, we link police staff to their geocoded workplaces. For the police station nearest to each neighborhood, we calculate the average headcount, contracted hours, and the proportion of those working overtime.[15] For

[13]An example of an intervention is the allocation of more foot patrol teams. According to Mission Investigate (in Swedish, Uppdrag granskning), the leading Swedish TV programme for investigative journalism, the police allocated a foot patrol team of two policemen on Tuesdays between 9 am and 3 pm to a troubled neighborhood in the city of Borlänge as a response to the release of the situation report in 2015. In 2017 the patrol shift was shortened to Tuesdays between 12 pm and 3 pm). Further, according to the same program, as of 2021, only three of the 28 municipalities had come up with any action plan for coming to terms with the social issues in troubled neighborhoods.

[14]We discuss the data in more detail in Section **??**.

[15]The results are similar also when using the two closest police stations and weighting by the inverse distance.

each of these three variables, we estimate a staggered difference-in-differences model of the effect of neighborhood listing on police resources using similar non-listed neighborhoods in urban areas as controls. Details on the estimation strategy are presented in Appendix 2.1.

The results in Figure 3 results show that the introduction of the list did not lead to any significant changes in manpower, average weekly contracted hours, or the share of police staff working overtime in the police stations closest to listed neighborhoods. Most of the point estimates are close to zero and relatively precisely estimated. In Appendix Figure **??** we show that the results for police staff hold when only considering police officers, or alternatively considering private security guards.

Taken together, both the qualitative and quantitative evidence suggest that the introduction of the list does not seem to have led to any meaningful immediate changes in police resources.

One potential concern is that, abstracting from any changes in the size of police staff, police forces might have engaged in tougher law enforcement due to the release of the report, for example more frequent stop-and-frisking of young men. To confirm that no such surges occurred, Figure 4 compares trends in conviction rates in listed neighborhoods and non-listed urban neighborhoods. The first thing to note is that trends in crime are remarkably parallel before the first release of the situation report in 2015. This supports the claim that the inclusion of neighborhoods on the list does not stem from sudden changes in neighborhood characteristics. Second, we find no discernible changes in the of conviction rate gap during the complete period of observation (2010–2021). Reassuringly, serious offenses defined as prison sentence, which are thought to capture organized gang crime, are remarkably stable over time in both types of neighborhoods.

2.4 The Swedish Justice System

The criminal court system in Sweden consists of three levels: the district court, the court of appeals, and the supreme court. The vast majority of criminal cases are settled at the district court level, where each district court is generally responsible for all cases originating in its jurisdiction. In this paper, we focus on criminal cases tried in any of the 48 district courts in Sweden. Appendix Table A1 provides additional details on each of the district courts in our data. The largest district courts are located in large cities, such as Stockholm and Göteborg, and have up to 40 judges, whereas the

Table 1: Police List of Troubled Neighborhoods

Figures/Police_list_cropped.pdf

Notes: This table shows the troubled neighborhoods listed by the police in each of the three situation reports that were released within our study period (2010-2020), i.e., 2015, 2017 and 2019 releases. The data are sourced from the National Operative Unit (NOA) of the Swedish Police Authority.

Figure 1: Media Mentions - "Troubled Neighborhoods"



Notes: This figure plots the number of articles in Swedish media including the term "Troubled neighborhoods" (in Swedish, Utsatta områden). Red dash vertical lines indicate months in which the list was released or updated. The lighter red dotted line in 2018 indicates an update that was expected and did not take place. The data was obtained from the GDELT project, `https://www.gdeltproject.org/`.

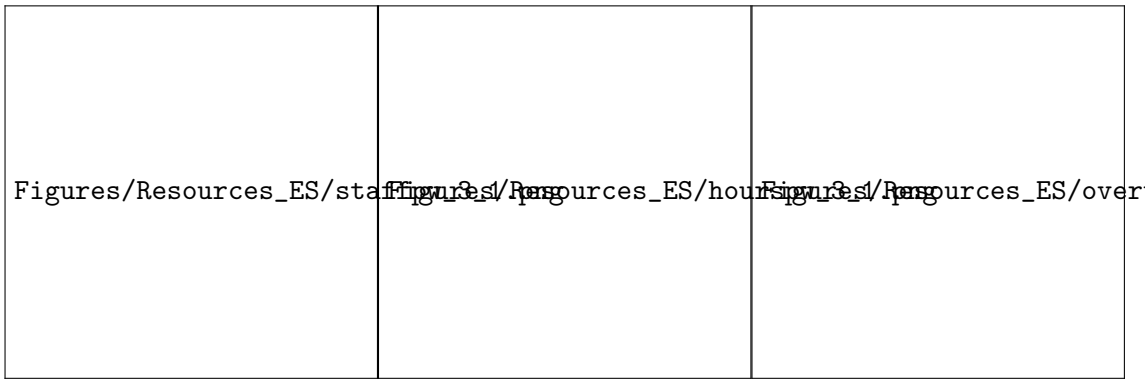
Figure 2: Negativity Index of Media Tone - Listed and Non-Listed Neighbourhoods



Notes: This figure plots the average negative index of the tone of the articles in Swedish media for neighborhoods included in the Police List, and a random sample of non-listed neighborhoods. Higher values of this negativity index indicate more negative tone in the article. Dashed lines denote the observed tone and solid lines the seasonality-adjusted second order local polynomial. The data was obtained from the GDELT project, `https://www.gdeltproject.org/`

Figure 3: Police Resources - Treatment Effect in Listed Neighborhoods

(a) Employees per station (b) Average weekly hours (c) Share working overtime



Notes: This figure plots the average treatment effect of the police list on neighbourhood police resources. These are estimated using a dynamic difference-in-differences strategy, where the treatment group includes all listed neighborhoods, and the control group includes non-listed neighborhoods weighted by their propensity of being treated on pre-policy characteristics (see Appendix Section 2.1 for the details of the empirical model). TWFE and **?** estimators are presented. Sub-figure **??** shows the effect on number of employees per station, Sub-figure **??** for average weekly contracted hours per police officer, and Sub-figure **??** for share of staff working overtime. 95% confidence intervals are based on standard errors clustered at the neighborhood level.

smallest courts are located in more rural areas and only have a few judges.

District courts in Sweden are usually divided into divisions (*avdelningar*) and then sections (*rotlar*), although some small courts are only divided into sections. Each section consists of one judge, one clerk, and several administrative personnel. At the beginning of each year, courts typically assign judges to their sections. Although judges may be reassigned to different sections in subsequent years, many remain in charge of the same section for several years. We refer to each section as a judge. District court judges are appointed for the duration of their career and can only lose their jobs if they are convicted of a serious crime. Before their appointment, district court judges must have a law degree, but they are not required to have prior experience working in the court system. Each district court also maintains a large pool of politically appointed lay jurors (*nämndemän*) that serve a similar function as juries in the American system. Each lay juror works approximately 10 to 15 days per year, with essentially random assignment of lay jurors to both cases and judges (Ahrsjö et al., 2024).[16]

In most district court trials, both the verdict and sentence are decided by both the judge and the three lay jurors. Following the hearing, the judge summarises the facts of the case and any relevant laws for the three lay jurors. The judge and the three lay jurors then discuss possible decisions, including the verdict and sentence. If the judge and the lay jurors disagree on the verdict, a vote is held to determine the outcome of the case. The votes of the judge and lay jurors have equal weight, but the judge holds the tiebreaker if there is no clear majority. If a defendant is found guilty, there is a second vote to determine the sentence, with the least severe option chosen if there is an even split between different sentencing options. If the severity ranking of the different options is unclear, then the judge holds the tiebreaker.

Appendix Figure A1 provides additional details on how suspected crimes are processed in Sweden's criminal justice system using information from cases in 2004. If there is suspicion of a crime, the police or a prosecutor begins a preliminary investigation. The prosecutor then decides whether the individual should be charged with a crime and whether the case should proceed to a

[16]Lay jurors indicate their availability for different fixed dates in the upcoming year (e.g., the first Monday of each month). Lay jurors are then assigned specific dates in advance of any knowledge about the cases to be tried on those dates. For each date, a court administrator then forms juror triplets, with some attempt to balance gender, age, and political party. Finally, the court coordinator assigns each juror triplet to a courtroom scheduled to be in session in a quasi-random fashion. See Anwar et al. (2019) and Ahrsjö et al. (2024) for additional details on lay jurors in Sweden.

court trial.[17]

Of these charged cases, 77% result in a court trial. The other charged cases are typically settled without a trial, usually because the suspect has confessed to a petty crime. A small number of charged crimes result in no prosecution, trial, or penalty, usually because the defendant is under 18 years of age. Once a case proceeds to trial, it is assigned to a judge in the relevant court. Of these court trials, 23% result in incarceration, 37% in a fine, 24% in probation, 10% in other types of punishment such as community service, and, in only 6% of the cases, the defendant is found not guilty. Our empirical strategy measures the impact of parental incarceration compared to a weighted average of these other forms of punishment, including acquittal.[18]

The criminal justice system in Sweden is broadly similar to many other developed countries, particularly other Nordic countries. This section briefly reviews the differences most relevant to our analysis. Online Appendix D discusses the differences in institutional contexts that may explain differences in results between studies.

Incarceration Rates: Appendix Figure A2 plots incarceration rates per 100,000 individuals in Sweden, the United States, and all remaining European and North American OECD countries. The incarceration rate in Sweden has been relatively stable over the last 35 years, increasing from 55 individuals per 100,000 in 1980 to 79 in 2006, then falling back to 61 in 2014. Incarceration rates in other OECD countries have followed a largely similar trend over time, albeit from a slightly higher base. In stark contrast, incarceration rates in the United States increased from 220 individuals per 100,000 in 1980 to 693 by 2014.

[17]Individuals arrested for a crime carrying a prison term of one or more years can be detained before trial if there is a risk that they will flee prosecution, obstruct the investigation, or commit a new crime. The initial decision on whether or not to detain an individual prior to trial is generally made by a randomly assigned judge at the time of the arrest. The assignment processes for the judge making the pretrial decision and the judge presiding over the trial are completely independent, meaning that the same judge will only be assigned to the pretrial and trial stages by chance.

[18]Sentence length, fine amounts, and probation length are all determined by the seriousness of the crime, with fine amounts also depending on taxable income. Individuals on probation (*skyddstillsyn*) are generally required to be in regular contact with a surveillance officer for the duration of their sentence. Individuals on probation may also be required to undergo regular drug tests, take courses in impulse control or psychiatric care, or even be institutionalised for additional treatment. Individuals with three-month or less prison sentences can also ask the prison and probation authorities to serve their sentence at home under electronic supervision. The decision of whether an individual can serve their sentence at home is made solely by the prison and probation authorities and does not depend on the assigned judge, meaning that our identification strategy is not affected by this possibility. We also find slightly larger point estimates if we define incarceration as a sentence of more than three months, suggesting that the actual prison stay matters more than the sentence itself.

Sentence lengths are also considerably shorter in Sweden compared to the United States. Conditional on any incarceration, the median prison sentence in our sample is only 3.0 months, and more than 80% of sentences are shorter than one year.

3. Data and empirical method

This section discusses the various data sources used in the empirical analysis. It also outlines the research design used to estimate the causal effect of the introduction of the list on criminal justice decisions.

3.1 Micro data

This study draws upon detailed administrative data covering all sentencing decisions in Swedish courts ("Tingsrätter") during 2007–2021. These data are merged with other administrative registers at Statistics Sweden using annonymized identifiers. Consequently, the dataset includes sociodemographic characteristics of the working-age population (ages 15–74) for all years, enabling us to characterize pre-determined demographic characteristics of all defendants and their geocoded residential locations and, therefore, to their neighborhood of residence in any given year.[19]. Online Appendix contains relevant information on the cleaning and coding of the variables used in our analysis. This section summarises the most relevant information from the Appendix.

Information on criminal behaviour and court cases comes from data provided by the Swedish National Council for Crime Prevention (see www.bra.se). The crime data include information on all court cases between 1985 and 2021, including cases that did not end in a conviction. We observe the date of the crime, the date of conviction, the type of crime committed, the sentence imposed by the court, whether there are any co-offenders, and unique identifiers for district courts, and defendants.

We merge these data with information on family linkages contained in the multi-generation register created and maintained by Statistics Sweden (Statistics Sweden 2017).[20] We then merge

[19]These registers are: Population register, Multigenerational register, School register, LISA register, Conviction register, and Suspicion register.

[20]The multi-generation register contains the personal identification numbers for all individuals born in Sweden starting in 1932 who were still alive in 1947 when the system was introduced, along with the personal identification numbers of each individual's parents and children.

these datasets with the LISA register provided by Statistics Sweden. LISA contains rich longitudinal data that include outcomes for every Swedish resident at least 16 years old. For each year, the data contain information on the families' entire formal sector earnings and transfers from the tax registers.

We restrict the estimation sample to defendants sentenced in a 10 week window around the week of the release and update of the report. Our main outcome variables are defined as the probability of being convicted, the probability of being sentenced to prison, and (log) sentence length in days.

3.2 Classifying Listed Neighborhoods

Table 2 presents descriptive statistics for individuals sentenced just before and just after the week of the release or update of the report pooling all years 2015, 2017, 2019 and 2021. To identify listed neighborhoods, we use geocoded maps from the Swedish police authority.[21]

Figure 5a shows the geographical distribution of the police drawn maps in Stockholm municipality and Figure 5b zooms in on one of these neighborhoods in Stockholm. It is clear from Figure 5a that listed neighborhoods are located in the suburban areas of Stockholm city, and this applies in general. As all listed neighborhoods are located in urban municipalities, for our empirical analysis we restrict our sample to defendants in urban municipalities.[22]

Ideally, we would be able to exactly identify if a defendant lives inside the areas identified as a "troubled neighborhood." However, the administrative data only provide their neighborhood of residence, or Regional statistical neighborhood units (hereafter, RegSO for the Swedish term Regionala statistikområden). There are approximately 3,360 RegSOs in Sweden, and each has between 650 and 23,000 inhabitants. Moreover, the police-drawn maps typically exclude commercial properties, highways, and green areas, and do not perfectly align with RegSO boundaries. We can see in Figure 5b that the police drawn map (shown in pink) overlaps relatively well with ... RegSOs (boundaries shown in solid black lines), with the exception of some green area.

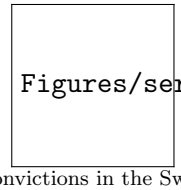
[21]The police authority publishes online geocoded maps of the listed neighborhoods as shapefiles for citizens and the media to freely download.

[22]We follow (BRÅ, 2018) and define urban municipalities as ones with at least one town larger than 10,000 individuals and whose share of dense neighborhoods (with at least 200 dwellings within a maximum distance of 200 meters) is above the national average.

To overcome these limitations, we identify a neighborhood (RegSO) as being on the list if its area has an overlap of 30% or more with a "troubled neighborhood" area.[23] Consequently, we define an individual as living in a "troubled neighborhood" if its neighborhood of residence (RegSO) was identified as being on the list. There are 92 neighborhoods (RegSO) with 16,582 defendants within the boundaries of the listed troubled neighborhoods as drawn by the police.

[23]In the robustness analysis we show that the results are insensitive to using alternative cutoffs. We also gauge the feasibility of this operationalization of exposure in Appendix Table **??** by comparing descriptive statistics for age structure and employment of listed neighborhoods based on the 50 percent overlap rule with the definition used by Statistics Sweden based on exact individual-level coordinates of residence and geocoded delimitations of listed neighborhoods provided by the police. The latter descriptives are only available for year 2018 (**?**). Reassuringly, our definition of listed neighborhoods shows on average almost exactly the same age structure and employment shares (by gender) as does the precise treatment definition of Statistics Sweden.

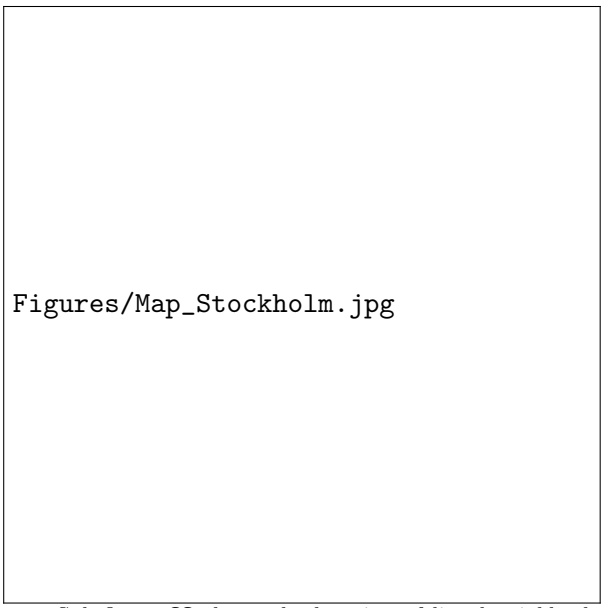
Figure 4: Conviction rates for Listed and Non-Listed Neighbourhoods

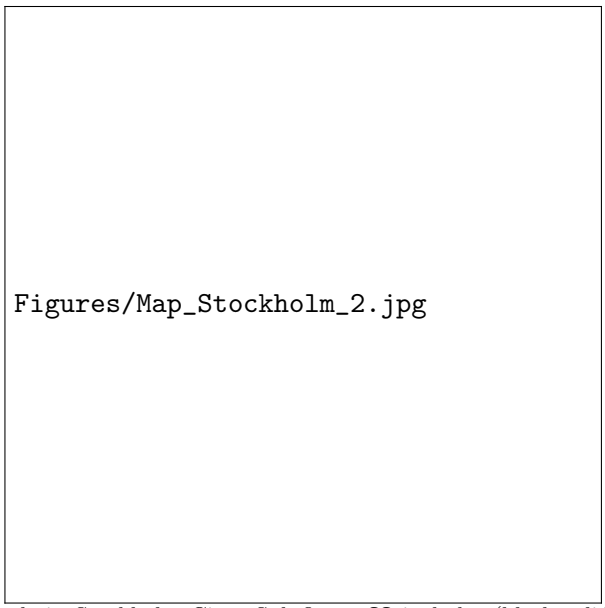


Notes: Statistics are based on the universe of convictions in the Swedish judicial system in years 2010-2019. Serious crime (orange time series) include all prison sentences. The statistics are aggregated from individual-level data that come from Statistics Sweden. The control group of non-listed neighborhoods refer to all other urban neighborhoods units except for the listed neighborhoods.

Figure 5: Map of Listed Neighborhoods in Stockholm City

(a) Listed neighborhoods in the city of Stockholm (b) One listed neighborhood (Bredäng)





Notes: Sub-figure **??** shows the location of listed neighborhoods in Stockholm City. Sub-figure **??** includes (black solid) boundaries of the neighborhood (DeSO) units belonging to a listed neighborhood in Stockholm called Bredäng. Zooming in on Bredäng, share of immigrants in 2023: 63.5 percent vs. Stockholm city avg. 34.9 percent; employment in 2021: 70.4 percent vs. Stockholm city avg. 79.5 percent (**?**). Geocoded data come from the National Operative Unit of the Swedish Police Authority. In the spirit of our paper, for the positive qualities of the surroundings of Bredäng, see https://www.flickr.com/photos/miljoforvaltningenstockholm/albums/72157646835975372/.

3.3 Identification strategy

Our research design leverages the distinct timing of the police lists labeling neighborhoods as "troubled" and combine this with individuals already waiting to face trial or those who have just done so to get at the causal effect of a negative neighborhood stigma shock on sentencing disparities. To do so, we employ a regression discontinuity design (RDD), where sentencing week is the running variable (RV) plotted against sentencing outcomes around the time of the list releases.

In the main analysis, we estimate the following conventional RDD specification around the defendants facing trial right before or just after the inclusion of its neighborhood in the police list of troubled neighborhoods:

$$\text{Outcome}_i = \gamma + RV + RV \times Listed_i + \beta Listed_i + \lambda X_i + \epsilon_i, \tag{1}$$

where Outcome_i is the outcome of interest. The model assumes that the unobserved characteristics of the defendants are similar for listed versus non-listed defendants. We expect the effect of neighborhood labeling to manifest directly after the publication of the situation report, in which one's own neighborhood was listed, i.e., in a neighborhood that was listed in 2015–2021.

Initially, we fixate the bandwidth to ± 10 weeks to keep the comparison tight within the individual list releases, but we also show that the results are unchanged for longer choices of bandwidth (e.g., 20 weeks). Since there is some mismeasurement in treatment/control status precisely around and just after the cutoff, due to potential lag for some cases between the court date and sentencing decision date (which is the RV we use), we run donut specifications at baseline where we exclude the cutoff week and the next week (t_0 and t_1). The RDD estimation employs triangular kernel weights, and the pre/post-trends are captured using linear fitted lines. Moreover, we ensure that no same individual is included in the sample as being or will be sentenced at multiple instances in the same list year.

We previously showed that the introduction of the list did not coincide with changes in underlying crime levels or the socioeconomic and demographic characteristics of listed and non-listed neighborhoods. We also presented both qualitative and quantitative evidence indicating that there was no immediate policy response associated with the introduction of the list. While reassuring,

the research design we adopt also accounts for these possibilities. However, due to some concerns regarding the seasonality of the list releases (they are generally released close to the summer and winter break), there may be risk of cases with certain characteristics showing up before and after the cutoff even though the list releases did not impact the judicial system before sentencing at the time. In order to alleviate such seasonality concerns, we also present results employing propensity score 1-1 nearest neighbor matching (with replacement) based on a range of background characteristics and case crime type for each case. These results will ensure that the RDD comparison around the cutoff is not affected by any imbalance driven by case seasonality in case characteristics.

i) Descriptive statistics

Descriptive statistics are presented in Table 2. This table shows that criminals in listed and non-listed neighborhoods are similar in terms of the sex ratio, employment rate, and their propensity to be convicted or sentenced to prison, but that individuals in listed neighborhoods tend to be younger, more urban, less educated, and are much more likely to have a foreign background. The composition of individuals around the running variable cutoff is also shown to be stable for both listed and non-listed neighborhoods. However, average sentence length is shown to increase starkly just after the cutoff for those in listed neighborhoods, while it is only increasing modestly for individuals residing in non-listed neighborhoods.

ii) Validating the design

The research design relies on the assumption that cases processed just before and just after the cutoff are similar in terms of background characteristics. Table 3 presents results supporting this assumption. The estimates are obtained from regressions similar to model 1, but using pre-determined characteristics as the dependent variable. None of the estimates are statistically significant.

The design further assumes that courts should not be able to sort cases just above or below the cutoff. Because the release and updating of the police list can be viewed as exogenous to the court, this minimizes the risk of such bunching. Still, while the release of the list was unexpected, the dates of later updates were sometimes announced in advance. In the presence of sorting, we

would expect to observe a jump in the density of the running variable at the cutoff. Figure 6 shows that the relative frequency of cases is similar on both sides of the cutoff, and the McCrary test for bunching is also statistically insignificant (p = 0.85).

4. Results

This section outlines results from our empirical analysis of the effect of neighborhood listing on criminal justice decisions. All specifications include indicators capturing the list year and our prefered specification also control for gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. Weeks 0–1 are excluded from the analysis (dougnnut) and the standard errors are clustered at the court level.

4.1 Main results

Table 4 presents the results for the effect of neighborhood listing on the probability that a defendant is convicted and on the probability of receiving a prison sentence. In our sample, 92.5 % of defendants are convicted, reflecting the high evidentiary standard required for a case to proceed to trial. Among the cases that are tried in court, 14.7 % result in a prison sentence. All estimated effects are negative, statistically insignificant, and small in magnitude. For example, the 95 % confidence interval for the probability of conviction rules out effect sizes larger (in absolute value) than –4.6 to 1.7 percent of the sample mean. Overall, the point estimates indicates that the list releases had no impact on these outcomes.

For sentence length, on the other hand, we find large and significant increases around the list releases throughout the different empirical specifications in Table 5. In the main empirical specification, we estimate that log sentence length increases by roughly 0.519 log points (s.e. 0.176), which is sizable increase statistically significant at the 1% level. Sentence length in days, similarly, increases by about 260 days (260.513, s.e. 122.725). This result is similar in relative terms (+69%) when you compare it to the mean of the dependent variable sentence length for individuals to the left of the cutoff. Figures 9 and 8 provide the graphical equivalence to those presented in the tables above.

The fact that we only observe an effect on prison sentence length is also telling as this it likely involves the greatest degree of human discretion, and could therefore be more susceptible to influence from salient events. Interestingly, our results are broadly consistent with those in Hanemaaijer et al. (2024), who also find no significant effect on the probability of conviction or on receiving a prison sentence in the Netherlands for individuals of Moroccan descent following the salience shock created by the assassination of a high-profile lawyer overseeing a case against the so-called "Mocro Maffia." Their study further shows that the sentence length for convicted individuals of Moroccan descent increased by 79 % after the shock.

4.2 Robustness

We have subjected the main results to a battery of robustness checks. Although the release and update of the report occurred on different dates, it is still possible that our estimates are capturing seasonal effects.[24] Appendix Figure A1 presents results from placebo tests that use fictitious release and update dates set exactly one year before the actual dates. We find no significant effects in this analysis, suggesting that our results are not driven by seasonal patterns.

Appendix Table A1 presents results in which we replicate our analysis of sentence length using different bandwidths—including week t+1—and by varying the degree of overlap required between a neighborhood and the police map for the neighborhood to be classified as listed. The results show that our estimates remain similar to the baseline and that they become statistically significant when we include non-prison sentence length in the dependent variable.

4.3 Mechanisms

As shown earlier, the neighborhoods included on the police's list had persistently higher levels of disadvantage; however, there appeared to be no meaningful changes in disadvantage prior to the release or updates of the list. The literature suggests that the list could nonetheless constitute a salience shock for judges, particularly in the short run. Several studies show that intensified media reporting of events unrelated to the cases at hand can lead to short-run changes in sentencing severity, especially for minority groups that are disproportionately represented in the criminal justice system.

[24] For instance, the release in 2015 and the update in 2021 occurred in early December, just before many courts process fewer cases due to Christmas.

For instance, Hanemaaijer et al. (2024) show that the sentence length of Moroccan defendants increased during a four-week period following the salience shock created by the assassination of a high-profile lawyer overseeing a case against the so-called "Mocro Maffia." Grosjean et al. (2023) show that Trump rallies raised the probability of Black drivers being stopped by police in the two months afterward. Moreover, Ouss et al. (2023) find that media coverage of crimes in France leads to harsher sentencing the following day, and McConnell and Rasul (2021b) and McConnell and Rasul (2021a) show that the 9/11 attacks increased sentencing severity in subsequent months for both Muslim and non-Muslim minorities in U.S. federal courts due to spillover effects.

To assess the feasibility of this mechanism in our context, we conducted a series of additional analyses. First, recall that media coverage spiked sharply around the release and update of the list and then declined within a few months, with the largest increases occurring in 2017 and 2019. Figure 10 presents results from an analysis in which we extended the doughnut from –20 to +10 weeks by shifting the doughnut window accordingly. Consistent with the short-run increase in media coverage, we observe that the estimated effect fades out approximately 6 to 8 weeks after the shock.

A related question concerns the extent to which judges are consistently shocked by each release or update of the list. To investigate this, we estimate regressions separately by list year. Table 6 shows that the effects are strongest in 2017–2019, coinciding with the largest spikes in media coverage. Thereafter, the effects appear more muted. One possible interpretation is stigma saturation. Supporting this explanation, media coverage increased the least in 2021.

In Table 9 we show evidence supporting the idea that judges with limited own personal experience of listed neighborhoods respond stronger to the introduction of the list. Using our administrative data we calculate that about 13 % of the judges in our sample have at some point in their lives since 1982 resided in a listed neighborhood. High share judges exposed is defined as an indicator for being above the 75th percentile of judge exposure. The results show that the increase in sentence length is significantly smaller in courts where a higher share of judges have been exposed to listed neighborhoods.

Not all neighborhoods were highlighted equally in media reporting. Figure GDELT Media Analysis shows that coverage tended to focus more heavily on the neighborhoods classified by the police as particularly troubled. Table 7 presents results from separate regressions by neighborhood

classification—highly troubled, moderately troubled, or at risk. We observe a tendency toward stronger effects for neighborhoods classified as highly troubled.

Spatial differences in criminal justice interactions are intimately linked to the concentration of minority populations and socioeconomic disadvantage. This raises the question of whether judges may use neighborhoods as a proxy for underlying structural disadvantages. Because minorities are disproportionately concentrated in certain neighborhoods, racial and ethnic disparities may generate place-based sentencing differences that cannot be explained by crime levels or case characteristics alone. The "race versus space" debate is central to understanding why minorities face persistent economic disadvantages. Zenou and Boccard present a theoretical model demonstrating that both racial identity and spatial location play important roles in explaining high unemployment rates among Black workers.[25]

To distinguish between "race" and "space," we present results from analyses estimating heterogeneous effects by predicted risk of reoffending, immigrant status, and co-offending. The idea is that if judges are using neighborhoods as a proxy for underlying disadvantages, then we would expect stronger effects in subgroups more closely linked to these disadvantages. We focus on immigrants and cases involving co-offenders because these neighborhoods are characterized by a high concentration of immigrants and are often associated with gang-related crime. We therefore use co-offending as a proxy for criminal networks. The results in Table 8 show that there is no significant difference in sentencing outcomes between immigrants and natives, nor between co-offending and non–co-offending defendants. These findings suggest that place-based stigma operates above and beyond ethnic stigma.

4.4 Long-term effects of neighborhood listing

The fact that our data contain information from several different registers allows us to investigate potential long-term effects of differential treatment on labor market outcomes and health. While we find no significant effects on various measures of prescriptions for mental health–related drugs (see Table 10), we do find a significant decrease in the probability of being employed (see Table 11). This

[25] A large literature studies racial and ethnic discrimination in the criminal justice system (Arnold et al., 2022; Abrams et al., 2012; Jordan et al., 2023; Hanemaaijer et al., 2024; Tebes and Fagan, 2022; Yang, 2015; Goncalves and Mello, 2021; Ang, 2021; Bindler et al., 2024; Agan, 2024).

effect persists three years after the trial, suggesting that it is not merely a mechanical consequence of time spent in prison. The point estimates indicate that defendants from listed neighborhoods experience a 16–percentage point decline in employment over the three years following their sentence.

5. Conclusion

The 2015 release of a police situation report publicly listing "troubled neighborhoods" triggered a significant negative information shock, unaccompanied by immediate policy interventions. Using data from various sources, we show that the introduction of the list led to a marked increase in negative media coverage, likely reinforcing the stigmatization of the listed neighborhoods.

Our main findings reveal that sentence lengths for individuals residing in listed neighborhoods increased by more than 60 percent immediately after the event, with the effect dissipating as media coverage declined. This temporal pattern aligns with models of decision-making under limited attention: when exposed to salient shocks, courts may overweight recent or widely publicized events—even when these events bear no direct relevance to the case at hand. We further document substantial downstream consequences. Defendants from listed neighborhoods experience a 16-percentage-point reduction in employment during the three years following their sentence, indicating sizable long-term economic costs.

These findings demonstrate that neighborhood reputation can systematically influence sentencing decisions in criminal courts. While we show that these sentencing disparities have downstream consequences for defendants' long-run labor-market outcomes, courts are institutions whose rulings shape not only individual trajectories but also broader perceptions of procedural fairness. This suggests an important avenue for future research: examining how place-based discrimination in sentencing may affect perceptions of fairness and trust in institutions both within affected communities and in the wider society. Moreover, because courts adjudicate cases drawn from their own jurisdictions, heightened responsiveness to neighborhood reputation risks reinforcing existing geographic inequalities and further disadvantaging residents of already stigmatized areas.

Taken together, the evidence points to place-based stigma as a meaningful—and previously underappreciated—mechanism behind neighborhood effects. From a policy standpoint, efforts

to counteract negative perceptions of disadvantaged neighborhoods may provide a cost-effective way to improve residents' outcomes without requiring substantial financial investments or major institutional reforms. This could also potentially be achieved by standardized sentencing guidelines that reduce judicial discretion or judicial training for judges on the effects of cognitive biases.

References

Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder, "The Effects of the 1930s HOLC "Redlining" Maps," *American Economic Journal: Economic Policy*, November 2021, *13* (4), 355–92.

_ , _ , _ , and Martha Stinson, "The Long-Run Effects of the 1930s Redlining Maps on Children," *Journal of Economic Literature*, September 2023, *61* (3), 846–62.

Abrams, David S., Marianne Bertrand, and Sendhil Mullainathan, "Do Judges Vary in Their Treatment of Race?," *Journal of Legal Studies*, 2012, *41* (2), 347–383.

Agan, A., J. Doleac, and A. Harvey, "Misdemeanor prosecution," *Quarterly Journal of Economics*, 2023, *138* (3), 1453–1505.

Agan, Amanda Y., "Racial Disparities in the Criminal Legal System: Shadows of Doubt and Beyond," *Journal of Economic Literature*, 2024, *62* (2), 761–806.

Ahrsjö, Ulrika, Susan Niknami, and Mårten Palme, "Identity in court decision making," *American Economic Journal: Economic Policy*, 2024, *16* (4), 142–164.

Aizer, Anna and Joseph J. Doyle, "Juvenile incarceration, human capital, and future crime: Evidence from randomly assigned judges," *Quarterly Journal of Economics*, 2015, *130* (2), 759–804.

Ang, Desmond, "The Effects of Police Violence on Inner-City Students," *The Quarterly Journal of Economics*, 2021, *136* (1), 115–168.

Anwar, Shamena, Patrick Bayer, and Randi Hjalmarsson, "Politics in the Courtroom: Political Ideology and Jury Decision Making," *Journal of the European Economic Association*, jun 2019, *17* (3), 834–875.

Arnold, David, Will Dobbie, and Peter Hull, "Measuring racial discrimination in bail decisions," *American Economic Review*, 2022, *112* (9), 2992–3038.

Backvall, Karin, "Constructing the suburb: Swedish discourses of spatial stigmatisation." PhD dissertation, Department of Social and Economic Geography, Uppsala University 2019.

Besbris, Max, Jacob William Faber, Peter Rich, and Patrick Sharkey, "Effect of neighborhood stigma on economic transactions," *Proceedings of the National Academy of Sciences*, 2015, *112* (16), 4994–4998.

Bhuller, Manudeep, Gordon B. Dahl, Katrine V. Løken, and Magne Mogstad, "Incarceration, recidivism and employment," *Journal of Political Economy*, 2020.

Bindler, Anna, Randi Hjalmarsson, Nadine Ketel, and Andreea Mitrut, "Discontinuities in the Age-Victimisation Profile and the Determinants of Victimisation," *The Economic Journal*, 2024, *134* (657), 95–134.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, "Salience Theory of Choice Under Risk," *Quarterly Journal of Economics*, 2012, *127* (3), 1243–1285.

_ , _ , and _ , "Salience Theory of Judicial Decisions," *Journal of Legal Studies*, 2015, *44* (S1), S7–S33.

Brottsförebyggande rådet (BRÅ), "Polisens arebete med medborgarlöften: Fallstudier från fyra områden i Sverige [Engl. Police and Community Contracts: Four Swedish Case Studies]," *Bråttsförebyggande rådets rapport*, 2018.

Chetty, Raj and Nathaniel Hendren, "The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects," *Quarterly Journal of Economics*, 2018, *133* (3), 1107–1162.

_ , _ , Patrick Kline, and Emmanuel Saez, "Where is the land of opportunity? The geography of intergenerational mobility in the United States," *Quarterly Journal of Economics*, 2014, *129* (4), 1553–1623.

Chyn, Eric and Lawrence F Katz, "Neighborhoods Matter: Assessing the Evidence for Place Effects," *Journal of Economic Perspectives*, 2021, *35* (4), 197–222.

Commission, United States Sentencing, "Inter-District Differences in Federal Sentencing Practices: Sentencing Practices Across Districts from 2005–2017," Technical Report, United States Sentencing Commission January 2020. GPO Stock Number 052-070-07772-7.

Dobbie, Will, Hans Grönqvist, Susan Niknami, Mårten Palme, and Mikael Priks, "The intergenerational effects of parental incarceration," Working Paper 24186, National Bureau of Economic Research 2018.

_ , Jacob Goldin, and Crystal S. Yang, "The effects of pre-trial detention on conviction, future crime, and employment: Evidence from randomly assigned judges," *American Economic Review*, 2018, *108* (2), 201–240.

Finlay, Keith, Michael Mueller-Smith, and Brittany Street, "Children's Indirect Exposure to the U.S. Justice System: Evidence from Longitudinal Links between Survey and Administrative Data," *The Quarterly Journal of Economics*, 2023, *138* (4), 2181–2224.

Fishback, Price V., Jessica LaVoice, Allison Shertzer, and Randall P. Walsh, "The HOLC Maps: How Race and Poverty Influenced Real Estate Professionals' Evaluation of Lending Risk in the 1930s," Working Paper 28146, National Bureau of Economic Research November 2020. Revised October 2021.

Garin, A., D. Koustas, C. McPherson, S. Norris, M. Pecenco, E. Rose, Y. Shem-Tov, and J. Weaver, "The impact of incarceration on employment, earnings, and tax filing," Working Paper, University of Chicago, Becker Friedman Institute for Economics 2023.

Garrouste, Manon and Miren Lafourcade, "Place-Based Policies: Opportunity for Deprived Schools or Zone-and-Shame Effect?," Discussion Paper CEPR Discussion Paper No. 17750, Center for Economic Policy Research 2022.

Gerell, M., M. Puur, and N. Guldåker, "Swedish conditions? Characteristics of locations the Swedish police label as vulnerable," *Nordic Journal of Urban Studies*, 2022.

Goncalves, Felipe and Steven Mello, "A Few Bad Apples? Racial Bias in Policing," *American Economic Review*, 2021, *111* (5), 1406–1441.

Grenet, Julien, Hans Grönqvist, and Susan Niknami, "The effects of electronic monitoring on offenders and their families," *Journal of Public Economics*, 2024, *230*, 105051.

Grosjean, Pauline, Federico Masera, and Hillel Yousaf, "Inflammatory Political Campaigns and Racial Bias in Policing," *The Quarterly Journal of Economics*, 2023, *138* (1), 413–463.

Hanemaaijer, Kyra, Nadine Ketel, and Olivier Marie, "Minority Salience and Criminal Justice Decisions," IZA Discussion Paper 17396, Institute of Labor Economics (IZA) 2024.

Hultqvist, Ola and Carl Ygge, "Granskning av särskilda satsningar - utsatta områden (Engl. Revision of interventions - Vulnerable neighborhoods)," *Internrevision*, 2018.

Ichino, Andrea, Michele Polo, and Enrico Rettore, "Are Judges Biased by Labor Market Conditions?," *European Economic Review*, October 2003, *47* (5), 913–944.

Jordan, Andrew, Ezra Karger, and Derek Neal, "Heterogeneous impacts of sentencing decisions," Working Paper 31939, National Bureau of Economic Research 2023.

Kling, Jeffrey R., "Incarceration length, employment, and earnings," *American Economic Review*, 2006, *96* (3), 863–876.

_ , Jeffrey B. Liebman, and Lawrence F. Katz, "Experimental analysis of neighborhood effects," *Econometrica*, 2007, *75* (1), 83–119.

Koster, Hans R.A. and Jos van Ommeren, "Neighbourhood stigma and place-based policies," *Economic Policy*, 2022.

McConnell, Brendon and Imran Rasul, "Contagious Animosity in the Field: Evidence from the Federal Criminal Justice System," *Journal of Labor Economics*, 2021, *39* (3), 739–785.

_ and _ , "Contagious Animosity in the Field: Evidence from the Federal Criminal Justice System," *Journal of Labor Economics*, 2021, *39* (3), 739–785.

_ , Kegon Teng Kok Tan, and Mariyana Zapryanova, "How Do Parole Boards Respond to Large, Societal Shocks? Evidence from the 9/11 Terrorist Attacks," *Journal of Public Economics*, 2024, *238*, 105206.

Mueller-Smith, Michael, "The criminal and labor market impacts of incarceration," Technical Report, Unpublished Working Paper 2015.

National Audit Office, "Rätt Insats på Rätt Plats; Polisens Arbete i Utsatta Områden," Technical Report, The Swedish National Audit Office 2020.

Nationella Operativa Avdelningen (NOA), "Utsatta områden - Sociala risker, kollektiv förmåga och oönskade effekter [Engl. Situation Report on Crime Trends in Vulnerable Neighborhoods]," *Polismyndigheten, Nationella Operativa Avdelningen [Engl. Police Authority, National Operative Unit]* , 2015.

_ , "Utsatta områden - Sociala ordning, kriminell struktur och utmaningar för polisen [Engl. Situation Report on Crime Trends in Vulnerable Neighborhoods]," *Polismyndigheten, Nationella Operativa Avdelningen [Engl. Police Authority, National Operative Unit]*, 2017.

_ , "Kriminell påverkan i lokalsamhället: En lägesbild för utvecklingen i utsatta områden (Engl. Situation Report on Crime Trends in Vulnerable Neighborhoods)," *Polismyndigheten, Nationella Operativa Avdelningen [Engl. Police Authority, National Operative Unit]*, 2019.

_ , "Lägesbild över utsatta områden [Engl. Situation Report on Crime Trends in Vulnerable Neighborhoods]," *Polismyndigheten, Nationella Operativa Avdelningen [Engl. Police Authority, National Operative Unit]*, 2021.

_ , "Lägesbild över utsatta områden [Engl. Situation Report on Crime Trends in Vulnerable Neighborhoods]," *Polismyndigheten, Nationella Operativa Avdelningen [Engl. Police Authority, National Operative Unit]*, 2023.

Ouss, Aurelie., John-Eric. Humphries, Kamelia. Stareva, Megan. Stevenson, and Winnie van Dijk, "Conviction, incarceration and recidivism: Understanding the revolving door," 2023. Manuscript.

Philippe, Arnaud and Aurélie Ouss, ""No Hatred or Malice, Fear or Affection": Media and Sentencing," *Journal of Political Economy*, 2018, *126* (5), 2134–2178.

Rasmussen, Sune Engel, "How Peaceful Sweden Became Europe's Gun-Murder Capital: Scandinavia's answer to Pablo Escobar orchestrates much of the growing violence from Turkey," 2023.

Sampson, Robert J., *Great American City Chicago and the Enduring Neighborhood Effect*, London: The University of Chicago Press, 2012.

_ **and Charles Loeffler**, "Punishment's Place: The Local Concentration of Mass Incarceration," *Daedalus*, 2010, *139* (3), 20–31.

Sampson, Robert J, Jeffrey D Morenoff, and Thomas Gannon-Rowley, "Assessing "neighborhood effects": Social processes and new directions in research," *Annual Review of Sociology*, 2002, *28* (1), 443–478.

Shayo, Moses and Asaf Zussman, "Judicial Ingroup Bias in the Shadow of Terrorism," *Quarterly Journal of Economics*, 2011, *126* (3), 1447–1484.

Tebes, Jonathan and Jeffrey Fagan, "Do Pedestrian Stops Deter Crime? Evidence from Reforming "Stop and Frisk"," 2022. Working paper; Revision requested at American Economic Journal: Economic Policy.

Tversky, Amos and Daniel Kahneman, "Judgment under Uncertainty: Heuristics and Biases," *Science*, 1974, *185* (4157), 1124–1131.

Wacquant, Loïc, "Territorial stigmatization in the age of advanced marginality," in "Symbolic power in cultural contexts," Brill Sense, 2008, pp. 43–52.

Yamagishi, Atsushi and Yasuhiro Sato, "Persistent Stigma in Space: 100 Years of Japan's Invisible Race and Their Neighborhoods," *The Review of Economics and Statistics*, 01 2025, pp. 1–46.

Yang, Crystal S., "Free at Last? Judicial Discretion and Racial Disparities in Federal Sentencing," *Journal of Legal Studies*, 2015, *44* (1), 75–111.

Zenou, Yves and Nicolas Boccard, "Racial Discrimination and Redlining in Cities," *Journal of Urban Economics*, 2000, *48* (2), 260–285.

Figures and tables

Result figures

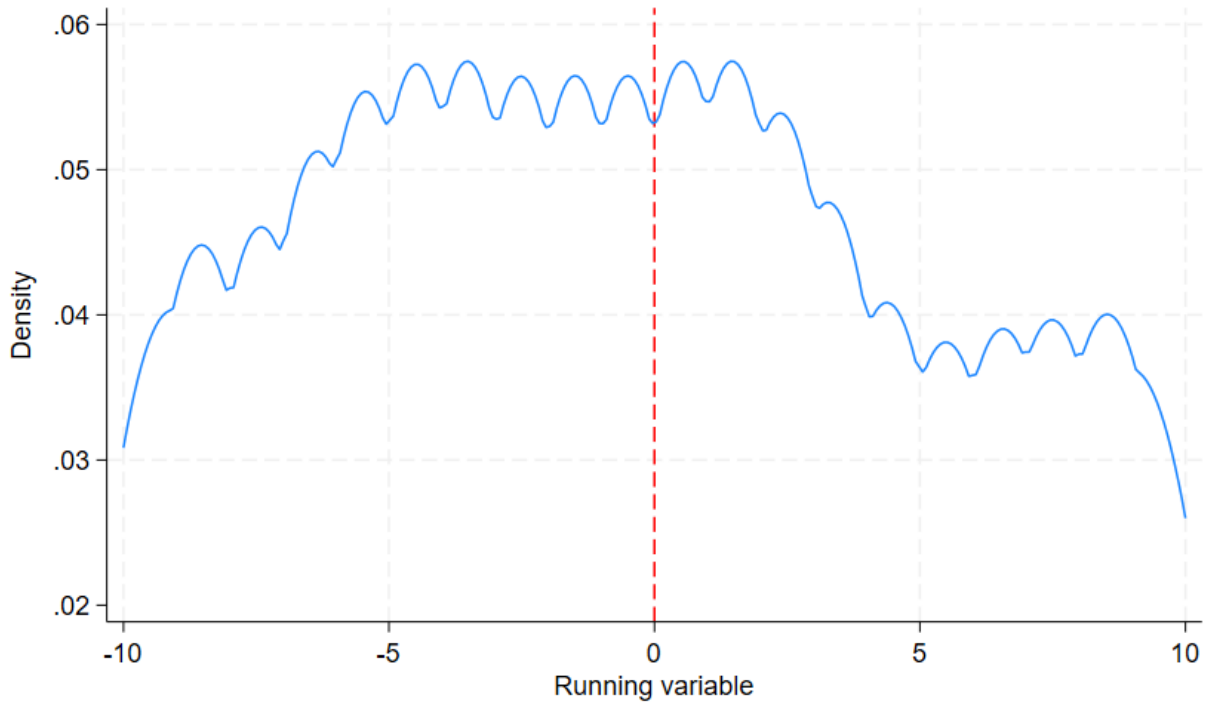
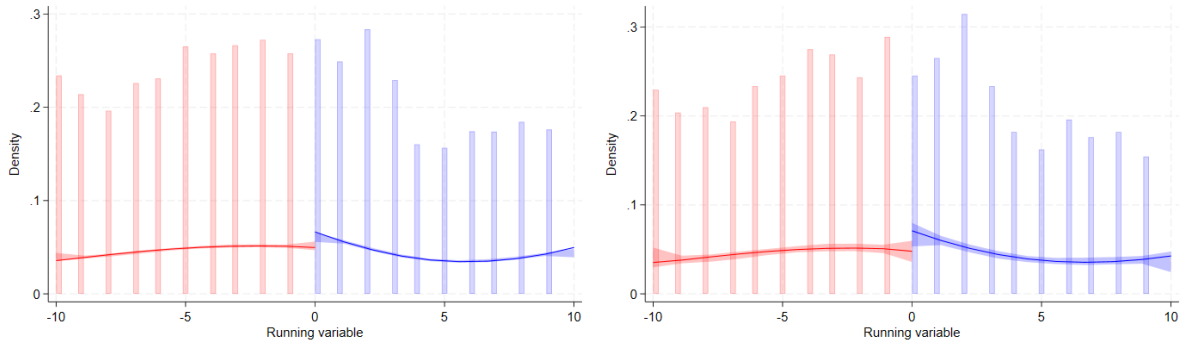


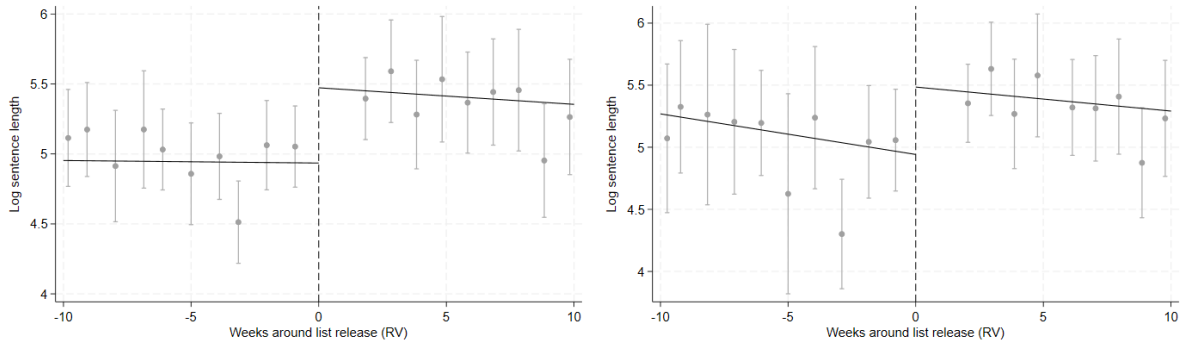
Figure 6: Density of cases around list release.
Appears to be relatively smooth. Not more or less cases just before or after list release. Re-format?



(a) McCrary test full sample (p-val. 0.18).

(b) McCrary test prison sample (p-val. 0.85).

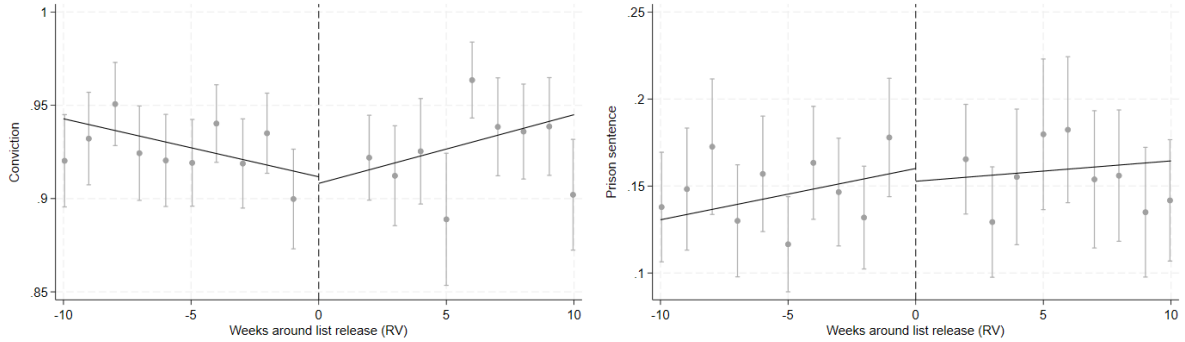
Figure 7: McCrary test figure around list release.
For vulnerable areas including all list release years, showing the test for both the full sample and the main sample of interest with a prison sentence. Appears to be relatively smooth. Not more or less cases just before or after list release.



(a) Log sentence length (days).

(b) Log sentence length (days) - Matched sample.

Figure 8: Stigma effect: RDD figure with ±10 weeks bandwidth.
The panels show RDD figures for troubled areas with list years, excluding week 0–1 to remove potential mismatches between the decision date matching to when the sentences are actually decided and the list release date. CI95 are indicated in black and gray. Propensity score nearest-neighbor matching with replacement is based on gender, list year, foreign born, arabic background, high school education, earnings, residence in large city, age, and including 37 indicators for crime type. Note that this is estimated using rdplot with a triangular kernel.



(a) Conviction.

(b) Prison sentence.

Figure 9: Stigma effect: RDD figure with ±10 weeks bandwidth.
The panels show RDD figures for troubled areas with list years, excluding week 0–1 to remove potential mismatches between the decision date matching to when the sentences are actually decided and the list release date. CI95 are indicated in black and gray. Note that this is estimated using rdplot with a triangular kernel.

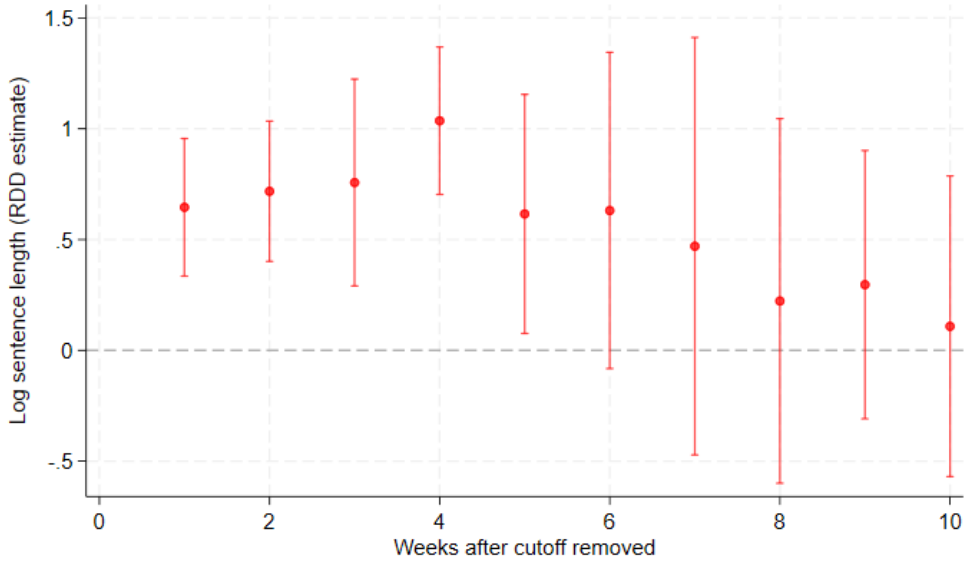


Figure 10: Extended doughnut figure indicating when effects fade. BW -20 up to 10 weeks (moving with doughnut).
Our treatment effects fade circa 6–8 weeks after list release. Note that this is with a uniform kernel. Fix this later.

Table 2: Descriptives table.

Sample:	Listed neighborhood			Non-listed neighborhood		
Time to sentencing:	t_{-3}–t_{-1}	t_0	t_1	t_{-3}–t_{-1}	t_0	t_1
Foreign bgr.	0.54	0.55	0.56	0.30	0.28	0.30
Male	0.83	0.84	0.83	0.82	0.82	0.81
High school	0.48	0.45	0.45	0.54	0.55	0.55
Birthyear	1984.41	1985.81	1985.39	1982.27	1981.69	1982.44
Nonemployed	0.44	0.48	0.45	0.44	0.44	0.43
Major city	0.51	0.51	0.50	0.25	0.24	0.25
Violent crime	0.12	0.11	0.14	0.13	0.13	0.13
Property crime	0.25	0.22	0.20	0.19	0.19	0.19
Drug crime	0.24	0.25	0.28	0.23	0.22	0.24
Sentence length (nonmissing)	313.20	342.37	440.97	291.68	308.69	333.89
Prison sentence	0.14	0.13	0.15	0.14	0.14	0.13
Convicted	0.92	0.92	0.90	0.92	0.92	0.93
Obs	2808	962	878	12750	4351	4302

... .

Table 3: RDD balancing table.

	Pred. sent. length	Foreign backgr.	Male	High school ed.	Age	Earnings	Non-empl.	Live in m. city	Drug sentence	Property sentence	Violent sentence
RDD estimate	0.064	0.049	−0.009	−0.084	−0.750	−12.841	0.021	0.096	−0.046	0.031	−0.082
	(0.079)	(0.067)	(0.051)	(0.085)	(2.981)	(194.108)	(0.076)	(0.095)	(0.058)	(0.082)	(0.072)
Mean dep. var.	0.317	0.126	0.902	0.465	37.659	760.544	0.554	0.302	0.178	0.211	0.148
Obs.	707	707	707	707	707	707	707	707	707	707	707
R^2	0.005	0.005	0.005	0.013	0.030	0.024	0.035	0.029	0.015	0.009	0.013
Matched sample	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
List overlap $\geq 30\%$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bandwidth	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.
Kernel	Triang.	Triang.	Triang.	Triang.	Triang.	Triang.	Triang.	Triang.	Triang.	Triang.	Triang.

Standard errors in parentheses are clustered at the court level. Predicted sentence length includes gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Matched sample is based on the covariates listed above and including 37 indicators for crime type, with nearest-neighbor-matching.

Table 4: RDD conviction and prison outcome table.

Sample:	Full sample			
Outcome:	Conviction probability		Prison probability	
RDD estimate	−0.011	−0.012	−0.002	−0.005
	(0.014)	(0.014)	(0.024)	(0.024)
Mean dep. var.	0.925	0.925	0.147	0.147
Obs.	6438	6355	6438	6355
R^2	0.002	0.009	0.002	0.025
Controls		✓		✓
List overlap $\geq 30\%$	✓	✓	✓	✓
Bandwidth	±10 weeks	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triang.	Triang.	Triang.

Standard errors in parentheses are clustered at the court level. Including controls for gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: RDD outcome table (matched and full prison sample).

Sample:	Prison sample			Prison sample		
Outcome:	Log sentence length			Sentence length		
RDD estimate	0.530***	0.519***	0.564***	267.009**	260.513**	235.400**
	(0.162)	(0.176)	(0.181)	(115.745)	(122.725)	(104.918)
Mean dep. var.	4.980	4.980	4.980	378.003	378.003	378.003
Obs.	707	707	1030	707	707	1030
R^2	0.021	0.067	0.088	0.021	0.047	0.047
Matched sample	✓	✓		✓	✓	
Controls		✓	✓		✓	✓
List overlap $\geq 30\%$	✓	✓	✓	✓	✓	✓
Bandwidth	±10 weeks	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triang.	Triang.	Triang.	Triang.	Triang.

Standard errors in parentheses are clustered at the court level. Including controls for gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Matched sample is based on the covariates listed above and including 37 indicators for crime type, with nearest-neighbor-matching.

Table 6: RDD outcome year table (matched sample).

List year:	Stacked	2015	2017 & 2019	2021
Outcome:	Log sentence length			
RDD estimate	0.519***	0.433	0.700***	0.205
	(0.176)	(0.535)	(0.214)	(0.359)
Mean dep. var.	4.980	4.980	4.980	4.980
Obs.	707	196	292	219
R^2	0.067	0.099	0.132	0.083
Matched sample	✓	✓	✓	✓
Controls	✓	✓	✓	✓
List overlap $\geq 30\%$	✓	✓	✓	✓
Bandwidth	±10 weeks	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triang.	Triang.	Triang.

Standard errors in parentheses are clustered at the court level. Including controls for gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Matched sample is based on the covariates listed above and including 37 indicators for crime type, with nearest-neighbor-matching.

Table 7: RDD sentence length, by vulnerable area status (not mutually exclusive).

Vul. area status:	High	Mid	Low
Outcome:		log(Sentence length)	
RDD estimate	0.740***	0.641	0.566
	(0.233)	(0.538)	(0.415)
Mean dep. var.	4.920	5.083	5.042
Obs.	423	130	277
R^2	0.074	0.175	0.099
Matched sample	✓	✓	✓
Controls	✓	✓	✓
List overlap $\geq 30\%$	✓	✓	✓
Bandwidth	$\pm$10 w.	$\pm$10 w.	$\pm$10 w.
Kernel	Triangular	Triangular	Triangular

Standard errors in parentheses are clustered at the court level. Including controls for gender, list year, foreign born, arabic background, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Heterogeneous treatment by predicted risk of reoffending, cooffending status, and foreign background.

Outcome:	Log sentence length		
RDD estimate (Reference group)	−0.244	0.401	0.627*
	(0.305)	(0.242)	(0.344)
Jump × Reoffending risk Q2	0.184		
	(0.421)		
Jump × Reoffending risk Q3	0.540		
	(0.466)		
Jump × Reoffending risk Q4	0.609*		
	(0.303)		
Jump × Cooffending		−0.161	
		(0.517)	
Jump × Foreign bgr.			−0.196
			(0.434)
Mean dep. var.	4.980	5.767	4.947
Obs.	707	707	707
R^2	0.450	0.216	0.092
Matched sample	✓	✓	✓
Controls	✓	✓	✓
List overlap ≥ 30%	✓	✓	✓
Bandwidth	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triangular	Triangular

Standard errors in parentheses are clustered at the court level. Including fully interacted models with controls for gender, foreign born, arabic background, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Heterogeneous treatment by judge exposure to troubled areas.

Outcome:	Log sentence length		Sentence length	
RDD estimate (Reference group)	0.596***	0.631	352.944***	475.274
	(0.180)	(0.471)	(127.220)	(300.492)
Jump × High share judges exposed	−0.658**		−463.009**	
	(0.306)		(192.134)	
Jump × Linear share of judges exposed		−0.013		−21.185
		(0.038)		(21.825)
Mean dep. var.	5.052	5.052	467.715	467.715
Obs.	707	707	707	707
R^2	0.099	0.072	0.072	0.059
Matched sample	✓	✓	✓	✓
Controls	✓	✓	✓	✓
List overlap ≥ 30%	✓	✓	✓	✓
Bandwidth	±10 w.	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triangular	Triangular	Triangular

Standard errors in parentheses are clustered at the court level. High share judges exposed is defined as an indicator for being above the 75th percentile of judge exposure (more than 13% of judges have lived in a troubled area between 1982–2015). Including fully interacted models with controls for gender, foreign born, arabic background, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: RDD labor market and recidivism relative to list release year (matched sample).

Outcome:	Earnings t+1	Earnings t+3	Employment t+1	Employment t+3	Reoffended t+1	Reoffended t+3
RDD estimate	−75.506	−145.358	−0.089**	−0.163*	−0.012	0.008
	(148.595)	(196.270)	(0.043)	(0.082)	(0.096)	(0.091)
Mean dep. var.	1043.504	1200.641	0.436	0.505	0.297	0.380
Obs.	700	686	700	686	707	707
R^2	0.168	0.178	0.161	0.153	0.193	0.300
Matched sample	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
List overlap $\geq 30\%$	✓	✓	✓	✓	✓	✓
Bandwidth	±10 weeks	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triang.	Triang.	Triang.	Triang.	Triang.

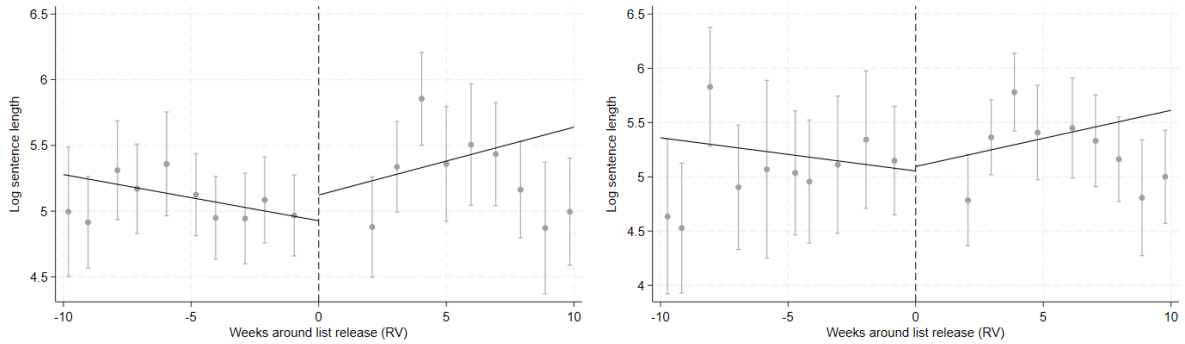
Standard errors in parentheses are clustered at the court level. Including controls for gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Matched sample is based on the covariates listed above and including 37 indicators for crime type, with nearest-neighbor-matching. Employment status is defined as having non-zero or non-missing earnings.

Table 11: RDD health outcome table (matched sample).

Outcome:	Any drug t+3	Antidep. t+3	Any incare t+3	Antidep. incare t+3	Any outcare t+3	Antidep. outcare t+3
RDD estimate	0.051	−0.040	−0.010	0.005	0.050	0.013
	(0.093)	(0.052)	(0.075)	(0.005)	(0.066)	(0.019)
Mean dep. var.	0.534	0.094	0.123	0.003	0.447	0.015
Obs.	488	488	707	707	707	707
R^2	0.095	0.051	0.063	0.014	0.095	0.034
Matched sample	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
List overlap $\geq$ 30%	✓	✓	✓	✓	✓	✓
Bandwidth	±10 weeks	±10 w.	±10 w.	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triang.	Triang.	Triang.	Triang.	Triang.

Standard errors in parentheses are clustered at the court level. Including controls for gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Matched sample is based on the covariates listed above and including 37 indicators for crime type, with nearest-neighbor-matching.

Appendix A: Figures and tables



(a) Log sentence length (days).

(b) Log sentence length (days) - Matched sample.

Figure A1: Placebo figure: RDD figure with ±10 weeks bandwidth for placebo years one year prior to the list release.

The panels show RDD figures for troubled areas with placebo years, excluding week 0–1 to remove potential mismatches between the decision date matching to when the sentences are actually decided and the list release date. CI95 are indicated in black and gray. Propensity score nearest-neighbor matching with replacement is based on gender, list year, foreign born, arabic background, high school education, earnings, residence in large city, age, and including 37 indicators for crime type. Note that this is estimated using rdplot with a triangular kernel.

Table A1: RDD robustness table.

Robustness:	Main spec.	Incl. t+1 w.	Bwidth 15 w.	Bwidth 20 w.	Overlap 20%	Overlap 40%	Include non-prison
Outcome:	Log sentence length		Log sentence length		Log sentence length		Sentence length
RDD estimate	0.519***	0.472***	0.710***	0.730***	0.560***	0.493**	41.413**
	(0.176)	(0.131)	(0.179)	(0.173)	(0.184)	(0.236)	(18.047)
Mean dep. var.	4.980	4.980	5.064	5.113	4.935	4.959	55.754
Obs.	707	1053	1476	1561	1167	876	6355
R^2	0.067	0.082	0.082	0.079	0.101	0.088	0.011
Matched sample	✓	✓					
Controls	✓	✓	✓	✓	✓	✓	✓
List overlap	$\geq$ 30%	$\geq$ 30%	$\geq$ 30%	$\geq$ 30%	$\geq$ 20%	$\geq$ 40%	$\geq$ 30%
Bandwidth	±10 weeks	±10 weeks	±15 w.	±20 w.	±10 w.	±10 w.	±10 w.
Kernel	Triangular	Triang.	Triang.	Triang.	Triang.	Triang.	Triang.

Standard errors in parentheses are clustered at the court level. Including controls for gender, foreign born, arabic background, age, high school education, earnings, residence in large city, and age. All specifications include indicators capturing the list year. Weeks 0–1 are excluded from the analysis (dougnnut). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Matched sample is based on the covariates listed above and including 37 indicators for crime type, with nearest-neighbor-matching. Employment status is defined as having non-zero or non-missing earnings.

6. Gemini Analysis

Two jobs were conducted in Gemini, following the paper by Modaressi, Spiess and Venugopal (2025). The first task consists of predicting the categorization of court cases into two groups, using a training and a testing sample. The second task consists of identifying differences in the text (for example themes, tone) across those two groups. We did this for three different partitions of the data.

In the first version, the treated group are cases that come from a vulnerable area, and the control group are cases that come from a non-vulnerable area. This was done for a sample of cases from Södertörn for Jan-Apr 2016. The prediction results in the testing data are the following:

Table A2: Prediction exercise - version 1 (T=vulnerable; C=non-vulnerable)

	Predicted 1	Predicted 0
Actual 1	31	111
Actual 0	27	267

Accuracy: (31 + 267) / 436 = 68%

Sensitivity (recall for vulnerable): 31 / (31 + 111) = 22%
Specificity (recall for non-vulnerable): 267 / (267 + 27) = 91%

The model rarely recognises vulnerable articles (only 22%), misclassifying the majority as non-vulnerable.

For this subsample, we also ran three different prompts asking Gemini to identify differences in text. The three prompts and their results are as follows:

- Prompt 1 - identical to original paper: Based on an analysis of the training documents, the main systematic differences in themes between Group 0 and Group 1 documents are subtle, as both appear to be in Swedish and concern court documents. The most significant differences emerge from the subject matter and the specific legal context implied by the word patterns. Group 0 documents consistently exhibit a higher frequency of words suggesting cases involving crimes of a more personal or violent nature, such as words associated with assault or domestic disputes (e.g., mention of skador (injuries) and specific details about the individuals involved and their conflicting testimonies, as seen in the snippet). Group 1 documents, while also legal, are more likely to involve themes associated with economic, property, or organized crime, such as theft (implying stöld or similar) and potentially issues related to taxes, smuggling, or declarations, as suggested by the high predictive power of documents in this group when a model is trained to differentiate them. The snippet for this group, for example, concerns a person confessing to a gärning (act/deed, often criminal) but then retracting, specifically mentioning the theft of goods (oxfilé and kaffe) with a kamrat (friend/associate). In summary, the documents appear to be Swedish court judgments, with Group 0 generally concerning cases of physical or interpersonal conflict, and Group 1 documents tending to focus on economic, property, or potentially white-collar crime.

- Prompt 2 - tailored to this context: Based on the text analysis, the main systematic differences between the groups are evident in the names of the individuals mentioned in the documents and the type of crime/topic. Group 0 documents are strongly associated with Swedish-sounding names like Patrik, Lars, Mikael, Mattias, Jens, and Anna, and frequently contain the word "narkotikabrott" (drug crime). Group 1 documents are strongly associated with a more

diverse range of names, including non-Western names and common English/European names like Robin, Marie, Marcin, Mohamed, Robert, and Luis. They also often contain words like "bilen" (the car), which, along with the distinctive names, suggests a possible theme of traffic/vehicle-related crimes or other offenses distinct from the drug-related theme of Group 0.

- Prompt 3 - falsification (asking differences in animals and colors): Based on a term frequency-inverse document frequency (TF-IDF) analysis of the documents, the main systematic differences between the groups suggest a distinction in the nature of the legal cases discussed. Group 1 documents appear to be heavily focused on specific individuals (e.g., süleyman, halil, nawroz, przemyslaw, marcin, aiman) who likely have very distinct names. The presence of the word rån (Swedish for robbery) also suggests that this group contains documents concerning specific crimes, possibly involving less common names in the corpus. Group 0 documents contain more frequent mentions of a different set of individuals (e.g., jens, jenny, viktor, lars, patrik, jan, björn, anna, roger, susanne, mattias) and also specific items or topics like tabletter (Swedish for pills/tablets) and hotet (Swedish for the threat). The individual names in Group 0 appear to be more common Swedish names. In summary, the documents in Group 1 are thematically centered around robbery or similar severe crimes, featuring names that are highly unique to this group. The documents in Group 0 appear to cover a broader range of cases, possibly including less violent crimes or other legal matters, featuring a set of more common names and terms related to substances (tablets) or coercion (threat).

Prompt 1 identifies substantive offence-type differences. Prompts 2–3 converge on name-origin differences and crime-severity clusters. This divergence suggests the themes extracted are not robust across prompting, and may reflect noise in the underlying text (e.g., name distributions) rather than meaningful "vulnerability" distinctions.

In the second version, the treated group are cases that come from a vulnerable area after the list release, and the control group are cases from a vulnerable area before the list release. This was done for a sample of cases from Södertörn for Apr-Aug 2017. The prediction results in the testing data are the following:

Table A3: Prediction exercise - version 2 (T=vulnerable after; C=vulnerable before)

	Predicted 1	Predicted 0
Actual 1	5	34
Actual 0	19	66

Accuracy: (5 + 66) / 124 = 57%

Sensitivity (after-list recall): 5 / 39 = 13%

Specificity (before-list recall): 66 / 85 = 78%

Performance is weaker than in the first experiment as the model very rarely recognises articles from the after-list treatment group.

For this subsample, we also ran three different prompts asking Gemini to identify differences in text. The three prompts and their results are as follows:

- Prompt 1 - identical to original paper: Texts in Group 0 primarily concern the sentencing phase of legal proceedings. The focus is on the defendant's personal circumstances, the assessment of the crime's severity (straffvärde), and the determination of the appropriate penalty (påföljd). Key Themes: Discussion of the defendant's background, lack of prior criminal record (tidigare ostraffad), orderly living conditions, and lack of substance abuse issues. Outcome: These factors are often cited as reasons for a more lenient sentence, such as a conditional sentence (villkorlig dom) combined with fines (dagsböter), or a reduced severity of the crime (e.g., ringa narkotikabrott). Tone/Style: Generally mitigating and focused on justifying the chosen penalty based on the individual's situation. Texts in Group 1 focus more on the substantive legal findings and immediate consequences of the conviction, often relating to forgery, fraud, or violations of specific acts. Key Themes: Detailed rulings on forfeiture (förverkande) of items (like a fake driver's license), the reimbursement of analysis costs to the state, and payments to the Crime Victim Fund (Brottsofferfond). The texts often mention specific legal acts being violated (e.g., brott mot lagen om för...). Outcome: The discussion centers on the legal necessity of confiscating forged items, dismissing motions (like lifting custody, häktningsbeslutet hävs), and mandating the payment of statutory fees and costs, which are direct consequences of the proven crime. Tone/Style: More formal and

prescriptive, concentrating on the mandatory legal consequences and rulings directly following the establishment of the facts and conviction. In summary, Group 0 focuses on the 'why' and 'how' of the sentence (the individual punishment), emphasizing personal factors for mitigation, while Group 1 concentrates on the statutory legal consequences (like forfeiture and mandatory fees) tied to the nature of the specific offense.

- Prompt 2 - tailored to this context: Group 0 is characterized by a prevalence of minor to moderate offenses, specifically traffic violations (speeding, driving without a license), shoplifting (petty theft from stores like IKEA or supermarkets), and minor drug possession. The narratives are generally shorter, often focusing on simple evidentiary questions (e.g., whether a suspect intended to pay for an item or who was driving a car), and the sanctions are frequently fines or short prison sentences. Group 1, in contrast, contains a significantly higher proportion of serious, violent, and complex crimes. This group includes detailed judgments regarding grave weapons offenses (involving automatic rifles and hand grenades), large-scale narcotics distribution, and sexual offenses (rape). Consequently, the texts in Group 1 are often longer and more technical, involving complex forensic evidence (DNA analysis, phone tracking) and resulting in severe penalties such as multi-year prison sentences, closed youth care, or deportation.

- Prompt 3 - falsification (asking differences in animals and colors): Group 0: These texts focus on the establishment of guilt and the choice of penalty. They frequently mention that the defendant has "acknowledged" (erkänt) the crime (often theft or narcotics offenses). The texts discuss the defendant's personal circumstances (e.g., income, previous record) to justify the choice of a specific sanction, such as a conditional sentence (villkorlig dom) or fines (dagsböter). Group 1: These texts focus on the specific legal and financial consequences that follow a conviction, rather than the guilt itself. They systematically mention: Repayment of costs: Specifically paying the state back for blood/urine analysis (analyskostnader) or defense counsel fees. Forfeiture/Confiscation: Taking away items used in crimes, specifically driver's licenses (körkort) or forged documents. Mandatory Fees: Payments to the Crime Victim Fund (Brottsofferfonden). Procedural Status: Decisions regarding detention (häktning)—specifically

releasing someone or keeping them detained. Summary: Group 0 deals with judging the person (guilt, personal history, and main penalty), while Group 1 deals with settling the account (confiscating licenses, paying analysis costs, and administrative fees).

Prompts 1 and 3 agree on a consistent pattern: Before list = sentencing/mitigation; after list = legal consequences/administrative follow-up. Prompt 2 introduces a much stronger and less plausible contrast (minor vs. severe crimes). This suggests Prompt 1/3 themes are more stable, while Prompt 2 may be overfitting to incidental signals.

In the third version, the treated group are cases that come from a non-vulnerable area after the list release, and the control group are cases from a non-vulnerable area before the list release. This was done for a sample of cases from Södertörn for Apr-Aug 2017. The prediction results in the testing data are the following:

Table A4: Prediction exercise - version 3 (T= non-vulnerable after; C= non-vulnerable before)

	Predicted 1	Predicted 0
Actual 1	40	45
Actual 0	10	160

Accuracy: (40 + 160) / 255 = 78%
Sensitivity (after-list recall): 40 / 85 = 47%
Specificity (before-list recall): 160 / 170 = 94%

This model performs substantially better. It still under-identifies after-list cases (47% recall), but far less severely.

For this subsample, we also ran three different prompts asking Gemini to identify differences in text. The three prompts and their results are as follows:

- Prompt 1 - identical to original paper: Texts in Group 0 are overwhelmingly focused on less severe or 'minor' offenses such as ringa narkotikabrott (minor drug offense), snatteri/stöld (petty theft/theft), and olovlig körning (unauthorized driving). Themes: The discussion centers on mitigating factors like the defendant's lack of prior criminal record (tidigare ostraffad), orderly living conditions (ordnade förhållanden), and limited straffvärde (punishment value).

Sentence: The outcome is typically a lenient non-custodial sentence, primarily fines (dagsböter) or a conditional sentence (villkorlig dom) often without the requirement for community service. Tone: The language is focused on justifying the most lenient penalty possible given the statutory minimums, with damages (skadestånd) and standard fees (like the Crime Victim Fund fee) forming part of the judgment. Texts in Group 1 address more severe crimes or crimes that are classified as a specific 'type' (artbrott) which carry a strong presumption for imprisonment (fängelsepresumtionen), such as Grovt Rattfylleri (Gross Drunk Driving) or offenses involving forgery and fraud. Themes: The core theme is the explicit effort to avoid a prison sentence. The text highlights the legal necessity to find 'särskilda skäl' (special reasons) to circumvent the presumption of prison, such as the defendant's suitability for community service (samhällstjänst). Sentence: The outcome, when prison is avoided, is typically a more intensive non-custodial sentence, specifically a conditional sentence (villkorlig dom) combined with a required amount of community service (samhällstjänst). Tone: The style is more serious and legalistic, focusing heavily on the severity of the crime and mandatory consequences like the forfeiture (förverkande) of forged items and the reimbursement of state analysis costs. In summary, Group 0 sentences are primarily justified by mitigation to secure a light penalty (fines), whereas Group 1 sentences are justified by finding 'special reasons' to substitute a severe default penalty (prison) with an alternative intensive community service requirement.

- Prompt 2 - tailored to this context: The texts in Group 0 and Group 1 differ primarily in the origin of the names of the defendants. Group 0: The names of the defendants in this group are typically of Nordic or Western origin (e.g., William, Joakim, Victoria, Viktor, Anders, Tommy, Hannes, Linus, Mikael, etc.). Group 1: The names of the defendants in this group are typically of non-Western or Eastern European origin (e.g., Wojciech, Heresh, Bani, Vasiliy, Vasile-Nicolae, Vaidas, Parviz, Timofey, Raimondas, Isak, Hossein, Hasan, Fadi, Antonio, Emin, Mats (exception), Daniel (exception), Ayub, Damian, Johnny, Thomas (exception), Desirée (exception), Innocent, Ashkan, Mika, Usman, Arlinda, Ülari, Tommy (exception), Tommi, Tomasz, Tomas, Tom, Alexander, Fethi, Nils (exception), Fatou, Björn-Tore, Mladen, Bozidar, Rauno, Shahzad, Pierre, Omar, Olof (exception), Alejandro, Per, Jan, Vladislav, Robin, Leonardo, Johannes, Stephane, Mårten, Ahmed, Tim, Daniel, Milasin, Mauricio,

Krister (exception), Jan, Hannes, Apollon, Anders (exception), Adam, Jack, Tina, Timothy, Tony, Raman, Thomas, Theo, Tatjana, Tatiana, Taisto, Susann, Sune, Vitali, Stephanie, Stanislav, Heidi, Rodrigo, Robin, Robert, Rakan, Victors, Richard, Rashed, O, Abbas, Piotr, Pierre, Philip, Peter, Per, Paulo, Paolo, Paiwand, Oskar, Olof, Olga, Gunnar, Ali, Carl, Björn, Sebastian, Josefin (exception), Elvira (exception), Märta (exception), Anton, Per, Dennis, Xiannan, Valbona, Tornike, Polad, Raup, Brandon, Frida, Simon, Vadim, Yana, Mohammed, Jan, Christoffer, Antony, Leif, Zoran, Zana, Youssef, Wiktor, Vjatseslav, Vitalii, André, Kaupo, Tongfeng, Tommy, Linda, Alessandro, Hamidreza, Hadi, Tamaz, Stefan, Stanislaw, Jesper, Franklen, Gabriel, Fredrik, Frank, Ferit, Ferdi, Felix, Faouzi). While there are exceptions in both groups, the systematic difference lies in the ethnicity or national origin suggested by the names. Group 0 predominantly features names common in Sweden and other Western countries, while Group 1 features a higher proportion of names associated with other regions, particularly the Middle East, Eastern Europe, and other non-Western areas. There are no other immediately obvious systematic differences in themes such as tone of language or geographical locations within the provided snippets. Both groups contain court documents (domar) from Södertörns tingsrätt concerning similar types of crimes (theft, traffic offenses, narcotics offenses, assault, etc.).

- Prompt 3 - falsification (asking differences in animals and colors): The key difference between Group 0 and Group 1 in the provided documents is the nature of the defendants' responses to the accusations against them. In Group 0, the defendants generally deny the charges, attempt to minimize their actions, or provide explanations intended to mitigate their responsibility (e.g., claiming they didn't know an item was stolen or illegal, or that their actions were accidental or in self-defense). Conversely, the documents in Group 1 consistently feature defendants who admit to the charges, often pleading guilty or acknowledging the facts as presented by the prosecutor, sometimes with explanations but without contesting the core accusation.

Prompt 1: Strong legal distinction. Prompt 2: Strong name-origin distinction. Prompt 3: Strong procedural distinction. The three prompts extract orthogonal differences (legal severity, name origin, defendant behaviour), suggesting that the underlying textual differences are relatively

weak and easily overshadowed by other patterns.

6.1 Summary

Task 1: Prediction: Across all three classification exercises, the models achieve moderate overall accuracy (57–78%) but consistently low sensitivity for the treatment group. The classifiers frequently misidentify treated articles as controls, indicating that textual differences between the groups are subtle and difficult for the model to learn. The best performance is observed in the non-vulnerable pre/post-list comparison, while the vulnerable-based classifications perform substantially worse. These patterns suggest that the introduction of the list produces limited or inconsistent textual changes detectable by large language models, particularly within the vulnerable category.

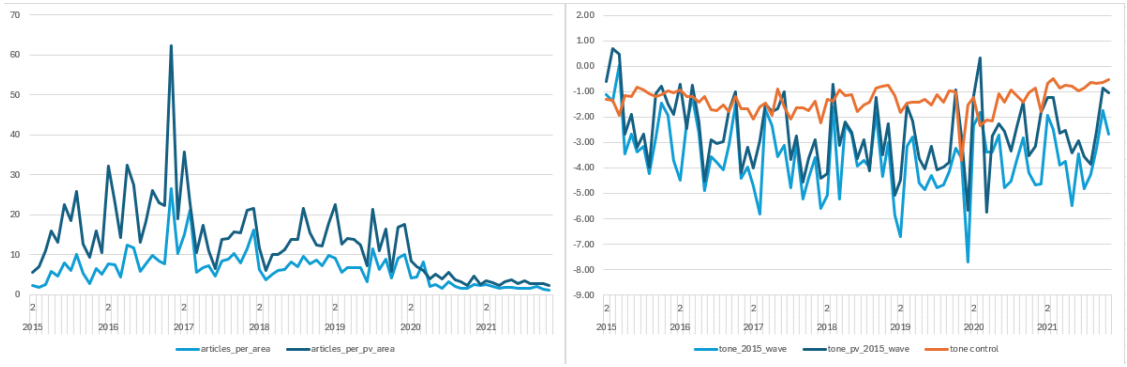
Task 2: Content of text: Across the three text-analysis exercises, extracted thematic differences between treatment and control groups vary substantially across prompting strategies. Prompts modelled on the paper's original approach (Prompt 1) consistently yield coherent legal distinctions—such as differences in offence severity, mitigation arguments, or statutory consequences—suggesting these represent the most stable patterns in the underlying text. By contrast, the tailored prompts (Prompt 2) frequently highlight differences in the origin of personal names or in crime stereotypes, which appear less substantively meaningful and may reflect noise or incidental correlations in the corpus. The falsification prompts (Prompt 3) tend to isolate procedural distinctions such as admission of guilt or administrative consequences. Overall, the variability of themes across prompts indicates that the textual signal distinguishing treatment from control is relatively weak, and that extracted themes are sensitive to model prompting and potential confounding features.

7. Media - GDELT

We took the media dataset to GDELT to produce (coarse) graphs of media attention to the neighborhoods on the list. Two main graphs are included below:

These graphs highlight the main point on why it might be better to focus on the particularly vulnerable areas. That is, the number of media mentions per neighborhood is larger for this group (left graph, even if the spike timing is strange as it does not coincide with the release of an update).

Figure A2: GDELT Media Analysis



However, it's always higher for this group. In terms of the tone of the articles, the average tone of the particularly vulnerable is quite similar to all vulnerable, and both of these are always worse than the average tone for our pool of control neighborhoods.

These graphs (as you can see) are quite coarse, but I wanted to include them for a first discussion.

8. Online appendix

Appendix For Online Publication

[sections] [sections]l1

A Institutional Background of the Police List

1.1 Swedish "No-Go" Zones in Comparison

Most large cities have neighborhoods notorious for their high crime rates, ethnic segregation, and socioeconomic disadvantage. Consequently, these neighborhoods often find themselves ranked unfavorably in reverse desirability lists across various outlets. A relevant question to ask is how comparable the Swedish troubled neighborhoods are to their, oftentimes more infamous, counterparts throughout the major cities in Europe and the US. Roughly 550,000 (5 percent) of the Swedish population live within the boundaries of a neighborhood that by the police qualified as troubled in 2019 (NOA, 2021).[26] Socioeconomically, the residents of these neighborhoods do clearly worse than the national average. Among the adult working-age population (ages 20-64), only 61.4 percent of the residents in troubled neighborhoods were employed in 2017 as compared to 80.2 percent in the rest of the country. There is also considerably more welfare dependence among the households in the troubled neighborhoods (13 percent) as compared to the rest of the country (4 percent). In Sweden, social housing does not technically exist, although an indication of the inequitable housing conditions is that 75 percent of the households in troubled neighborhoods live in rental housing whereas only 27 percent of the households in the rest of the country do so. Roughly 30 percent of the ninth graders in troubled neighborhoods do not complete compulsory school as compared to the 13 percent nationwide (**?**). When it comes to gun violence, the troubled neighborhoods are in a league of their own in Sweden. Roughly 45 percent of all shootings take place in these neighborhoods (which make up 0.16 percent of Sweden's land area) (NOA, 2021).

By an international comparison, the crime rates in these neighborhoods are however not exceptional. In total, 130 shootings were reported in these neighborhoods in 2020 and in the entire Stockholm county, 39 gun related homicides were reported in the same year. Compared to the most notorious neighborhoods in the U.S., these figures are relatively modest. The Cook County's Medical Examiners Office alone confirmed 881 gun-related homicides in 2020 among its roughly 2.3 million inhabitants (including the City of Chicago), roughly the size of Stockholm county. Baltimore with its 600,000 inhabitants, roughly the same size as Gothenburg (the second largest city in Sweden), saw 298 gun-related homicides in 2020. Even though crime rates have gone down in New York City during the past decades, the Bronx with its 1.5 million inhabitants still has roughly 150 murders annually. In the European context though, the Swedish capital Stockholm is

[26] In metropolitan Stockholm, the share of residents living in a troubled neighborhood is larger. Roughly 260,000 in Stockholm county live in these neighborhoods, which is 11 percent of the population.

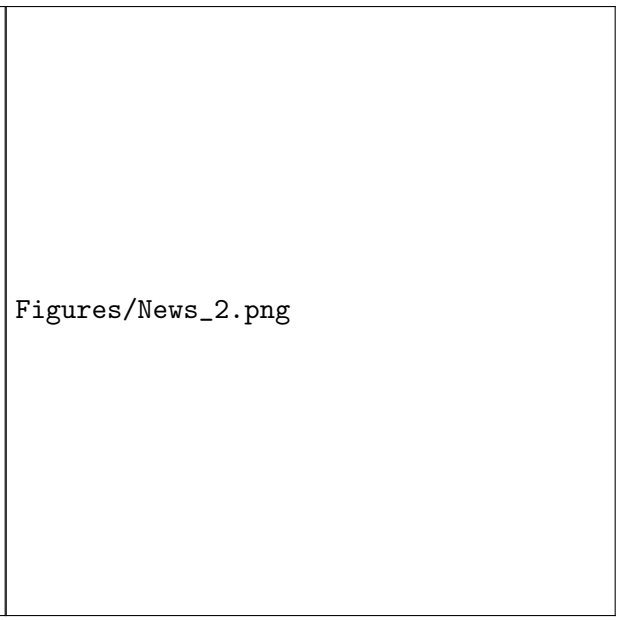
almost an outlier, having for example recorded a 30-fold gun murder rate in comparison to London in 2022 (Engel Rasmussen, 2023).

1.2 Additional evidence of media coverage

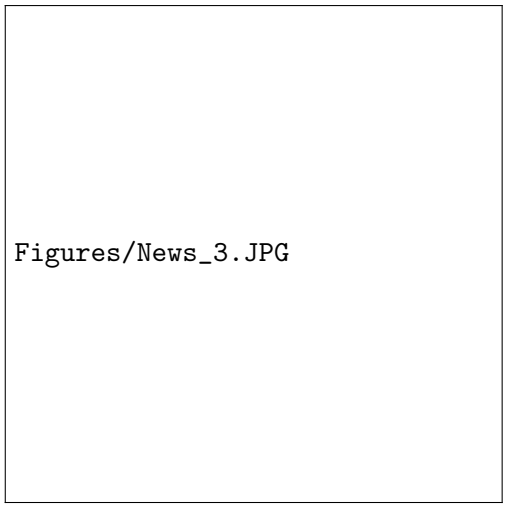
Figure A.1: Examples of Media Coverage in the Main National News Outlets



(a) Headline from Dagens Nyheter: "Vulnerable neighbourhoods become drug shops as gangs take over"



(b) Headline from Dagens Nyheter: "Police: '5000 criminals and 200 networks in vulnerable areas"'



(c) Headline from Svenska Dagbladet: "55 'no go' zones in Sweden"

Notes: The Figures show headlines in the two major Swedish newspapers, Dagens Nyheter and Svenska Dagbladet associating social problems with the troubled neighborhoods using the specific term for these neighborhoods coined by the Swedish police authority, i.e., "utsatta områden".

Figure A.2: Google Searches for "Troubled Neighborhoods" and "Best Restaurants"



Notes: This figure plots the relative number of searches on Google for the terms "Troubled neighborhoods" and "Best restaurants". The data was obtained from Google Trends. Google Trends normalizes search data to make comparisons between terms easier. Search results are normalized to the time and location of a query by dividing each data point by the total searches of the geography and time range it represents. The resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion of all searches on all topics.

B Evidence Against Policy Responses

This Appendix Section describes the empirical strategy employed to shut down any place-based policies by the police authorities, other security forces, and schools simultaneous to or as a response to the situation report issued by the police.

2.1 Event-Study Specification

We estimate a staggered difference-in-differences model of the effect of neighborhood listing on neighborhood resources using non-listed neighborhoods in urban areas as controls. Here we describe our regression model used to estimate the effect of neighborhood listing on its resources shown in Figure 3 and Figure **??** presented in the main text. The regressions are weighted by the propensity to be treated based on pre-policy characteristics. The estimating equation is as follows:

$$Y_{nt} = \alpha + \sum_{k} \beta^{k} \mathbb{1}\left[\mathrm{L}_{n} = t - k\right] + \phi_{mt} + \eta_{n} + \delta X_{nt} + \epsilon_{nt}, \tag{2}$$

where Y_{nt} is an outcome of interest in neighborhood n at year t, and $\mathbb{1}\left[\mathrm{L}_{in} = t - k\right]$ is an indicator for the listing of neighborhood n occurring k periods from t (negative k indicating a future event date). We also control for neighborhood η_n, and municipality-by-year ϕ_{mt} fixed effects, as well as for neighborhood specific linear time trends X_{nt}. The model assumes conditional parallel trends in outcomes for listed and non-listed neighborhoods, which we are able to verify by testing whether the anticipatory effects at $k = 3, 2, 1$ are statistically significant. This strategy provides estimates of the effect of neighbourhood listing on police manpower by year since the first release of the list (year 0). We estimate the model using two way fixed effects ordinary least squares (TWFE) and an estimator proposed by and **?**, the results both for which are shown in Figure 3.