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Urban Regeneration Projects and Crime: Evidence from Glasgow*

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Abstract

This study investigates the effects of urban regeneration on crime, leveraging recent large-scale regeneration projects – called Transformational Regeneration Areas (TRAs) – in Glasgow, Scotland. We employ a difference-in-differences approach that makes use of variation in both the timing of TRA implementation, and in proximity to these areas to measure exposure to urban regeneration projects. Our findings are consistent with changing neighbourhood composition and the elimination of physical spaces that harbour criminal activity driving local crime reductions. We find a large and significant reduction in crime within 400 metres of TRAs but this effect fades as we move further away. Simultaneously, we find no evidence of city-wide reductions in crime after urban regeneration.

JEL classification numbers: I38, R20, K42

Keywords: Crime, Housing, Spatial Spillovers, Urban Regeneration

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1 Introduction

Large public housing estates became the dominant form of social housing in many of the UK's largest cities during the decades following WW2. These housing estates were built to tackle issues around affordable housing and growing populations, but over time developed a reputation as areas of deprivation and crime.¹

In recent years, large-scale urban regeneration policies in multiple UK cities have attracted considerable attention.² These policies usually entail the replacement of decaying residential estates with mixed-income housing along with the redevelopment of surrounding areas. Advocates of urban regeneration projects often argue that deprivation becoming less concentrated as a result of such policies will also lead to less crime (Newman, 1996; Turner et al., 2007).³ This line of reasoning is partly based on the theory of 'defensible spaces' outlined in Newman (1972), which states that large public housing estates provide a setting where disincentives to criminal activity are weak and criminals (and gangs) are particularly difficult to police – consequently, the elimination of these spaces should reduce crime on aggregate. Crime could also decrease if urban regeneration projects lead to better access to employment opportunities, making criminal activity less attractive (Aliprantis and Hartley, 2015). Critics, on the other hand, point out that regeneration projects simply lead to a relocation of crime to other areas, while the gentrification of neighbourhoods generates residential displacement which exacts a heavy psychological toll on former

¹A recent summary of evidence reports that between 1990s and 2014 social renters in the UK experienced at least twice the national average of household crimes (Osborn and Tseloni, 1998; Tseloni et al., 2004; Tseloni, 2006; Hunter and Tseloni, 2016). In addition, relative to home owners, social renters are 40% more likely to fall victims of personal crimes with close distance to their homes (Tseloni and Pease 2015). See also research and policy recommendations from the Quantitative and Spatial Criminology Research Group at Nottingham Trent University: <https://gtr.ukri.org/publication/overview?outcomeid=5aa98d6e3ca5b3.97637440&projectref=ES/K003771/1>

² See for example, 'The real cost of regeneration', The Guardian, 21-07-2017.

³There is evidence showing that when poverty is spatially concentrated this could lead to a breakdown of informal social controls, leading to more crime (see Sampson and Raudenbush, 1999; Morenoff et al., 2001).

residents, many of whom are from a low-income background (Atkinson, 2000).⁴ In this paper, we examine the effects of urban regeneration projects on both local and city-wide crime levels using the city of Glasgow as a case study.

In general, public housing is a more prevalent form of tenure in the UK when compared to most other OECD countries (OECD, 2020). Even within this context, the city of Glasgow, Scotland's largest and most populous metropolitan area, has a particularly strong tradition in public housing. Under the leadership of the Glasgow City Council (GCC) and its predecessors, the city's history includes repeated large-scale state interventions aimed at increasing the supply of public housing, which by the end of the 1960s accounted for almost 40% of the city's housing stock (GHS, 2022). In the first round of large-scale demolitions in the 1960s and 70s, a considerable share of the city's population were transferred from traditional tenement buildings – often overcrowded and in poor condition – to housing estates and high-rises. These estates, often built near the city limits, tended to have poor access to amenities, which, paired with neglect, has resulted in deprivation and a concurrent increase in crime rates, drug abuse and health issues (Garnham, 2018; Davies, 2019). To tackle these issues, in 2009 Glasgow City Council, together with the Glasgow Housing Association (GHA), started implementing Transformational Regeneration Areas (TRAs). These projects involved the demolition and replacement of existing estates with new mixed tenure housing, and endowing these areas with green spaces and other amenities.

To examine how TRAs affected crime in local areas, and in areas nearby, we use geo-referenced locations of the eight TRAs implemented in the last decade, alongside administrative data on neighbourhood-level crime numbers from 2007 to 2020. Since TRAs were implemented at different dates, we make use of a staggered difference-in-differences

⁴ See also 'Glasgow homes under the jackhammer - A photo essay', The Guardian, 18-02-2022 or 'Regeneration - or pushing out the poor? Labour divides in bitter housing battle.', The Guardian, 29-10-2017.

(DiD) approach with spatial spillovers. This method leverages two sources of variation in exposure to TRAs. First, by exploiting the staggered implementation of the regeneration projects we compare crime numbers across TRAs before and after their implementation. We show that the timing of the implementation was not driven by diverging trends in crime across areas. Second, to assess how crime effects change with proximity to TRAs, we implement a ring approach as common in the literature (Sandler, 2017; Blanco and Neri, 2021). This approach relies on the assumption that proximity to TRAs determines treatment intensity, and compares crime numbers within short distances (inner rings) of a TRA to those in surrounding areas (outer rings). We estimate these models using a standard two-way fixed effects (TWFE) method, but also complement them by a two-stage DiD2S (Gardner, 2021) approach that accounts for treatment effect heterogeneity and spatial spillovers (Butts, 2021). Finally, following the time-series approach first outlined in Bruhn (2018) we also examine whether the TRAs led to changes in aggregate (city-wide) crime levels.

Our analysis presents three main results. First, we find that the implementation of TRAs is followed by a large (up to 33%) reduction in crime numbers within 400 metres of TRA sites. In DiD2S specifications that account for potential bias from treatment effect heterogeneity, these effects are considerably smaller (a 7% reduction in our main specification) but still point in the same direction. We argue that these findings point to local effects on crime whereby TRAs eliminate the convenient physical setting created by public housing estates where crime can take place (Newman, 1972, Aliprantis and Hartley, 2015). This argument is supported by the large reduction in crimes such as theft and drug-related crime, which typically tended to occur in the environments created by large public housing estates. In robustness checks, we exclude areas that TRAs are nested in to alleviate concerns about our baseline effects being purely mechanical ones, and report similar findings, but only within close vicinity (400 metres) of TRAs. Our baseline results are also robust to the choice of the radii by which we define our distance rings and to

delaying the timing of TRA implementations. Second, we report that TRAs are associated with lower deprivation across multiple dimensions in affected areas, but these effects are also mostly confined to the immediate location of the TRA site. These results are likely explained by the mechanical effect of the replacement of low-income housing with mixed-income units, and the resulting changes in neighbourhood composition. Improved employment and health outcomes in neighbourhoods can nonetheless act as a channel for further (local) crime reductions by making crime less attractive (Aliprantis and Hartley, 2015). Finally, we find no evidence of aggregate-level reductions in crime levels in response to TRA projects. Our aggregate-level effects are a bit smaller than what the size of the local reductions in crime would suggest at the city-level, implying that it might be a small positive crime displacement effect that leaves city-wide crime levels unchanged after TRA implementations.

The main contribution of our paper is to the small literature on the effects of urban regeneration projects on crime. Our work builds on a small body of evidence from the U.S. that looks at the effects of public housing demolitions on crime, which mostly finds evidence of crime reductions at the local and aggregate-level (Aliprantis and Hartley, 2015; Sandler, 2017). Contrasting findings by Bruhn (2018) suggest negative local effects but a city-wide increase in crime. Our paper contributes to this literature by examining the local crime effects of urban regeneration projects using a version of the standard spatial difference-in-differences approach (Aliprantis and Hartley, 2015; Sandler, 2017) that accounts for potential treatment effect heterogeneity and spatial spillovers (Butts, 2021). We complement this approach to also examine city-wide crime changes in response to urban regeneration projects by following the time-series approach outlined in Bruhn (2018). Our results are consistent with the literature in that we also report negative crime effects in the vicinity of urban regeneration sites, but are novel in that we find no evidence of an aggregate-level crime effect.

Our study is also among the first ones (to our knowledge) to analyse the effects of urban regeneration projects on crime in a UK context, where, despite the country's strong tradition in public housing and related spatial concentration of crime, there is a relative lack of evidence on this topic. The only study looking at the link between urban regeneration projects and crime in the UK that we are aware of is a current working paper by [Blanco and Neri \(2021\)](#). They find a negative effect from such projects in London, and also show positive effects on house prices and desirable neighbourhood amenities. We add to this literature by providing evidence on the crime effects of urban regeneration through the case study of Glasgow, where these effects are likely to be particularly pertinent given the city's peculiar history of public housing and high crime numbers concentrated near housing estates. We also contribute to the wider literature on the effects of urban regeneration, which examines the effects of these projects on a variety of outcomes such as house prices ([Brown, 2009](#); [Zielenbach and Voith, 2010](#); [Blanco and Neri, 2021](#)); neighbourhood socio-economic composition ([Tach and Emory, 2017](#)); employment ([Zhang et al., 2021](#); [Gibbons et al., 2021](#)); and student achievement ([Neri, 2021](#)).

The rest of the article is structured as follows. [Section 2](#) provides an overview of the historical and policy background; [Section 3](#) describes the data; [Section 4](#) outlines our empirical strategy and presents the results. [Section 5](#) concludes.

2 Background

Scotland has a strong tradition of public housing. After WW1, the 1919 Housing Act paved the way for a shift from private landlords to council housing as the dominant form of tenure. By the end of the 1970s, public housing accounted for almost three-quarters of the entire Scottish housing stock, compared to hardly one-third in England ([Robertson and Serpa, 2014](#)).

Even within Scotland, the city of Glasgow provides a unique case study in public housing. In Glasgow, the Glasgow City Council (GCC) became the main builder of new housing after WW2, and was also in charge of large-scale urban planning policies that would shape the city for decades (Davies, 2019). Glasgow's post-industrial background required state intervention to accommodate the rising demand in housing of a fast-growing, predominantly working-class population. By the end of the 1960s, with a stock of about 126,500 dwellings, Glasgow City Council owned (and managed) nearly 40% of the entire housing stock of the city (GHS, 2022). By the 1970s, only Russian cities had greater state involvement in the housing market than Glasgow (Davies, 2019). The city's ambitious programme also involved the development of large public housing estates, among them many high-rise buildings, that would house tens of thousands of residents across the city. Often times the people who occupied flats in these housing estates were rehoused from Victorian tenement buildings – tenements themselves were built to cope with Glasgow's extreme population growth in the 18th and 19th centuries⁵ – fracturing the local community ties established in existing neighbourhoods (Davies, 2019). Housing estates often had poor access to amenities and, due to a lack of ongoing investment, their surrounding areas experienced high rates of deprivation, with overcrowded housing, gang culture and growing crime, drug abuse, and low life expectancy among residents (Garnham, 2018).

Starting in the early 2000s, large-scale housing regeneration projects were implemented in Glasgow to address issues with its crumbling housing stock. In September 2003, the responsibility to manage Glasgow's housing stock transferred from the Scottish Government to the Glasgow City Council, who in the same year delegated the management to the

⁵Traditional Glaswegian tenements are a type of sandstone building, usually three or four stories high, with most facilities shared by tenants. Tenement housing was incredibly dense, and often times entire families occupied a single room in a tenement building. Despite overcrowding, tenements were important centres of social life, as tenants formed various clubs and societies and provided each other with community support (Davies, 2019).

Glasgow Housing Association (GHA) (Zhang et al., 2021).⁶ Since 2005, the Glasgow City Council has been working in partnership with the GHA and the Scottish Government to establish a new approach to the regeneration of eight key areas in the city, known as Transformational Regeneration Areas (TRAs). In 2009, the Scottish Parliament gave the go ahead for the programme to be initiated. The TRA programme aims to provide new sustainable mixed tenure communities through the provision of new housing, community facilities and local amenities, green space, and commercial units.⁷ Across the TRA programme, approximately 600 homes for social housing are planned along with an estimated 6,500 homes for mid-market rent. TRA implementation dates for the eight areas are summarised in Table A.1. We consider each TRA to be ‘active’ when the first phase of the new building construction was completed. The locations of each TRA within Glasgow City are shown in Figure A.1.

According to the GoWell Research and Learning Programme, a qualitative study that looks at the effects of housing regeneration on the well-being of local residents, TRAs mostly involved demolishing existing mass housing estates in the affected areas, and replacing them with mixed-income and social housing, leaving residents with the option to stay in the area in newly built homes (Kearns and Lawson, 2017). A before and after comparison of the housing built at the £250 million Sighthill TRA project is a good example of how TRAs led to the redevelopment of affected urban areas (see Figure 1). The Sighthill estate has been for decades one of the most deprived areas of Glasgow, with poor living

⁶GHA is the largest provider of social housing in Scotland with about 40,000 affordable properties throughout the city. Since its creation in 2003, it has invested more than £1.5 billion in improving current stock and building more than 2,000 new properties (Black and Roy, 2019). In addition, GHA provides a wider range of support activities for the community, e.g. financial advice, apprenticeships (Black and Roy, 2019).

⁷ Information on TRAs can be found on this website: <https://www.gha.org.uk/about-us/regeneration/new-build-homes-transformational-regeneration-areas-tras>. Additional information is available on the Glasgow City Council website: <https://www.glasgow.gov.uk/article/19842/Transforming-Communities-Partnership>.

conditions, high rates of unemployment, drug abuse and crime.⁸ At Sighthill – and in fact in the case of most TRAs – large high-rise buildings in poor condition were demolished to give place to smaller, more densely packed housing units, and the surrounding residential areas were redeveloped. The report by [Kearns and Lawson \(2017\)](#) also states that despite the fact that old tenants of demolished housing estates had the option to remain, most of them sought housing in nearby areas instead of staying in newly built housing.⁹

Figure 1. TRA - Before and After Regeneration



Notes: The Sighthill area before and after TRA implementation, in December 2015. High-rise buildings are replaced by modern terraced estates for mixed-income tenure.

3 Data

We use crime data on the universe of recorded crimes in Scotland provided by Police Scotland through a Freedom of Information (FOI) request.¹⁰ Our data consist of monthly

⁸ Disappearing Glasgow, a photo documentary project by Chris Leslie, documents the demolition of public housing estates, and among them the Sighthill housing estate, whilst providing a qualitative account of the experience of living at these housing estates before the regeneration projects. See <https://www.disappearing-glasgow.com/portfolio/sighthill-3/>.

⁹ We have not been able to find data on how many former residents moved away from TRAs and where they moved.

¹⁰FOI 22-1505.

Data Zone level crime counts for the time period 2007 to 2020. Data Zones are the second lowest level of territorial designation in Scotland (similar to U.S. census blocks) and are composed of aggregates of the country's 46,351 Output Areas. They are designed to each include roughly between 500 and 1,000 residents and to constitute socio-economically and geographically homogeneous areas.¹¹ There are 6,976 Data Zones in Scotland, 746 of which are located within Glasgow City.

To avoid low cell sizes (few or zero crimes) in many Data Zones, we aggregate the crime data to the annual level.¹² We then construct a balanced panel of Data Zones over the fourteen year period between 2007 and 2020. The data consist of all subcategories of crimes and offences.¹³ We calculate the overall, Data Zone level, crime/offence numbers by aggregating all instances that fall within each category, based on Scottish Government classifications.¹⁴ We also aggregate crime data across the five major crime subcategories used in Scotland: violent crimes (non-sexual), sexual crimes, crimes of dishonesty, fire-raising and vandalism, and other crimes. These subcategories are described in more detail in [Table A.3](#). As base period controls, we use the Data Zone level scores for the different components (income, housing, access to services, health and employment) of the Scottish Index of Multiple Deprivation (SIMD) from 2006. The SIMD ranks all small areas in Scotland in terms of relative deprivation.¹⁵

We also use data on deprivation from SIMD waves 2006, 2009, 2012, 2016 and 2020 as additional outcome measures. We make use of the following outcomes: the income deprivation rate which is the percentage of population in receipt of the main forms of

¹¹These are the equivalent to the English Lower Layer Super Output Areas (LSOA).

¹² We also use monthly data for the time-series analysis in [Section 4.2](#).

¹³Offences are classified under a separate crime category in Scottish Criminal Law and include more minor crimes such as speeding, dangerous and careless driving, drunkenness and other disorderly conduct, breach of the peace, et cetera.

¹⁴For more detail on these classifications, see <https://www.gov.scot/publications/user-guide-recorded-crime-statistics-scotland/pages/16/>.

¹⁵ Note, that we do not use the Crime domain of SIMD as we use data from Police Scotland to measure crime numbers.

means-tested benefits; the employment deprivation rate which is the percentage of working age population who are not in employment and receive employment or disability-related benefits; the standardised mortality ratio; the standardised ratio of drug-related hospital stays; and the overall SIMD rank deciles, ranging from 1 to 10, where 1 is the most deprived. Official definitions of SIMD components are summarised in [Table A.2](#).

Information on TRAs and their location coordinates is collected from the GHA. We use QGIS to calculate distance rings around each TRA using a set of (200m, 400m, 600m, 800m, 1000m) distance radii. If a Data Zone's area centroid falls within a specific distance radius, then the Data Zone is indicated to be part of the corresponding ring. For our main analytical sample, we limit our data to those Data Zones within 1km of a TRA. This is so that our ring approach (see below) only relies on data for treated areas (the four rings within 800 metres) and the control areas (the outer ring between 800 and 1000 metres). When restricted this way our sample contains 119 Data Zones, and on average there are 60.3 crimes and 54.4 offences committed in each Data Zone each year. The average Data Zone in our sample stretches across $.17 \text{ km}^2$ and, as per 2011, contains 763 residents. Summary statistics are provided in [Table 1](#).¹⁶

¹⁶ There are two and three years missing in the data for two Data Zones, while for the rest of the sample there are no gaps in the data.

Table 1. Summary Statistics - Analytical Sample - 2007-2020

	Mean	SD	Data Zone - Years
<i>Outcomes</i>			
Crimes	60.30	67.63	1661
Offences	54.38	74.17	1661
<i>Base Controls</i>			
SIMD Income (2006)	29.06	12.94	1661
SIMD Employment (2006)	24.54	11.63	1661
SIMD Health (2006)	1.07	0.87	1661
SIMD Housing (2006)	47.53	14.69	1661
SIMD Access (2006)	5.57	3.99	1661
<i>Data Zone Characteristics</i>			
Total DZ Population (2011)	805.41	248.13	1661
Resident DZ Population (2011)	763.08	159.66	1661
Distance to Closest TRA (km)	0.66	0.24	1661

Notes: This table provides summary statistics for our main analytical sample. This sample is limited to include only those Data Zones whose centroid is within 1km of a TRA site. Base controls are level scores for each domain of the Scottish Index of Multiple Deprivation (SIMD) 2006. Data are missing for Data Zone code S01010206 for 2017, 2018, and 2020, and for Data Zone code S01010226 for 2017 and 2019. For the rest of our sample there are no missing values for key variables.

4 Empirical Evidence

The main goal of our study is to determine the average change in crime numbers in response to urban regeneration projects (TRAs). Our empirical strategy therefore aims to identify the appropriate counterfactual level of crime had an area not undergone urban regeneration through the TRA programme. To estimate this counterfactual we exploit two key sources of variation in: *i*) treatment timing and *ii*) spatial distance to TRA areas.

Relying on variation in treatment timing means comparing crime numbers across TRA areas before and after these programmes are implemented. Following this strategy prevents us from estimating spurious effects via comparison of ‘treated’ areas to areas without large public housing projects – where TRAs would not have been implemented in the first place – which would have likely followed different crime trajectories. On the other hand, simply estimating effects using variation in treatment timing would ignore potential spatial spillover effects from TRAs to neighbouring areas. To mitigate this, our analysis complements a simple model that relies on treatment timing with more complex strategies

that incorporate this spatial dimension. Following the related literature (Aliprantis and Hartley, 2015; Sandler, 2017; Blanco and Neri, 2021), we estimate the following model:

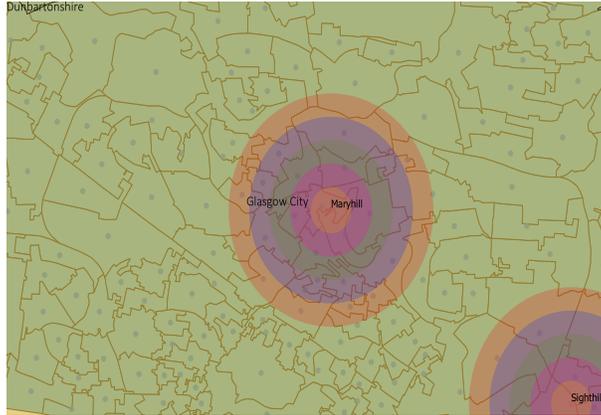
$$Crime_{it} = \sum_{r \in R} \beta_r \times TRA_i \times Post_t \times D_{r \in R} + \gamma' X_{i,2006} \times \theta_t + \theta_i + \theta_c t + \epsilon_{it} \quad (1)$$

where our dependent variable is the inverse hyperbolic sine (IHS) of crime (and offence) numbers in each Data Zone i for each year t . Using the inverse hyperbolic sine provides a helpful transformation of right-skewed data which preserves the log-interpretation, i.e. $\beta_r \times 100$ change in crime following TRAs implementation, while still accommodating null values, and is a common approach in the literature (Blanco and Neri, 2021).¹⁷

Our main parameters of interest are the β_r coefficients corresponding to each distance ring $r \in R$. These identify changes in crime in Data Zone i within ring r distance of each TRA. We operationalise this by constructing a set of indicators (represented by $D_{r \in R}$) switching to 1 if a Data Zone's centroid falls within ring radius $r \in R = (200m, 400m, 600m, 800m)$, following the implementation of the local TRA ($TRA_i \times Post_t$). The timing indicator $Post_t$ varies by TRAs as these programmes were implemented at different dates in different areas. Our identification strategy relies on the fact that treatment status is determined by proximity to each TRA. TRA centroids in our case are nested within specific Data Zones, but these areas (and their effects on crime) likely extend Data Zone boundaries. We therefore also assign treated status to Data Zones whose centroids are within a wider set of radii of the centroid of the TRA Data Zone. Data Zones with centroids located between 800 and 1000 meters from the TRA are designated to be part of the 'outer ring', which serves as our control group. The approach we use is illustrated in Figure 2, and relies on the stipulation that, conditional on observables and Data Zone fixed effects, the only difference between rings will be distance to the TRA.

¹⁷For the number of crimes c , IHS transformation is $\sinh^{-1}(c) = \ln(c + \sqrt{c^2 + 1})$

Figure 2. Distance Rings - Maryhill TRA



Notes: This figure reports the rings around Maryhill’s TRA. The inner ring has a radius of 200m, whereas the one immediately after (purple) is within 200m to 400m from the TRA’s centroid. The outer (orange) ring is instead within 800m to 1000m from the TRA’s centroid. The green polygons, and the dots within them, represent our statistical units, Data Zones, alongside their centroids. According to our mapping strategy, seven Data Zones’ centroids lie within 200 to 400 metres from the TRA site. These seven Data Zones are therefore ‘treated’ by that ring.

Any difference in crime *levels* across Data Zones is accounted for by estimating [Equation 1](#) with a two-way fixed effects (TWFE) approach using θ_i and θ_t . The term θ_i controls for Data Zone-specific effects, whereas θ_t takes into account any time-specific variation which is common to all Data Zones. We want to rule out the possibility that Data Zone-specific and time-varying shocks would bias our results by simultaneously driving the timing of the implementation of the TRA and changes in crime rates, for example city-level population shocks that heterogeneously affect neighbourhoods, resulting in higher population density, simultaneously urging urban redevelopment and providing a larger pool of victims for criminals.¹⁸ Unfortunately, limited variation at the Data Zone level means we need to use a higher level of aggregation, and therefore we include time trends specific to each Intermediate Data Zone ($\theta_c t$). An Intermediate Zone includes two to nine Data Zones. This approach was previously employed by [Sandler \(2017\)](#). Finally, we control for $X_{i,2006}$, namely our base period set of Data Zone level controls. These include SIMD scores

¹⁸We only observe population in 2011 as a result of the latest census, thus year-to-year population changes are unobserved to us.

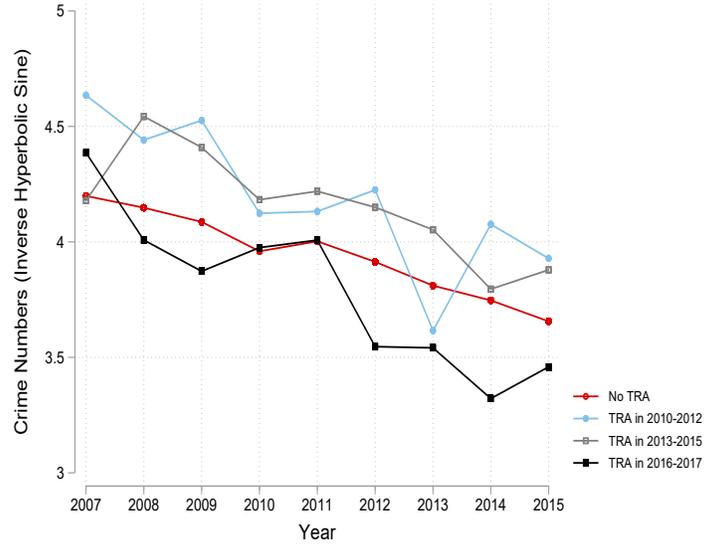
for income, employment, health, housing and access to services. By using these values in 2006, we control for neighbourhood characteristics which are pre-determined relative to the treatment, and thus are not potential outcomes of the regeneration.¹⁹ Naturally, since these covariates are fixed across Data Zones, estimation of γ is only possible by interacting them with year indicators.

We combine this spatial approach with a staggered difference-in-differences (DiD) strategy, whereby crime numbers of the inner rings are compared with those of the outer ring, before and after the implementation of each TRA. A crucial assumption for our identification strategy is that trends in crime numbers did not influence TRA implementation dates in affected neighbourhoods. In other words, neighbourhoods that adopted TRAs early did not do so in response to increased crime numbers in the surrounding area. Following [Aliprantis and Hartley \(2015\)](#), we test this by plotting time trends in crime numbers for groups of data zones where TRAs were implemented at different points in time ([Figure 3](#)). We can see from [Figure 3](#) that time trends are mostly very similar across the different groups, and that for all groups the overall negative trend in crime numbers tends to precipitate TRA implementations.

A characteristic of our set up is that TRA implementations occur at different points in time (see [Table A.1](#)). A burgeoning literature discusses how the standard TWFE approach might not be suitable in the context of staggered timing due to the possibility of heterogeneous treatment effects (see [Roth et al. \(2022\)](#) for a review). For this reason, alternatively to our TWFE model we also estimate our baseline model using a two-stage DiD (DiD2S) approach, as first proposed by [Gardner \(2021\)](#). We also modify the DiD2S model to allow incorporation of spatial spillovers, as suggested by [Butts \(2021\)](#). This approach consists of estimating [Equation 1](#) in two stages.

¹⁹Our sample starts in 2007 and the first TRA was implemented in 2010.

Figure 3. Trends in Crime Numbers - TRA Timing Groups



Notes: This figure reports (inverse hyperbolic sine) crime numbers' trends, broken down by time of implementation of the TRAs. Each line is a trend for all Data Zones' affected by TRAs' implementation within a specific time window. For instance, the red line is the average crime numbers for all Data Zones whose centroid did not fall within a (at most) 1000m radius from a TRA. The turquoise line instead is the average crime numbers for all Data Zones matched to any TRA whose implementation occurred between 2010 and 2012 and so forth.

1. First, we estimate

$$Crime_{it} = \gamma' X_{i,2006} \times \theta_t + \theta_i + \theta_t + \theta_c t + \eta_{it} \quad (2)$$

for observations where both the treatment indicator and the distance ring dummy (for all rings $r \in R$) are equal to zero. This equation contains all of our controls and fixed effects from Equation (1) on the right hand side, and is used to remove the fixed and common trend component.

2. Regress the residualised outcome \widetilde{Crime}_{it} for all observations on treatment and spillover dummies corresponding to treated areas and distance rings the treatment effect could spill over into. The spillover dummies are created as the interaction term between the control group ($TRA_i = 0$) and rings $r \in R$.

According to [Gardner \(2021\)](#), under a parallel trends assumption the second-stage equation identifies the Average Treatment Effect on the Treated (ATT) and is robust to the issues raised by standard TWFE models.²⁰ The results for our baseline TWFE and DiD2S specifications, for both crimes and offences, are summarised in [Table 2](#). Our preferred specification is the DiD2S specification (columns (5) and (10) in [Table 2](#)) incorporating area-specific time trends as this should account for potential treatment effect heterogeneity and also reduce the likelihood that time-varying shocks specific to local areas drive our results.

Our data structure also allows us to estimate event study specifications, where we interact treated distance rings with event time indicators to estimate treatment effects over time. The event study specification takes the following form:

$$Crime_{it} = \sum_{\tau=-M}^L \sum_{r \in R} \beta_{\tau,r} \times TRA_i \times \mathbb{1}(t - E_i = \tau) \times D_{r \in R} + \gamma X_{i,2006} \times \theta_t + \theta_i + \theta_c t + \epsilon_{it} \quad (3)$$

where $\beta_{\tau,r}$ are the changes in crime across treated rings in years before ($-M$) and after (L) the local TRA implementation. This allows us to formally test for the absence of pre-trends in crime rates and examine how crime effects change over time. Event studies for our DiD2S specifications are plotted in [Figure 4](#).

4.1 Results

4.1.1 Baseline Results

[Table 2](#) helps us shed light on the aggregate size of TRAs' effect on local crime. We split our results by crimes and offences, based on the classifications of the Scottish Government.

²⁰The parallel trends assumption takes the form:

$$E[Y_{it}|i, t, T_{it}^k] = \alpha_i + \gamma_t + T_{it}^k \delta_{it}^k$$

where T_{it} is the treatment indicator equivalent to $TRA_i \times Post_t$ in [Equation 1](#).

For crimes, Columns (1)-(3) present results from our TWFE specifications, whereas (4)-(5) report coefficients from our DiD2S estimations. Columns (6) to (10) present the same results for offences. The standard errors in every specification are clustered at the Data Zone level. Our TWFE results suggest a 16-30% reduction in crime in the immediate vicinity of the site (200m), relative to outer ring areas within 800m-1000m from the TRAs, following their implementation. DiD2S specifications indicate a reduction in crime of between 4-7%. In addition, these models seem to be more precisely estimated when compared to TWFE ones. The negative crime effects in the TWFE models within the inner ring are considerably larger than the 5% reduction in crime (12% for large projects more similar to TRAs) found by [Blanco and Neri \(2021\)](#) for regeneration projects in London, but the effect size in our DiD2S specifications are much more in line with their findings. A reduction in crime of 7% from our full DiD2S specification would correspond to roughly 4.22 fewer crimes, on average, for each immediate TRA site each year. Considering that 763 people live in the average Data Zone, this is roughly equal to a decrease in the crime rate of 3.22 crimes per 1,000 people for these local areas. We find no evidence of a reduction in offences following TRA implementation.

As we move further away from the first ring, the negative crime effect remains for the 200-400m ring, then disappears in the 400-600m ring, and becomes a moderately sized but mostly statistically insignificant negative effect in the outermost (600-800m) treated ring.

Our event study estimates confirm the negative effects on crime within close proximity of TRAs (see Panel (a), [Figure 4](#)). The post-treatment negative deviation in trends is particularly notable within 200m of TRAs, three and four years after the event, suggesting a 20 and 30 percent reduction, respectively. Before then, none of the coefficients are statistically significant at the 5% significance level. In addition, we observe a strong, statistically significant reduction in crime of about 30% immediately after the event in the 200-400m ring, followed by a partial reversion towards 15-20%, where the point

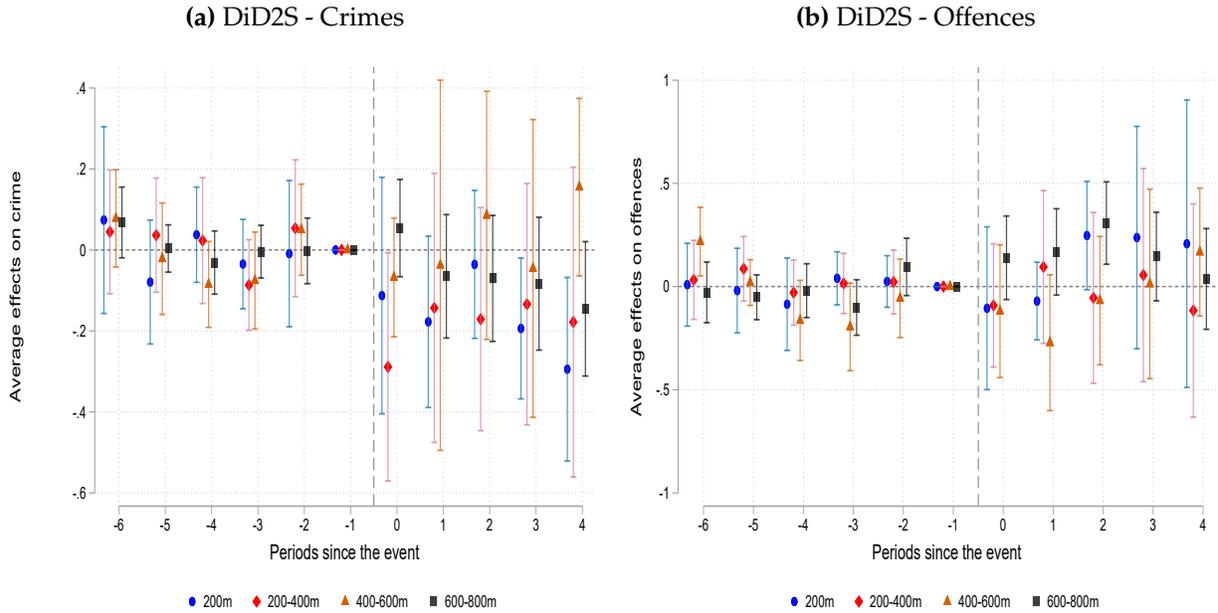
Table 2. Baseline Results

	Crimes					Offences				
	TWFE		DiD2S			TWFE		DiD2S		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Crime (TRA within 200m)	-0.16* (0.08)	-0.15* (0.09)	-0.30*** (0.08)	-0.04 (0.04)	-0.07*** (0.03)	0.05 (0.15)	0.11 (0.15)	0.12 (0.16)	0.04 (0.06)	0.05 (0.05)
Crime (TRA within 200m to 400m)	-0.23 (0.17)	-0.18 (0.16)	-0.33*** (0.09)	-0.04 (0.14)	-0.18* (0.10)	-0.11 (0.20)	-0.05 (0.20)	-0.13 (0.14)	-0.03 (0.16)	-0.09 (0.16)
Crime (TRA within 400m to 600m)	-0.03 (0.14)	-0.04 (0.15)	-0.02 (0.08)	0.07 (0.12)	0.10 (0.07)	-0.12 (0.15)	-0.08 (0.15)	-0.07 (0.10)	-0.06 (0.11)	-0.07 (0.10)
Crime (TRA within 600m to 800m)	-0.06 (0.06)	-0.07 (0.06)	-0.10* (0.06)	-0.02 (0.06)	-0.06 (0.09)	0.12 (0.09)	0.14 (0.09)	0.10 (0.10)	0.12 (0.10)	-0.15 (0.17)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE X Base Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Int Data Zone Linear Trend	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Notes: This table reports estimated coefficients β_r from Equation 1. Columns (1)-(5) contain specifications whose dependent variable is the inverse hyperbolic sine (IHS) of crime numbers in each Data Zone area, whereas Columns (6)-(10) repeat the same exercise but using offence numbers. Columns (1)-(3) and (6)-(8) report estimates from a two-way fixed effects (TWFE) model, whereas columns (4)-(5) and (9)-(10) refer to the two-stage difference-in-differences (DiD2S) model. Base controls include income, employment, health, housing and access to services scores from the 2006 edition of the Scottish Index of Multiple Deprivation (SIMD). This analysis pertains to years 2007-2020. The number of observations in all specifications are 1,661 data zone-years. Standard errors are clustered at the Data Zone level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

estimates are no longer statistically significant. Moreover, in line with columns (4) and (5) of Table 2, there is evidence of a positive trend in the 400-600m ring following the event. However, none of these coefficients are statistically significant. We find no evidence that TRAs implementation led to a reduction in offences. In fact, we observe a slight increase in some of the rings (especially further away) but hardly any of these are statistically significant. Finally, Figure 4 documents the absence of pre-trends for both outcomes, within any distance from each TRA. Point estimates are close to zero and not significant at any reasonable level. The negative crime effects we observe post-treatment are therefore predicated on the absence of pre-existing deviations in crime trends between treated and control units. Overall, evidence from the event studies suggest that post-implementation, crime has gradually, yet strongly, reduced in closer proximity of the regeneration sites (within 400m).

Figure 4. Event Studies - Baseline Model



Notes: This figure reports estimated coefficients $\beta_{\tau,r}$ from Equation 3 using two-stage difference-in-differences (DiD2S) model. Outcomes are the inverse hyperbolic sine (IHS) of crime -panel (a)- and offence numbers -panel (b)- in each Data Zone area. The models' specification is equivalent to those in columns (4) and (9) of Table 2, whereby we interact year FE with base controls. Base controls include income, employment, health, housing and access to services scores from the 2006 edition of the Scottish Index of Multiple Deprivation (SIMD). This analysis pertains to years 2007-2020. The whiskers are 95% confidence intervals, built using standard errors clustered at the Data Zone level.

Table 3 summarises our main results by different subcategories of crime, such as violent crimes (murder, assault, etc), sexual crimes, dishonesty and theft (theft, attempted housebreaking and housebreaking), vandalism and other crimes.²¹ Overall, we observe larger (and less precisely estimated) point estimates when using the TWFE model, as opposed to DiD2S. The negative effects for the innermost ring are consistent across all subcategories, with the exception of sexual crimes. For this category, these results are not statistically significant. The most striking (and significant) result is the reduction in thefts by 9-38% in close proximity (within 400 meters) to TRA sites, and a 7-38% reduction in 'other crimes' within 400 meters of urban regeneration projects. The latter category

²¹ For a detailed breakdown of these categories, see Table A.3.

consists mainly of weapon and drugs possession, with drug related crimes accounting for about 70% of the overall category. Therefore, this result is consistent with the idea that regeneration projects remove the physical setting where certain types of crimes (for example theft or drug-related crimes) could take place (Newman, 1972; Aliprantis and Hartley, 2015). As we move to the outermost distance ring, our estimates for this category are also suggestive of a positive spillover effect, although these effects are not statistically significant.

Table 3. TRA Effects by Crime Subcategory

	Violent Crimes		Sexual Crimes		Dishonesty & Theft		Vandalism		Other	
	TWFE	DiD2S	TWFE	DiD2S	TWFE	DiD2S	TWFE	DiD2S	TWFE	DiD2S
Crime (TRA within 200m)	-0.16 (0.18)	-0.04 (0.06)	0.28 (0.25)	0.10 (0.08)	-0.38*** (0.09)	-0.09*** (0.03)	-0.26* (0.14)	-0.06 (0.04)	-0.27** (0.14)	-0.07 (0.04)
Crime (TRA within 200m to 400m)	-0.23* (0.14)	-0.19* (0.11)	-0.01 (0.11)	0.02 (0.12)	-0.30*** (0.07)	-0.18* (0.10)	-0.26** (0.10)	-0.11 (0.11)	-0.38** (0.17)	-0.25** (0.12)
Crime (TRA within 400m to 600m)	0.02 (0.09)	0.07 (0.08)	-0.01 (0.13)	0.03 (0.16)	-0.12 (0.08)	0.04 (0.09)	-0.03 (0.09)	0.03 (0.10)	-0.05 (0.10)	0.03 (0.09)
Crime (TRA within 600m to 800m)	0.01 (0.08)	0.04 (0.11)	-0.18* (0.10)	-0.26** (0.13)	-0.08 (0.06)	-0.11 (0.09)	-0.14** (0.07)	-0.10 (0.10)	0.07 (0.10)	0.21 (0.16)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE X Base Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Int Data Zone Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimated coefficients β_r from Equation 1. Outcome variables are the inverse hyperbolic sine (IHS) of crime numbers, by crime subcategory, in each Data Zone area. Base controls include income, employment, health, housing and access to services scores from the 2006 edition of the Scottish Index of Multiple Deprivation (SIMD). This analysis pertains to years 2007-2020. The number of observations in all specifications are 1,661 data zone-years. Standard errors are clustered at the Data Zone level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.1.2 Robustness Checks

Sensitivity to distance ring radii. In this section, we address some residual concerns in relation to our baseline model. First, one could be concerned that our results are sensitive to the choice of distance radii used to specify treated areas. If this was true, we might see the effects disappear within a larger radius. Alternatively, it could be a concern that in

our baseline analysis, we use a control ring (800-1000m) that contains a small cluster of observations leading to less precise estimates. For this reason, we re-run the exercise in [Section 4.1.1](#) but use a wider set of radii, e.g. $R=\{400m, 800m, 1200m, 1600m\}$ and a control ring of 1600m to 2000m. Results from this robustness check are summarised in [Table 4](#). Overall, our results remain very similar to our baseline estimates, with clear evidence of a negative crime effect within 400m of TRA sites. Effects for rings further away are close to zero and not significant at any reasonable level. For offences, this specification suggests negative effects, although these are still only marginally significant.

Table 4. Robustness Check - Wider Distance Rings

	Crimes					Offences				
	TWFE		DiD2S			TWFE		DiD2S		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Crime (TRA within 400m)	-0.22 (0.14)	-0.22* (0.13)	-0.40*** (0.10)	-0.08 (0.05)	-0.12*** (0.04)	-0.12 (0.16)	-0.13 (0.16)	-0.27* (0.15)	-0.05 (0.06)	-0.08* (0.04)
Crime (TRA within 400m to 800m)	-0.05 (0.05)	-0.05 (0.05)	-0.06 (0.05)	-0.02 (0.05)	-0.00 (0.05)	-0.01 (0.07)	-0.01 (0.07)	-0.04 (0.06)	0.02 (0.07)	-0.00 (0.07)
Crime (TRA within 800m to 1200m)	-0.01 (0.02)	-0.02 (0.02)	0.02 (0.02)	0.00 (0.03)	0.04 (0.03)	-0.02 (0.04)	-0.02 (0.04)	-0.01 (0.03)	-0.00 (0.05)	-0.01 (0.05)
Crime (TRA within 1200m to 1600m)	0.00 (0.03)	0.00 (0.03)	0.02 (0.02)	-0.01 (0.03)	0.01 (0.03)	-0.02 (0.04)	-0.01 (0.04)	-0.00 (0.04)	0.00 (0.05)	0.04 (0.05)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE X Base Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Int Data Zone Linear Trend	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Notes: This table reports estimated coefficients β , from [Equation 1](#). Unlike [Table 2](#), we consider wider radii, starting with a 400m radius, and moving up in 400m increments. Columns (1)-(5) contain specifications whose dependent variable is the inverse hyperbolic sine (IHS) of crime numbers in each Data Zone area, whereas Columns (6)-(10) repeat the same exercise but using offence numbers. Columns (1)-(3) and (6)-(8) report estimates from a two-way fixed effects (TWFE) model, whereas columns (4)-(5) and (9)-(10) refer to the two-stage difference-in-differences (DiD2S) model. Base controls include income, employment, health, housing and access to services scores from the 2006 edition of the Scottish Index of Multiple Deprivation (SIMD). This analysis pertains to years 2007-2020. Standard errors are clustered at the Data Zone level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sensitivity to inclusion of immediate TRA site. Another concern is that the large reduction in crime observed within close distance of TRA centroids is purely a mechanical one. As old estates are demolished, and large parts of the surrounding areas are turned into

work sites, the setting where crime could happen becomes unavailable. Even when newer buildings are occupied, criminal activity may have already spilled over to nearby areas. This is likely not due to residents of old housing estates being engaged in criminal activity themselves, but that the estates served as a centralised location for crime where both victims and perpetrators were present (Sandler, 2017). Therefore, we run an additional robustness check, in the same fashion as Sandler (2017), whereby we exclude the innermost ring from our estimations, to assess whether there are crime effects once the immediate regeneration sites are not considered. Results are reported in Table 5. We can see that now the ring closest to the TRA site is the one spanning within 200m to 400m. Our TWFE models suggest an 18 to 34 percent reduction in crime, but only the latter is statistically significant. Our DiD2S estimates are suggestive of a 4-20% reduction in crime, a rather wide range of effect sizes, and only the specification controlling for block-level trends leads to significant estimates. Overall, these findings suggest that local crime reductions remain even if we exclude the immediate (central) TRA area. It is possible that this is due to the wider effects of TRAs on local neighbourhoods, where amenities are improved within a wider area. Equally, since TRAs tend to cover large areas that may span multiple Data Zones, it is possible that in some cases effects concentrate within 400 metres simply because the TRA extends this radius. Once again, none of the results regarding offences are statistically significant.

Table 5. Robustness Check - TRA Data Zone Excluded

	Crimes					Offences				
	TWFE		DiD2S			TWFE		DiD2S		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Crime (TRA within 200m to 400m)	-0.23 (0.17)	-0.18 (0.16)	-0.34*** (0.09)	-0.04 (0.14)	-0.20** (0.10)	-0.11 (0.20)	-0.04 (0.20)	-0.11 (0.14)	-0.02 (0.17)	0.01 (0.15)
Crime (TRA within 400m to 600m)	-0.02 (0.15)	-0.03 (0.16)	0.01 (0.08)	0.08 (0.13)	0.11 (0.07)	-0.11 (0.16)	-0.07 (0.16)	-0.02 (0.09)	-0.05 (0.12)	-0.01 (0.11)
Crime (TRA within 600m to 800m)	-0.06 (0.06)	-0.07 (0.06)	-0.10* (0.06)	-0.03 (0.06)	-0.07 (0.09)	0.13 (0.09)	0.14 (0.09)	0.11 (0.10)	0.13 (0.10)	-0.14 (0.17)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE X Base Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Int Data Zone Linear Trend	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Notes: This table reports estimated coefficients β , from Equation 1. Unlike Table 2, we exclude the 200m-radius ring from the sample. Columns (1)-(5) contain specifications whose dependent variable is the inverse hyperbolic sine (IHS) of crime numbers in each Data Zone area, whereas Columns (6)-(10) repeat the same exercise but using offence numbers. Columns (1)-(3) and (6)-(8) report estimates from a two-way fixed effects (TWFE) model, whereas columns (4)-(5) and (9)-(10) refer to the two-stage difference-in-differences (DiD2S) model. Base controls include income, employment, health, housing and access to services scores from the 2006 edition of the Scottish Index of Multiple Deprivation (SIMD). This analysis pertains to years 2007-2020. Standard errors are clustered at the Data Zone level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Sensitivity to imprecise treatment timing. Finally, another concern is that results might be sensitive to changing the treatment date, in case some TRAs were implemented with effective delays whereby residents could only move in much later than the indicated implementation date. Table 6 implements our baseline regression but pushing treatment dates one year later. Results are unchanged relative to our baseline estimates.

Table 6. Robustness Check - Treatment Starts One Year Later

	Crimes					Offences				
	TWFE		DiD2S			TWFE		DiD2S		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Crime (TRA within 200m)	-0.13 (0.11)	-0.12 (0.11)	-0.28*** (0.09)	-0.04 (0.05)	-0.08** (0.03)	0.10 (0.19)	0.18 (0.18)	0.21 (0.18)	0.07 (0.07)	0.09 (0.06)
Crime (TRA within 200m to 400m)	-0.13 (0.15)	-0.09 (0.15)	-0.23*** (0.07)	0.03 (0.13)	-0.10 (0.09)	-0.09 (0.19)	-0.02 (0.19)	-0.07 (0.13)	-0.02 (0.17)	-0.08 (0.18)
Crime (TRA within 400m to 600m)	0.01 (0.16)	-0.01 (0.16)	0.01 (0.10)	0.10 (0.14)	0.12 (0.08)	-0.11 (0.14)	-0.05 (0.15)	-0.03 (0.11)	-0.03 (0.11)	-0.03 (0.11)
Crime (TRA within 600m to 800m)	-0.05 (0.07)	-0.08 (0.06)	-0.13** (0.06)	-0.04 (0.06)	-0.11 (0.08)	0.10 (0.09)	0.12 (0.09)	0.07 (0.09)	0.11 (0.10)	-0.11 (0.14)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE X Base Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Int Data Zone Linear Trend	No	No	Yes	No	Yes	No	No	Yes	No	Yes

Notes: This table reports estimated coefficients β , from Equation 1. Unlike Table 2, the year of the treatment is pushed back by one year. Columns (1)-(5) contain specifications whose dependent variable is the inverse hyperbolic sine (IHS) of crime numbers in each Data Zone area, whereas Columns (6)-(10) repeat the same exercise but using offence numbers. Columns (1)-(3) and (6)-(8) report estimates from a two-way fixed effects (TWFE) model, whereas columns (4)-(5) and (9)-(10) refer to the two-stage difference-in-differences (DiD2S) model. Base controls include income, employment, health, housing and access to services scores from the 2006 edition of the Scottish Index of Multiple Deprivation (SIMD). This analysis pertains to years 2007-2020. Standard errors are clustered at the Data Zone level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.1.3 Additional Outcomes

Here, we examine how TRAs affected various types of deprivation in their own Data Zone and in areas nearby. The main aspects of deprivation we focus on are income, employment, mortality, drug-related hospitalisations, where lower numbers indicate lower deprivation, and overall SIMD rank, where a higher rank indicates lower deprivation. [Section 3](#) describes our outcome variables in more detail, while [Table 7](#) summarises our results for these outcomes when estimating our baseline DiD2S specification. The mean and standard deviation for each dimension of deprivation are reported at the bottom of the table.

Overall, the results summarised in [Table 7](#) suggest that TRAs reduced neighbourhood deprivation across several dimensions. All types of deprivation are reduced in the immediate vicinity of TRAs, and the overall SIMD rank of the main Data Zones affected improves substantially. Nonetheless, these effects are much less clear when we assess them even as much as 400 meters away, and the effects disappear (or change sign) further away. While this evidence is only suggestive, taken together with the effects observed for crime numbers, it does imply that TRA effects are mostly confined to the areas they contain. Our results are consistent with a mechanical effect on neighbourhood composition whereby the change from low-income to mixed-income housing leads to gentrification, as new TRA residents are less likely to struggle with unemployment, have higher incomes and better expected health outcomes. It is possible that all of these changes are in turn making crime less attractive for new and existing residents ([Aliprantis and Hartley, 2015](#)). Overall, our findings suggest that local crime reductions in and near TRAs could materialise through 1) the removal of physical spaces (high-rises) where criminal activity was taking place and 2) through improved neighbourhoods with stronger disincentives to crime. Nonetheless, both of these channels are in a large part mechanical – they are a result of replacing one type of housing with another in a specific local area – and do not imply crime reducing effects on the aggregate. The next section deals with this issue in more detail.

Table 7. DiD2S Results - SIMD Outcomes

	DiD2S				
	Deprivation in				Overall SIMD
	Income	Employment	Mortality	Drugs	SIMD Rank
TRA within 200m	-0.27*** (0.01)	-0.18*** (0.01)	-42.11*** (7.29)	-315.64*** (34.61)	2.79*** (0.13)
TRA within 200m to 400m	-0.02 (0.02)	-0.02*** (0.01)	24.07* (14.09)	-105.72** (49.98)	0.72 (0.47)
TRA within 400m to 600m	-0.01 (0.01)	-0.01 (0.01)	14.55* (7.98)	53.16 (55.77)	0.22 (0.33)
TRA within 600m to 800m	0.00 (0.01)	0.00 (0.01)	14.55* (7.58)	18.63 (36.07)	0.37* (0.19)
Mean DV	0.24	0.20	129.06	216.86	3.27
SD DV	0.12	0.11	47.60	265.89	2.64
Observations	459	459	459	459	460
Year FE	Yes	Yes	Yes	Yes	Yes
Data Zone FE	Yes	Yes	Yes	Yes	Yes
Year FE X Base Controls	Yes	Yes	Yes	Yes	Yes
Int Data Zone Linear Trend	No	No	No	No	No

Notes: This table reports estimated coefficients β_r from Equation 1. All columns present results from a two-stage difference-in-differences (DiD2S) model. Outcome variables are the rate of income deprived people by Data Zone, the rate of employment deprived people, the standardised mortality ratio, standardised drug-related hospital visits, and overall SIMD rank in deciles. Base controls include overall income, employment, health, housing and access to services scores from the 2006 edition of the Scottish Index of Multiple Deprivation (SIMD). This analysis pertains to years 2006-2020, and includes SIMD waves 2006, 2009, 2012, 2016 and 2020. Standard errors are clustered at the Data Zone level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2 Aggregate-level evidence

The evidence presented in the previous sections point towards a reduction in crime in close proximity of urban regeneration sites. However the question remains as to how appropriate our empirical approach is to detect aggregate-level (city-wide) changes in crime in response to urban regeneration projects. While we find strong evidence of highly localised reductions in crime, criminals could simply relocate to other parts of the city, leaving overall crime numbers unchanged. Following Bruhn (2018), we therefore implement a time-series approach to examine the aggregate effect of TRAs on crime in the city of Glasgow. To do this, we make use of monthly crime data for the whole of the city of Glasgow (see Section 3).

Figure 5 shows monthly trends in all of our indicators from January 2007 to December 2020. We can notice an overall decreasing trend in most of our measures of crime.²² We want to investigate whether city-wide crime has experienced a similar reduction to the localised one we observe in the micro-data after the implementation of TRAs. Following Bruhn (2018), we estimate the following Vector Autoregressive Model (VAR):

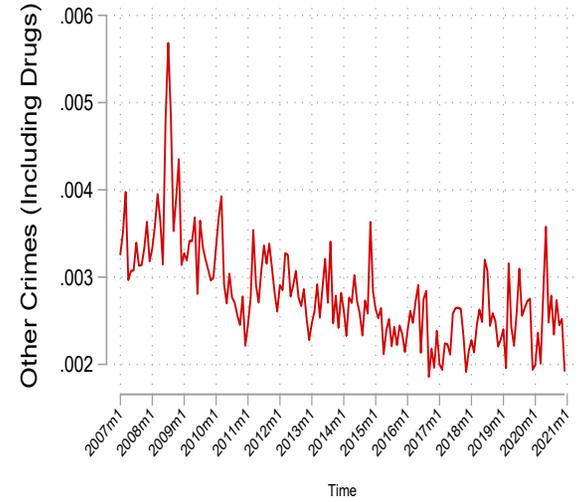
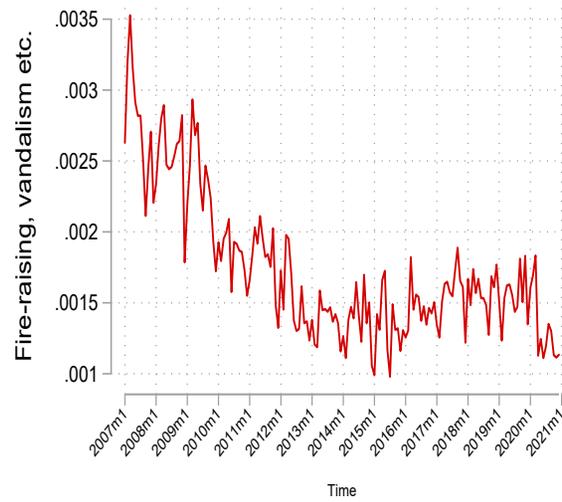
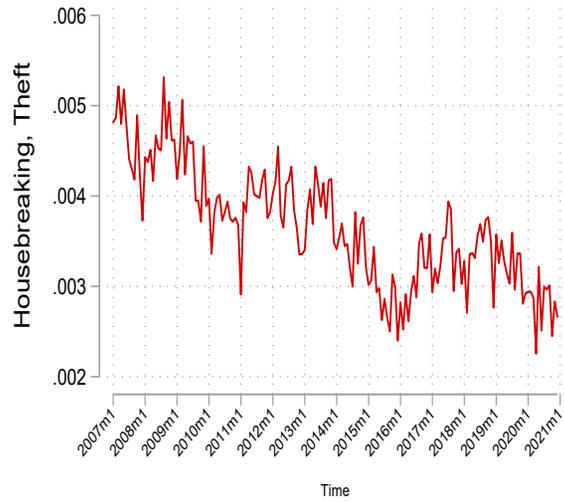
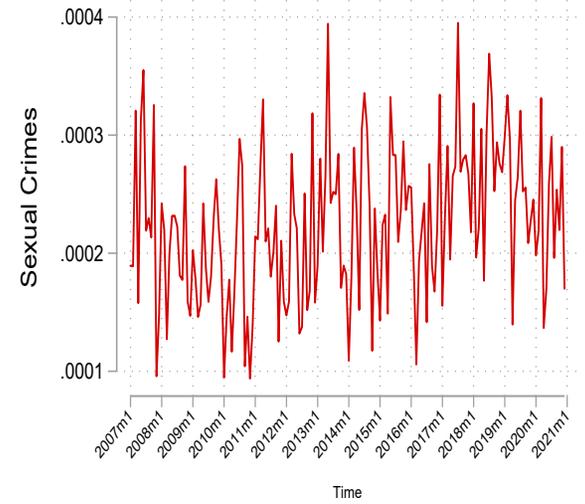
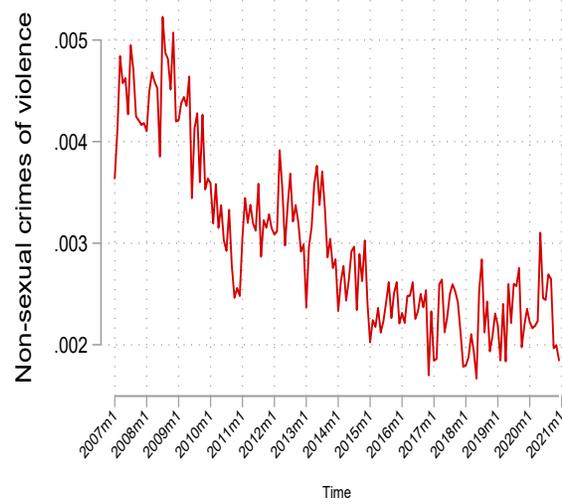
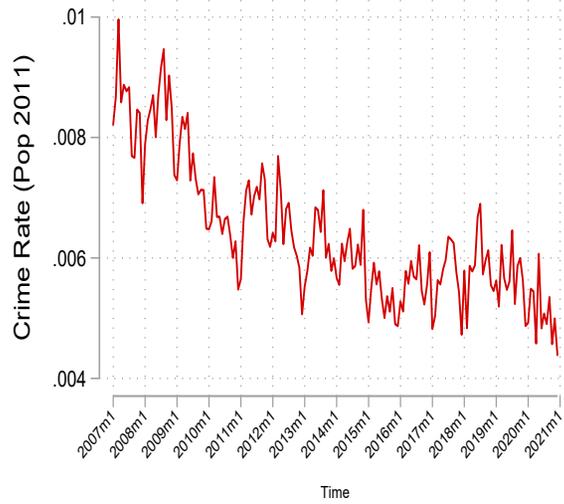
$$Crime_t = \delta_{(m)t} + \alpha t + \sum_{j=1}^J \beta_j Crime_{t-j} + \sum_{j=1}^J \gamma_j TRA_{t-j} + \epsilon_t \quad (4)$$

$$TRA_t = \delta'_{(m)t} + \alpha' t + \sum_{j=1}^J \beta'_j Crime_{t-j} + \sum_{j=1}^J \gamma'_j TRA_{t-j} + u_t \quad (5)$$

Where $Crime_t$ is the city-wide, monthly time series of crime rate, which is modeled as a function of monthly dummy variables ($\delta_{(m)t}$) a flexible time trend t as well as its own lagged values $Crime_{t-j}$ and finally TRA implementation. This is operationalised through TRA_{t-j} , which switches to one every j months after any TRA is implemented.

²²With the exception of sexual crimes, which exhibit a less obvious time trend.

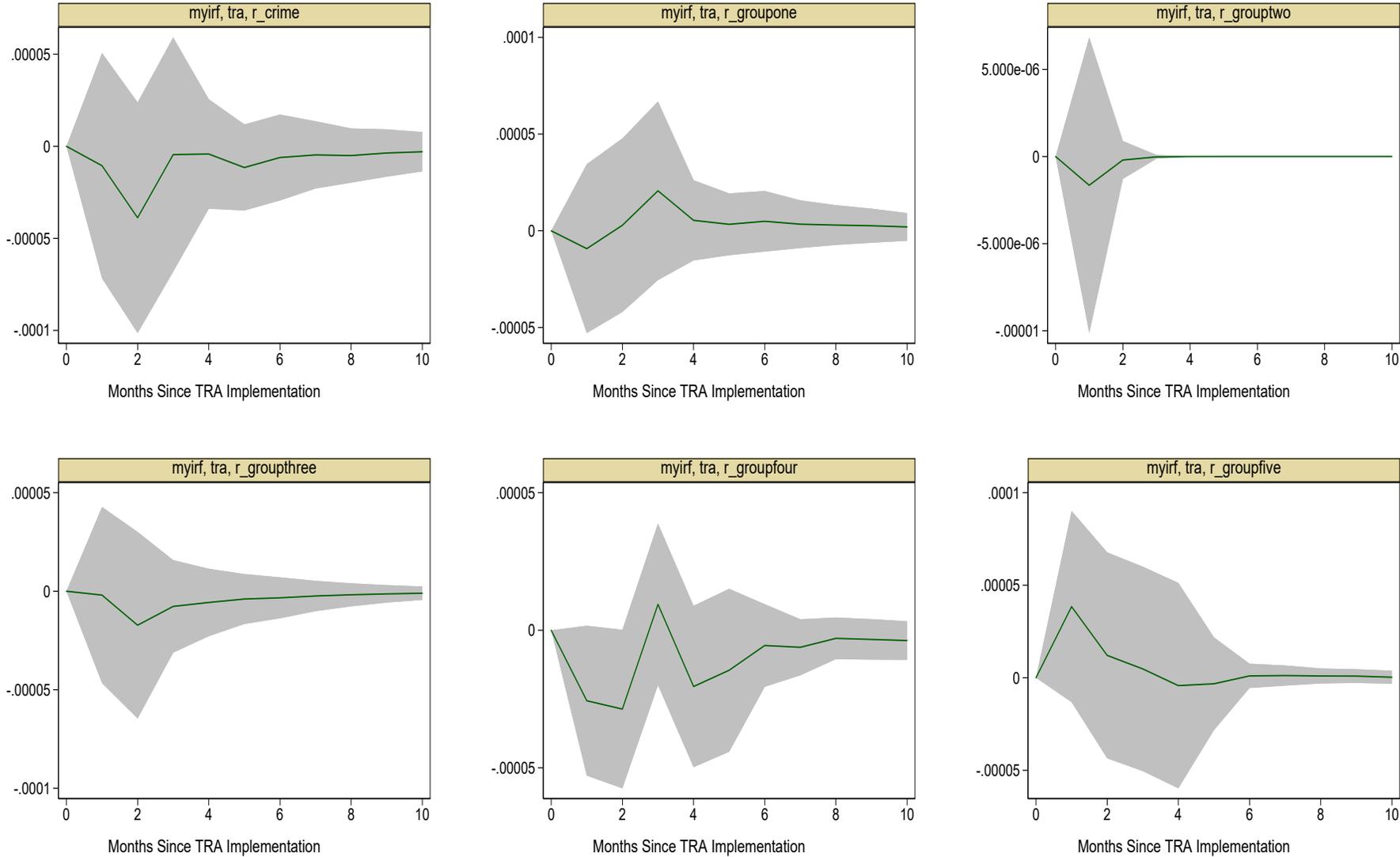
Figure 5. Crime Trends - Relative to 2011 Population



Notes: This figure shows trends for our six measures of crimes. We calculated mean crime rates at the month level for all Data Zones within the City of Glasgow.

While we allow for TRA implementation to be predicted by past values of crime and past implementation by mean of the second equation, our main focus is on the first equation, which tells us how crime rates respond to TRAs. We estimate the above model for the overall crime rate as well as for crime subcategories and select lag length based on information criteria. For instance, for the overall crime rate we have FPE and AIC, suggesting three lags, whilst HQIC and SBIC suggest two and one lag respectively. We therefore pick the number of lags suggested by the majority of information criteria. [Figure 6](#) plots the impulse response functions for all of our outcomes. For most of the crimes, we notice a small decrease up to two months after TRA implementation, followed by a reversion toward zero. None of these effects are, however, economically significant. For instance, the observed drop in crime following two months from the implementation is less than 0.05 cases per 1,000 inhabitants. Assuming no crime effects elsewhere, and considering that, according to our data, 2.73 percent of Glasgow's population lives within 400 metres of a TRA, our baseline crime effect of 3.22 crimes per 1,000 inhabitants for local areas would translate into roughly 0.09 cases per 1,000 inhabitants on the aggregate-level. The fact that we find aggregate-level crime effects that are generally lower than this could suggest spillover effects away from TRA areas or that the local crime reductions near TRAs are simply too small to lead to a noticeable city-wide effect. Regardless, we can conclude that while we find evidence of localised (negative) crime effects from TRAs, we find no evidence of a corresponding aggregate-level reduction in crime, and the general equilibrium effect of urban regeneration on crime seems to be a null one.

Figure 6. Impulse Response Function



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Notes: This figure shows impulse responses to TRA implementation of our six measures of crimes. These include overall crime (the top left panel) and five subcategories, from group 1 (violent crimes) to group 5 (other crimes, bottom right panel). We averaged crime rates at the month level and estimate six different Vector Autoregressive Models (VARs) between each single crime variable and a TRA dummy variable.

5 Conclusions

Urban regenerations involving large-scale demolitions of public housing estates have often been endorsed on account of their alleged crime-reducing outcomes. In this paper, we test this by examining the effects of recent urban regeneration projects on crime in the city of Glasgow, in Scotland. These projects – called Transformational Regeneration Areas (TRAs) – included the demolition of old public housing estates and their replacement with mixed-income housing, along with the redevelopment of surrounding public spaces. We match a rich panel data set of block-level crime numbers to the location of these projects, and exploit variation in both the timing of TRA implementation, and in proximity to these areas as a way to measure treatment intensity. We document a large, up to 33% reduction in crime in close vicinity (within 400 metres) of TRAs but these effects get smaller (and insignificant) as we move further away from TRA locations. We argue that the large reductions in crime within the immediate TRA locations are likely mechanical and driven by the fact that urban regeneration removed (or replaced) the physical setting where crime could take place. We further find reductions in neighbourhood deprivation following urban regeneration, but once again these findings are confined to immediate TRA locations, and are therefore likely driven by changes in neighbourhood composition as local housing units are replaced by mixed-income housing. Nonetheless such neighbourhood changes could act as a channel for local crime reductions as the incentives to engage in crime get weaker. Finally, we find no evidence of aggregate-level reductions in crime for the city of Glasgow, suggesting that the crime reducing effects of TRAs are confined to their immediate locations.

Our work carries a number of policy implications. While our study finds that any crime spillovers are generally offset by the large reduction experienced near the demolished estates, public authorities need to carefully contemplate the potential spillover and general equilibrium effects of these interventions. In other words, the fact that crime reducing

effects are so spatially concentrated to the TRA area implies that it is simply the setting for crime that changes, and general equilibrium effects (an overall reduction in crime) are limited. Simply put, we find no evidence that urban regeneration projects are successful in reducing crime at the aggregate (city-wide) level. Our findings can also advise urban planners on the benefits of mixed-income communities, as opposed to models facilitating segregation. These communities seem to be characterised by lower levels of deprivation compared to the ones they replaced across a variety of domains (crime, employment, health), but it is unclear whether it is long-term residents of these areas who enjoy these benefits or whether they accrue to (and are driven by) new residents.

Further areas remain for future research. First, one main limitation of this paper is that it does not provide insights on criminal behaviour. While we find some evidence of local crime reductions specific to certain types of crime, future research could focus on substitution effects between different criminal activities. Second, research can shed light on the mechanisms through which regeneration improves the lives of local residents, e.g. better housing conditions or peer effects within mixed-income communities. Finally, researchers could explore which other domains of deprivation are affected by regeneration, if any. Future work, potentially using micro data on residents, can investigate how these projects affect a wider range of outcomes such as public health, social cohesion, or neighbourhood segregation.

References

- Aliprantis, D. and Hartley, D. (2015), 'Blowing it up and knocking it down: The local and city-wide effects of demolishing high concentration public housing on crime', *Journal of Urban Economics* **88**, 67–81. [1](#), [3](#), [4](#), [12](#), [14](#), [20](#), [25](#)
- Atkinson, R. (2000), 'Measuring gentrification and displacement in Greater London', *Urban Studies* **37**(1), 149–165. [2](#)
- Black, J. and Roy, G. (2019), 'The economic contribution of Glasgow Housing Association', *Fraser of Allander Institute, University of Strathclyde* . [7](#)
- Blanco, H. and Neri, L. (2021), 'Knocking it down and mixing it up: The impact of public housing regenerations', *Working Paper* . [3](#), [5](#), [12](#), [17](#)
- Brown, L. N. (2009), 'Hope vi: An analysis to determine the hope vi program's influence on home sales', *Community Development* **40**(1), 54–63. [5](#)
- Bruhn, J. (2018), 'Crime and public housing: A general equilibrium analysis', *Available at SSRN 3064909* . [3](#), [4](#), [27](#)
- Butts, K. (2021), 'Difference-in-differences estimation with spatial spillovers', *arXiv preprint arXiv:2105.03737* . [3](#), [4](#), [14](#)
- Davies, R. (2019), *Extreme Economies: Survival, Failure, Future—Lessons from the World's Limits*, Random House. [2](#), [6](#)
- Gardner, J. (2021), 'Two-stage differences in differences', *Working Paper* . [3](#), [14](#), [16](#)
- Garnham, L. (2018), 'Exploring neighbourhood change'. [2](#), [6](#)
- GHS (2022), Glasgow local housing strategy 2017-2022 - housing change timeline, Technical report, Glasgow's Housing Strategy. [2](#), [6](#)

- Gibbons, S., Overman, H. and Sarvimäki, M. (2021), 'The local economic impacts of regeneration projects: Evidence from UK's single regeneration budget', *Journal of Urban Economics* **122**, 103315. [5](#)
- Hunter, J. and Tseloni, A. (2016), 'Equity, justice and the crime drop: The case of burglary in England and Wales', *Crime Science* **5**(1), 1–13. [1](#)
- Kearns, A. and Lawson, L. (2017), Living in new homes in Glasgow's regeneration areas: The experience of residents in the Pollokshaws and Sighthill Transformational Regeneration Areas, Technical report, Go Well Research and Learning Programme. [7](#), [8](#)
- Morenoff, J. D., Sampson, R. J. and Raudenbush, S. W. (2001), 'Neighborhood inequality, collective efficacy, and the spatial dynamics of urban violence', *Criminology* **39**(3), 517–558. [1](#)
- Neri, L. (2021), Moving opportunities: The impact of public housing regenerations on student achievement, Technical report, Working Paper. [5](#)
- Newman, O. (1972), *Defensible space*, Macmillan New York. [1](#), [3](#), [20](#)
- Newman, O. (1996), *Creating defensible space*, US Department of Housing and Urban Development, Office of Policy Development [1](#)
- OECD (2020), Social housing: A key part of past and future housing policy, Technical report, OECD. [2](#)
- Osborn, D. R. and Tseloni, A. (1998), 'The distribution of household property crimes', *Journal of Quantitative Criminology* **14**(3), 307–330. [1](#)
- Robertson, D. and Serpa, R. (2014), 'Social housing in Scotland', *Social Housing in Europe* pp. 43–59. [5](#)

- Roth, J., Sant'Anna, P. H., Bilinski, A. and Poe, J. (2022), 'What's trending in difference-in-differences? a synthesis of the recent econometrics literature', *arXiv preprint arXiv:2201.01194* . 14
- Sampson, R. J. and Raudenbush, S. W. (1999), 'Systematic social observation of public spaces: A new look at disorder in urban neighborhoods', *American Journal of Sociology* **105**(3), 603–651. 1
- Sandler, D. H. (2017), 'Externalities of public housing: The effect of public housing demolitions on local crime', *Regional Science and Urban Economics* **62**, 24–35. 3, 4, 12, 13, 22
- Tach, L. and Emory, A. D. (2017), 'Public housing redevelopment, neighborhood change, and the restructuring of urban inequality', *American Journal of Sociology* **123**(3), 686–739. 5
- Tseloni, A. (2006), 'Multilevel modelling of the number of property crimes: Household and area effects', *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **169**(2), 205–233. 1
- Tseloni, A. and Pease, K. (2015), 'Area and individual differences in personal crime victimization incidence: The role of individual, lifestyle/routine activities and contextual predictors', *International Review of Victimology* **21**(1), 3–29. 1
- Tseloni, A., Wittebrood, K., Farrell, G. and Pease, K. (2004), 'Burglary victimization in England and Wales, the United States and the Netherlands: A cross-national comparative test of routine activities and lifestyle theories', *British Journal of Criminology* **44**(1), 66–91. 1
- Turner, M. A., Woolley, M., Kingsley, G. T., Popkin, S. J., Levy, D. and Cove, E. (2007), 'Estimating the public costs and benefits of hope vi investments: Methodological report', *The Urban Institute* . 1

Zhang, M. L., Galster, G., Manley, D. and Pryce, G. (2021), 'The effects of social housing regeneration schemes on employment: The case of the Glasgow stock transfer', *Urban Studies* p. 00420980211047044. [5](#), [7](#)

Zielenbach, S. and Voith, R. (2010), 'Hope vi and neighborhood economic development: The importance of local market dynamics', *Cityscape* pp. 99–131. [5](#)

Appendix – For Online Publication

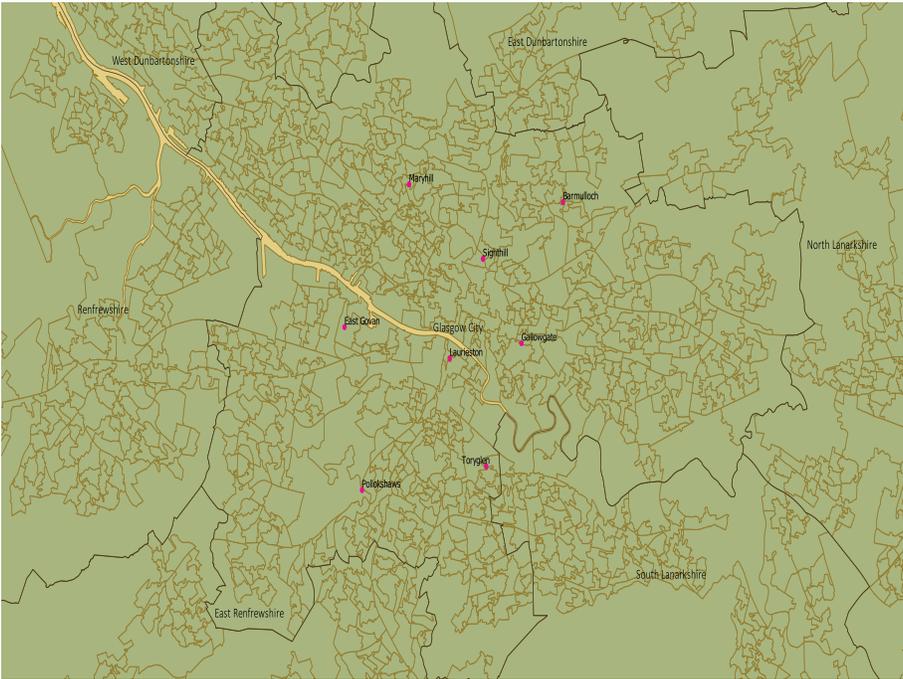
A Additional Tables and Figures

Table A.1. TRA Implementation Dates

TRA	Month	Year
Maryhill	1	2010
Pollokshaws	1	2012
East Govan	1	2013
Gallowgate	9	2013
Laurieston	11	2014
Sighthill	12	2015
Toryglen	1	2016
Barmulloch	1	2017

Notes: This table lists each Transformational Regeneration Area alongside the month and year of implementation.

Figure A.1. TRA Locations



Notes: This figure reports the exact location of all eight Transformational Regeneration Areas within the Glasgow City.

Table A.2. SIMD Domains Description

SIMD Domain	Components
Income	Income Deprivation Rate: Percentage of working age population in receipt of the main forms of means-tested benefits
Employment	Employment Deprivation Rate: Percentage of working age population who are not in employment and receive employment or disability-related benefits
Health	Comparative Illness Factor: standardised ratio ¹ Hospital stays related to alcohol misuse: standardised ratio ¹ Hospital stays related to drug misuse: standardised ratio ¹ Standardised mortality ratio ² Percentage of population being prescribed drugs for anxiety, depression or psychosis Percentage of live singleton births of low birth weight Emergency stays in hospital: standardised ratio ¹
Education, Skills and Training	School pupil attendance ³ Attainment of school leavers ⁴ Working age people with no qualifications: standardised ratio Percentage of people aged 16-19 not in full time education, employment or training Percentage of 17-21 year olds entering in to full time higher education
Access to Services	Average drive time to a petrol station in minutes Average drive time to a GP surgery in minutes Average drive time to a post office in minutes Average drive time to a primary school in minutes Average drive time to a retail centre in minutes Average drive time to a secondary school in minutes Average drive time to a secondary school in minutes Public transport travel time to a GP surgery in minutes Public transport travel time to a post office in minutes Public transport travel time to a retail centre in minutes Percentage of premises without access to superfast broadband (at least 30Mb/s download speed) ⁶
Crime	Crime Rate per 10,000 inhabitants
Housing	Percentage of people in households that are overcrowded Percentage of people in households without central heating

Notes: This table provides a breakdown of the Scottish Index of Multiple Deprivation (SIMD) domains. We use 2006, 2009, 2012, 2016 and 2020 editions. As base period controls we use income, employment, health, education, access to services and housing scores. For access to services, health and education, the scores are calculated by ranking the indicators, standardising them to a standard normal distribution and combining them using weights generated by Factor Analysis. Income and employment scores are simply their own rates as reported in the *Components* column. The housing score is the sum of its own components. **Source:** Scottish Index of Multiple Deprivation. © Crown copyright 2006, 2009, 2012, 2016 and 2020.

¹ This indicator is an indirectly age/sex standardised rate of episodes per person.

² This indicator is a directly age/sex standardised measure of mortality and morbidity.

³ Previously collected as *School Pupil Absence*

⁴ Previously collected as *Pupil Performance on SQA at Stage 4*.

⁵ This indicator is an indirectly age/sex standardised rate.

⁶ Only available in 2020.

Figure A.2. TRA Locations with Distance Rings



Notes: This figure reports the exact location of all eight Transformational Regeneration Areas within Glasgow City, alongside their buffer zones (rings). Each concentric circle around the TRA represents a ring with a 200m radius.

Table A.3. Crime Classifications

Crime and Office Group Name	Crime Description
Overall Crime Rate	Attempted Murder, Fireraising, Fraud, Housebreaking (houses and other premises), Murder, Possession of drugs, Other drugs offences (incl. importation), Possession of offensive weapon (incl. restriction), Robbery and assault with intent to rob, Theft by shoplifting, Theft from a Motor Vehicle, Insecure etc, Theft of a motor vehicle, Vandalism (incl. reckless damage, etc.), Other Group 1, 2, 3 and 5 crime.
Non-Sexual Crimes of Violence	Attempted Murder, Cruel & Unnatural treatment of children, Culpable Homicide, common law, Culpable Homicide, (others), Domestic Abuse (of female), Domestic Abuse (of male), Murder, Offensive weapon (used in other criminal activity), Possession of offensive weapon (incl. restriction), Robbery and assault with intent to rob, Reckless conduct (with firearms), Serious Assault (incl. culpable & reckless conduct - causing injury), Threatening and abusive behaviour, Other Group 1 Crime.
Sexual Crimes	All Group 2 crimes.
Crimes of dishonesty	Attempt theft of motor vehicle, Common Theft, Fraud, Failure to insure against third party risks, Housebreaking (houses and other premises), Theft by shoplifting, Theft of a motor vehicle, Threats and extortion, Other Group 3 crimes.
Fire-raising, vandalism	Culpable & reckless conduct (not firearms), Fireraising, Vandalism (incl. reckless damage, etc.).
Other Crimes	Bladed/pointed instrument (used in other criminal activity), Breach of the Peace, Carrying of knives/bladed instruments, Offensive weapon (used in other criminal activity), Other drugs offences (incl. importation), Possession of drugs, Production, manufacture or cultivation of drugs, Supply of drugs (incl. possession with intent), Possession of offensive weapon (incl. restriction), Other Group 4 and 5 crimes.
Offences	Dangerous driving, Driving Carelessly, Driving without a licence, Driving while disqualified, Drivers neglect of traffic directions (NOT pedestrian crossings), Speeding, Drink, Drug driving offences incl. Failure to provide a specimen, Other alcohol related offences, Minor Assault, Other Group 6 offences.

Notes: This table provides a breakdown of the six measures of crime used in this paper.