What’s Good in the Neighbourhood? Examining the Short Run Wellbeing Impacts of Urban Regeneration Using Administrative Data

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Abstract: New Zealand (NZ) faces substantial housing challenges including persistent housing shortages, rising housing costs, poor quality stock and overcrowding issues. Kāinga Ora is the primary government agency responsible for social housing and urban development in NZ. Since 2018, Kāinga Ora has built nearly 10,000 new homes, most of these being social housing, and plans to further increase the housing supply by 35,000 homes over the next 15 years. By developing or regenerating urban areas ("urban regeneration") that people live in, there is the potential to improve health and wider social outcomes in affected communities. However, given the substantial monetary investment into urban regeneration, there is little empirical evidence on the impact of urban regeneration on the wellbeing of affected communities and individuals in New Zealand. There is potential to use "big data" to derive data-driven evidence that supports Kāinga Ora's aim to enhance wellbeing through its housing-led initiatives.

This research evaluates the wellbeing impacts of urban regeneration using administrative data to assess the social return-on-investment of Kāinga Ora-led urban development. The Wellbeing Outcomes Framework developed in this study is guided by the NZ Treasury Living Standards Framework and the NZ Index of Multiple Deprivation. It is designed to measure population-wide wellbeing indicators using administrative data from Stats NZ's Integrated Data Infrastructure across three domains: (1) human capital – education and labour market; (2) physical and mental health and (3) crime and safety. Detailed housing intensification data from Kāinga Ora is used to measure urban regeneration in Auckland, New Zealand. The empirical strategy uses staggered difference-in-differences methods to causally estimate the impact of urban regeneration on wellbeing outcomes for residents living in regenerated areas, relative to those living in non-regenerated areas between 2018 to 2021.

The results broadly show no impact of urban regeneration on area-level wellbeing outcomes in the short run. While most outcomes were insignificant, there are stronger impacts found for residents living in high urban regeneration areas and social housing residents. Where significant, the impact of urban regeneration on health is mixed while the impact on crime is negative. As urban regeneration is still ongoing at the end of the analysis period, the short run impacts likely reflect negative impacts of ongoing disruption and possible displacement of residents during urban regeneration. However, these results serve as a useful starting point for policymakers to understand how individuals and communities are impacted by large housing-led policies that is guided by an empirical evidence base. Future analysis is needed to examine longer term impacts of urban regeneration once developments are complete. The Wellbeing Outcomes Framework developed in this study means longer-term wellbeing impacts of urban regeneration can be readily examined once more time has elapsed.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed,

Linda Kirkpatrick

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1 Introduction

New Zealand faces substantial housing challenges including persistent housing shortages, rising housing costs, poor quality stock and overcrowding issues (Cole, 2021; Kāinga Ora, 2022; Ministry of Housing and Urban Development, 2023). Kāinga Ora is the primary government agency responsible for the provision of social housing and urban development in New Zealand (Kāinga Ora, 2023). The agency is making significant investments towards increasing the housing supply and improving the quality of the existing housing stock in New Zealand. In 2021, the New Zealand government established the $3.8 billion dollar Housing Acceleration Fund – of this, $1.4 billion was allocated to building homes in large Auckland-based projects over the next ten years (Ministry of Housing and Urban Development, 2022). In 2022, Kāinga Ora invested $2.3 billion into upgrading and building new homes. Despite this large investment, there is little empirical evidence on the impact of urban regeneration on the wellbeing of affected communities and individuals in New Zealand. This thesis aims to fill this knowledge gap.

Since 2018, Kāinga Ora has built nearly 10,000 new homes with most of these being social housing (Kāinga Ora, 2023). It also plays a pivotal role in the Ministry of Housing and Urban Development's Public Housing Plan to increase the supply of social housing in New Zealand (Ministry of Housing and Urban Development, 2023). Of the 12,000 social housing being built under the Public Housing Plan, Kāinga Ora has delivered 70 to 80% of those dwellings.[1] Kāinga Ora has further plans to increase the housing supply by 35,000 homes over the next 15 years (Kāinga Ora, 2022, 2023). Of the 35,000 homes expected to be delivered, approximately half of these homes (17,800) will be in New Zealand's largest city, Auckland.

Kāinga Ora means "wellbeing through places and communities" (Kāinga Ora, 2023, p. 23). These urban development investments aim to improve wellbeing through the provision of affordable homes, shared community spaces and active transport options to support access to employment, amenities and services (Kāinga Ora, 2023). Urban planning characteristics such as housing development, noise, lighting, housing quality, access to nature and transport availability can play a crucial role in improving or deteriorating the quality of life for residents.

[1] The remaining dwellings are built by Māori-led organisations aimed at increasing housing supply for Māori, and by Community Housing Providers who are alternative providers of social housing for low-income households.

In New Zealand, housing intensification is the main policy tool used by Kāinga Ora to deliver its urban regeneration initiatives (Kāinga Ora, 2023). It involves redeveloping larger blocks of land, that usually consists of a single dwelling, into multi-unit dwellings such as apartments or units (Henry, Menzies, & Paul, 2019; Levin & Arthurson, 2020). By developing or regenerating urban areas ("urban regeneration") via housing intensification, there is the potential to improve health and wider social outcomes for individuals in affected communities. However, there is limited research evaluating the wellbeing impacts of housing intensification, and this is likely due to lack of appropriate data.

At this thesis will illustrate, there is potential to use "big data" to derive data-driven evidence that supports Kāinga Ora's aim to enhance wellbeing through its housing-led initiatives. This relies on wellbeing indicators being "collected with sufficient frequency, timeliness and granularity to meet the needs of policy makers" (OECD, 2019, p. 107). Therefore, the first aim of this research is to develop a robust framework that measures monthly population-wide wellbeing indicators using administrative data from the Integrated Data Infrastructure (IDI).

The IDI is administered by Stats NZ and houses a wide range of population-wide data collected from government organisations, as well as survey data. Individuals can be linked across different datasets within the IDI using unique individual-level confidential identifiers. Compared to survey data, administrative records are more consistently and accurately collected, updated regularly, cover almost the entire population over longer periods of time, and relatively more cost-effective to collect. While data is collected for administrative purposes (as opposed to research), administrative data is being increasingly used as a data source for scientific research due to several analytical advantages (Graeff & Baur, 2020; Künn, 2015).

In terms of measuring wellbeing outcomes, this research draws on the New Zealand Treasury's Living Standards Framework (LSF) and is supplemented by the New Zealand Index of Multiple Deprivation (IMD) (Exeter, Zhao, Crengle, Lee, & Browne, 2017; NZ Treasury, 2021). The LSF is a policy tool that can be used by government to understand the drivers of wellbeing for New Zealanders in a systematic and evidenced manner (NZ Treasury, 2021). Prior wellbeing analysis using the LSF has primarily been undertaken with survey information such as the General Social Survey, which is collected every two years, or the Household Labour Force Survey which is collected every quarter for 15,000 households. Data for these surveys are not frequently updated and available for only a small subset of the population. This restricts the scope for tracking wellbeing indicators at a more granular level. Current wellbeing data in the LSF is only as recent as the latest survey data, only available as often as the timing at which survey data is released and covers a subset of the population.

Previous empirical research shows positive associations between urban regeneration and wellbeing. However, these studies are mostly descriptive or qualitative in nature and offer limited longitudinal causal evidence related to the impact of urban regeneration on socio-economic and wellbeing outcomes. Further, most of the international literature examining wellbeing impacts of urban regeneration relies on survey data. Small sample sizes in these studies mean it is often not possible to understand how wellbeing outcomes are distributed among different subpopulations. Urban regeneration projects, especially those that involve housing intensification, tend to be large-scale developments for which wellbeing impacts are likely to be unevenly distributed among the population.

Thus, the second aim of this research is to use the current wellbeing frameworks in New Zealand (LSF and IMD) and extend them to create wellbeing indicators that can be derived at the population-wide level. This enables analysis of area-level initiatives, such as urban regeneration, using population-wide administrative data from the IDI. Detailed housing intensification data from Kāinga Ora is a key feature of the empirical strategy used in this research as it provides a measure of both presence and intensity of urban regeneration development. Housing intensification data, covering the period between 2018 and 2021, is used to identify which areas are undergoing urban regeneration ("treated areas") and when these developments begin. This data is then linked to individual-level residential address information in the IDI to identify those living in treated areas and those not living in treated areas ("control areas").

This research exploits the variation in timing of different urban regeneration projects across regenerated areas to estimate the wellbeing impacts of urban regeneration using staggered difference-in-differences modelling. The empirical analysis incorporates entropy balancing and propensity score matching methods to identify a comparable set of non-regenerated areas (individuals) as a control group for areas (individuals) undergoing urban regeneration. The use of administrative population-wide data allows for subpopulation analyses which have not been extensively explored in the literature. Results from these analyses can help explain differences in wellbeing outcomes and provide suggestive evidence as to what underlying mechanisms may be driving observed effects. For example, wellbeing outcomes may differ for areas with high levels of urban regeneration compared to those with low levels of regeneration. Thus, the empirical analysis in this research permits a clear knowledge contribution in terms of empirically assessing the social return-on-investment of housing intensification initiatives.

This study therefore contributes to the existing urban regeneration literature by addressing two research aims:

1. Developing a robust framework and method to measure population-wide wellbeing indicators using administrative data and,
2. Evaluating the short run wellbeing impacts of urban regeneration, specifically housing intensification, in New Zealand using the Wellbeing Outcomes Framework developed in this study.

This provides policymakers with a data-driven evidence base to guide current and future housing developments which can be updated more easily and frequently compared to the LSF. It is important to note that this research permits only short run impacts of urban regeneration to be evaluated as housing intensification data only began in 2018 and is available up until the end of 2021. However, one of the key purposes of this research is to create an evaluation framework which uses regularly collected administrative data such that long-term impacts can be readily examined in the future.

This thesis proceeds as follows. Section 2 provides background information on urban regeneration in New Zealand and reviews the existing literature related to wellbeing outcomes of urban regeneration. Section 3 describes the Living Standards Framework and the Index of Multiple Deprivation. Section 4 and 5 outlines the data and empirical methods used in this research. Sections 6 to 9 presents results related to first order effects, human capital, physical and mental health and crime and safety, respectively. Section 10 discusses these results and Section 11 concludes.

2 Literature Review

This section first describes urban regeneration and what it broadly encompasses. It then discusses urban regeneration, housing intensification, and social housing within the New Zealand context. The section reviews the domestic and international literature related to outcomes of urban regeneration, broadly organised into the following domains: human capital, physical and mental health and crime and safety. The section concludes with the current knowledge gaps in the relevant literature and describes how this research aims to address these gaps.

2.1 What is urban regeneration?

The physical environment in which people live can affect their health and wellbeing (Berglund, Westerling, & Lytsy, 2017; Olin et al., 2022). Urban planning characteristics such as housing development, noise levels, lighting, housing quality, access to nature and transport availability can play a crucial role in improving or deteriorating the quality of life for residents. By developing or regenerating urban areas ("urban regeneration") that people live in, there is the potential to improve health and wider social outcomes for individuals in affected communities.

Urban regeneration is a broad term that encompasses a range of government initiatives and policies such as:

- increasing the housing supply by building multi-unit dwellings on vacant land or replacing single dwellings with multi-unit dwellings (Henry et al., 2019; Levin & Arthurson, 2020);
- making physical improvements to neighbourhoods such as improving street lighting and road conditions (Bull, Hooper, Foster, & Giles-Corti, 2015; Egan et al., 2010);
- revitalising town centres and expanding retail opportunities (Batty et al., 2010; Mackay, Taylor, & Perkins, 2018; Perkins et al., 2019);
- renewing and improving old housing through refurbishments or improved heating (Egan, Lawson, Kearns, Conway, & Neary, 2015; Thomson, Thomas, Sellstrom, & Petticrew, 2009);
- redesigning urban spaces for walkability and cycling (Bull et al., 2015; Perkins et al., 2019);
- improving or building public transport and road infrastructure linkages near new developments (Berglund et al., 2017);
- creating public and green spaces such as playgrounds and parks (Bull et al., 2015);
- providing community interventions such as employment and training hubs and addiction support (Batty et al., 2010; Henry et al., 2019);

- engaging and empowering communities by involving them in consultations and decision-making related to urban regeneration (Baba, Kearns, McIntosh, Lewsey, & Tannahill, 2017; Heath, Rabinovich, & Barreto, 2017; Karaminejad, Vallance, & Montgomery, 2020).

Urban regeneration initiatives that develop the physical environment are known as “top down” approaches and typically involve government intervention to implement due to scale and cost (Egan et al., 2010). Alternatively, “bottom-up” initiatives involve the communities impacted by the urban regeneration process. These include hosting events to bolster community connection, providing employment and training hubs to help residents find work and helping navigate the displacement process for residents whose homes are set to be demolished (Corcoran, 2020; Egan et al., 2015; Heath et al., 2017; Henry et al., 2019).

2.2 Urban regeneration in New Zealand

New Zealand faces substantial housing challenges including persistent housing shortages, rising housing costs, poor quality stock and overcrowding issues (Cole, 2021; Howden-Chapman et al., 2021; Kāinga Ora, 2022; Ministry of Housing and Urban Development, 2023; O’Sullivan, Olin, Pierse, & Howden-Chapman, 2023). Addressing these policy challenges requires large-scale urban development that increases housing supply, affordability and quality. Housing intensification is the main policy tool used in New Zealand for implementing urban regeneration initiatives to meet these challenges.

2.2.1 Kāinga Ora and housing intensification

Kāinga Ora is the primary government agency responsible for the provision of social housing and urban development in New Zealand (Kāinga Ora, 2023). It serves two main roles: 1) to provide and manage social housing and 2) to plan, coordinate and undertake government-led urban development. Kāinga Ora means “wellbeing through places and communities” (Kāinga Ora, 2023, p. 23). These urban development investments aim to improve wellbeing through the provision of affordable homes, shared community spaces and active transport options to support access to employment, amenities and services (Kāinga Ora, 2023). By developing or regenerating urban areas (“urban regeneration”) that people live in, there is the potential to improve health and wider social outcomes in affected communities.

Kāinga Ora plays a pivotal role in the Ministry of Housing and Urban Development's Public Housing Plan to increase the supply of social housing in New Zealand (Ministry of Housing and Urban Development, 2023). Of the overall 12,000 social housing built under the Public Housing Plan, Kāinga Ora has delivered 70 to 80% of those dwellings.[2] As such, the bulk of Kāinga Ora's work programme is focused on increasing both the social and private housing stock through housing intensification. Housing intensification involves redeveloping larger blocks of land, that may have consisted of a single dwelling, into multi-unit dwellings such as apartments or units (Henry et al., 2019; Levin & Arthurson, 2020). Housing intensification increases the housing supply in large urban areas that are typically closer to amenities and public transport while also limiting urban sprawl (Allen, Haarhoff, Beattie, & McKay, 2018; Badland et al., 2017; Haarhoff, Beattie, Dupuis, & Derudder, 2016; O'Sullivan et al., 2023; Olin et al., 2022; Opit, Witten, & Kearns, 2019).

The agency is making significant investments towards increasing the housing supply and improving the quality of the existing housing stock in New Zealand. Since 2018, Kāinga Ora has built nearly 10,000 new homes, most of which are social housing (Kāinga Ora, 2023). Kāinga Ora plans to further increase the housing supply by 35,000 homes over the next 15 years (Kāinga Ora, 2022, 2023). Half of these homes (17,800) will be in Auckland, New Zealand's largest city. In 2021, the New Zealand government established the $3.8 billion dollar Housing Acceleration Fund – of this, $1.4 billion was allocated to build homes in large Auckland-based projects over the next ten years (Ministry of Housing and Urban Development, 2022). In 2022, Kāinga Ora invested $2.2 billion into building new homes as part of its urban regeneration initiatives (Kāinga Ora, 2023).

Kāinga Ora increases the housing supply through:

- Redevelopment – Kāinga Ora owns a piece of land that may have existing housing stock. These houses may be demolished or relocated elsewhere to allow for new properties to be built.
- New builds – new houses are built by private developers. Kāinga Ora then purchases these from the developers.
- Buy-ins – existing houses and/or land is purchased by Kāinga Ora. These may be updated or renovated.
- Land acquisition – empty land is purchased by Kāinga Ora and used to build new properties.

[2] The remaining dwellings are built by Māori-led organisations aimed at increasing housing supply for Māori and by Community Housing Providers who are alternative providers of social housing for low-income households.

2.2.2 Neighbourhood improvements and community wellbeing

Other urban planning characteristics such as noise, lighting, housing quality, access to nature and transport availability can play a crucial role in improving or deteriorating the quality of life for residents. While Kāinga Ora primarily focuses on housing intensification in its urban regeneration efforts, it also aims to create “sustainable, inclusive and thriving communities that provide people with good-quality, affordable housing choices that meet diverse needs; support access to jobs, amenities and services; and otherwise sustain or enhance the overall community and wellbeing of current and future generations” (Kāinga Ora, 2023, p. 23). To give effect to this aim, Kāinga Ora uses several top-down and bottom-up interventions to improve wellbeing not only for residents of new developments, but the overall neighbourhood where these developments are built. Improvements to the wider neighbourhood include neighbourhood infrastructure, better lighting, new green and public spaces and improved transport linkages.

For example, Kāinga Ora has developed major urban Auckland suburbs, such as Roskill South and Tāmaki, and partnered with regional water and transport agencies to help plan, fund and deliver infrastructure to support growth in these neighbourhoods. These infrastructure projects benefit not only Kāinga Ora residents but all residents living in these communities. Since these areas are often already higher-density suburbs prior to regeneration, additional housing development can place pressures on existing infrastructure, including transport, water, and flood management systems. As part of its urban regeneration initiatives, Kāinga Ora invested in improving flood protection for both newly developed homes and the entire neighbourhood (Kāinga Ora, 2023). For example, in Roskill South, the Freeland Reserve was completed as a nature-based solution for stormwater treatment and mitigation.

Kāinga Ora's top-down urban regeneration initiatives also include increasing tree cover in neighbourhoods to boost greenery and reduce heat impacts, installing solar panels, retrofitting older homes to meet heating and drying standards, and making homes more accessible for people with disabilities (Kāinga Ora, 2023). Additionally, Kāinga Ora implements various bottom-up, community-led initiatives (Kāinga Ora, 2023). These initiatives include engaging with communities where developments occur, providing employment and training hubs to help residents find jobs, sending out community teams to engage with local residents, and organising and funding community events. By combining both approaches, Kāinga Ora aims to improve wellbeing through warm, stable housing and meaningful community connections.

In New Zealand, several urban regeneration projects have focused on both developing the physical environment and involving communities throughout the development process. For example, an urban regeneration project in Christchurch was initially focused on renewing existing houses (Karaminejad et al., 2020). Project managers took a holistic approach by actively engaging with community residents to understand their concerns about the existing housing stock, including safety issues with public facilities, tenancy management, and the physical condition of homes. While the primary goal was to renew housing, these concerns were incorporated into project plans, ensuring that needs and perspectives of local residents were considered throughout the process.

Similarly, an urban regeneration project in Glen Innes, Auckland was focused on housing intensification (Henry et al., 2019). During this process, local residents were displaced as older homes were demolished to make way for new developments. Project managers worked with the community to address the uncertainty and challenges of displacement and help residents navigate these changes. Community interventions, such as employment hubs and community engagement events, helped upskill residents to increase their employability and maintain social cohesion during redevelopment.

2.2.3 A brief history of social housing in New Zealand

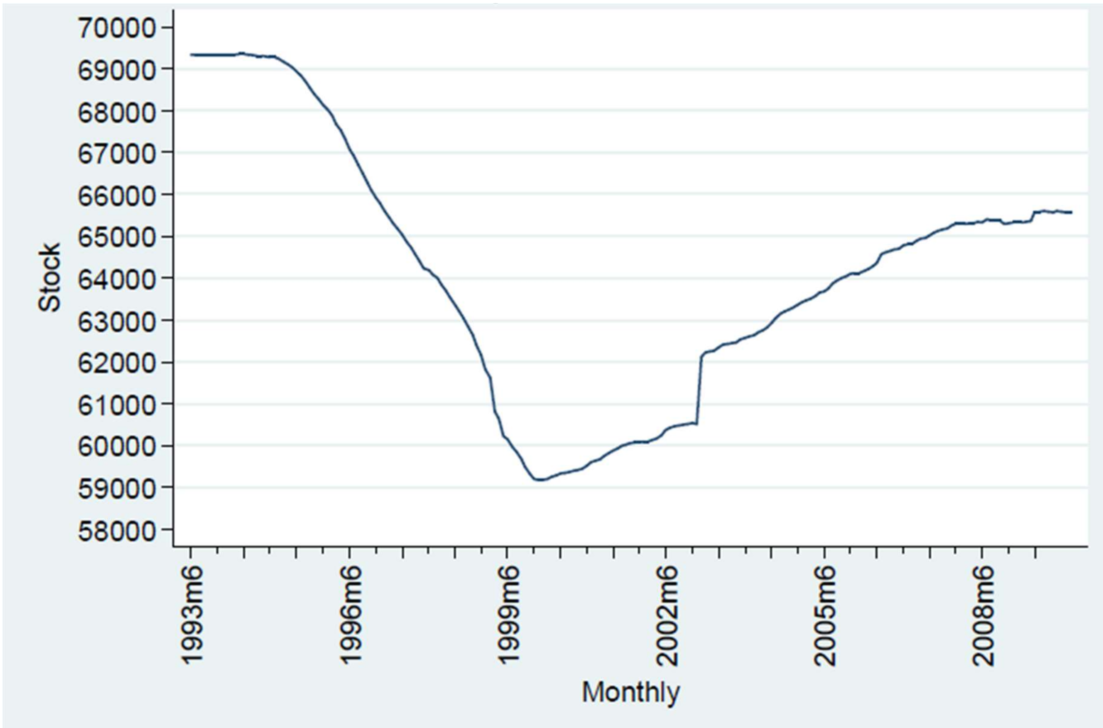
Social housing is primarily provided by the government as a means for secure and affordable housing for high-need households (Cole, 2021; Olssen, McDonald, Grimes, & Stillman, 2010). Early forms of social housing has existed in New Zealand as early as 1905 (Olssen et al., 2010). This was formalised in 1935 where the first Labour government announced they would build 5,000 social housing dwellings with rents typically tied to household income. By 1950, over 30,000 homes had been built, though the waiting list for social housing continued to grow, with 45,000 households on the waitlist.

Significant reforms took place in the 1990s, during which the government sold off much of its social housing stock and shifted to market-based rents, contributing to a substantial reduction in social housing availability. Homes were sold either to social housing tenants who could afford market prices, through real estate channels, or to non-priority applicants. This period saw a sharp decline in social housing as illustrated in Figure 1.

In the early 2000s, reforms under a new government stopped social housing sales and reintroduced income-based rents. A needs-based allocation system was also implemented to prioritise those most in need of housing. The social housing stock in New Zealand somewhat recovered in the 2000s – however, Figure 1 shows this did not recover to levels prior to the large 1990s institutional reforms.

Over the years, the management of New Zealand's social housing has shifted with changing political ideologies, reflecting ongoing debates over the best way to address housing shortages and the needs of low-income households (Cole, 2021; Olssen et al., 2010).

Figure 1 Monthly stock of social housing in New Zealand between 1993 and 2009



Source: From "A State Housing Database: 1993 - 2009," by Olssen et al. (2010). Retrieved from https://www.motu.nz/our-research/urban-and-regional/housing/a-state-housing-database-1993-2009/

2.2.4 The current supply and demand of social housing in New Zealand

Kāinga Ora plays a critical role in providing and maintaining social housing in New Zealand, managing a portfolio of 72,000 social housing dwellings to accommodate 185,000 residents (Kāinga Ora, 2023). The current social housing stock is only slightly higher than that in 1993 before reforms took place. However, there is a growing need for social housing and the demand for social housing outstrips the supply. As of March 2024, there were 25,380 applicants who were eligible but had not yet been placed into social housing (Ministry of Social Development, 2024).

The Social Allocation System determines the priority of social housing applicants based on five key criteria (Ministry of Social Development, 2022). These are rated from one (lowest need) to four (highest need):

- **Adequacy** – not living in any accommodation, or living in emergency accommodation, lack of basic facilities, overcrowding or lack of secure tenancy of current accommodation.
- **Suitability** – medical, disability or personal needs, family or other violence or neighbourhood tension.
- **Affordability** – ability to afford alternative, suitable housing in the private market.
- **Accessibility** – ability to access and afford suitable housing due to discrimination or financial means.
- **Sustainability** – difficulties in financial management, social functioning or lack of social skills.

Applicants scoring high in these criteria are assigned a priority rating. Priority A applicants, those with the most severe needs, make up over 90% of the current waitlist (Ministry of Social Development, 2024; Work and Income New Zealand, 2024). Only those classified as Priority A or Priority B are eligible for placement into social housing. The social housing waitlist data shows nearly half the applications are from individuals who are single and aged 25 or older, accounting for 12,387 applicants. The second-largest group consists of single parents with children, representing 33.3% of the waitlist (8,451 applicants). With respects to ethnicity, almost half the applicants are Māori (12,603 applicants), while European applicants make up 36.5% of the list (9,264 applicants).

Based on the Social Allocation System, applicants eligible for social housing in New Zealand tend to be homeless or at risk of homelessness, vulnerable and low-income. If applicants are unable to secure social housing, they are typically forced into the private rental market, which presents additional hardships. Private rentals in New Zealand are generally more expensive than social housing, often of poorer quality, damp, and cold compared to owner-occupied homes (Cole, 2021; Howden-Chapman et al., 2021). Moreover, these rentals do not offer the same housing stability as social housing, exacerbating the housing crisis for high-need households.

The shortage of social housing, combined with the poor quality of rental housing, can worsen existing inequalities. Inadequate housing conditions, such as damp and cold dwellings, have been linked to respiratory issues, and other health problems, which disproportionately affects vulnerable populations such as low-income families and Māori. Without access to stable and affordable social housing, these groups face greater risks of deteriorating health and deepening socioeconomic inequities.

Kāinga Ora-led urban regeneration can help alleviate these inequities by increasing social housing, providing housing stability, maintaining community connections and improving living environments. Neighbourhood improvements can also benefit non-social housing residents by improving public transport linkages, green spaces and neighbourhood amenities.

However, social housing developments are often met with resistance and backlash from local communities. Drivers for these sentiments include fear of antisocial behaviour from social housing tenants, the potential for neighbourhoods to be devalued from high concentration of social housing developments and increased crime rates (Cole, 2021; Kāinga Ora, 2021; Olssen et al., 2010; Saville-Smith, Saville-Smith, & James, 2015). Additionally, debates persist around the optimal balance of social and non-social housing, with some arguing that an overconcentration of social housing could lead to stigmatisation (Chisholm, Robertson, Howden-Chapman, & Pierse, 2022; Saville-Smith et al., 2015).

2.3 Outcomes of urban regeneration: a brief review

The literature review examines outcomes of housing intensification and urban regeneration, particularly focusing on health impacts and broader social outcomes such as human capital and crime. As housing intensification tends to increase the population density of neighbourhoods, this can correspond to increasing demand for improvements in neighbourhood amenities, aesthetics and transport infrastructure to accommodate the needs of growing communities (Allen et al., 2018; Badland et al., 2017; Giles-Corti, Ryan, & Foster, 2012; McCrea & Walters, 2012; Olin et al., 2022). Thus, the literature review focuses on outcomes related to housing intensification, neighbourhood improvements and increased density.

There is limited research in New Zealand that specifically examines the socioeconomic and wellbeing outcomes of urban regeneration. Much of the existing literature focuses on housing improvements and the liveability of medium to high-density housing, rather than the impact of large-scale urban development on broader socioeconomic outcomes. Therefore, the literature review draws on international studies from countries like Australia and the United Kingdom, which have similar policy settings to New Zealand. Outcomes of urban regeneration are broadly categorised into the following subsections: (1) human capital outcomes including labour market and educational attainment, (2) physical and mental health and (3) crime and safety.

There are studies on "neighbourhood quality", which relate to gentrification, which provide insight into how exposure to different population compositions can influence socioeconomic outcomes. For example, research by Chyn and Katz (2021) and Chetty, Hendren, and Katz (2016) show children who move to lower-poverty neighbourhoods experience better long-term outcomes, such as higher future earnings and educational attainment. Similarly, Brummet and Reed (2019) found that living near highly educated residents positively influenced children's future labour market outcomes. However, Almagro, Chyn, and Stuart (2023) found low-income households were worse off with respects to welfare when residential compositions and housing market conditions changed after public housing demolition.

Although there is overlap between research on neighbourhood quality and urban regeneration, the former primarily examines changes in population composition following urban development, while the latter examines the impact of physical improvements and community-led initiatives on neighbourhood outcomes. Therefore, the thesis acknowledges but does not focus on the neighbourhood quality literature.

2.3.1 Literature search strategy

This thesis undertook both a traditional and scoping literature review to 1) identify and review relevant studies that examined wellbeing impacts of urban regeneration and 2) identify the data sources and methodological approaches used in relevant studies.

The literature search was conducted using electronic resources available through the Auckland University of Technology Library & Learning Services. This provided access to a range of academic databases such as Scopus, JSTOR and Google Scholar from which peer-reviewed journal articles and reports were collected. EndNote 20 was used to store, categorise and manage articles and citations.

The search strategy combined terms related to urban regeneration and wellbeing outcomes. Related terms for urban regeneration included: urban renewal, urban revitalisation, housing renewal, urbanisation, urban redevelopment, housing intensification, housing renewal, neighbourhood renewal. Related terms for wellbeing outcomes included: qualify of life, socioeconomic, human capital, education, labour market, employment, physical health, general health, mental health, hospitalisations, crime, accidents, injuries and safety. Boolean operators (AND, OR) were used to refine searches. Searches were conducted in ‘Title’, ‘Abstract’ and ‘Keywords’ fields to identify relevant literature.

Studies were initially screened based on their titles and abstracts. The following criteria were applied for inclusion: countries who shared similar policy settings to New Zealand such as Canada, Australia and the United Kingdom, published in English, peer-reviewed journal articles and government reports, empirical studies with qualitative or quantitative analysis, published from 2006 onwards and focused on neighbourhood or housing developments. As noted previously, studies related to neighbourhood quality and gentrification were noted but not included in the literature.

2.3.2 Urban regeneration literature in New Zealand

Recent New Zealand studies have explored the impacts of urban regeneration developments on individuals and communities. The case studies described in Section 2.2.2 from Henry et al. (2019) and Karaminejad et al. (2020) highlight the importance of implementing both physical and community-led urban regeneration initiatives to provide beneficial outcomes for the local community. In contrast, Mackay et al. (2018) explored urban regeneration in Oamaru, which focused more on revitalising cultural heritage sites and boosting retail and tourism rather than housing. Boarin, Besen, and Haarhoff (2018) provide a framework for how New Zealand could evaluate urban regeneration developments with metrics involving sustainability and neighbourhood liveability.

A common thread in the New Zealand literature is the relationship between liveability and urban regeneration. Studies by Allen et al. (2018), Haarhoff et al. (2016) and Opit et al. (2019) interviewed residents and found increased housing density was often associated with improved local amenities, better public transport, and reduced car dependency which can enhance the liveability of regenerated neighbourhoods. Residents in Auckland areas such as Albany, New Lynn, and Onehunga cited benefits such as improved walkability and access to amenities as key factors for choosing medium-density housing over low-density options. Conversely, Yeoman and Akehurst (2015) surveyed Auckland residents and found low preferences for housing typologies that encouraged medium to high density dwellings.

Additionally, other New Zealand studies examined health and safety outcomes associated with housing improvements, which are closely related to urban regeneration initiatives as they aim to enhance residents' health and safety through housing improvements (Howden-Chapman et al., 2021; Howden-Chapman et al., 2008; Keall et al., 2015; Keall et al., 2021; O'Sullivan et al., 2023). For example, Howden-Chapman et al. (2008) found non-polluting home heating reduced respiratory symptoms for children, their likelihood to take days off school and their healthcare utilisation. Studies by Keall et al. (2015) and Keall et al. (2021) examined housing improvements and physical safety in New Zealand, which are discussed in further detail in Section 2.3.5.

2.3.3 Urban regeneration and human capital outcomes

Urban regeneration can impact human capital outcomes such as educational attainment and labour market characteristics. Housing intensification within regenerated urban areas which tend to place residents closer to amenities, public transport, schools, and employment hubs, which can improve school attendance and labour force participation (Bull et al., 2015).

Community-led regeneration initiatives such as employment and training hubs can provide better employment opportunities for residents and reduce their reliance on government financial assistance (Batty et al., 2010). Urban regeneration initiatives aimed at subsiding investment into local small businesses may provide local employment opportunities for residents (Gibbons, Overman, & Sarvimäki, 2021). Teaching and tutoring services have the potential to raise students' test scores and encourage students to go on to participate in and achieve higher qualifications (Batty et al., 2010).

Education outcomes

Batty et al. (2010) conducted an in-depth evaluation of a large-scale urban regeneration programme in England that aimed to improve 39 historically deprived neighbourhoods. The evaluation primarily focused on the impact of housing-led initiatives on human capital outcomes between 2002 and 2008. Key aspects of this programme included building new housing, improving existing homes, and implementing community-led initiatives such as career and training hubs and tutoring services for students. Data for outcomes were sourced from a household survey.

The programme's impact on educational outcomes showed promising results when compared to the national average over the six-year period. Students' test scores improved by 18 percentage points, the share of individuals without any qualifications decreased by 5-percentage points, and participation in education and training increased by 2-percentage points. When compared to similarly deprived but non-regenerated areas, regenerated areas had higher participation in education and training, and a lower proportion of people without qualifications. However, regenerated neighbourhoods had lower average student test scores compared to non-regenerated areas.

Thomson, Atkinson, Petticrew, and Kearns (2006) conducted a systematic review that analysed 19 evaluations of urban regeneration projects in the United Kingdom. The urban regeneration projects reviewed ranged from top-down, housing-led initiatives to more community-focused, bottom-up approaches such as career and training hubs. The review found mixed results regarding educational outcomes; some studies reported positive effects, while others found negative or negligible changes in educational attainment following regeneration efforts. Even where improvements in educational attainment were found, they were often not significantly different from the national average. This made it challenging to definitively attribute educational improvements to urban regeneration, as changes in broader education policy may have played a role.

Thomson et al. (2009) conducted a systematic review examining the association between housing improvements from international urban regeneration projects and the impact on health and human capital outcomes. Their review focused specifically on existing residents, as area-level outcomes of urban regeneration may reflect characteristics of new residents rather than improvements for existing residents. One specific area of their analysis was school absences, which is likely to be correlated with secondary school attainment rates. After reviewing various studies (excluding those deemed low quality), the authors found no significant difference in school absenteeism between groups that had received housing improvements and those that had not.

Labour market outcomes

Batty et al. (2010) examined the impact of urban regeneration initiatives such as community-based career and training hubs on labour market participation. Their findings indicated a 3-percentage point increase in employment rates in regenerated neighbourhoods compared to the national average. However, they also observed a 2-percentage point increase in benefit receipt, which suggests that while some residents found employment, others still had to rely on government support. When compared with non-regenerated areas that were similarly deprived, the authors reported higher employment rates in regenerated neighbourhoods.

In contrast, Thomson et al. (2006) found mixed impacts regarding housing-led urban regeneration and its effects on employment rates and household income in their review of urban regeneration evaluations. The authors concluded it was uncertain if urban regeneration had significant impacts on human capital outcomes.

Berglund et al. (2017) conducted a study using Swedish survey data to explore the effects of different housing typologies on various human capital, health, and safety outcomes. They compared residents living in high-density housing—such as condominiums and apartments—to those in low-density private houses. The study controlled for demographic factors including age, gender, financial status, and social support. The findings showed that residents in high-density housing experienced a higher frequency of work incapacity days compared to their counterparts in low-density housing. Theirs findings suggest that living in denser environments may be associated with increased health-related work absences.

In a separate study, Gibbons et al. (2021) focused on an urban regeneration initiative which invested in commercial infrastructure in deprived neighbourhoods in the United Kingdom. This initiative aimed to lower barriers to establishing and growing small businesses, thereby creating local employment opportunities. By utilising detailed microdata on business activity and demographic information from Census data, the authors assessed changes in local employment in areas that received investment. However, the results indicated that urban regeneration investments did not significantly impact local employment rates.

2.3.4 Urban regeneration and physical and mental health outcomes

The association between the built environment, particularly in high-density neighbourhoods, and health is well-researched (Bond et al., 2012; Bull et al., 2015; Egan et al., 2010; Giles-Corti et al., 2012; A Kearns, Tannahill, & Bond, 2009; Owen, Humpel, Leslie, Bauman, & Sallis, 2004). The quality of residential environments, including both the home and surrounding neighbourhood, can impact people's physical and mental health (Batty et al., 2010; Egan et al., 2013; Egan et al., 2015; Giles-Corti et al., 2012; Thomson, Thomas, Sellstrom, & Petticrew, 2013). Warm and well-insulated homes can reduce respiratory illnesses (Barton et al., 2007; Egan et al., 2015; Thomson et al., 2009, 2013). Living in better quality homes can also reduce work-limiting illnesses (Batty et al., 2010).

Building green spaces can promote physical activity while proximity to local amenities can encourage walking, cycling and public transport use (Bull et al., 2015; Giles-Corti et al., 2012). High-density dwellings that are well connected to amenities can promote both physical activity and access to healthier food options such as fresh fruit and vegetables (Bull et al., 2015; Giles-Corti et al., 2012). Community-based approaches like providing drug and alcohol addiction services, improving access to healthcare and actively engaging communities in the urban regeneration process can improve both the physical and mental health of residents (Baba et al., 2017; Batty et al., 2010).

General/physical health

The Glasgow Community Health and Wellbeing (GoWell) Research and Learning Programme, developed by Egan et al. (2010), aimed to evaluate the health and wellbeing impacts of large urban regeneration projects in Glasgow, Scotland. The study focused on various aspects of urban regeneration, particularly housing-led interventions, which included the construction of new social and private housing as well as improvements to existing social housing.

In addition to housing, the GoWell programme focused on developing the physical neighbourhood environment, local amenities, and services. Community-led initiatives were also a significant component of the programme, targeting a wide array of needs through employment and training hubs, support services for vulnerable populations, addiction recovery programs, and assistance for elderly residents. Data for the GoWell Programme was collected through interview, cross-sectional and longitudinal survey data to evaluate the effects of urban regeneration on a broad range of environmental, social, economic and health outcomes.

Egan et al. (2013) examined the impact of demolition on the health of households in GoWell regenerated areas. Households were categorised into three groups: those experiencing ongoing demolition as part of urban regeneration, those receiving home improvements, and those who received no improvements. The authors hypothesized that residents in areas undergoing demolition might face poorer health outcomes due to the uncertainties associated with the regeneration process, such as potential disruption and the destruction of local communities. Their findings indicated no significant difference in health outcomes between areas undergoing demolition and those not facing demolition.

In another study, Egan et al. (2015) conducted interviews with residents who had been relocated from homes that were demolished as part of the GoWell urban regeneration initiative. The residents moved into nearby neighbourhoods, with some occupying newly built homes and others moving into older refurbished houses. Through qualitative thematic analysis, the authors explored residents' feelings regarding their relocation experiences. They found that residents who moved into newly built homes appreciated the improved kitchens, which encouraged them to engage in more home cooking, potentially leading to healthier dietary choices. However, those who relocated to older refurbished homes did not report any significant improvements in their physical health.

In their evaluation, Batty et al. (2010) examined the physical and mental health outcomes of residents in regenerated communities in England during and after urban regeneration initiatives.[3] Several urban regeneration initiatives were aimed at improving physical and mental health which included improving access and quality of services of local health facilities, community-based approaches such as smoking, drug and alcohol cessation services, providing winter warmth for low-income households, programmes for childhood obesity, food co-ops and mental health support for those facing difficulties getting into the labour force.

The findings from the study found that between 2002 and 2008, residents in regenerated communities experienced a 4-percentage point increase in self-reported physical health status, a 1-percentage point decrease in the rate of work-limiting illnesses, and 1 percentage point increase in satisfaction with primary care providers. Similar improvements in physical health status were observed when comparing outcomes from regenerated neighbourhoods to the national average. When comparing to similarly deprived neighbourhoods that had not undergone regeneration, self-reported physical health status in regenerated areas improved by 1 percentage point, although satisfaction with primary care providers was lower. The authors noted no significant differences in the rates of work-limiting illnesses between the two groups.

[3] See Section 2.3.2 for more details on the evaluation conducted by Batty et al. (2010) on regenerated neighbourhoods.

Mohan, Longo, and Kee (2017) conducted a study to assess the impact of urban regeneration in Northern Ireland on various health indicators for highly deprived neighbourhoods, using a difference-in-differences modelling approach. The authors used survey data from the British Household Panel Survey (2001–2008) and the Understanding Society (2009–2012) Survey which provided longitudinal information on respondents over twelve years. Urban regeneration initiatives included physical improvements and community-led interventions such as promoting physical activity, providing nutrition information, assisting with food poverty and providing services for mental health, suicide and drug and alcohol awareness and smoking cessation.

In their analysis, the authors controlled for various demographic characteristics, such as age, gender, education, employment status, and household income. They compared health outcomes of respondents in regenerated areas (the treatment group) to those in non-regenerated areas (the control group). The study found no significant differences in self-reported health status or other health indicators between treated respondents in regenerated areas and untreated respondents in non-regenerated areas. The authors concluded that urban regeneration did not result in improved health outcomes for individuals in regenerated areas compared to those in control areas. However, they noted that urban regeneration initiatives might have helped prevent the widening of health inequalities between the two groups.

Badland et al. (2017) investigated the relationship between dwelling density and self-reported health outcomes in Australia using data from the 2011 VicHealth Indicators Survey. The study incorporated explanatory and outcome variables derived from the survey, while administrative geospatial data from the Census was used to calculate dwelling density. Dwelling density was defined as the number of residential dwellings in metropolitan and urban areas divided by the size of each Statistical Area 1 (SA1).[4] The authors categorised dwelling density into four quartiles, ranging from the lowest to the highest density, and employed logistic regression models to analyse self-rated health across these quartiles. The model controlled for various demographic factors including sex, age, employment status, household income, and household composition.

[4] SA1 = Statistical Area 1 which is a geospatial unit that contains approximately 400 individuals and constitutes as a neighbourhood in the author's study. Note that this is the size of Australian SA1s which differs to NZ SA1s which are approximately 100-200 individuals.

The authors initially hypothesized that higher dwelling densities could encourage healthy behaviours, such as increased walking for transport, thereby reducing cardiovascular disease mortality and minimising the risk associated with pedestrian traffic. However, the findings showed medium-density SA1s (dwelling densities between 10 and 16 dwellings per hectare) reported poorer self-reported health outcomes compared to the lowest density SA1s. No significant differences in self-reported health outcomes were observed between the lowest and highest density SA1s. The authors noted that while higher dwelling densities can encourage healthy behaviours, they are also linked to increased exposure to air and noise pollution, which may adversely affect mental health.

Respiratory illnesses

Egan et al. (2015) used GoWell Survey data to examine the association between residents moving into newly built homes and their respiratory health outcomes. Prior to their relocation, residents felt their homes were damp and cold, which contributed to respiratory issues such as asthma and pneumonia. Following their move to into newly built homes, residents noted improvements in respiratory-related symptoms, suggesting a positive impact of housing quality on health.

Barton et al. (2007) conducted a randomised trial to assess the effects of housing improvements on respiratory health. The study found homes that underwent improvements reported better respiratory health three years post-intervention compared to those that did not receive any improvements. This aligns with the findings of Thomson et al. (2009) who conducted a literature review focused on the health impacts of housing improvements, particularly in terms of warmth and insulation. Their review indicated that residents who received housing improvements experienced better respiratory health compared to those who did not receive housing improvements.

The evaluation conducted by Batty et al. (2010) showed community-based urban regeneration initiatives of smoking, drug, and alcohol cessation services were effective in reducing smoking rates within regenerated communities. Between 2002 and 2008, these communities experienced a 5-percentage point decrease in smoking rates, which was also evident when comparing to the national average. Additionally, smoking rates in regenerated neighbourhoods decreased by 2 percentage points relative to similarly deprived areas that did not undergo urban regeneration. However, Mohan et al. (2017) observed that while smoking rates decreased in regenerated areas, similar declines were noted among respondents in non-regenerated areas which resulted in no significant impact in smoking rates.

Giles-Corti et al. (2012) conducted a literature review examining the impact of residential density on health. Higher residential density was positively associated with more green spaces, proximity to shops and services and increased walking behaviour. However, the literature found mixed evidence regarding the impact of density on respiratory health as factors such as self-selection could complicate these findings – individuals adversely affected by air pollution might choose to relocate away from environments that negatively impact their health.

Cardiovascular health

Bull et al. (2015) conducted a comprehensive meta-analysis of 60 publications examining urban regeneration initiatives in Perth, Western Australia. The initiatives aimed to create new housing developments that were designed to reduce car dependence and promote active transportation options like walking, cycling, and public transport usage. Neighbourhoods were developed to be walkable, featuring cycling paths that improved access to community centres, local shops, public parks, schools, and green spaces. The development process began in 1998, with residents moving in between 2003 and 2005.

To assess the impact of these initiatives, homeowners relocating to these new developments participated in four surveys regarding their health behaviours over a nine-year period from 2003 to 2012. The study reported positive associations between neighbourhood design and residents' health behaviours. Residents living in neighbourhoods with well-connected streets and comprehensive footpath networks reported higher rates of walking and cycling compared to those in less accessible areas. Additionally, residents within a 15-minute walking distance to train stations or bus stops were more inclined to engage in walking for active transport.

Giles-Corti et al. (2012) examined the association between higher residential density, green spaces and proximity to shops and services and walking behaviour. Their findings suggested that increased residential density could positively influence cardiovascular disease risk factors, such as obesity levels and blood pressure, by promoting higher levels of physical activity among residents. However, the authors noted challenges in isolating the effects of density from confounding factors like socioeconomic status and exposure to air pollution or traffic, which might exacerbate cardiovascular disease risks.

Batty et al. (2010) evaluated the impacts of urban regeneration initiatives on physical activity levels. They reported a 2-percentage point decrease in the proportion of individuals engaging in exercise for more than 20 minutes when comparing regenerated neighbourhoods between 2002 and 2008. Additionally, when comparing these regenerated areas with similarly deprived neighbourhoods that had not undergone urban regeneration, the findings indicated that regenerated neighbourhoods had a lower percentage of residents who exercised for 20 minutes or more. Relatedly, Mohan et al. (2017) reported no significant difference in weekly exercise uptake for respondents in regenerated areas compared to those in non-regenerated areas.

Bull et al. (2015) reported that residents in high-density neighbourhoods were more likely to adopt cycling as a form of active transport and tended to spend less time sitting each day. Similarly as with Bull et al. (2015), Giles-Corti et al. (2012) highlighted that high-density neighbourhoods equipped with walking infrastructure and proximity to amenities encouraged physical activity and provided better access to healthier food options, such as fresh fruits and vegetables. However, Owen et al. (2004) noted that while residents in high-density neighbourhoods were more likely to walk for errands or breaks, there was no significant difference in their overall walking behaviour or likelihood to walk for exercise.

Berglund et al. (2017) identified negative associations between high-density housing and health outcomes, reporting that residents in high-density environments had lower self-rated health and poorer physical and mental health compared to those in lower-density housing.[5] The authors suggested that these disparities might be linked to reduced access to green spaces and increased sedentary behaviour, as residents in high-density areas often experience longer sitting times. Relatedly, Egan et al. (2015) found that homes with access to green spaces, such as gardens, offered residents safe areas for physical activity, emphasizing the role of natural environments in promoting healthier lifestyles.

Mental health

Urban regeneration has the potential to improve mental health for residents through various mechanisms, including the removal of stressors that negatively affect mental wellbeing and the development of safer, greener, and more aesthetically pleasing neighbourhoods. Bull et al. (2015) highlighted positives correlation between the number and size of parks and improved mental health outcomes, suggesting that access to green spaces can play a critical role in mental wellbeing.

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[5] See Section 2.3.2 for more details on the model used by Berglund et al. (2017).

However, in the short run, large scale redevelopment can impact mental health due to ongoing disruption, noise, dust and debris (Henry et al., 2019). Additionally, local communities and support networks may disband when residents are displaced which can negatively impact mental health (Cole, 2021; Egan et al., 2015; Henry et al., 2019).

Residents who were relocated to newly built homes or received housing improvements, such as warmth and insulation, reported improved mental health and wellbeing (Egan et al., 2015; Thomson et al., 2009). Egan et al. (2015) found that mental health only improved for those who relocated into newly built homes, with no difference in mental health for those who relocated into older but refurbished homes.

Bond et al. (2012) used GoWell survey data and logistic regression models to examine the association between urban regeneration initiatives and mental health. The authors hypothesised that residents of regenerated areas living in higher quality homes and neighbourhoods should have better mental health. The empirical findings supported their hypothesis; residents' perception of a neighbourhood's reputation, satisfaction with their home exterior and well-maintained buildings were positively associated with mental health.

Baba et al. (2017) also drew from GoWell data, focusing on community engagement during the regeneration process. The authors used linear regression models and controlled for individual level demographic characteristics. Their findings showed residents who actively participated in decision-making felt more empowered and reported higher levels of positive mental health, suggesting community involvement is a critical factor in fostering mental wellbeing.

As part of the GoWell Research programme, A Kearns, Ghosh, Mason, and Egan (2020) conducted qualitative interviews with residents undergoing urban regeneration in Glasgow, examining the impacts of urban regeneration on mental health over a nine-year period. They found no overall improvement in mental health for residents living in areas with large-scale developments, which may have been attributable to developments being incomplete at the time of analysis. They noted that individuals who relocated away from these areas experienced negative mental health effects, likely due to the loss of social ties and community connections.

In the evaluation by Batty et al. (2010), urban regeneration initiatives included mental health support tailored for residents facing challenges in entering the labour market. Between 2002 and 2008, communities undergoing regeneration reported a 4-percentage point increase in self-evaluated mental health status, with a notable 7-percentage point improvement compared to similarly deprived neighbourhoods that did not undergo regeneration.

Different housing typologies and mixture of buildings can be associated with better mental health. Levin and Arthurson (2020) conducted interviews with residents of multi-unit dwellings in Victoria, Australia to examine the impact of living in multi-unit dwellings on residents' health and wellbeing. Residents noted negative impacts from noise problems due to proximity to neighbours and conflicts that reduced their desire to go outside in case they encountered their neighbours. Positive impacts on health and wellbeing were attributed to connectedness and a feeling of community.

Giles-Corti et al. (2012) explored the impact of housing density and its potential adverse effects on mental health. Similar to some of the aforementioned studies, they identified factors such as crowding, noise pollution, and poor indoor air quality as contributors to stress and anxiety among residents of high-density housing. Their findings indicated a potential association between living on higher floors and an increased risk of mental health issues, likely related to safety concerns and diminished social interactions.

Despite the challenges associated with high-density living, the review by Giles-Corti et al. (2012) emphasized that access to green spaces can mitigate some of these negative impacts. Green space was important for residents living in high-density buildings, as they substitute for private green space available to residents of low-density housing. The presence of natural environments provides an essential counterbalance to the stresses of urban living by encouraging physical activity and improving psychological wellbeing.

2.3.5 Urban regeneration and crime and safety outcomes

Urban regeneration initiatives can play a significant role in enhancing safety and reducing crime in communities. Improvements to physical features like neighbourhood aesthetics and street lighting contribute to a greater sense of safety among residents (Bull et al., 2015). The introduction of mixed-tenure housing can attract more non-social housing tenants, creating a more diverse community that may help deter crime (Borbely & Rossi, 2023). However, in the short run, demolition sites or empty homes cleared for redevelopment can become residence for squatters or sites for drug manufacturing or crime (Egan et al., 2015; Henry et al., 2019).

Higher density living increases the number of people in an area, which can create a sense of natural surveillance and enhance feelings of security among residents (Badland et al., 2017; Bull et al., 2015). Additionally, urban regeneration can involve interventions such as increased police presence and neighbourhood warden schemes, which provides reassurance to residents and help reduce crime rates (Batty et al., 2010). In terms of physical safety, home improvements can significantly lower the likelihood of falls and accidents within the home (Keall et al., 2015; Keall et al., 2021). Medium to high-density housing can decrease reliance on cars, potentially leading to fewer road accidents and fatalities (Giles-Corti et al., 2012).

Borbely and Rossi (2023) examined the impact of large-scale urban regeneration projects in Glasgow, Scotland on crime outcomes. These projects involved replacing older existing homes with multi-unit dwellings and improving neighbourhood amenities such as green spaces and community facilities. Using a staggered difference-in-differences approach, the authors analysed crime data from 2007 to 2020 to assess changes before and after regeneration in different areas. Their findings showed that while localised crime rates within 200 meters of urban regeneration zones decreased, there was no overall reduction in crime at the city-wide level. This suggested a displacement effect, where crime shifted to other parts of the city, rather than an overall reduction in crime across Glasgow.

In their evaluation, Batty et al. (2010) compared crime and safety outcomes for residents of regenerated communities in England during and post urban regeneration.[6] Crime and safety urban regeneration initiatives included physical improvements to neighbourhoods and public spaces, enhanced police services and neighbourhood warden schemes. Wardens provided a visible street presence and referred issues to local agencies for action. These initiatives were intended to make neighbourhoods feel safer and provide reassurance to residents.

[6] See Section 2.3.2 for more details on the evaluation conducted on regenerated neighbourhoods by Batty et al. (2010)

From 2002 to 2008, the study found significant improvements in residents' perceptions of safety and crime reduction. There was an 18-percentage point decrease in reports of lawlessness and dereliction, a 14-percentage point reduction in fear of crime, and a 12-percentage point decrease in feeling fear after dark. Additionally, overall crime victimisation rates dropped by 6 percentage points, while specific incidents like burglary and criminal damage decreased by 3 percentage points. When comparing these outcomes with national averages, crime rates in regenerated neighbourhoods were lower, although the reduction was not as pronounced as the over-time improvements within regenerated areas. When compared with similarly deprived neighbourhoods that had not undergone regeneration, residents of regenerated neighbourhoods reported better outcomes in terms of reduced lawlessness, lower crime victimisation rates, and increased feelings of safety after dark.

Bull et al. (2015) found that residents who moved into regenerated neighbourhoods with improved aesthetics, such as better street lighting and less visible signs of decay like graffiti and vandalism, reported feeling significantly safer compared to their previous homes.[7] The study highlighted that housing design features promoting passive surveillance—such as visible windows, porches, verandas, and low walls—contributed to a 60% reduction in the likelihood of disorderly conduct incidents.

Badland et al. (2017) examined the association between dwelling densities and self-reported feelings of safety, hypothesising that higher population densities would lead to enhanced natural surveillance, which in turn might make residents feel safer.[8] However, their findings revealed no significant relationship between safety perceptions and dwelling density. They concluded that although higher densities attract more people, this may also lead to an increase in actual crime rates. Giles-Corti et al. (2012) reached similar conclusions to those of Badland et al. (2017) who found that higher dwelling densities, while promoting natural surveillance, might actually increase the incidence of crime.

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[7] See Section 2.3.4 for more details on the meta-analysis conducted by Bull et al. (2015)

[8] See Section 2.3.4 for more details on the model used by Badland et al. (2017)

In their literature review, Giles-Corti et al. (2012) examined the relationship between urban density and road fatalities, particularly in sprawling metropolitan cities. They expected road mortality to decrease as density increased, as high-density cities should have fewer road fatalities due to shorter trips and slower traffic speeds. However, their findings reported high-density areas often experienced heavier traffic volumes and higher speeds, which increased the likelihood of road mortality. The lack of safe play areas and parks for children in these high-density environments also contributed to higher pedestrian fatalities, particularly among young residents.

Keall et al. (2015) and Keall et al. (2021) conducted randomised controlled trials to evaluate the impact of home modifications on reducing the likelihood of injuries related to slips and falls. Modifications included installing handrails on stairs, increasing lighting, and adding slip-resistant surfaces to outdoor areas. The results from both studies showed a significant reduction in the rate of falls and accidents within homes that underwent these modifications, compared to homes that did not receive such improvements.

2.4 Contribution to the urban regeneration literature

The New Zealand literature related to the impacts of urban regeneration and housing intensification are qualitatively measured, cross-sectional in nature or explore concepts of liveability. The international urban regeneration literature shows mixed impacts of urban regeneration on human capital, health, crime and safety outcomes. Particularly, it is saturated with health-related impacts of urban regeneration with human capital and crime and safety outcomes not covered as broadly. Literature related specifically to housing intensification is limited, with much of the literature focusing on community-led initiatives and neighbourhood improvements.

Several reviews and empirical studies point towards the positive impacts of urban regeneration on health and socioeconomic outcomes (Berglund et al., 2017; Egan et al., 2013; Egan et al., 2010; Giles-Corti et al., 2012; Thomson et al., 2013). However, many of these studies are observational or descriptive in nature and often rely on cross-sectional survey data. As a result, while they capture correlations between urban regeneration and its impact on outcomes, they do not causally demonstrate that urban regeneration interventions are the direct cause of these improvements. Studies that attempt to use more rigorous approaches, such as Borbely and Rossi (2023) and Mohan et al. (2017), provide better evidence of causal relationships between urban regeneration and outcomes. However, these studies are limited in numbers.

The use of survey and qualitative data in these studies captures only a very small subset of the population. Given that urban regeneration generally involves large-scale interventions that can affect multiple neighbourhoods or geographic areas, the reliance on surveys can overlook broader population impacts. Moreover, urban regeneration initiatives can have spillover effects, influencing nearby areas not directly involved in the project, making it challenging to determine whether the sampled survey population is representative of all those affected.

Further, urban regeneration is an area-level treatment for which outcomes are likely to be unevenly distributed based on area- and individual-level characteristics. Neighbourhoods that receive higher levels of investment are more likely to experience significant changes, while others may see limited benefits (Egan et al., 2010; Mohan et al., 2017). Those with poorer socioeconomic outcomes, such as those living in social housing, are likely to benefit the most from urban regeneration, whereas non-social housing residents who are not directly involved in housing improvements may still benefit from upgraded amenities and infrastructure (Cole, 2021; Thomson et al., 2009).

The literature also highlights differential effects depending on whether residents stay in or leave regenerated areas. Long-term residents who remain in regenerated areas may see improvements in mental health and wellbeing, while those who leave may face higher mental health burden. Gentrification, characterised by the influx of higher educated residents, may also drive observed outcomes in regenerated areas. In these cases, improvements in wellbeing may reflect the changing population rather than the direct effects of regeneration (Brummet & Reed, 2019). Gentrification can also increase the cost of housing which can price out lower income residents (Almagro et al., 2023; Cole, 2021).

Urban regeneration is likely to drive changes that affect the population post the study period, with several studies focusing only on the short run impacts of urban regeneration. For example, Thomson et al. (2013) found most studies in their systematic review evaluated outcomes within one year of housing improvements, with only a small share of studies examining outcomes beyond this timeframe. This limits the understanding of the long-term effects of urban regeneration. Studies like A Kearns et al. (2020), which examines mental health outcomes over nine years, emphasise that regeneration impacts may materialise well beyond the typical study period.

Studies from the GoWell Research and Learning Programme (Borbely & Rossi, 2023; Egan et al., 2010) and urban regeneration in Northern Ireland (Mohan et al., 2017) closely resemble the approach used in this study. These studies highlight a gap in the urban regeneration literature, specifically regarding the limitations of existing methodologies: (1) the reliance on associations or correlations that limit causal interpretation, and (2) the lack of longitudinal analysis examining the longer-term effects of large-scale urban regeneration initiatives.

Most GoWell studies rely on qualitative methods such as thematic analysis, offering in-depth insights into a subset of the population. Although these findings are compelling, they cannot conclusively attribute changes to urban regeneration. Alternatively, Mohan et al. (2017) used a difference-in-differences approach to study the causal impact of urban regeneration on health outcomes over a twelve-year period. However, their reliance on survey data limited their statistical power, as the analysis was based on a subset of the regenerated population. The study by Borbely and Rossi (2023) provides a more direct match to the methodology and data used in this research. The authors used staggered difference-in-differences to measure the causal impact of urban regeneration on crime outcomes, leveraging administrative police data and variations in the timing of regeneration across neighbourhoods.

There is the potential to use administrative data to longitudinally measure the causal impacts of urban regeneration that have not yet been fully explored in the literature. Administrative data is collected by government agencies while conducting business or its legislative duties (Bycroft et al., 2021; Graeff & Baur, 2020). For example, in New Zealand, the Department of Internal Affairs is legally required to register events such as births, deaths, and marriages. Inland Revenue records transactions and events such as tax payments.

In the literature, Badland et al. (2017) used administrative housing and geospatial data to investigate the relationship between housing density and health and safety outcomes. Similarly, Brummet and Reed (2019) used longitudinal census administrative data in the United States to study how gentrification impacts human capital outcomes like income and educational attainment. Almagro et al. (2023) explored the effects of large-scale social housing demolition in Chicago using administrative social housing data and Census records.

Researchers in New Zealand can access population-wide individual-level administrative data for public good research. These administrative datasets can be used to create wellbeing outcomes that include human capital, physical and mental health and crime and safety indicators. This administrative data can be linked to Kāinga Ora housing intensification data that is available to this research to examine the impacts of urban regeneration on wellbeing outcomes. Housing intensification is the main policy tool used by Kāinga Ora to deliver its urban regeneration initiatives, with this policy acting as a 'natural' experiment with those living in regenerated areas being "treated", and those not living in regenerated areas being the "control" group.

This research uses statistical methods such as entropy balancing and staggered difference-in-differences methods to compare wellbeing outcomes between treated and control areas to determine the causal impact of urban regeneration. As administrative data is collected for almost all the population over a long period of time, this allows for longitudinal analyses that have not yet been thoroughly explored in the cross-sectional studies so far.

The use of individual-level administrative data allows for subpopulation heterogeneity analysis to help understand if wellbeing outcomes are unevenly distributed across different populations. Given Kāinga Ora-led urban regeneration is expected to build more social housing, it is reasonable to expect social housing residents to be most impacted by these developments. There may also be differential wellbeing impacts for residents living in areas prior to urban regeneration compared to those who moved in afterwards, and for those who leave regenerated areas.

This research therefore contributes to the urban regeneration literature by:

1 Developing a robust framework and method to measure population-wide wellbeing indicators using administrative data across the following domains:
   i. Human capital (education and labour market)
   ii. Physical and mental health
   iii. Crime and safety; and
2 Evaluating the short run wellbeing impacts of urban regeneration, specifically housing intensification, in New Zealand using the wellbeing framework developed in this study.

This provides policymakers with a data-driven evidence base to guide current and future housing developments.

Note that this research permits only short run impacts of urban regeneration to be evaluated as housing intensification data is available from the beginning of 2018 to the end of 2021. Additionally, many developments are still under construction by the end of 2021 and therefore the full impact of urban regeneration cannot yet be assessed. However, one of the key purposes of this research is to create an evaluation framework using regularly collected administrative data such that long-term impacts can later be assessed in future analyses.

It is important to note that the data available to this research measures only housing intensification. As such, urban regeneration initiatives such as neighbourhood aesthetics, training and employment hubs and public green spaces –which are part-in-parcel of urban regeneration in New Zealand as described in Section 2.2 – cannot be measured. While it is almost certain these initiatives are occurring at the same time as housing intensification, these cannot be disentangled in the data.

3 Wellbeing Frameworks in New Zealand

This research draws on the New Zealand Treasury Living Standards Framework, supplemented by the New Zealand Index of Multiple Deprivation, to form the wellbeing framework developed in this study. These two frameworks are discussed in further detail below.

3.1 The Living Standards Framework

The Living Standards Framework (LSF) measures multi-dimensional wellbeing using economic, social and environmental outcomes (NZ Treasury, 2021). An increasing body of literature is shifting the focus from traditional economic measures of prosperity, such as GDP growth and wealth, to non-monetary indicators that encompasses happiness, life satisfaction and quality of life (Dodge, Daly, Huyton, & Sanders, 2012; Trueman, Cornelius, Franks, & Lawler, 2013).

The primary purpose of the LSF is to serve as a policy tool for the government to understand the drives of wellbeing for New Zealanders in a systematic and evidence-based manner. The LSF helps policymakers understand the interdependencies and trade-offs of various policies across different dimensions of wellbeing which ultimately guides budget priorities.

While the LSF does not provide a precise definition of wellbeing, it encompasses various life aspects that contribute to enhanced wellbeing. These aspects, known as wellbeing 'domains,' have been identified through international research and local engagement as essential indicators for people and their wellbeing. The framework is underpinned by the capability approach, whereby enhancing these domains and therefore capabilities, people can live lives they value and be and do what they value (NZ Treasury, 2021).

Introduced in 2011 and updated in 2018, the LSF is based on the OECD's *How's Life* framework for measuring wellbeing, tailored to the specific context of New Zealand (OECD, 2019). The alignment with the OECD framework provides New Zealand with a standardised tool to compare its wellbeing metrics with those of other countries. The LSF is currently in its third iteration (NZ Treasury, 2021), reflecting improved measures of children's wellbeing and incorporating perspectives from te ao Māori and Pacific Peoples.

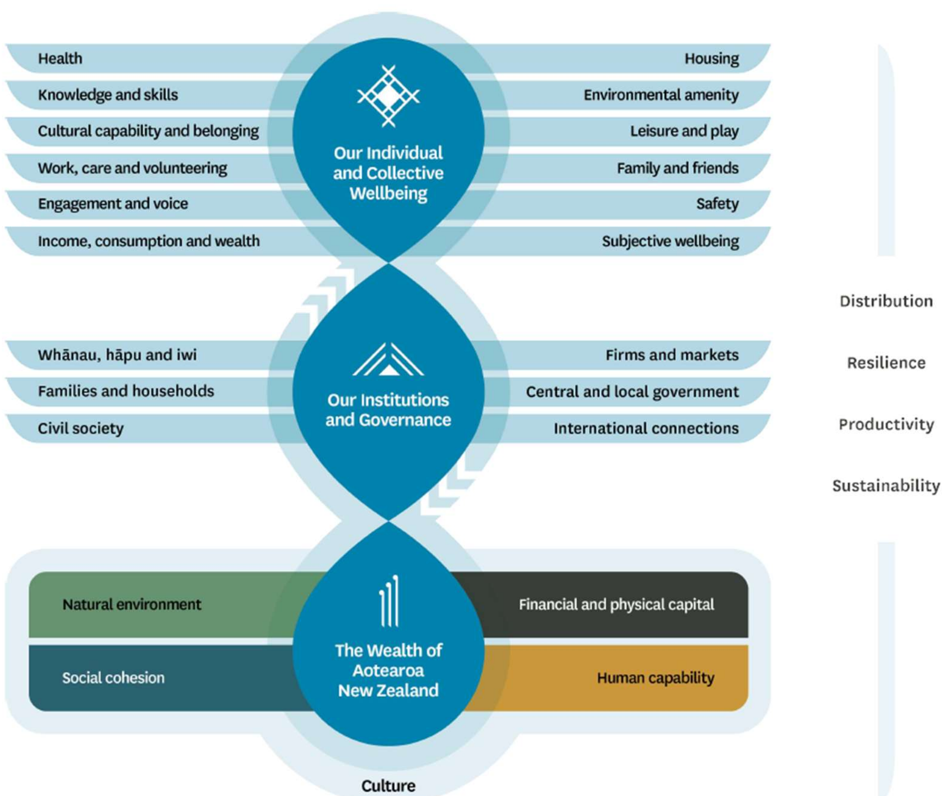
As illustrated in Figure 2, the LSF is comprised of three levels:

- the domains of individual and collective wellbeing,
- the role of institutions and government play in facilitating individual and collective wellbeing, as well as safeguarding and building wealth,
- and the wealth of New Zealand measured by physical, financial, human and natural capital.

Cultural context underpins all levels of individual and collective wellbeing, highlighting the significance of culture in enhancing overall wellbeing.

This research focuses on the first level of the LSF, individual and collective wellbeing, which forms the foundation for the wellbeing framework developed in this research. As shown in Figure 2, there are twelve domains of wellbeing support the capability approach taken by the Treasury by enhancing capabilities and functioning. These are defined in Table 1. Each domain is measured by indicators as defined in Table 36 in Appendix 1, providing a "point in time" measure of wellbeing according to the LSF.

Figure 2 Individual and collective wellbeing in the Living Standards Framework



Source: From "The Living Standards Framework 2021", by NZ Treasury (2021). Retrieved from https://www.treasury.govt.nz/

Table 1 Living Standards Framework wellbeing domains

Domain	Definition
Health	Being in good mental and physical health and exhibiting health-related behaviours and lifestyles that reduce morbidity and mortality, such as eating well and keeping active.
Knowledge and skills	Having knowledge and skills appropriate to one's life stage and continuing to learn through formal and informal channels.
Cultural capability and belonging	Having the language, knowledge, connection and sense of belonging necessary to participate fully in one's culture or cultures, and helping others grow their cultural capability and feel a sense of belonging.
Work, care and volunteering	Directly or indirectly producing goods and services for the benefit of others, with or without compensation.
Engagement and voice	Participating in democratic debate and governance at a national, regional or local level, such as through membership of a charitable society, political party or school board.
Income, consumption and wealth	Using income or in-kind transfers to meet today's needs and save for future needs, as well as being protected from future shocks by adequate wealth, private insurance and public insurance (the social safety net).
Housing	Having a place to call home that is healthy, suitable, affordable and stable.
Environmental amenity	Having access to and benefiting from a quality natural and built environment, including clean air and water, green space, forests and parks, wild fish and game stocks, recreational facilities and transport networks
Leisure and play	Using free time to rest, recharge and engage in personal or shared pursuits
Family and friends	Loving and supporting close friends, family and community members, and being loved and supported in turn.
Safety	Being safe from harm and the fear of harm and keeping oneself and others safe from harm.
Subjective wellbeing	Being satisfied with one's life overall, having a sense of meaning and purpose, feeling positive emotions, such as happiness and contentment and not feeling negative emotions.

Source: From "The Living Standards Framework 2021" by NZ Treasury (2021). Retrieved from https://www.treasury.govt.nz/publications/tp/living-standards-framework-2021-html

3.2 The Index of Multiple Deprivation

The Index of Multiple Deprivation (IMD) is a tool which measure area-level deprivation in New Zealand using administrative data (Exeter et al., 2017). Deprivation is defined as the relative disadvantage experienced by an individual, family or community compared to other communities or the wider society. It includes not only material deprivation relating to resources and amenities, but also social deprivation related to relationships, roles and functions within society. The cumulative effects of multiple deprivation can significantly impact individuals and the communities they live in. In this regard, the IMD serves as an alternative and complementary framework to the LSF where deprivation can be considered the absence or deficit of wellbeing.

The purpose of the IMD is to provide a measure of area-based deprivation that informs policy and enables efficient resource allocation to areas most in need. Area-based deprivation is calculated at the Data Zone level, with each zone housing a population of 500 to 1000 residents. Data Zones are intended to reflect true community boundaries rather than statistical delineations, with each Data Zone corresponding to a distinct neighbourhood.

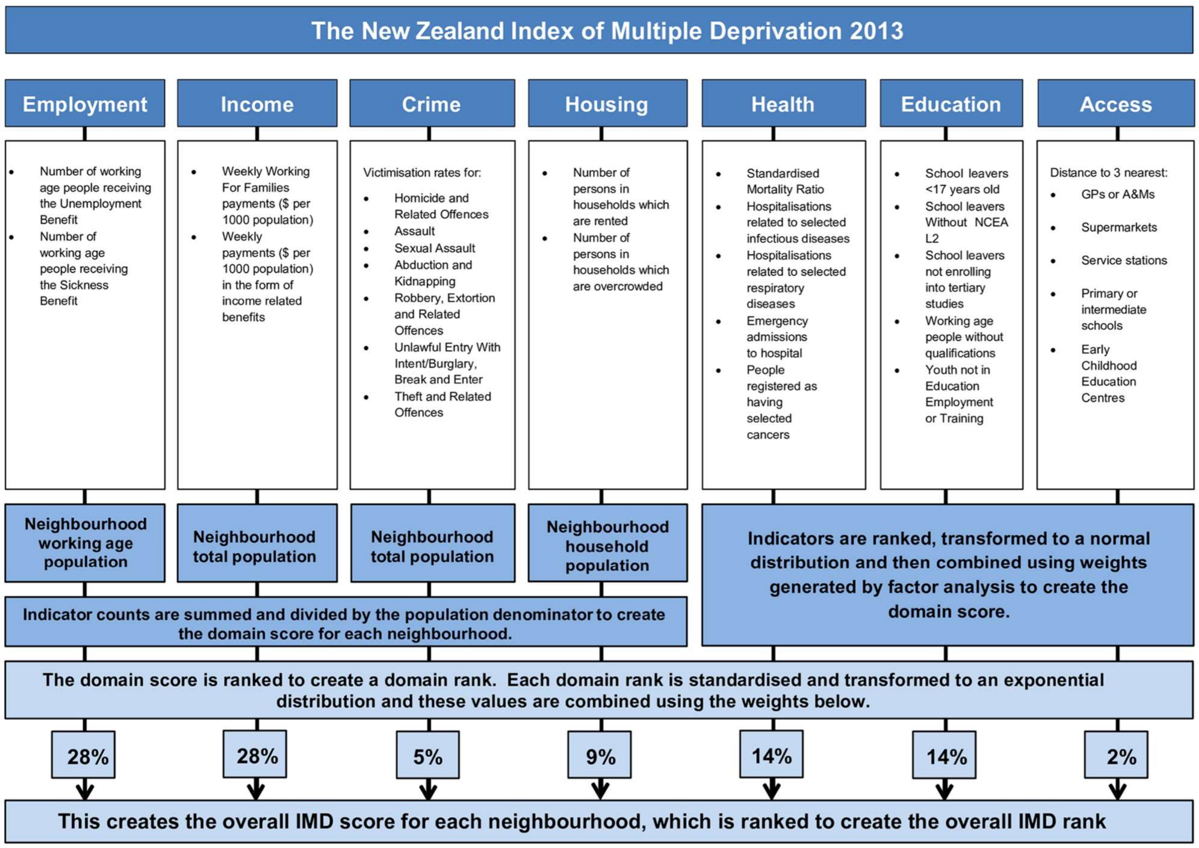
The IMD was developed in response to limitations of existing deprivation measures used in New Zealand such as the New Zealand Index of Deprivation (NZDep) (Salmond & Crampton, 2012). The NZDep is derived from Census data, which is collected every five years. This infrequency can lead to the index becoming outdated, particularly for communities that experience significant population or social changes between Census periods (Exeter et al., 2017).

To address these limitations, the IMD constructs population-based indicators using routinely collected administrative data in New Zealand. These indicators are organised across seven domains of deprivation: Employment, Income, Crime, Housing, Health, Education and Access (Figure 3). Deprivation can be measured by individual domains or in combination with one another, which helps to understand different aspects of deprivation within communities.

Each indicator in the IMD is selected for its theoretical ability to measure its respective deprivation domain, and is:

- nationally available at the small geographic level,
- not limited in geographic or demographic exposure,
- reflective of New Zealand circumstances,
- up-to-date and easily updatable, and
- statistically robust.

Figure 3 New Zealand Indices of Multiple Deprivation



Source: From "The New Zealand Indices of Multiple Deprivation," by Exeter et al. (2017). Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/28771596

4 Data and Definitions

The aim of this research is to develop the Wellbeing Outcomes Framework, which measures wellbeing using administrative data, to examine the wellbeing impacts of urban regeneration. This research draws on two data sources: (i) Kāinga Ora housing intensification data between 2018 to 2021 (inclusive) and (ii) administrative data from the Integrated Data Infrastructure (IDI). Housing intensification data is used to create treatment variables that measure urban regeneration. Administrative data from the IDI is used to create demographic variables and wellbeing outcome variables related to human capital, health, crime, and safety.

This section begins by describing the IDI and its advantages and limitations. It then defines the Wellbeing Outcomes Framework, detailing the wellbeing outcome variables included in the framework and how these are measured using administrative data. Next, the section describes Kāinga Ora housing intensification data and how it is used to measure urban regeneration. The section concludes with outlining how the sample and panel used in this research is constructed and the demographic variables used to characterise the population of interest.

4.1 The Integrated Data Infrastructure

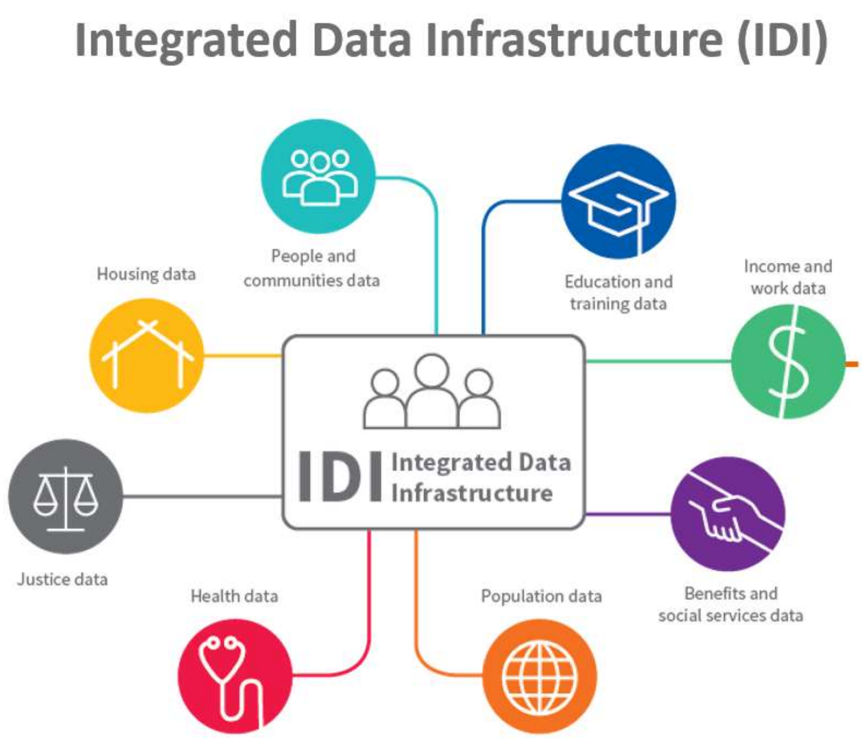
Stats NZ collects data from various government agencies, the Census, and surveys. Stats NZ collates, stores, and manages this data within a database called the IDI. The IDI is a centralised collection of New Zealand population-wide administrative datasets that spans several sectors such as health, social services and education (Figure 4). Individuals who interact with government services are assigned a unique, confidential, and anonymised identifier. This allows multiple datasets to be linked at the individual level across various government departments.

As described by Milne et al. (2019), the IDI offers several analytical advantages:

- **High population coverage**: Administrative data often includes information on a large number of individuals, which typically encompasses the entire population. This allows researchers to stratify their analyses by sub-groups such as ethnicity or age, which is difficult with smaller sample sizes.
- **Timely updates:** The IDI is updated three times per year, making the data timely. Its granularity enables analysis at regular intervals, such as monthly or quarterly, allowing for more up-to-date research.

- **Linkage across datasets:** One of the advantages of administrative data is the ability to link different datasets, which allows researchers to examine drivers across several sectors. For example, health outcomes may be partially driven by different levels of education and income. The IDI allows health data to be linked with education and income datasets to examine these associations.
- **Consistency and accuracy:** Administrative data is consistently and accurately collected over time, providing highly reliable data. There is no risk of recall bias as data collection is based on service use such as hospital admissions or pharmaceutical dispensing.
- **Longitudinal analysis:** Information is collected continuously over long periods of time, allowing for longitudinal analyses. This is important for cohort studies where primary data collection may not have been available at the time. For example, researchers may be interested in longitudinal health outcomes for a birth cohort study. Even if no primary data was collected at the time of birth, the IDI can be used to track outcomes for birth cohorts.
- **Cost-effectiveness**: Since administrative data is already collected for administrative purposes, accessing it for research is relatively inexpensive. Researchers typically pay a nominal fee to access the data through the IDI.

Figure 4 The Integrated Data Infrastructure



Source: From "The Integrated Data Infrastructure", by Stats NZ (2021). Retrieved from https://www.stats.govt.nz/

Most wellbeing indicators in the Living Standards Framework (LSF) are derived from survey data, which are often collected less frequently compared to administrative data in the IDI. For example, the LSF collects data from the Household Labour Force Survey (HLFS), the General Social Survey (GSS) and the Census. The HLFS surveys approximately 15,000 households every three months, the GSS surveys 12,000 individuals every two years and the Census is conducted every five years and covers the entire population. Table 36 in Appendix 1 shows which LSF indicators are populated from these surveys.

As survey data collection occurs at less frequent intervals, the wellbeing data in the LSF is only updated as often as new survey results are released. Additionally, since these surveys use relatively small representative samples of the New Zealand population, further disaggregation by characteristics like age, gender, and ethnicity is often limited by sample size, reducing the statistical power needed for detailed subgroup analysis. This is particularly important as wellbeing impacts are likely to be unevenly distributed across different economic and demographic populations in almost any policy setting.

Administrative data, used in the context of research, offers researchers the opportunity to examine policy changes and societal issues at a more granular level compared to survey data. As such, the IDI has been used in several wellbeing-related research projects. Meehan, Pacheco, and Schober (2023) examined educational and labour market outcomes for young people using earnings and education administrative data in the IDI. Davie and Lilley (2018) used injury data from the Accident Compensation Corporation to quantify the impact of injury on financial wellbeing for older workers.

Teng, Blakely, Ivory, Kingham, and Cameron (2017) assessed the effect of earthquake damage in Christchurch on cardiovascular health. Individuals living in earthquake-damaged areas were identified using address information from the IDI. Cardiovascular health was measured using cardiovascular disease-related hospital admissions and mortality data from the Ministry of Health. Donovan, Gatziolis, Longley, and Douwes (2018) examined the association between the natural environment and childhood asthma. Children with asthma were identified using hospital admissions related to asthma events and pharmaceutical data for asthma-related prescriptions.

There are limitations to using administrative data for research purposes, which are important to consider:

- **Limited scope of variables:** Only variables needed to fulfil administrative functions are collected. This can limit the range of variables available for research. For example, before April 2019, there was no information on hours accompanying earnings data as it was not required for tax collection purposes.
- **Limited insight into mechanisms:** Objective indicators derived from administrative data sources may not allow researchers to explore underlying economic relationships. For example, monthly tax records from Inland Revenue can be used to study gender wage gaps in the labour market. However, the data cannot be used to understand more subjective drivers contributing to the pay gap such as family dynamics and workplace interactions.
- **Proxy variables and measurement issues**: Researchers can construct proxy variables to measure concepts and variables used for analysis. However, these proxies may not always accurately reflect the intended concept, leading to potential measurement errors.
- **Gaps for certain populations:** Administrative data generally only exists for individuals who access government agencies and services. This makes it challenging to distinguish between different types of non-events. For example, administrative records may not differentiate between an individual who is unemployed and not receiving income and someone who is out of the labour force altogether but similarly not receiving income or benefits.

4.2 Wellbeing Outcomes Framework

This research provides a framework for measuring monthly population-wide wellbeing indicators using administrative data from the IDI. The Wellbeing Outcomes Framework developed in this research corresponds to four wellbeing domains from the LSF and the corresponding indices in the Index of Multiple Deprivation (IMD), as described in Table 2. The framework provides a systematic approach to assessing wellbeing through administrative data across various dimensions.

Figure 5 provides a graphical representation of the Wellbeing Outcomes Framework. Table 3 provides a tabular overview of wellbeing outcomes and their definitions. A comprehensive tabular format of the Wellbeing Outcomes Framework is presented in Table 37 in Appendix 2, which includes the relevant IDI datasets used to derive each measure.

Each indicator within the Wellbeing Outcomes Framework serves as an outcome variable in this thesis. These domains and indicators were selected based on 1) the literature reflecting their importance in measuring wellbeing and 2) their ability to be measured or approximated with administrative data.

Where possible, this research continues to use existing LSF wellbeing indicators that can be measured by administrative data at the population level. Where indicators in the LSF are populated by survey data, this research uses proxy indicators that can be measured with administrative data, as guided by related literature. By design, all deprivation indicators in the IMD can be measured using administrative data and therefore this research continues to use the same measures as those in the IMD. The selection of specific variables and indicators is detailed in the following sections.

The use of monthly administrative data enables more frequent assessment of wellbeing outcomes compared to the survey-based measures typically used in the LSF. For example, tax data from Inland Revenue is reported at the individual-month level, which allows for changes in median wages and salary to be assessed at the monthly level.

Table 2 Research outcomes and related measures

Research Outcome	Living Standards Framework Domains	Index of Multiple Deprivation Indices
Human Capital (Education & labour market)	Knowledge and skills	Education
	Work, care and volunteering	Employment
Physical and mental health	Health	Health
Crime and safety	Safety	Crime

Figure 5 Wellbeing Outcomes Framework

WELLBEING OUTCOMES FRAMEWORK

HUMAN CAPITAL

Education
- Educational attainment of the adult population (secondary)
- Educational attainment of the adult population (tertiary)
- Youth NEET rate

Labour market
- Employment rate
- Median/average earnings
- Benefit recipiency (any benefit)
- Benefit recipiency (unemployment or sickness-related)

PHYSICAL AND MENTAL HEALTH

Physical health:
- Emergency department (ED) admissions
- Cardiovascular disease (CVD) related hospitalisations
- Respiratory-related hospitalisations

Mental health
- Mental health services access
- Self-harm events (including self-harm resulting in death)

CRIME AND SAFETY

Crime
Victimisation rates of offences related to:
- Family violence
- Assault
- Sexual assault
- Theft
- Abduction and harassment
- Robbery and extortion

Safety
Accidents and injuries related to:
- Work
- Home
- Road

4.2.1 Human capital outcomes

Knowledge and skills are intrinsically valuable to people as it allows them to grow their capabilities (NZ Treasury, 2021). Obtaining higher educational qualifications and being in paid employment can help build knowledge and skills that build human capital. As such, human capital outcomes comprise of education and labour market indicators as they are intrinsically linked. Higher educational attainment is positively associated with labour market outcomes such as steady employment and higher earnings. Youth participation in education and employment indicate their inclusion in society and ability to improve their economic situation.

This study uses the same education and labour market outcome variables as the LSF and IMD, as they are already measured with administrative data. In addition to these variables, this study also examines two benefit recipiency indicators as measured by Rea et al. (2019) and Exeter et al. (2017). Benefit receipt measures the financial assistance provided by the government to support individuals with insufficient means of income. This may be due to unemployment, poor health, disability, or sole parental duties. All working-age benefits in New Zealand are means-tested, meaning those receiving benefits are likely to be facing material hardship as they must be earning below a threshold to qualify. Receipt of unemployment or sickness benefits measure those who may be willing to work but are unable to do so.

Rea et al. (2019) compared wellbeing outcomes between benefit recipients and non-recipients using benefit receipt data from the IDI. They found means-tested benefit recipients had lower standards of living compared to non-recipients, were more likely to postpone doctor visits due to costs, living in overcrowded and poor-quality housing and struggled to afford basic necessities. In addition, they scored lower on subjective wellbeing measures, such as life satisfaction and sense of purpose.

4.2.2 Physical and mental health

The LSF highlights health as "arguably the single most important aspect of our wellbeing" (NZ Treasury, 2021, p. 29). Health plays a critical role in enabling individuals to sustain their capabilities, which in turn affects their ability to work, study, care for others, and engage in leisure activities. Research has shown that health status is a key determinant of life satisfaction, explaining much of the variation in wellbeing between individuals (ibid).

Many health indicators in the LSF are based on self-reported survey measures, such as general health status and psychological distress. However, this research uses objective health indicators derived from administrative data, particularly those included in the IMD. These include emergency department, respiratory-related and cardiovascular disease-related hospitalisations, which have been widely used in the literature as proxies for physical health.

Higher volumes of emergency admissions may indicate gaps in community-based primary care, as observed in Dasgupta and Pacheco (2019). While primary healthcare data is not available in the IDI, emergency department admissions are used as a proxy for access to and quality of primary healthcare. For example, higher volumes of emergency department admissions may reflect inadequacies in local health facilities. This would drive more individuals to rely on emergency departments for healthcare, increasing the burden on emergency services.

Respiratory-related hospitalisations can signal the quality of residential environments, while cardiovascular disease-related hospitalisations may reflect the availability of healthy infrastructure like active transport options and green spaces, which promote physical activity and heart health. Improvements in respiratory and cardiovascular health is likely to result in fewer respiratory-related and cardiovascular disease-related hospitalisations.

The LSF measures mental health with survey questions related to self-reported psychological distress, which is a subjective measure that cannot be measured using administrative data. However, administrative records of mental health interactions with healthcare services can provide an alternative measure. Data from secondary mental health services, pharmaceutical prescriptions related to mental health, and mental health-related hospital admissions are available in the IDI and can be used to identify individuals experiencing mental health distress. Similar methods have been used by Bowden et al. (2020) to identify individuals who interact with mental health services using administrative data. Gibb, Brewer, and Bowden (2021) identified individuals with schizophrenia using administrative datasets available in the IDI.

Additionally, self-harm and suicide are extreme indicators of poor mental health. While the LSF uses the Mortality Collection to track suicide rates, the two-year lag in this data makes it difficult to assess recent trends. Therefore, this research uses alternative datasets from the IDI to identify both fatal and non-fatal self-harm events that are updated more regularly.

4.2.3 Crime and safety

Being a victim of a crime can have profound impacts on wellbeing and significantly affect individuals' sense of security and overall quality of life. In the LSF, safety is measured using self-reported survey questions asking how safe people feel walking alone in their neighbourhood at night. While subjective safety perceptions are important, administrative data allows researchers to measure objective incidences of crime. The IMD measures crime by victimisation rates for major offences such as assaults using administrative victimisation data from the New Zealand Police. This research uses the same datasets to measure crime outcomes.

Safety also extends to the environments created by organisations and individuals. For example, workplace safety can be measured by the number of work-related injuries, reflecting how well employers uphold their duty to protect their employees. Road safety can be captured by the number of road accidents, highlighting the responsibility drivers have to ensure the safety of pedestrians, other drivers, and themselves. Home-based injuries reflect the safety of housing conditions, an environment where people spend much of their time. This research incorporates data from the Accident Compensation Corporation to track work-related injuries, as well as non-work-related injuries such as those occurring on roads and in homes.

Table 3 Wellbeing outcome variables and definitions

Variable	Definition	
	Individual at time t	Area at time t
Human capital		
Secondary educational attainment	Dummy variable: 1 = achieved at least Level 1 Certificate; 0 otherwise	Proportion of individuals aged between 16-19 (inclusive) who were born in New Zealand and/or were enrolled in at least two years in secondary institutions in New Zealand
Tertiary educational attainment	Dummy variable: 1 = achieved at least Bachelor's Degree; 0 otherwise	Proportion of individuals aged between 25 to 64 (inclusive) who were born in New Zealand and/or were enrolled in at least two years in secondary or tertiary institutions in New Zealand
Employment rate	Dummy variable: 1 = earning at least $100 in wages and salary	Proportion of individuals aged between 25 to 64 (inclusive)
Median and average earnings	Monthly earnings from wages and salary across all employers >= 100, adjusted for $NZD 2021.	Median and average earnings for individuals aged between 25 to 64 inclusive
Youth NEET	Dummy variable: 1 = not in employment, education or training datasets; 0 otherwise	Proportion of individuals aged between 15 and 24 (inclusive)
Benefit receipt (any benefit)	Dummy variable: 1 = receive any benefit as per Inland Revenue Employee Monthly Schedule data; 0 otherwise	Proportion of individuals aged 15+
Benefit receipt (unemployment or sickness-related benefits)	Dummy variable: 1 = receive unemployment or sickness related benefit in Ministry of Social Development Benefit dynamics table related to benefit codes: 115, 601, 602, 604, 607, 608, 609, 610, 611, 675; 0 otherwise	
Physical and mental health [a]		
Emergency department admissions	Number of emergency department attendances where event type code = 'ED', attendance code = 'ATT' and purchase unit code like 'ED%' or health speciality code in M05, M06, M07, M08	Age-standardised rate for individuals aged 15+
Cardiovascular disease-related hospitalisations	Number of hospitalisations for cardiovascular disease-related reasons	Age-standardised rate for individuals aged 30+
Respiratory-related hospitalisations	Number of hospitalisations for any respiratory-related disease	Age-standardised for all age groups
Mental healthcare utilisation	Dummy variable: 1 = accessed mental health services including mental health related pharmaceuticals, secondary mental health referrals and mental health related hospital admissions; 0 otherwise	Age-standardised rate for individuals aged 15+
Self-harm (including self-harm that results in death)	Dummy variable: 1 = have self-harmed; 0 otherwise	
Crime and safety		
Victims of offences related to:		
Family violence [b]	Dummy variable: 1 = victim of family violence; 0 otherwise	Rate per 1,000 population
Assault	Dummy variable: 1 = victim of assault corresponding to ANZSOC codes 0211, 0212, 0213, 0299; 0 otherwise	
Sexual assault	Dummy variable: 1 = victim of sexual assault corresponding to ANZSOC codes 0311, 0312, 0321, 0322, 0329; 0 otherwise	
Theft	Dummy variable: 1 = victim of theft corresponding to ANZSOC codes 0800, 0811, 0812, 0813, 0821, 0822, 0823, 0829, 0831, 0841; 0 otherwise	

Abduction and harassment	Dummy variable: 1 = victim of abduction and harassment corresponding to ANZSOC codes 0511, 0521, 0531, 0532; 0 otherwise	
Robbery and extortion	Dummy variable: 1 = victim of robbery and extortion corresponding to ANZSOC codes 0611, 0612, 0621; 0 otherwise	
Home-related accidents and injuries	Number of Accident Compensation Corporation claims earned through 'Earners Account' and 'Non-Earners Account', scene of accident = 'Home' and claim decisions one of: Accredited Employer, Accept or Interim Accept	
Road-related accidents and injuries	Number of Accident Compensation Corporation claims earned through 'Motor Vehicle Account', road accident flag = Y and claim decisions one of: Accredited Employer, Accept or Interim Accept	
Work-related accidents and injuries	Number of Accident Compensation Corporation claims earned through 'Work Account', work indicator flag = Y and claim decisions one of: Accredited Employer, Accept or Interim Accept	Rate per 1,000 employed population aged between 25 and 64 inclusive

Source: IDI 2024. See Appendix 2 for the comprehensive tabular format of the Wellbeing Outcomes Framework.

[a] See Appendix 5 for corresponding codes for physical and mental health outcomes

[b] See Appendix 6 for corresponding codes for family violence offences.

4.3 Housing intensification data

Urban regeneration is measured using housing intensification ("pipeline") data from Kāinga Ora, which is a register of current and future Kāinga Ora-led urban regeneration projects.[9] This dataset, available from January 2018 to December 2021, provides monthly records of urban regeneration projects which includes geographic information, making it possible to identify the areas that undergo urban regeneration. These areas are referred to as "treated" areas, while locations that have not undergone regeneration within this period serve as the control group ("untreated" areas) for comparison. One key feature of the pipeline data is that it records the number of dwellings expected to be built by each project. This allows for analysis that incorporates the scale of urban regeneration initiatives which may have differential impacts on wellbeing outcomes.

From January 2018 to December 2021 (inclusive), projects are assigned different statuses that indicate where they are in the development process, as outlined in Table 4. Projects generally begin at the Opportunity status where they are preliminary scoped out by Kāinga Ora for potential development but have low levels of actual investment. Only projects which have proceeded past the Opportunity phase, i.e. from Planning onwards, are of interest to this research as this is when Kāinga Ora has signalled clear intentions for urban development.

[9] Kāinga Ora housing intensification data was made available to AUT/Te Hotonga Hapori as part of a signed data access agreement.

Additionally, projects where Kāinga Ora purchases existing homes to add to its housing portfolio ('Buy-In' method as in Section 2.2.1) are excluded from the analysis as they are not housing intensification, thereby urban regeneration, initiatives.

This research aggregates project statuses into broader phases which correspond to the development process:

1 The *'Planning'* phase, which includes planning and feasibility project statuses, is when projects begin to incur cost, plans for redevelopment have been accepted for construction and tenants and neighbours are notified that future construction will take place.

2 The *'Contracted'* phase, which includes procurement and contracted project statuses, is when Kāinga Ora has signed formal contracts with partners and contractors who will build the new developments.

3 The *'Construction'* phase is when construction of housing developments commences.

4 The *'Delivered'* phase is when construction is completed.

While there is an ordinal ranking for project phases, not all projects have corresponding dates for when they transitioned into a new phase. For example, a project may be recorded as being in the Planning phase as of March 2019, but there might be no entry for the Contracted phase, followed by a new entry in the Construction phase as of December 2019. This discrepancy made it challenging to calculate the duration between each phase.

Based on the available data, the average time for projects to move from the Planning to the Contracted phase is approximately 31 months. On average, projects took around 10 months to progress from the Contracted to the Construction phase, and about 14 months to move from Construction to the Delivered phase.[10]

[10] Kāinga Ora noted projects are marked as Delivered when one tranche of development was completed. Construction may still be ongoing for projects marked as Delivered.

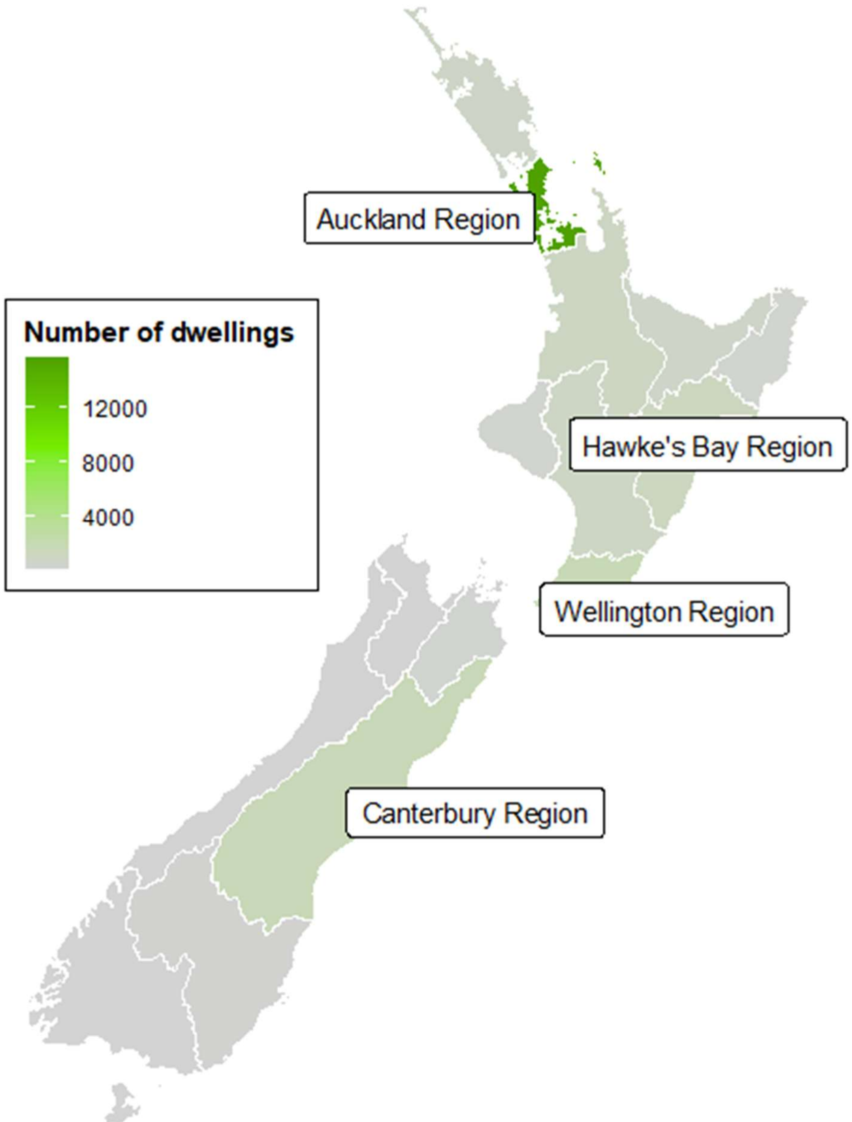
Figure 6 shows the expected number of dwellings to be built across all pipeline projects in New Zealand (excluding those in the Opportunity phase), by regional council. Regions projected to build more than 1,000 dwellings are labelled. The Auckland region has the highest number of expected dwellings by far, accounting for over half of the total expected dwellings to be built in New Zealand (15,789 out of 24,012 dwellings). Following Auckland, the regions with the highest number of expected dwellings are Wellington (1,685), followed by Canterbury (1,564) and Hawke's Bay (1,109). Given the large majority of dwellings will be built in Auckland, this research focuses on urban regeneration in Auckland.

Table 4 Housing intensification/pipeline data variables

Variable	Definition
ProjectID	Unique identifier assigned to each project in the pipeline.
Meshblock (2018)	Geographic identifier where project is taking place. Meshblocks are the smallest geographical unit for which statistical data is collected and processed by Stats NZ.
Project status	Ordinal phase for each project at each month, where project can be in only one phase at a time. These are binary in nature and include a start date.
1. Opportunity	Projects in the 'opportunity' phase are in the preliminary stages of planning, with low levels of actual investment allocated to it. Projects that have been scoped out in the 'opportunity' phase have low likelihood of progressing onto the next stage and often disappear from the pipeline.
2. Planning	Projects that proceed to the 'planning' phase are assigned a projectID. Planning briefs and investment planning begins for projects in this phase, where projects begin incurring actual costs.
3. Feasibility	Planning briefs are completed and accepted by the construction team to progress with design and analysis. Tenants and neighbours are notified of future construction which includes sending out letters to neighbours and the community.
4. Procurement	The business case is approved and a request for proposals are sent out to potential partners and contractors.
5. Contracted	The preferred partners and contractors are chosen with formal contracts signed between Kāinga Ora and partners.
6. Construction	Phase begins when construction of housing developments commences.
7. Delivered	Construction is completed.
Supply type	Type of dwelling built as below:
Social	Social housing provided by the government in New Zealand.
Transitional	Temporary accommodation for those with immediate housing needs before they transition to longer-term housing solutions which includes emergency and community group housing.
Market	Housing built by private developers with Kāinga Ora involvement and sold to the public at market rates.
Affordable/ Kiwibuild	Similar to market housing where housing is built by private developers but sold to eligible residents who earn below an income threshold at discounted values compared to Market homes.
Bedrooms	Number of bedrooms being built which includes 0 (studio), 1, 2, 3, 4, 5 and 6 plus.
Building typology	Type of home being built which includes house, apartment (this includes walk-ups), duplex and terrace.

Source: Kāinga Ora housing intensification data.

Figure 6 Expected housing intensification dwellings to be built as of 2018 – 2021, by region



Source: Stats NZ Regional Council 2018 boundary lines and Kāinga Ora housing intensification data.

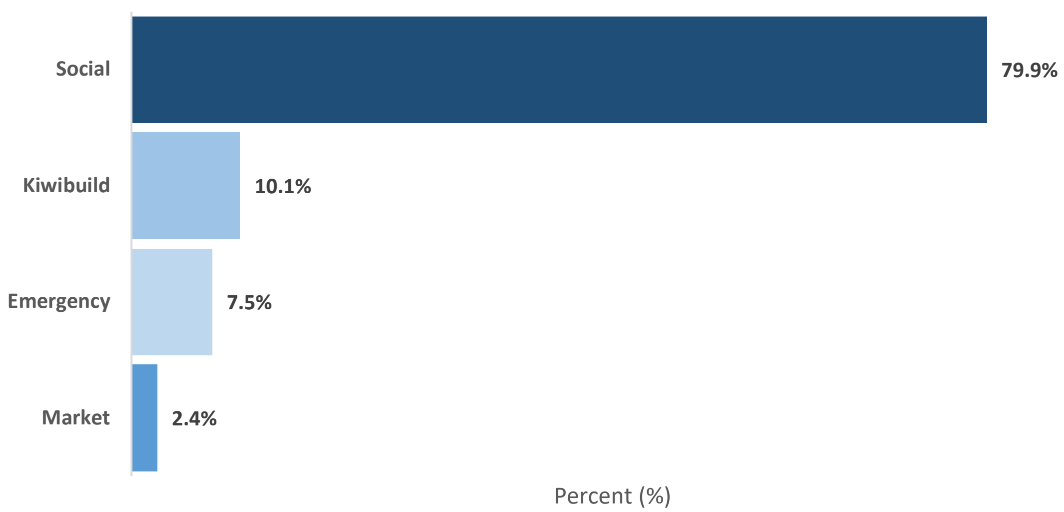
Note: Only regions where there are more than 1,000 expected dwellings are labelled. Expected dwellings is the count of all expected dwellings from projects in the 'Planning' phase onwards that started between 2018 and 2021.

4.3.1 Housing supply built by urban regeneration

The vast majority of dwellings being constructed in treated areas consist of social housing, accounting for 79.9% of the new builds in Auckland (see Figure 7). KiwiBuild housing makes up the next largest share of dwellings being built (10.1%), followed by transitional housing (7.5%). KiwiBuild homes are developed by Kāinga Ora, or purchased from private developers on its behalf, which are aimed at providing affordable housing below market rates. While social housing is rented to tenants, KiwiBuild homes are available for purchase by individuals or families earning below a certain income threshold. Transitional housing, on the other hand, offers temporary accommodation for those with immediate housing needs before they transition to longer-term housing solutions.

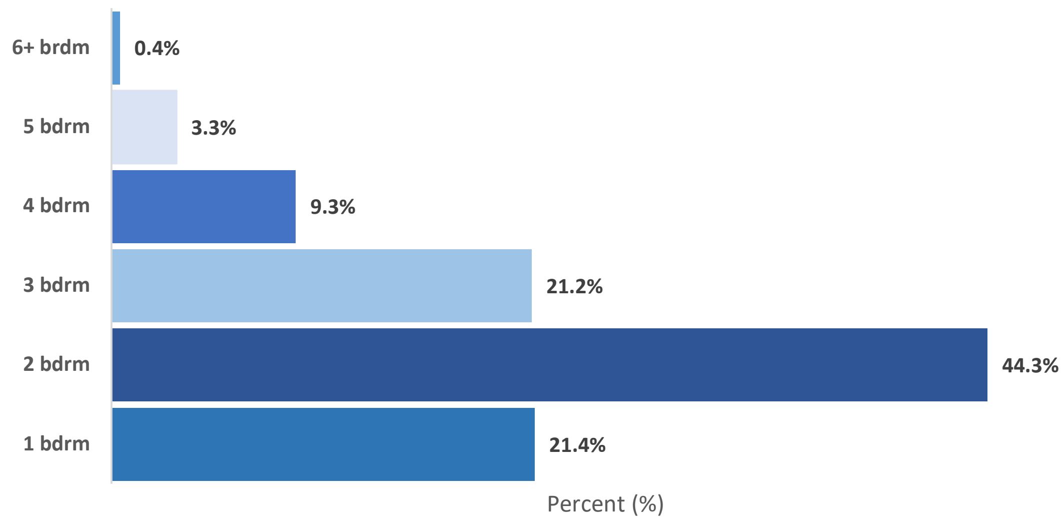
Among all housing types being constructed, 44.3% are 2-bedroom dwellings, followed by 1-bedroom (21.4%) and 3-bedroom (21.2%) units (Figure 8). This distribution aligns with the overall demand for social housing indicated by the Ministry of Development Housing Register, which shows that nearly 90% of the dwellings needed to service the social housing waitlist are for 1- to 3-bedroom dwellings (Ministry of Social Development, 2024).

Figure 7 Dwellings being built by supply type



Source: Kāinga Ora housing intensification data. Note this includes only dwellings in treated SA2s and excludes those in pre-treated SA2s.

Figure 8 Dwellings being built by bedroom type



Source: Kāinga Ora housing intensification data. Note this includes only dwellings in treated SA2s and excludes those in pre-treated SA2s.

4.3.2 Area-level unit of analysis

The geographic unit of analysis for this research are Statistical Area Unit 2 (SA2) observations, which provide a broad aggregation of population-level data. Housing intensification data is provided at the meshblock-level, which is the smallest geographic unit used by Stats NZ and usually contains 30 to 60 dwellings and around 60 to 120 residents. Meshblocks can be aggregated into a Statistical Area Unit 1 (SA1) which contain approximately 100 to 200 residents, and then further aggregated into SA2s.

The boundaries of SA2s are designed to reflect communities that interact socially and economically within populated areas (Stats NZ, 2017b). As such, SA2s are often named after the suburb that is contained within its geographic boundary. Urban SA2s generally have high population counts (more than 1,000 people) or address points (over 200 addresses), with larger cities typically housing around 2,000 to 4,000 residents and smaller cities containing 1,000 to 3,000 residents. Conversely, rural SA2s usually have fewer than 1,000 residents. In major urban areas, one or several SA2s often represent a single suburb; for example, a small urban area with about 5,000 residents may be represented by one SA2.

Using SA2 as the geographic unit of analysis is particularly relevant for this research. Urban regeneration can impact not only residents of the regenerated areas but also the surrounding neighbourhoods and communities. Using a larger geographic boundary such as SA2, as opposed to more granular meshblocks used in the pipeline data, can help capture some of the potential spillover impacts of urban regeneration. Therefore, the analysis measures urban regeneration at the SA2-level for which the meshblock corresponds.

The use of SA2 means the geographic unit used in this research is similar compared to other geographic units in related literature. For example, Mohan et al. (2017) used geographic units that contained 900 to 4,200 residents while the geographic units used by Borbely and Rossi (2023) contained 500 to 1,000 residents. As a robustness check, this research also examines wellbeing impacts of urban regeneration at the SA1-level which provides a more localised measure of urban regeneration. Comparing the wellbeing impacts at the SA2 and SA1 levels may reveal whether significant impacts of urban regeneration spillover into broader neighbourhoods or if the impacts are confined to those living within or near the developments.

4.3.3 Housing intensification inclusions and caveats

There are 2,141 projects that comprise Kāinga Ora housing intensification developments across New Zealand between 2018 and 2021, which are expected to build a total of 21,994 new dwellings. Auckland-based housing intensification projects account for 44.3% (947 out of 2,129) of all projects in the pipeline and represents 68.1% (14,967 out of 21,994) of expected dwellings.

As this study uses a difference-in-differences (DiD) model to estimate the wellbeing impacts of urban regeneration, there are two critical assumptions that need to be satisfied for estimates to be causal and unbiased (further detail is provided in Section 5). First, both the treatment and control group must not have been treated in the past; that is, they should not have previously undergone Kāinga Ora-led housing intensification. If areas have received treatment in the past, differences in wellbeing outcomes may be driven by both current and previous urban regeneration initiatives, potentially leading to an overestimation of the impacts from current urban regeneration efforts.

Second, residents should not have anticipated future urban regeneration. If they do anticipate urban regeneration, it is possible their behaviour in response to this anticipation could bias wellbeing outcomes. For example, residents who do not live in social housing may decide to relocate upon learning of upcoming urban regeneration, which could skew the analysis of wellbeing impacts.

To address the first assumption, projects and their corresponding SA2 that were in at least the Planning phase as of January 2018 are classified as pre-treated and are excluded from both the treatment and control group. Additionally, two other datasets related to Kāinga Ora housing intensification – the *Large Projects* and *Pre-pipeline* datasets – are used to refine the treatment and control group.

The *Large Projects* dataset details large-scale urban developments in the Auckland suburbs of Oranga, Aorere, Waikowhai and Wesley. The corresponding SA2s for these suburbs are excluded from the control group. However, they are included in the treatment group if they appeared in the pipeline from February 2018 onwards; otherwise, they are excluded and considered pre-treated. The *Pre-pipeline* dataset contains meshblocks for Auckland-based housing intensification that occurred between the beginning of 2013 until the end of 2017. Any SA2 that had built more than 10 dwellings during this period are considered pre-treated and excluded from the treatment and control group.

To address the second assumption, this research uses the earliest month an SA2 enters the Planning phase as the beginning of treatment. This timing signifies the point at which Kāinga Ora begins to incur actual costs related to planning and investment, and it is also when tenants and nearby communities are informed about forthcoming construction. The Planning phase is chosen as the starting point for treatment instead of later phases (such as Construction or Delivery) to avoid any potential bias, as these later phases could be endogenous to wellbeing outcome variables.

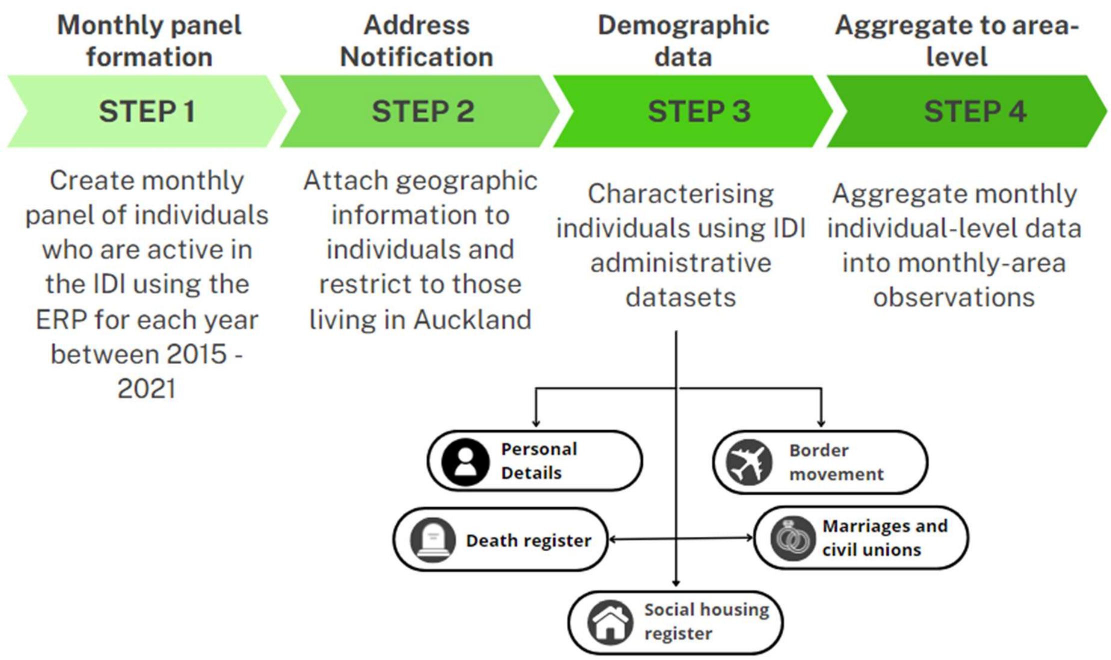
Of the 947 Kāinga Ora-led housing intensification projects in Auckland, 22.5% (213 out of 947) are situated in SA2s that have not experienced urban regeneration in the past. These projects are projected to build 21.7% (3,252 out of 14,967) of the total expected dwellings. The remaining projects and associated dwellings are located in SA2s that have previously undergone urban regeneration.

One caveat of this research is that housing intensity is treated as a static measure rather than a dynamic one. Due to the structure of Kāinga Ora's housing intensification data, generating a dynamic count of built houses over time proved challenging. Although projects had expected completion dates, these timelines often changed throughout the pipeline, which made it challenging to accurately assess when developments would be finished and maintain a real-time count of constructed houses. However, Kāinga Ora indicated that despite variations in completion timelines, the expected number of dwellings will ultimately align with the actual number built. Therefore, in favour of a more robust and reliable urban regeneration measure, this research uses expected housing as a measure of urban regeneration intensity, rather than a dynamic cumulative housing measure.

4.4 Sample and panel formation

To assess wellbeing changes over time, outcomes are measured prior to urban regeneration and post urban regeneration, where post urban regeneration is defined as after the Planning phase begins (See Section 4.3.3). As urban regeneration begins at different time points for each area, relative time periods are used to indicate months from treatment. The relative time period of interest is three years leading up to the first month the Planning phase begins, and the following three years after. The first calendar period that urban regeneration begins is February 2018 – therefore, the earliest calendar period for which the panel begins is January 2015, as this is three years prior to the first treatment event. The final calendar period is December 2021, which was the latest calendar period used in the analysis. Figure 9 provides a graphical overview of how the sample and panel is formed. Each step is discussed in further detail below.

Figure 9 Creating the sample



Source: IDI 2024.

4.4.1 Step 1 – Create monthly panel of 'active individuals'

The Stats NZ-derived Estimated Resident Population (ERP) dataset identifies active New Zealand residents at specific reference dates using various administrative data sources. Individuals are considered active residents if they had IDI activity within the 24 months preceding each reference date. For example, an individual is included in the 2015 ERP if they had interactions with government services—such as the Ministry of Education or Health—between 1 July 2013 and 30 June 2015.

Individuals aged five and over are included in the ERP if they had any accident claims, paid taxes to Inland Revenue or interacted with government health services such as prescriptions, primary health care and hospital visits (Stats NZ, 2018). For those aged five and under, inclusion in the ERP relies on birth registration or visa approvals (excluding visitor or transit visas) prior to the reference date.

Linked death records are used to exclude individuals who passed away before the reference date and linked migration data is used to exclude individuals who permanently migrated overseas or were short-term visitors to New Zealand. Each ERP year is represented as a monthly panel from January to December for all individuals who were "active". On average, there are 4.8 million individuals in each ERP year between 2015 and 2021.

4.4.2 Step 2 – Attach residential geographic information

This research uses residential geographic data to identify individuals living in treated and control areas for each month in the observation period. There are two sources of residential geographic data in the IDI – the Address Notification (AN) dataset and the Address Notification Full (AN Full) dataset which are both derived tables by Stats NZ. Raw addresses are provided to Stats NZ by various government agencies which are then linked to the New Zealand National Postal Address Database (Stats NZ, 2018).

Each address in the National Postal Address Database is assigned a unique and confidential identifier, similar to that given to individuals in the IDI, along with other geographic information such as meshblock and region. Where an individual has multiple addresses across different agencies (for example, from the Ministry of Social Development and Ministry of Education), Stats NZ applies a set of prioritisation rules to determine the most accurate estimate of an individual's residential location. This forms the Stats NZ AN dataset where individuals can only reside at only one address at any given time, while the AN Full dataset captures address history, allowing individuals to have multiple addresses concurrently.

For this research, a derived Address Notification dataset is used which is based on the AN Full dataset but modified with a different set of prioritisation rules. The derived dataset was chosen over the standard AN dataset because the latter gives higher priority to Census addresses, which could bias residential location data. The derived Address Notification dataset uses similar prioritisation rules to form the AN dataset but excludes Census addresses to ensure a more accurate representation of individuals' residences. Further details detailing how the AN Full dataset is used to form the Stats NZ AN dataset and the derived Address Notification dataset is available in 0.

Since meshblock boundaries may change over time as populations and communities evolve, this study maps all meshblocks to 2018 meshblock boundaries (and thereby their corresponding 2018 SA2), using a meshblock concordance table to maintain consistency across years.

On average, there are approximately 1.7 million individuals living in Auckland for each ERP year between 2015 and 2021. This estimate aligns with Auckland Council's 2018 estimate of the 2017 Auckland population, providing confidence that the ERP is a good estimation of the overall Auckland population (Auckland Council, 2018).

4.4.3 Step 3 – Attach demographic data

Table 5 describes the datasets used to characterise the ERP population. The Stats NZ derived [personal_detail] dataset is used to populate age, gender, and prioritised ethnicity. The Department of Internal Affairs [marriages] and [civil_unions] datasets are used to identify if individuals are legally partnered. The Social Housing Register [houses_snapshot] is used to identify if the unique address identifier of an individual, as per the derived Address Notification dataset, corresponds to a social housing address.

Individuals born after January 2015 (beginning of the panel) are included in the sample from the month they are born. The ERP generally excludes most individuals who are deceased, have relocated overseas or have no ethnicity, date of birth, or gender information. However, additional criteria were specified to ensure further exclusions for individuals not already filtered out in the ERP. The final panel consists of approximately 2.2 million individuals who were identified as active in the ERP and lived in Auckland at some point between January 2015 and December 2021.

4.4.4 Step 4 – Summarise to area-level observations

Individual-level observations are aggregated into area-level observations for each month between January 2015 and December 2021, as described in Table 5. These area-level observations serve as demographic explanatory variables. To prevent skewed outcomes due to small counts, all monthly-SA2 observations with populations fewer than 100 residents were removed from the sample.

Table 5 Individual and area-level explanatory variables

Variable	Definition		IDI Dataset
	Individual at time t	Area at time t	
Population	Equal to 1 if reside in urban regeneration area; 0 otherwise	Number of distinct individuals	Stats NZ [personal_detail]
Household Size		Number of distinct individuals divided by the number of unique address identifiers in the urban regeneration area and 1 address identifier is equal to 1 dwelling i.e. multi-unit dwellings will have an identifier for each dwelling.	
Ethnicity	6 dummy variables for prioritised ethnicity: Māori, Pacific, Asian, MELAA, Other, European	Proportion by prioritised ethnicity	Stats NZ [personal_detail]
Age Group	4 dummy variables for age groups: under 18, 18-24 (inclusive), 25-64 (inclusive), 65+	Proportion by age group	Stats NZ [personal_detail]
Partnered	Dummy variable equal to 1 if married or in a civil union and aged 25+; 0 otherwise	Proportion partnered	Department of Internal Affairs [marriages] and [civil_unions]
Social Housing	Dummy variable equal to 1 if living in social housing; 0 otherwise	Number of distinct individuals living in social housing	Housing New Zealand [houses_snapshot]
Social Housing Proportion		Number of distinct individuals living in social housing divided by the number of distinct individuals	
Quintile 5[a]	Dummy variable equal to 1 if live in NZDep2018 levels 9 and 10; 0 otherwise	Proportion in living in deprivation quintile 5	NZDep2018 reference tables based on 2018 meshblock of residence

Source: IDI 2024. MELAA = Middle Eastern, Latin American and African.

[a] Used only for matching methods and descriptive statistics. Not used in regressions.

5 Method

This section first describes the empirical approach used to identify the treatment and control group, both at the area and individual level, to evaluate the wellbeing impacts of Kāinga Ora-led urban regeneration. It then describes the model for estimating area-level wellbeing impacts of urban regeneration and the demographic characteristics of treated and control areas. It then presents the model for estimating individual-level wellbeing impacts across subpopulations of interest and their demographic characteristics.

5.1 Identification strategy

To assess the wellbeing impacts of urban regeneration, this research compares wellbeing outcomes for treatment and control areas (and individuals) before and after urban regeneration begins. Auckland consists of 563 SA2s – of these 563 SA2s, 88 are in the treatment group, 323 are in the control group and 152 SA2s are pre-treated and in neither the treatment nor control group. Figure 10 illustrates the distribution of treated, control and pre-treated SA2s in Auckland. Figure 11 provides a closer look at the more densely populated SA2s in the centre of Auckland. Figure 12 shows how SA1s are nested within SA2s.

The 88 SA2s in the treatment group are considered treated if at least one project has progressed to at least the Planning phase from February 2018 onwards (shown in green in Figure 10 and Figure 11). The 152 pre-treated SA2s include those that appeared in the *Pre-pipeline* data (indicating treatment before 2018), those listed in the *Large Projects data* but not in the pipeline, or those that were in at least the Planning phase as of January 2018 (see Section 4.3.3 for details on exclusions). These pre-treated areas are excluded from both the treatment and control groups (shown in grey in Figure 10 and Figure 11). The remaining 323 SA2s form the control group which are SA2s that did not undergo Kāinga Ora-led urban regeneration prior to 2018 and between 2018 and 2021 (shown in blue in Figure 10 and Figure 11).

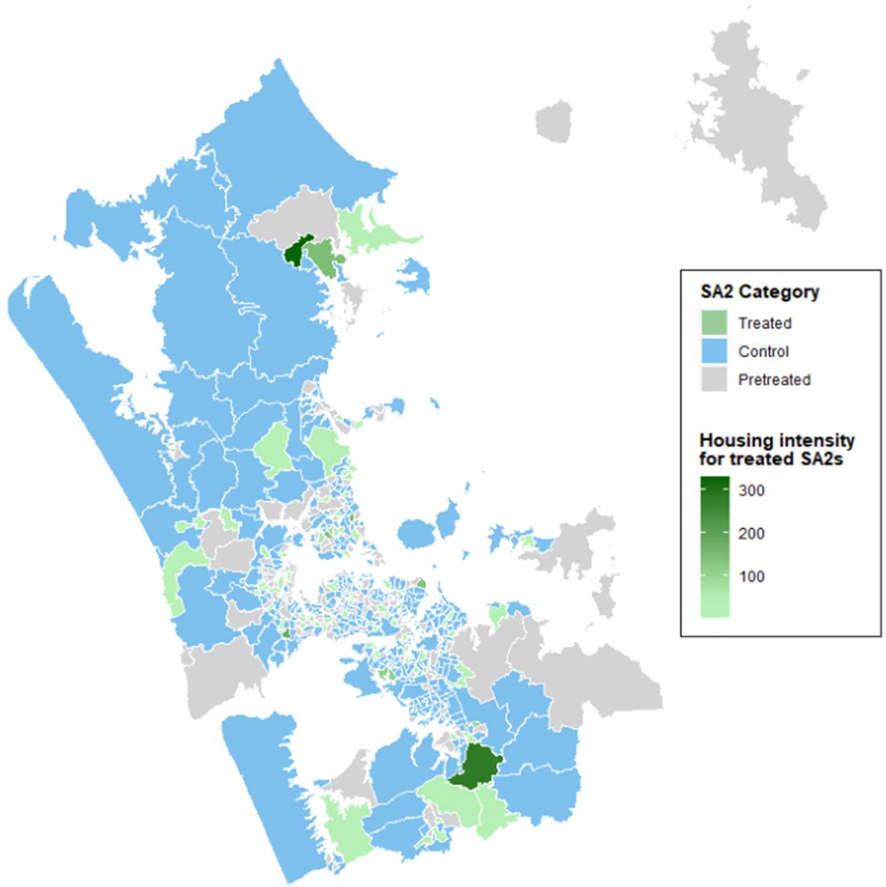
Figure 13 illustrates the cumulative proportion of Auckland SA2s undergoing urban regeneration. As detailed in Section 4.3.3, urban regeneration begins when Kāinga Ora begins to incur cost related to planning and investing in urban regeneration projects and notifies tenants and neighbourhoods about upcoming construction. Between 2018 to 2019, only a small number of SA2s begin urban regeneration. This number steadily increases between 2019 and 2020, with a large number of SA2s beginning urban regeneration at the start of 2021. The remaining SA2s begin urban regeneration during 2021 and by the end of 2021, all SA2s in the treatment group have been treated.

In the area-level analysis, there are 46,858 SA2-month observations between January 2015 to December 2021. The panel is unbalanced as SA2-month observations with fewer than 100 residents are dropped from the sample. For example, if an SA2 had 101 residents in one month and 99 in the next month, the month with 101 residents is included while the month with 99 residents is excluded. Of the 46,858 SA2-month observations, 7,353 are treated SA2-month observations while there are 27,241 control SA2-month observations. The remaining 12,264 SA2-month observations are in pre-treated SA2s and thus excluded from the analysis. Therefore, there is a total of 34,594 SA2-month observations available for the area-level analysis.

In the individual-level analysis, there are approximately 260,000 individuals residing in the 88 treated SA2s each month, translating to approximately 2,900 individuals per SA2-month observation. Those living in treated SA2s form the treatment group. On average, 820,000 individuals live in the 323 control SA2s each month, averaging about 2,500 individuals per SA2-month observation, which forms the control group. The remaining population consists of pre-treated individuals, averaging 480,000 individuals per month across all 152 pre-treated SA2s, or about 3,300 residents per SA2-month observation.

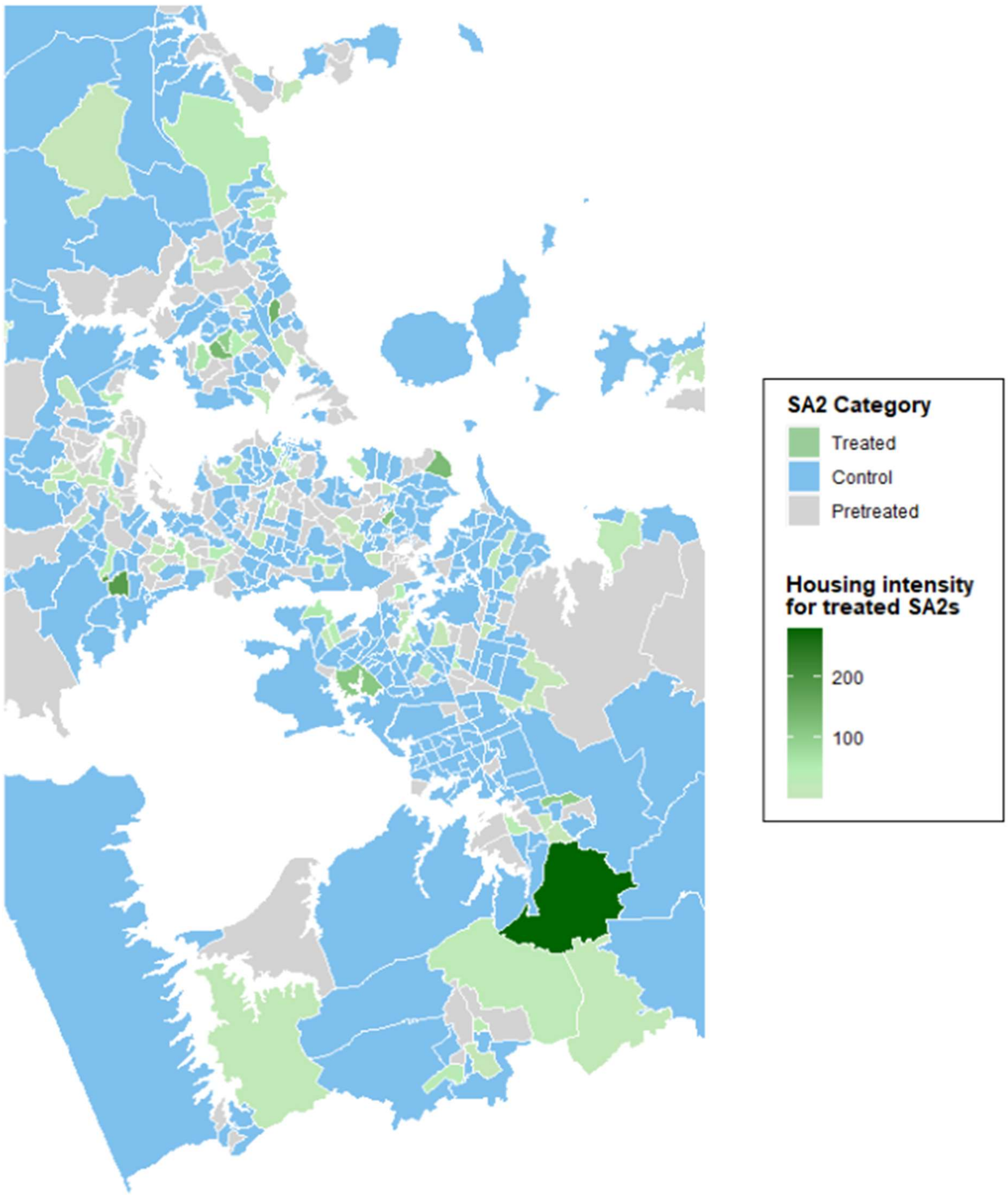
Individuals in the treatment and control groups are included in the sample for each month they reside in a treated or control SA2. They are excluded for any month spent outside of Auckland or in a pre-treated SA2. For example, if an individual resides in Auckland in March 2019, they are included in the sample for that month. However, if they move to a pre-treated SA2 or leave Auckland in April 2019, they will be excluded from the sample for that month.

Figure 10 Auckland SA2s and expected dwelling intensity between 2018 – 2021 (full size)



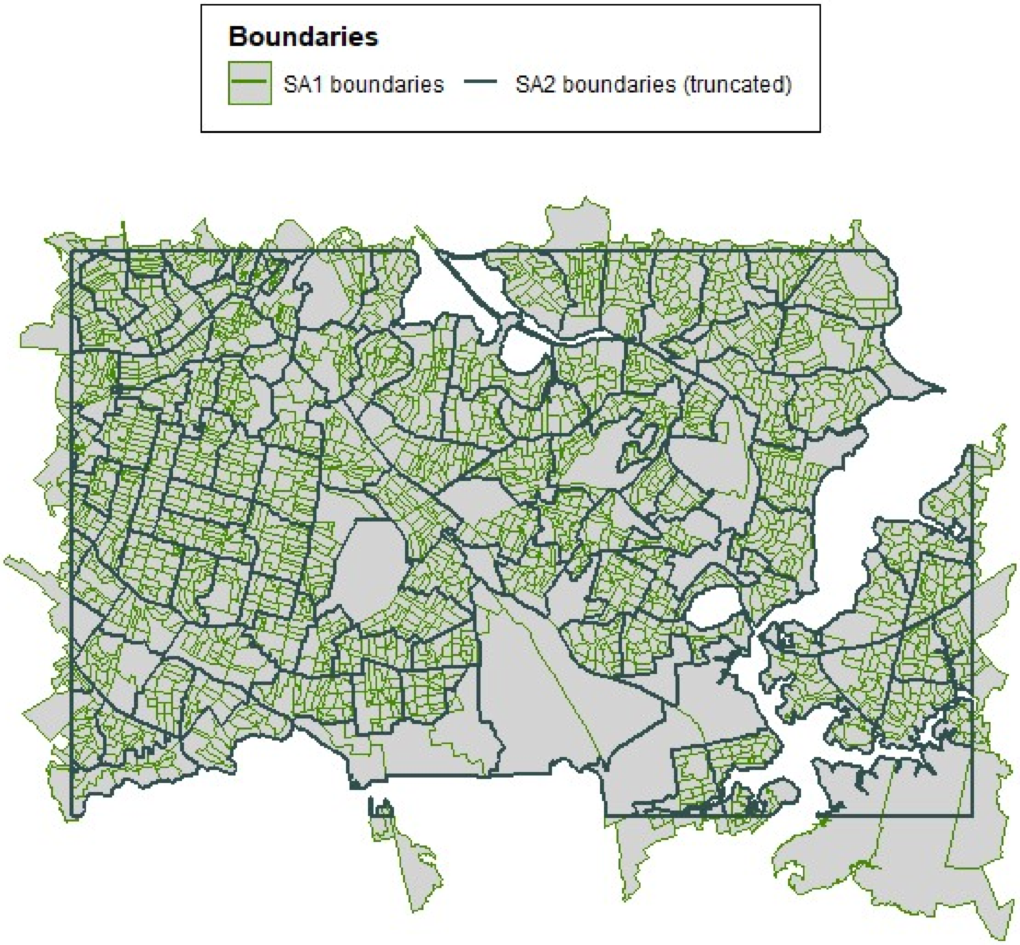
Source: Stats NZ 2018 SA2 boundary lines and Kāinga Ora housing intensification data.

Figure 11 Auckland SA2s and expected dwelling intensity between 2018 - 2021 (zoomed)



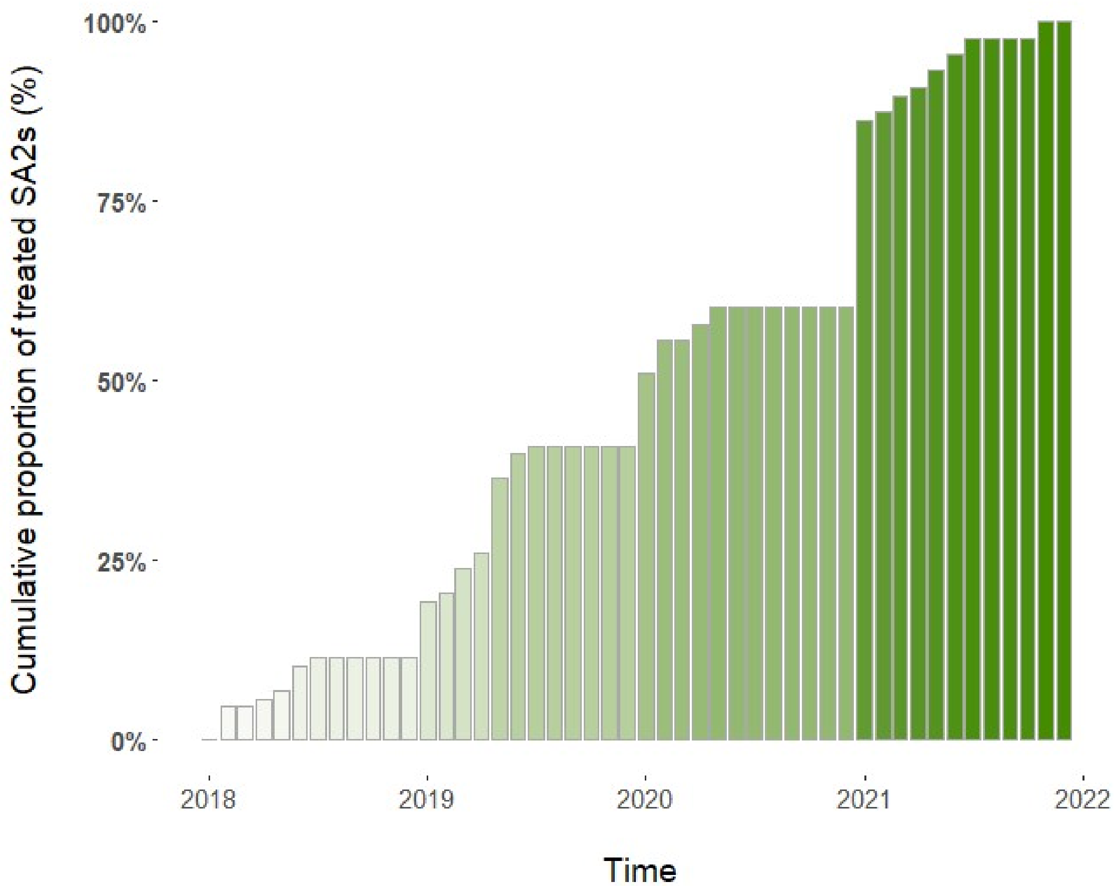
Source: Stats NZ 2018 SA2 boundary lines and Kāinga Ora housing intensification data.

Figure 12 Example of SA1 boundaries nested within (truncated) SA2 boundaries (zoomed)



Source: Stats NZ 2018 SA1 and SA2 boundary lines.

Figure 13 Cumulative proportion of SA2s starting urban regeneration within treated group (2018 – 2021)



Source: Kāinga Ora housing intensification data. Note: start of urban regeneration is the start of the Planning phase.

5.2 Heterogeneity analysis

Wellbeing outcomes of urban regeneration may differ based on area- and individual-level characteristics. Heterogeneity analyses that incorporate these characteristics can help identify mechanisms and drivers that impact wellbeing outcome variables. At the area-level, wellbeing outcomes may differ according to intensity of urban regeneration and social housing status. At the individual-level, wellbeing outcomes of urban regeneration may differ by characteristics such as being long-term residents, newcomers, or leavers. Subpopulations of interest for the heterogeneity analysis are characterised and defined in Table 6.

5.2.1 Area-level heterogeneity analysis

Areas with high levels of urban regeneration have the greatest potential to improve wellbeing outcomes, compared to areas with lower levels of urban regeneration. More houses are expected to be built in high urban regeneration areas and neighbourhood amenities may be built or improved to accommodate the new developments. Mohan et al. (2017) noted areas with higher levels of urban regeneration investment had more positive impacts on health. However, higher levels of urban regeneration can also lead to short to medium-term disruptions while construction is ongoing which can adversely impact wellbeing in the short run.

The analysis categorises treated SA2s into high and low intensity urban regeneration based on the expected number of dwellings to be built. Treated SA2s where 50 or more dwellings are expected to be built are defined as 'high intensity' urban regeneration, while SA2s where less than 50 dwellings are expected to be built are defined as 'low intensity'. Among treated SA2s, 18 are identified as high intensity areas which account for 20% of all treated SA2s, and the remaining 80% are classified as low intensity SA2s.

Individuals in social housing often experience greater vulnerability, lower incomes, housing instability, and poorer socioeconomic outcomes compared to other residents (Cole, 2021; Howden-Chapman et al., 2021; Saville-Smith et al., 2015). Given that most dwellings developed by Kāinga Ora-led urban regeneration are social housing, social housing tenants moving into these developments are most likely to be impacted by urban regeneration. Urban regeneration has the potential to improve wellbeing for social housing residents by providing improved housing quality, better neighbourhood aesthetics, enhanced amenities, and greater housing stability.

Conversely, urban regeneration can also have negative impacts on wellbeing for social housing residents. Urban regeneration can lead to the displacement of social housing residents if their homes are set for demolition and redevelopment. Those who remain in regenerated areas may endure ongoing construction and disruption, which can create uncertainty and stress for residents as changes in the neighbourhood may disband their communities, leaving them uncertain about their future.

Assessing wellbeing outcomes for the entire treated population may mask any potential adverse (or positive) outcomes on the social housing population and thereby potentially overlook worsening (or improving) outcomes for an already vulnerable population. Therefore, the analysis differentiates between social housing and non-social housing within the treated population.

Non-social housing residents may not be directly affected by urban regeneration, as they are unlikely to move into the new homes developed by Kāinga Ora. However, they can potentially benefit from improved neighbourhood amenities, better public transport connections, and expanded green spaces. Conversely, non-social housing residents may experience negative impacts such as increased construction noise, congestion, and potential antisocial behaviour from social housing tenants moving into new Kāinga Ora developments.

Additionally, non-social housing residents may be concerned that neighbourhoods with a high concentration of social housing could decline in value. If this is the case, individuals with higher education and income levels may be less inclined to move into regenerated areas, as they have more options in choosing where to live. This could be observed through lower rates of tertiary educational attainment, employment, and earnings in treated areas compared to control areas, along with an increase in benefit receipt.

5.2.2 Individual-level heterogeneity analysis

Urban regeneration generally involves large-scale projects for which outcomes are likely to be unevenly distributed among affected individuals in an area. Changes in outcomes may be driven by new residents moving in who have better outcomes, original residents benefitting from urban regeneration or residents with poorer outcomes moving out of treated areas. Evaluating outcomes for specific subpopulations can provide insights into the impacts of urban regeneration that might otherwise be missed when assessing wellbeing at the area level.

Long-term residents are likely to have different circumstances to other subpopulations, such as leavers or newcomers, as they potentially benefit from having housing stability. This stability allows for long-term communities and social networks to be developed, allows for stable attachment to employment and education opportunities to be formed and alleviates stressors related to housing instability. Comparing long-term residents in treated areas with those in control areas who share similar circumstances can help demonstrate if urban regeneration improves outcomes for existing residents who were already living in treated areas before they were treated.

Evaluating outcomes for *newcomers* can provide insight as to whether wellbeing outcomes are improving as a result of urban regeneration initiatives or if regenerated areas are beginning to gentrify, where higher educated and earning individuals move into regenerated areas (Cole, 2021). Urban regeneration projects tend to occur in more deprived areas and are often characterised by medium to high density housing (Allen et al., 2018; Batty et al., 2010; Giles-Corti et al., 2012). These characteristics are also common with gentrified areas, which tend to occur in low-income and medium to high density areas that are centrally located and well serviced by local amenities (Brummet & Reed, 2019).

As gentrified areas tend to attract highly educated individuals who are likely to have better outcomes, changes in wellbeing outcomes may be driven by better-off individuals moving into regenerated areas. This can potentially lead to an overestimation of the positive impacts of urban regeneration. For example, increased wages and salary in treated areas may be partially attributed to urban regeneration but may also be driven by higher-earning individuals moving into regenerated areas. In this context, the former is related to urban regeneration, while the latter is indicative of gentrification.

Assessing outcomes for *leavers* may help understand factors driving individuals to leave areas undergoing urban regeneration. Many residents face displacement or relocation during urban regeneration, especially while construction is ongoing (Egan et al., 2015; Henry et al., 2019). Additionally, urban regeneration can lead to gentrification, which may displace disadvantaged existing residents who can no longer afford to live in these areas (Brummet & Reed, 2019; Cole, 2021). Conversely, social housing development may incentivise non-social housing residents to move to areas with less or no social housing development.

Changes in wellbeing outcomes may be influenced by individuals with poorer outcomes moving out of regenerated areas, potentially resulting in an overestimation of the positive impacts of urban regeneration. Conversely, if individuals with better outcomes leave these areas, it may lead to an overestimation of the negative impacts of urban regeneration. For example, there may be significant increases in tertiary educational attainment in treated areas. At the area level, this is measured by the proportion of working-age individuals who hold at least a Bachelor's Degree. If working-age individuals without tertiary qualifications are leaving treated areas, this would raise the overall level of tertiary educational attainment. Such changes would result from shifts in population composition rather than from urban regeneration positively influencing tertiary educational attainment.

Table 6 Definitions for subpopulations used for heterogeneity analysis

<table>
<tr><th>Variable</th><th>Level</th><th colspan="2">Definition</th></tr>
<tr><td colspan="4">Area-level characteristics</td></tr>
<tr><td rowspan="3">Urban regeneration intensity</td><td>All</td><td colspan="2">Equal to 1 if SA2 is treated; 0 otherwise.</td></tr>
<tr><td>High</td><td colspan="2">Equal to 1 if SA2 is treated and 50 or more dwellings are expected to be built.</td></tr>
<tr><td>Low</td><td colspan="2">Equal to 1 if SA2 is treated and less than 50 dwellings are expected to be built.</td></tr>
<tr><td rowspan="3">Population</td><td>All</td><td colspan="2">Sum of all individuals who live in treated SA2 dwellings.</td></tr>
<tr><td>Social Housing</td><td colspan="2">Sum of all individuals who live in treated SA2 social housing dwellings.</td></tr>
<tr><td>Non-Social Housing</td><td colspan="2">Sum of all individuals who live in treated SA2 non-social housing dwellings.</td></tr>
<tr><td colspan="2">Individual-level characteristics</td><td>Social housing inclusion</td><td>Treatment date</td></tr>
<tr><td>Long-term residents</td><td>Equal to 1 if individual has lived in the same SA2 between January 2015 to December 2021 (inclusive); 0 otherwise.</td><td>For treatment and control groups, equal to 1 if individual lived in social housing for all time periods between January 2015 to December 2021 (inclusive); 0 otherwise</td><td>Month where ‘Planning’ phase for urban regeneration begins</td></tr>
<tr><td>Newcomers</td><td>Equal to 1 if individual moved to a treated SA2 (after urban regeneration began) from a control SA2, did not live in any other treated SA2 after it began urban regeneration, and did not live in any pre-treated SA2s; 0 otherwise.</td><td>Equal to 1 if moved into social housing after urban regeneration began; 0 otherwise.</td><td>Month moved into treated SA2 from a control SA2 (after ‘Planning’ phase begins for urban regeneration)</td></tr>
<tr><td>Leavers</td><td>Equal to 1 if an individual moved to a control SA2 from a treated SA2 (after urban regeneration began), did not live in any other treated SA2s in the future, and did not live in any pre-treated SA2s; 0 otherwise.</td><td>Equal to 1 if an individual left social housing after urban regeneration began; 0 otherwise.</td><td>Month moved from a treated into control SA2 (after ‘Planning’ phase begins for urban regeneration)</td></tr>
<tr><td>Residual</td><td>Equal to 1 if an individual was not a long-term resident, newcomer, leaver or transient control; 0 otherwise.</td><td>Equal to 1 if individual lived in social housing; 0 otherwise.</td><td>Month where ‘Planning’ phase for urban regeneration begins</td></tr>
<tr><td>Transient control</td><td>Equal to 1 if individual moved within control areas after January 2020 (midway point where 50% of treated SA2s have begun the ‘Planning’ phase for urban regeneration); 0 otherwise.</td><td>Equal to 1 if individual lived in social housing in January 2020; 0 otherwise.</td><td>N/A – control group</td></tr>
</table>

5.3 Demographic profile of treated and control areas

Table 7 presents average area-level demographic characteristics between 2015 to 2017 (2015/17) and 2018 to 2021 (2018/21). Note that time bands are used in the descriptive statistics, as opposed to pre- and post-urban regeneration, as there is no equivalent pre- and post-treatment for non-treated SA2s with staggered treatment timing (described in further detail in Section 5.5). Columns (I) – (IV) presents averages for all treated areas, treated areas with high urban regeneration (high UR), treated areas with low urban regeneration (low UR) and control areas in Auckland in 2015/17. Likewise, columns (V) – (VIII) presents averages for 2018/21.

In 2015/2017, treated areas have a higher average population (2,877 in column I) compared to control areas (2,498 in column IV). The average population size increased by similar magnitudes (6%) in both treated and control areas between 2015/17 and 2018/21. Population growth in low UR areas was larger (6.8% - 2,902 in column III to 3,099 in column VII) than in high UR areas (4.9% - 2,781 in column II to 2,917 in column VI). The non-social housing population make up the large majority of residents, irrespective of treatment status. On average, treated areas in 2015/17 have the highest proportion of social housing, especially in high UR areas (23% in column II) compared to control areas (3% in column IV). However, both the number and proportion of social housing residents in high UR areas decreased in 2018/21 (21% in column VI) compared to 2015/17 (23% in column II).

Both treated and control areas experience significant increases in the number of new dwellings. Between 2015/17 and 2018/21, the number of dwellings rose by 6.6% in treated areas and by 5.9% in control areas. In high and low UR areas, the increases were 5.8% and 6.7%, respectively. The average number of social housing addresses remain largely unchanged across both treated and control areas during this period. As growth rates for both population and number of new dwellings were similar, household size remains mostly unchanged between the two periods.

It would be reasonable to expect greater growth in population, dwelling, and household sizes in high UR areas, as housing intensification usually involves replacing a single dwelling with multiple dwellings. However, by the end of 2018/21, not all dwellings expected to be built by urban regeneration have been completed. Moreover, the completed dwellings may have only replaced the housing stock that was demolished as part of the urban regeneration process.

The population and dwelling growth observed for low UR areas indicates that non-Kāinga Ora urban development is also taking place in low UR areas. This is also the case for control areas – dwellings in control areas increased by 5.9%, from 851 (column IV) to 901 (column VIII). Therefore, both treated and control areas are experiencing similar increases in completed housing developments. Future analyses could benefit from examining dwelling and population growth once Kāinga Ora-led urban regeneration has fully completed.

On average, treated areas have a significantly higher proportion of individuals residing in the highest deprivation quintile, with 34% in 2015/17 and 32% in 2018/21 (columns I and V, respectively), compared to control areas (7% for both periods, column IV and VIII). This is largely driven by high UR areas – in 2015/17, 50% of individuals lived in the highest deprivation, which decreased to 46% (column VI) in 2018/21. This indicates that high levels of urban regeneration tend to be concentrated in higher deprivation areas. Across all areas, irrespective of treatment, a large share of social housing residents —ranging from 73% to 90%—live in the highest deprivation

There are similar proportions of gender and marriage/civil union across treated and control areas. The population age distribution is also similar in the treatment and control areas. There is large variation in ethnic distribution between treated and control areas. On average, treated areas have almost twice the proportion of Māori (16%) compared to control areas (9%) in both periods. Māori account for almost one-third of the social housing population in both 2015/17 and 2018/21. The proportion of Pacific living in treated areas (20%) is almost three times that of control areas (6%) in both periods, and Pacific make up over half of the social housing population. On average, the proportion of Asians in treated and control areas are similar. All areas, irrespective of treatment status, saw increases in the proportion of Asians residents. This was especially the case in high UR areas which saw an increase from 18% in 2015/17 to 22% in 2018/21 (22% increase between periods).

Treated areas have a lower proportion of Europeans (33% and 36% in 2015/17 and 2018/21, respectively) compared to control areas (58% and 55%). The overall proportion of Europeans residing in Auckland declined from 2015/17 to 2018/21, regardless of treatment status. This trend suggests that Europeans may be relocating out of Auckland, or that the population growth in the city is primarily driven by non-Europeans, or possibly both factors. The latter is likely to be the largest driver given the large number of international immigrants to New Zealand during this period, with the majority of migrants settling in Auckland.

Table 7 Average demographic characteristics for treated and control SA2s

Demographic characteristics	2015 – 2017				2018 – 2021			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
	T – All UR	T – High UR	T – Low UR	C	T – All UR	T – High UR	T – Low UR	C
All population	2,877	2,781	2,902	2,498	3,061	2,917	3,099	2,652
Social housing (n) *(% of all population)*	416 *(13%)*	688 *(23%)*	343 *(11%)*	151 *(3%)*	410 *(13%)*	644 *(21%)*	346 *(10%)*	143 *(3%)*
Non-social Housing (n) *(% of all population)*	2,490 *(87%)*	2,132 *(77%)*	2,584 *(89%)*	2,423 *(97%)*	2,676 *(87%)*	2,296 *(79%)*	2,776 *(90%)*	2,578 *(97%)*
All addresses	870	823	883	851	927	871	942	901
Social housing addresses *(% all addresses)*	99 *(10%)*	149 *(18%)*	74 *(8%)*	19 *(2%)*	92 *(10%)*	148 *(17%)*	77 *(8%)*	19 *(2%)*
Non-social housing addresses *(% all addresses)*	780 *(90%)*	673 *(82%)*	808 *(92%)*	832 *(98%)*	835 *(90%)*	723 *(83%)*	864 *(92%)*	882 *(98%)*
Household size (popn / addresses)	3.3	3.4	3.3	2.9	3.3	3.4	3.3	2.9
Social household size	4.3	4.4	4.3	3.9	4.2	4.2	4.2	3.8
Non-social household size	3.2	3.2	3.2	2.9	3.2	3.2	3.2	2.9
Demographic distribution (% of population)								
Female	50%	50%	50%	51%	50%	50%	50%	50%
Social housing	51%	51%	51%	51%	51%	51%	51%	51%
Non-social housing	50%	50%	50%	51%	50%	50%	50%	50%
Living in highest deprivation [a]	34%	50%	29%	7%	32%	46%	28%	7%
Social housing	81%	90%	76%	76%	79%	89%	74%	73%
Non-social housing	26%	37%	24%	5%	25%	35%	23%	5%
Married/in civil union	21%	21%	21%	21%	21%	21%	22%	22%
Social housing	20%	20%	20%	17%	20%	20%	20%	18%
Non-social housing	21%	21%	21%	21%	22%	21%	22%	22%
Ethnicity distribution (% of population)								
Māori	16%	17%	16%	9%	16%	17%	15%	9%
Social housing	30%	27%	31%	30%	29%	26%	31%	29%
Non-social housing	14%	14%	14%	8%	14%	14%	14%	8%
Pacific	20%	27%	18%	6%	20%	26%	18%	6%
Social housing	55%	59%	53%	48%	55%	59%	53%	48%
Non-social housing	15%	18%	14%	5%	15%	17%	14%	5%
Asian	25%	18%	27%	24%	29%	22%	30%	27%
Social housing	6%	5%	6%	8%	6%	6%	6%	9%
Non-social housing	28%	22%	29%	25%	32%	27%	33%	28%
MELAA	2%	2%	2%	2%	2%	3%	2%	3%
Social housing	3%	2%	3%	2%	3%	3%	3%	3%
Non-social housing	2%	2%	2%	2%	2%	3%	2%	3%
Other	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%
Social housing	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%
Non-social housing	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%	< 1%
European	36%	35%	37%	58%	33%	32%	34%	55%
Social housing	7%	7%	7%	9%	6%	6%	6%	9%
Non-social housing	41%	44%	40%	60%	37%	39%	37%	56%

Age group distribution (% of population)								
Under 18	**26%**	**27%**	**26%**	**22%**	**25%**	**26%**	**25%**	**22%**
Social housing	38%	37%	39%	35%	36%	35%	37%	33%
Non-social housing	24%	24%	24%	22%	23%	23%	24%	21%
18 to 24	**11%**	**12%**	**11%**	**10%**	**10%**	**11%**	**10%**	**9%**
Social housing	13%	14%	13%	12%	13%	13%	13%	12%
Non-social housing	11%	11%	11%	10%	10%	10%	10%	9%
25 to 64	**53%**	**52%**	**53%**	**54%**	**54%**	**54%**	**54%**	**54%**
Social housing	41%	42%	41%	43%	43%	43%	43%	45%
Non-social housing	54%	55%	54%	54%	56%	56%	56%	55%
65 +	**10%**	**9%**	**11%**	**14%**	**11%**	**10%**	**11%**	**15%**
Social housing	7%	7%	7%	6%	7%	8%	7%	8%
Non-social housing	11%	10%	11%	14%	11%	10%	11%	15%

Source: IDI 2024. Note: UR = urban regeneration; T = treated and C = control; SH = social housing; MELAA = Middle Eastern, Latin American and African.

[a] Quintile 5 Deprivation/Decile 9 and 10 (highest deprivation).

5.4 Demographic profile of treated and control individuals

Table 8 presents the average individual-level demographic characteristics for treated and control long-term residents between 2015 to 2017 (2015/17) and 2018 to 2021 (2018/21). Table 9 presents newcomers and leavers and Table 10 presents the residual population.[11] These populations are described in Section 5.2.

5.4.1 Long-term residents

Columns (I)-(III) in Table 8 presents the average number of long-term residents in treated areas in 2015/2017 with each column corresponding to urban regeneration intensity - all, high urban regeneration (high UR) and low urban regeneration (low UR). Column (IV) presents the average number of long-term residents in control areas in 2015/2017. Columns (V)-(VIII) provides the averages for 2018/21. Since long-term residents are defined as individuals who have lived in the same SA2 from 2015 to 2021, their demographic characteristics remain largely consistent over time.

As observed in Table 7, both treated and control areas experienced population growth between 2015/17 and 2018/21. As a result, Table 8 shows the proportion of long-term residents, relative to the total population, decreased between 2015/17 to 2018/21. Treated areas have a higher number of long-term residents compared to control areas. However, due to the lower overall population in control areas, long-term residents comprise a larger share of the control population (24.1% and 22.9% in control and treated areas in 2018/21, column V and VIII respectively).

[11] Averages are calculated per SA2 using the count of individuals divided by the number of months in each period and the number of SA2s.

Table 8 Average SA2 demographic characteristics for treated and control long-term residents

Demographic characteristics	2015 – 2017				2018 – 2021			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
	Long-term residents				Long-term residents			
	T – All UR	T – High UR	T – Low UR	C	T – All UR	T – High UR	T – Low UR	C
Population (n)	702	665	711	640	702	665	711	640
% of total population[a]	24.4%	23.9%	24.5%	25.6%	22.9%	22.8%	22.9%	24.1%
Number living in social housing (% of population)								
Social housing	103 (14.7%)	175 (26.3%)	84 (11.8%)	20 (3.1%)	103 (14.7%)	174 (26.2%)	84 (11.8%)	20 (3.1%)
Non-social housing	599 (85.3%)	491 (73.8%)	627 (88.2%)	620 (96.9%)	599 (85.3%)	491 (73.8%)	627 (88.2%)	620 (96.9%)
Gender (% of population)								
Female	360 (51.3%)	344 (51.7%)	364 (51.2%)	324 (50.6%)	360 (51.3%)	344 (51.7%)	364 (51.2%)	324 (50.6%)
Male	342 (48.7%)	321 (48.3%)	347 (48.8%)	316 (49.4%)	342 (48.7%)	321 (48.3%)	347 (48.8%)	316 (49.4%)
Quintile 5 deprivation (% of population)								
Living in quintile 5	232 (33.0%)	351 (52.8%)	201 (28.3%)	39 (6.1%)	232 (33.0%)	349 (52.5%)	201 (28.3%)	39 (6.1%)
Not living in quintile 5	470 (67.0%)	315 (47.4%)	510 (71.7%)	601 (93.9%)	470 (67.0%)	316 (47.5%)	510 (71.7%)	601 (93.9%)
In marriage/civil union (% of population)								
Legally partnered	109 (15.5%)	103 (15.5%)	111 (15.6%)	110 (17.2%)	114 (16.2%)	107 (16.1%)	116 (16.3%)	114 (17.8%)
Not legally partnered	592 (84.3%)	563 (84.7%)	600 (84.4%)	530 (82.8%)	588 (83.8%)	558 (83.9%)	595 (83.7%)	526 (82.2%)
Ethnicity (% of population)								
Māori	102 (14.5%)	104 (15.6%)	101 (14.2%)	55 (8.6%)	102 (14.5%)	104 (15.6%)	101 (14.2%)	55 (8.6%)
Pacific	157 (22.4%)	221 (33.2%)	141 (19.8%)	40 (6.3%)	157 (22.4%)	221 (33.2%)	141 (19.8%)	40 (6.3%)
Asian	124 (17.7%)	67 (10.1%)	138 (19.4%)	99 (15.5%)	124 (17.7%)	67 (10.1%)	138 (19.4%)	99 (15.5%)
MELAA	9 (1.3%)	7 (1.1%)	9 (1.3%)	7 (1.1%)	9 (1.3%)	7 (1.1%)	9 (1.3%)	7 (1.1%)
Other	3 (0.4%)	2 (0.3%)	3 (0.4%)	3 (0.5%)	3 (0.4%)	2 (0.3%)	3 (0.4%)	3 (0.5%)
European	308 (43.9%)	264 (39.7%)	319 (44.9%)	435 (68.0%)	308 (43.9%)	264 (39.7%)	319 (44.9%)	435 (68.0%)
Age group (% of population)								
0-4	36 (5.1%)	35 (5.3%)	36 (5.1%)	27 (4.2%)	5 (0.7%)	4 (0.6%)	5 (0.7%)	3 (0.5%)
5-9	63 (9.0%)	64 (9.6%)	62 (8.7%)	53 (8.3%)	49 (7.0%)	49 (7.4%)	49 (6.9%)	38 (5.9%)
10-14	59 (8.4%)	62 (9.3%)	58 (8.2%)	53 (8.3%)	64 (9.1%)	67 (10.1%)	63 (8.9%)	56 (8.8%)
15-19	39 (5.6%)	40 (6.0%)	39 (5.5%)	32 (5.0%)	53 (7.5%)	55 (8.3%)	52 (7.3%)	47 (7.3%)
20-24	25 (3.6%)	25 (3.8%)	26 (3.7%)	17 (2.7%)	34 (4.8%)	34 (5.1%)	34 (4.8%)	26 (4.1%)
25-29	23 (3.3%)	22 (3.3%)	23 (3.2%)	14 (2.2%)	23 (3.3%)	23 (3.5%)	24 (3.4%)	15 (2.3%)
30-34	33 (4.7%)	29 (4.4%)	33 (4.6%)	22 (3.4%)	25 (3.6%)	23 (3.5%)	25 (3.5%)	15 (2.3%)
35-39	46 (6.6%)	41 (6.2%)	47 (6.6%)	36 (5.6%)	37 (5.3%)	33 (5.0%)	38 (5.3%)	26 (4.1%)
40-44	56 (8.0%)	55 (8.3%)	57 (8.0%)	53 (8.3%)	49 (7.0%)	45 (6.8%)	50 (7.0%)	40 (6.3%)

45-49	65 (9.3%)	64 (9.6%)	66 (9.3%)	65 (10.2%)	60 (8.5%)	59 (8.9%)	60 (8.4%)	59 (9.2%)
50-54	66 (9.4%)	59 (8.9%)	67 (9.4%)	64 (10.0%)	65 (9.3%)	62 (9.3%)	66 (9.3%)	65 (10.2%)
55-59	54 (7.7%)	48 (7.2%)	55 (7.7%)	55 (8.6%)	63 (9.0%)	57 (8.6%)	65 (9.1%)	62 (9.7%)
60-64	42 (6.0%)	40 (6.0%)	42 (5.9%)	43 (6.7%)	50 (7.1%)	44 (6.6%)	51 (7.2%)	51 (8.0%)
65+	96 (13.7%)	83 (12.5%)	99 (13.9%)	108 (16.9%)	124 (17.7%)	111 (16.7%)	128 (18.0%)	139 (21.7%)

Source: IDI 2024. Note: UR = urban regeneration; T = treated and C = control; MELAA = Middle Eastern, Latin American and African. Not all percentages add up to 100% due to random rounding of small numbers as per Stats NZ confidentiality rules and the averaging across SA2s and months.

[a] Total population numbers corresponding to row 'All Population' columns (I)-(IV) and (VI)-(XI) in Table 7.

5.4.2 Leavers and newcomers

Columns (I)-(III) in Table 9 presents the average number of leavers in treated areas in 2015/17 with each column corresponding to all, high urban regeneration (high UR) and low urban regeneration (low UR). Recall that leavers are individuals who leave treated areas after urban regeneration began. Column (IV) presents the average number of transient residents in control areas in 2015/17, defined as individuals having moved within control areas sometime after January 2020. Columns (V)-(VIII) presents the average number of newcomers in treated areas for the period 2018/21 with each column corresponding to urban regeneration intensity. These are individuals who moved from control areas into treated areas after urban regeneration began. Column (VIII) presents the average number of newcomers in control areas for 2018/21, who are leavers from treated areas in 2015/17. Column (IX) presents the average number of transient individuals in control areas in 2018/21.

On average, leavers comprise 3.9% of the treated population in 2015/17, with the majority of leavers moving from non-social housing (column I). There are more leavers in high UR areas, with almost 12% of leavers moving from social housing (column II). One possible explanation for this could be that high UR areas experience greater disruption due to ongoing urban regeneration activity. Almost a third of leavers from high UR areas were from high deprivation areas (column II), much higher compared to overall leavers (21.2% in column I) and transient control residents (5.2%).

Europeans and by Asian constitute the majority of leavers among both treated and control individuals. Low UR areas have the highest proportion of Asian leavers (29.4% in column III) while high UR areas have the lowest proportion of Asian leavers (19.7% in column II). Europeans make up 62.4% of transient control individuals (column IV).

When examining age groups, those aged 20 to 39 represent the largest share of leavers, comprising over a third of leavers in treated areas (columns I-III). In the transient control population, the highest shares of leavers are among 15- to 19-year-olds and individuals aged 65 and older, at 9.3% and 9.8%, respectively (as shown in column IV). Shares by gender and legal partnered status are similar across all groups in 2015/17.

In the 2018/21 period, there are higher numbers of newcomers relocating to high UR areas compared to low UR areas (96 and 64, respectively in column VI and VII). This may be attributed to the increased availability of housing due to ongoing urban regeneration developments in high UR areas. Additionally, these areas may offer more neighbourhood amenities, proximity to public transport, and attractive housing options which may also incentivise individuals to move into high UR areas.

Most newcomers move into non-social housing, with high UR areas having the most social housing newcomers (7.3% in column VI). Over a quarter of high UR newcomers move into highly deprived areas (26.0% in column VI), likely reflecting urban regeneration projects being concentrated in areas with historically high deprivation. Only 5.1% of the transient control population move into highly deprived control areas (column IX) while 18.2% of newcomers from treated areas move into highly deprived control areas (column VIII).

There are similar shares of Māori leavers and newcomers (12.4% and 11.3% in column I and V). However, there were more Pacific leavers than there were Pacific newcomers (10.6% and 8.5% in column I and V). Asian newcomers comprise a third of those moving into treated and control areas (column V to VIII) while they comprise only a quarter of the transient control population (column XI). Less than half of newcomers are European (columns V to VIII) while Europeans make up 57.9% of the transient control population (column XI). This suggests that Europeans are more likely to move within control areas, rather than move between treated and control areas. Almost half of newcomers in treated and control areas are aged between 20 and 30. This is less than 40% for transient control individuals (column XI). Shares by gender and legal partnered status are similar across all groups in 2018/21.

Table 9 Average SA2 demographic characteristics for treated and control leavers and newcomers

Demographic characteristics	2015 – 2017				2018 – 2021				
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
	Leavers (from T areas)			C	Newcomers (from C areas)			C	
	T - All UR	T - High UR	T - Low UR	Transient	T – All UR	T – High UR	T – Low UR	Newcomers (from T areas)	Transient
Population (n)	113	127	109	194	71	96	64	33	254
% of total population[a]	3.9%	4.6%	3.8%	7.8%	2.3%	3.3%	2.1%	1.2%	9.6%
Number living in social housing (% of population)									
Social housing	7 (6.2%)	15 (11.8%)	5 (4.6%)	4 (2.1%)	3 (4.2%)	7 (7.3%)	3 (4.7%)	2 (6.1%)	4 (1.6%)
Non-social housing	106 (93.8%)	111 (87.4%)	104 (95.4%)	191 (98.5%)	67 (94.4%)	89 (92.7%)	62 (96.9%)	31 (93.9%)	250 (98.4%)
Gender (% of population)									
Female	57 (50.4%)	63 (49.6%)	55 (50.5%)	100 (51.5%)	35 (49.3%)	48 (50.0%)	32 (50.0%)	16 (48.5%)	130 (51.2%)
Male	56 (49.6%)	63 (49.6%)	54 (49.5%)	95 (49.0%)	36 (50.7%)	48 (50.0%)	33 (51.6%)	16 (48.5%)	124 (48.8%)
Quintile 5 deprivation (% of population)									
Living in quintile 5	24 (21.2%)	42 (33.1%)	20 (18.3%)	10 (5.2%)	13 (18.3%)	25 (26.0%)	10 (15.6%)	6 (18.2%)	13 (5.1%)
Not living in quintile 5	89 (78.8%)	84 (66.1%)	90 (82.6%)	184 (94.8%)	57 (80.3%)	71 (74.0%)	54 (84.4%)	27 (81.8%)	241 (94.9%)
In marriage/civil union (% of population)									
Legally partnered	17 (15.0%)	18 (14.2%)	17 (15.6%)	29 (14.9%)	10 (14.1%)	13 (13.5%)	9 (14.1%)	5 (15.2%)	38 (15.0%)
Not legally partnered	96 (85.0%)	109 (85.8%)	93 (85.3%)	166 (85.6%)	61 (85.9%)	83 (86.5%)	55 (85.9%)	28 (84.8%)	217 (85.4%)
Ethnicity (% of population)									
Māori	14 (12.4%)	17 (13.4%)	13 (11.9%)	16 (8.2%)	8 (11.3%)	11 (11.5%)	7 (10.9%)	4 (12.1%)	20 (7.9%)
Pacific	12 (10.6%)	16 (12.6%)	11 (10.1%)	7 (3.6%)	6 (8.5%)	8 (8.3%)	6 (9.4%)	3 (9.1%)	9 (3.5%)
Asian	31 (27.4%)	25 (19.7%)	32 (29.4%)	44 (22.7%)	24 (33.8%)	30 (31.3%)	23 (35.9%)	10 (30.3%)	67 (26.4%)
MELAA	3 (2.7%)	4 (3.1%)	2 (1.8%)	5 (2.6%)	2 (2.8%)	4 (4.2%)	2 (3.1%)	1 (3.0%)	8 (3.1%)
Other	0 (0.0%)	1 (0.8%)	0 (0.0%)	1 (0.5%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	2 (0.8%)
European	53 (46.9%)	64 (50.4%)	50 (45.9%)	121 (62.4%)	29 (40.8%)	43 (44.8%)	26 (40.6%)	14 (42.4%)	147 (57.9%)
Age group (% of population)									
0-4	8 (7.1%)	8 (6.3%)	8 (7.3%)	10 (5.2%)	5 (7.0%)	5 (5.2%)	5 (7.8%)	3 (9.1%)	14 (5.5%)
5-9	7 (6.2%)	8 (6.3%)	7 (6.4%)	11 (5.7%)	4 (5.6%)	4 (4.2%)	4 (6.3%)	2 (6.1%)	13 (5.1%)
10-14	7 (6.2%)	8 (6.3%)	7 (6.4%)	14 (7.2%)	4 (5.6%)	4 (4.2%)	4 (6.3%)	2 (6.1%)	14 (5.5%)
15-19	9 (8.0%)	11 (8.7%)	9 (8.3%)	18 (9.3%)	4 (5.6%)	5 (5.2%)	4 (6.3%)	2 (6.1%)	19 (7.5%)
20-24	10 (8.8%)	11 (8.7%)	9 (8.3%)	17 (8.8%)	7 (9.9%)	9 (9.4%)	6 (9.4%)	3 (9.1%)	24 (9.4%)
25-29	11 (9.7%)	14 (11.0%)	10 (9.2%)	16 (8.2%)	9 (12.7%)	13 (13.5%)	8 (12.5%)	4 (12.1%)	25 (9.8%)
30-34	10 (8.8%)	12 (9.4%)	10 (9.2%)	15 (7.7%)	9 12.7%)	13 (13.5%)	8 (12.5%)	4 (12.1%)	24 (9.4%)

35-39	9 (8.0%)	9 (7.1%)	9 (8.3%)	14 (7.2%)	7 (9.9%)	9 (9.4%)	7 (10.9%)	3 (9.1%)	21 (8.3%)
40-44	8 (7.1%)	9 (7.1%)	8 (7.3%)	14 (7.2%)	5 (7.0%)	6 (6.3%)	5 (7.8%)	2 (6.1%)	18 (7.1%)
45-49	7 (6.2%)	8 (6.3%)	7 (6.4%)	14 (7.2%)	4 (5.6%)	6 (6.3%)	4 (6.3%)	2 (6.1%)	17 (6.7%)
50-54	6 (5.3%)	8 (6.3%)	5 (4.6%)	12 (6.2%)	4 (5.6%)	6 (6.3%)	3 (4.7%)	2 (6.1%)	15 (5.9%)
55-59	5 (4.4%)	6 (4.7%)	5 (4.6%)	10 (5.2%)	3 (4.2%)	4 (4.2%)	3 (4.7%)	1 (3.0%)	13 (5.1%)
60-64	4 (3.5%)	5 (3.9%)	4 (3.7%)	8 (4.1%)	2 (2.8%)	3 (3.1%)	2 (3.1%)	1 (3.0%)	10 (3.9%)
65+	10 (8.8%)	10 (7.9%)	10 (9.2%)	19 (9.8%)	5 (7.0%)	7 (7.3%)	4 (6.3%)	3 (9.1%)	26 (10.2%)

Source: IDI 2024. Note: UR = urban regeneration; T = treated and C = control; MELAA = Middle Eastern, Latin American and African. Not all percentages add up to 100% due to random rounding of small numbers as per Stats NZ confidentiality rules and the averaging across SA2s and months.

[a] Total population numbers corresponding to row 'All population' columns (I)-(IV) and (VI)-(XI) in Table 7.

5.4.3 Residual residents

Columns (I)-(III) in Table 10 presents the average number of residual residents in treated areas in 2015/17 with each column corresponding to all, high urban regeneration (high UR) and low urban regeneration (low UR). Recall that residual residents are neither long-term residents, leavers or newcomers. Residual residents include individuals who move to and from pre-treated areas, moved from outside of Auckland or moved into treated areas before urban regeneration started but had not lived in treated areas for the entire January 2015 to December 2021 period. Column (IV) presents the average number of residual residents in control areas in 2015/17. Columns (V)-(VIII) are the averages for 2018/21.

Residual residents represent the largest share of the population compared to other subpopulations in both 2015/17 and 2018/21. The share of residual residents is higher in treated areas compared to control areas (68.7% and 61.9%, respectively in column V and VIII) and this is consistent across both periods.

Social housing residual residents comprise 23.2% and 21.2% of the high UR population in 2015/17 and 2018/21 (column II and VI, respectively) which most likely reflects the availability of more social housing in these areas. Almost half of the residual population in high UR areas live in the highest deprivation, again most likely reflecting that urban regeneration tends to occur in historically highly deprived areas. In contrast, only 7.2% of control residual residents live in high deprivation (column VIII).

The share of Māori residual residents in treated areas remain consistent regardless of urban regeneration intensity. In contrast, Pacific residual residents are predominantly found in high UR areas, a trend that persists across both periods. The proportion of Asian residual residents in treated areas increased between 2015/17 and 2018/21. This is also supported by the increase in the share of Asians residing in treated areas from Table 7. The increase in the Asian population residing in treated areas means the share of Europeans in treated areas has decreased (33.1% in 2015/17 and 29.0% in 2018/21, column I and V respectively). A similar pattern is observed in the control residual population, where the percentage of Europeans dropped from 54.2% in 2015/17 (column IV) to 49.4% in 2018/21 (column VIII).

The proportion of residual residents aged 15 to 24 decreased from 2015/17 to 2018/21 in both treated and control areas. In contrast, the share of residents aged 30 to 39 increased, along with the proportion of those aged 0 to 4. Since this trend is observed in both treated and control areas, it suggests that individuals aged 30 to 39 are beginning to start families, while younger residents may be relocating due to different life stages, rather than as a result of urban regeneration. Additionally, the share of residual residents by gender and legal partnered status remained similar across all groups in both 2015/17 and 2018/21.

Table 10 Average SA2 demographic characteristics for treated and control residuals

Demographic characteristics	2015 – 2017				2018 – 2021			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
	Residual				Residual			
	T – All UR	T – High UR	T – Low UR	C	T – All UR	T – High UR	T – Low UR	C
Population (n)	1,978	1,969	1,980	1,566	2,103	2,029	2,121	1,641
% of total population[a]	68.8%	70.8%	68.2%	62.7%	68.7%	69.6%	68.4%	61.9%
Number living in social housing (% of population)								
Social housing	267 (13.5%)	457 (23.2%)	218 (11.0%)	48 (3.1%)	265 (12.6%)	430 (21.2%)	222 (10.5%)	46 (2.8%)
Non-social housing	1,711 (86.5%)	1,512 (76.8%)	1,762 (89.0%)	1,518 (96.9%)	1,838 (87.4%)	1,599 (78.8%)	1,899 (89.5%)	1,595 (97.2%)
Gender (% of population)								
Female	983 (49.7%)	971 (49.3%)	987 (49.8%)	789 (50.4%)	1,040 (49.5%)	1,004 (49.5%)	1,049 (49.5%)	823 (50.2%)
Male	994 (50.3%)	998 (50.7%)	993 (50.2%)	777 (49.6%)	1,063 (50.5%)	1,025 (50.5%)	1,072 (50.5%)	818 (49.8%)
Quintile 5 deprivation (% of population)								
Living in quintile 5	682 (34.5%)	983 (49.9%)	605 (30.6%)	121 (7.7%)	679 (32.3%)	943 (46.5%)	612 (28.9%)	118 (7.2%)
Not living in quintile 5	1,296 (65.5%)	986 (50.1%)	1,375 (69.4%)	1,445 (92.3%)	1,423 (67.7%)	1,086 (53.5%)	1,510 (71.2%)	1,523 (92.8%)
In marriage/civil union (% of population)								
Legally partnered	255 (12.9%)	244 (12.4%)	257 (13.0%)	213 (13.6%)	283 (13.5%)	256 (12.6%)	290 (13.7%)	236 (14.4%)
Not legally partnered	1,723 (87.1%)	1,725 (87.6%)	1,723 (87.0%)	1,353 (86.4%)	1,820 (86.5%)	1,773 (87.4%)	1,832 (86.4%)	1,405 (85.6%)

Ethnicity (% of population)								
Māori	337 (17.0%)	358 (18.2%)	331 (16.7%)	147 (9.4%)	344 (16.4%)	356 (17.5%)	341 (16.1%)	153 (9.3%)
Pacific	393 (19.9%)	521 (26.5%)	361 (18.2%)	93 (5.9%)	417 (19.8%)	512 (25.2%)	393 (18.5%)	104 (6.3%)
Asian	541 (27.4%)	396 (20.1%)	579 (29.2%)	432 (27.6%)	670 (31.9%)	522 (25.7%)	709 (33.4%)	517 (31.5%)
MELAA	46 (2.3%)	53 (2.7%)	45 (2.3%)	39 (2.5%)	54 (2.6%)	62 (3.1%)	52 (2.5%)	48 (2.9%)
Other	6 (0.3%)	6 (0.3%)	7 (0.4%)	7 (0.4%)	7 (0.3%)	7 (0.3%)	7 (0.3%)	8 (0.5%)
European	654 (33.1%)	636 (32.3%)	658 (33.2%)	848 (54.2%)	609 (29.0%)	570 (28.1%)	619 (29.2%)	810 (49.4%)
Age group (% of population)								
0-4	172 (8.7%)	170 (8.6%)	173 (8.7%)	102 (6.5%)	191 (9.1%)	177 (8.7%)	194 (9.1%)	115 (7.0%)
5-9	141 (7.1%)	143 (7.3%)	141 (7.1%)	90 (5.7%)	160 (7.6%)	155 (7.6%)	161 (7.6%)	106 (6.5%)
10-14	119 (6.0%)	125 (6.3%)	118 (6.0%)	84 (5.4%)	131 (6.2%)	136 (6.7%)	130 (6.1%)	92 (5.6%)
15-19	143 (7.2%)	155 (7.9%)	140 (7.1%)	108 (6.9%)	129 (6.1%)	140 (6.9%)	127 (6.0%)	94 (5.7%)
20-24	193 (9.8%)	207 (10.5%)	190 (9.6%)	139 (8.9%)	173 (8.2%)	180 (8.9%)	171 (8.1%)	120 (7.3%)
25-29	207 (10.5%)	217 (11.0%)	205 (10.4%)	144 (9.2%)	220 (10.5%)	222 (10.9%)	220 (10.4%)	148 (9.0%)
30-34	177 (8.9%)	171 (8.7%)	178 (9.0%)	129 (8.2%)	214 (10.2%)	201 (9.9%)	217 (10.2%)	147 (9.0%)
35-39	142 (7.2%)	137 (7.0%)	143 (7.2%)	107 (6.8%)	174 (8.3%)	156 (7.7%)	179 (8.4%)	133 (8.1%)
40-44	123 (6.2%)	120 (6.1%)	123 (6.2%)	101 (6.4%)	134 (6.4%)	123 (6.1%)	137 (6.5%)	109 (6.6%)
45-49	115 (5.8%)	113 (5.7%)	115 (5.8%)	101 (6.4%)	120 (5.7%)	118 (5.8%)	121 (5.7%)	104 (6.3%)
50-54	104 (5.3%)	100 (5.1%)	105 (5.3%)	97 (6.2%)	105 (5.0%)	103 (5.1%)	106 (5.0%)	94 (5.7%)
55-59	88 (4.4%)	82 (4.2%)	90 (4.5%)	87 (5.6%)	95 (4.5%)	87 (4.3%)	97 (4.6%)	90 (5.5%)
60-64	72 (3.6%)	67 (3.4%)	74 (3.7%)	76 (4.9%)	77 (3.7%)	68 (3.4%)	79 (3.7%)	78 (4.8%)
65+	181 (9.2%)	163 (8.3%)	186 (9.4%)	201 (12.8%)	179 (8.5%)	163 (8.0%)	183 (8.6%)	210 (12.8%)

Source: IDI 2024. Note: UR = urban regeneration; T = treated and C = control; MELAA = Middle Eastern, Latin American and African. Not all percentages add up to 100% due to random rounding of small numbers as per Stats NZ confidentiality rules and the averaging across SA2s and months.

[a] Total population numbers corresponding to row 'All Population' columns (I)-(IV) and (V)-(VIII) in Table 7.

5.5 Empirical model for area-level analysis

To examine the wellbeing impacts of urban regeneration, we would like to know what would have happened to individuals living in areas undergoing urban regeneration, had the area not undergone regeneration (their potential outcome). However, this counterfactual scenario is unobservable – we can only observe what happens to individuals living in areas that have undergone regeneration (their actual outcome). Therefore, we need to compare areas that underwent urban regeneration compared to areas that did not.

However, a direct comparison is unlikely to attribute changes in wellbeing outcomes to the impacts of urban regeneration. As shown in Section 5.3 above, the characteristics of those in treated areas differ to those of control areas and these differences are likely to be related to (changes in) wellbeing outcomes. Thus, a simple comparison of areas that did and did not undergo urban regeneration would yield bias results.

For example, past literature has shown that Māori and Pacific tend to have poorer outcomes compared to Europeans across a range of dimensions, such as health and educational attainment outcomes (Howden-Chapman et al., 2021; Meehan, Pacheco, & Pushon, 2018; Meehan et al., 2023). Given the large Māori and Pacific population in treated areas, changes in educational attainment rates in treated areas may reflect the different characteristics of treated and control populations, rather than from urban regeneration.

To address this, treated areas can be matched with control areas that have similar observable characteristics. This research uses weighted entropy balancing methods to weight control areas based on population, household size, ethnicity, age, gender, partnership status and deprivation for the 2015 to 2017 period (inclusive).[12] A monthly weight is calculated for each control area between 2015 to 2017. The average weight across the 36 months is calculated for each control SA2 and applied to all its monthly SA2 observations between 2015 and 2021.

[12] Entropy balancing is a matching method for treatment and control observations that uses maximum entropy reweighting to force a balance between conditions such as means and variances (Hainmueller, 2012). Note that the deprivation measure used for balancing was % living in quintile 5 (highest deprivation) based on the corresponding 2018 meshblock.

Note that entropy balancing methods can only be applied using observable characteristics and as such, there is a risk that unobservable characteristics not accounted for may be correlated with wellbeing outcomes. For example, individual risk preferences are often correlated with health and labour market outcomes and are unobservable in the data. Individuals with riskier tendencies may be more prone to health shocks, such as concussions, which can adversely affect their health and labour market outcomes (Fouquet, Meehan, Pacheco, & Theadom, 2024).

However, unobservable characteristics of individuals living in treated urban regeneration areas are very unlikely to be correlated with the probability of being in the treated group. There is a register detailing where Kāinga Ora developments are located, which may enable individuals to make educated guesses about potential sites for redevelopment, such as a single dwelling on a large plot of land being developed into higher-density housing. Kāinga Ora also purchases homes from developers and buy sites that they may redevelop later.

While individuals might be able to identify areas where Kāinga Ora-led developments are likely to occur and decide whether to move into those neighbourhoods, thus influencing their likelihood of being treated, this scenario is unlikely. Predicting where Kāinga Ora will build is not straightforward. Therefore, once observable characteristics are controlled for—especially since Kāinga Ora developments typically occur in more deprived areas—it can be reasonably assumed that treatment is mostly random, and the unobservable characteristics of individuals are unlikely to be correlated with their probability of being treated.

Column V in Table 11 shows the average demographic characteristics of control areas after adjustment. The averages are the same as column I (treated areas), and columns VI and VII confirms that both treated and control areas have similar observable characteristics.

Table 11 Covariate balance for area-level demographic characteristics (2015-2017)

	Unmatched				Matched		
	I	II	III	IV	V	VI	VII
Variable	Treatment: Mean	Control: Mean	SMD	Balanced?	Control: Mean	SMD	Balanced?
Population	2,877	2,498	0.37	No	2,877	0.00	Yes
Household size	3.37	2.94	0.60	No	3.37	0.00	Yes
% Female	0.50	0.50	0.00	Yes	0.50	0.00	Yes
% European	0.38	0.60	-1.00	No	0.38	0.00	Yes
% Māori	0.16	0.10	0.68	No	0.16	0.00	Yes
% Pacific	0.18	0.05	0.70	No	0.18	0.00	Yes
% Asian	0.25	0.23	0.16	No	0.25	0.00	Yes
% MELAA	0.02	0.02	-.0.01	Yes	0.02	0.00	Yes
% Other	0.00	0.00	-0.57	No	0.00	0.00	Yes
% Under 18	0.25	0.22	0.51	No	0.25	0.00	Yes
% 18 to 24	0.11	0.10	0.32	No	0.11	0.00	Yes
% 25 to 64	0.53	0.55	-0.27	No	0.53	0.00	Yes
% 65+	0.11	0.13	-0.57	No	0.11	0.00	Yes
% living in Q5 deprivation	0.31	0.07	0.71	No	0.31	0.00	Yes
% married or in civil union	0.21	0.21	-0.11	No	0.21	0.00	Yes

Source: IDI 2024. SMD = Standardized Mean Difference. MELAA = Middle Eastern, Latin American and African. Note that balance assessment was performed using the Cobalt/MatchIt packages in R which does not use hypothesis testing such as t-test to assess covariate balance. Instead, standardised mean differences are assessed against a threshold (<0.05) to determine balance in covariates after adjustment. See https://cran.r-project.org/web/packages/cobalt/vignettes/cobalt.html for further information on why t-tests are not used.

The empirical model used in this research is based on a difference-in-differences (DiD) event study model, also known as a dynamic DiD. Canonical DiD models are designed to assess the impact of treatment on an outcome variable between two groups across two time periods (Lechner, 2010). The first period refers to T = 0 and the second period refers to T = 1. The group that receives treatment in T = 1 is referred to as the treatment group, while the group that does not receive treatment is referred to as the control group. Neither group is assigned treatment at T = 0, meaning treatment = 0 for both the treated and control groups. In the second period (T = 1), treatment is assigned and is equal to 1 for the group that receives treatment and equal to 0 for the group that does not receive treatment.

The average treatment effect on the treated (ATT) is determined by the difference between the average change in outcomes for treated units and the average change in outcomes for untreated units. This DiD parameter estimates the causal effect of treatment, based on the assumption that the treatment group would have experienced changes in outcomes similar to those of the control group in the absence of treatment. This assumption is known as the parallel trends assumption.

The related literature builds on the canonical DiD approach by extending it from a two-period to a multiple-period model, allowing for the evaluation of treatment effects over time. These models are referred to as dynamic DiD or dynamic two-way fixed effects (TWFE) models. Dynamic TWFE models assume treatment effects are constant across all groups and time periods (de Chaisemartin & D'Haultfœuille, 2020).

However, units may receive treatment at different time periods (referred to as staggered treatment), leading to variations in treatment effects based on the timing of treatment assignment and the duration of exposure to treatment. In cases of staggered treatment, the effect of treatment is heterogeneous. As a result, coefficients estimated using a dynamic TWFE model are potentially biased as treatment effects are assumed to be homogeneous across all groups and time periods. Several strands of literature address these issues in TWFE models by estimating an unbiased ATT that remains robust to treatment effect heterogeneity under staggered treatment adoption - see Goodman-Bacon (2021), Callaway and Sant'Anna (2021) and Sun and Abraham (2021).

Estimating unbiased treatment effects in the context of staggered treatment is relevant to this study as housing intensification in the Kāinga Ora data is staggered – not all areas begin urban regeneration at the same time. This study uses the method proposed by Sun and Abraham (2021) to estimate an "interaction-weighted" (IW) estimator when there is staggered treatment adoption (Sun & Abraham, 2021, p. 186). This model was selected as it allows for a "never treated" control group to serve as the comparison group for treated units. Other staggered DiD models in the literature use the cohort of "not-yet-treated" observations in the treated group as the comparison group.[13] Callaway (2023) notes while model specifications related to staggered DiDs may differ in the literature, these methodologies are qualitatively the same.

The staggered DiD model is given by Equations (1.1) and (1.2). Equation (1.1) first estimates the "cohort average treatment effect on the treatment group" (Sun & Abraham, 2021, p. 176) or $CATT_{e,\ell}$.

[13] Sun and Abraham (2021) notes their procedures are most similar to Callaway and Sant'Anna (2021). Main differences include: Sun and Abraham (2021) allows either not-yet-treated and never treated units as a control group whereas Callaway and Sant'Anna (2021) use a set of 'not-yet-treated cohort' as their control group and rely on different parallel trend assumptions. Goodman-Bacon (2021) shows that their TWFE DiD estimator is a weighted average of all possible 2x2 DiD estimators and addresses the potential biases that can occur when strong assumptions of a TWFE DiD model do not hold. Goodman-Bacon (2021) notes that alternative models such as that proposed by Sun and Abraham (2021) can deliver meaningful causal estimates.

(1.1) $$Y_{st} = \alpha_i + \lambda_t + \sum_{e \notin C} \sum_{\ell \neq -1} \delta_{e,\ell}\left(1\{E_s = e\} \cdot D_{s,t}^{\ell}\right) + X_{st}\Gamma + \varepsilon_{st}$$

where $s = 1, \ldots, N$ SA2, $t = 0, \ldots, T$ are calendar months between January 2015 to December 2021 (inclusive). ℓ are relative months to treatment where $\ell = -36$ up to $\ell = 36$, and $\ell = 0$ is the month that urban regeneration begins. For example, SA2s treated in February 2018 will have February 2018 as $\ell = 0$ and are followed until February 2021 where $\ell = 36$. SA2s treated in December 2021 ($\ell = 0$) have no positive ℓ observations as there are no further calendar months in the analysis. $\ell > 0$ indicates months post treatment and $\ell = -1$ is the base month which is the month before urban regeneration begins.

$e = 1, \ldots, E$ is the month SA2s are first treated and $e \notin C = \{\infty\}$ as this study uses a group of SA2s who never undergo Kāinga Ora-led urban regeneration as a control group ("never treated"). Treated SA2s that undergo urban regeneration for the first time in the same month have the same e i.e SA2s that begin urban regeneration in February 2018 will have the same e. $D_{s,t}$ indicates if SA2 s has begun urban regeneration by time t. Standard errors are clustered at the SA2 level.

$\delta_{e\ell}$ is the DiD estimator of interest and estimates $CATT_{e,\ell}$, which is the average treatment effect for the cohort of SA2s that began urban regeneration at time e, at ℓ periods from time e. Simply, this is the causal difference in wellbeing outcomes for treated areas that began urban regeneration at the same time, compared to control areas, having undergone urban regeneration for ℓ periods.

Starting from the left-hand side:

- Y_{st} is the variable of interest for SA2 s at time t, where the variable of interest is one of the area-level wellbeing indicators related to education, labour, health, crime and safety wellbeing outcomes defined in Table 3.
- α_s incorporates SA2-specific fixed effects to account for unobserved SA2 heterogeneities that may affect assignment of urban regeneration initiatives and wellbeing.
- λ_t incorporates time-specific fixed effects to account for unobserved time heterogeneities that may affect assignment of urban regeneration initiatives and wellbeing.
- D_{st}^{ℓ} is a relative time dummy that interacts with group dummies (for those $e \notin C$)
- X_{st} is a vector that incorporates time-variant SA2-specific covariates, including population, household size, prioritised ethnicity, gender, age group, and partnered status as defined in Table 5.

Equation (1.2) gives the weighted average of $CATT_{e,\ell}$, using $\hat{\delta}_{e\ell}$ estimated in Equation (1.1). Weights are the shares of each cohort for cohorts that experience at least ℓ periods of treatment, normalised by the size of g. The period of analysis is 36 months pre- and post-treatment, such that $-36 \leq g \leq 36$ and $\ell \in g$.

(1.2)
$$\hat{\upsilon}_g = \frac{1}{|g|} \sum_{\ell \in g} \sum_{e} \widehat{\delta_{e,\ell}}\, \widehat{Pr}\{E_s = e \mid E_s \in [-\ell, T - \ell]\}$$

Equation (1.2) yields $\hat{\upsilon}_g$ which is the IW estimator, the ATT, and estimator of interest for the area-level impacts of this study.

Equations (1.1) and (1.2) are used to estimate area-level wellbeing outcomes for the different subpopulations described in Table 6. To understand how wellbeing outcomes differ by urban regeneration intensities, Equations (1.1) and (1.2) are run separately for i) all treated areas (all urban regeneration), ii) all treated areas expected to build 50 or more dwellings (high urban regeneration) and iii) all treated areas expected to build less than 50 dwellings (low urban regeneration). To understand how wellbeing outcomes differ by population compositions, Equations (1.1) and (1.2) are run separately for i) all treated population, ii) all social housing and iii) all non-social housing for each level of urban regeneration intensity.

Aggregating the cohort average treatment effect, $CATT_{e,\ell}$ which is estimated by $\hat{\delta}_{e\ell}$ in Equation (1.1), yields the ATT for each relative time period which is presented graphically for the overall treated population for each wellbeing indicator. The ATT of interest to this study, the IW estimator $\hat{\upsilon}_g$ estimated in Equation (1.2), is presented in tabular format, separately for all, high and low urban regeneration and all, social and non-social housing population.

It is important to note that the measurement and impact of urban regeneration is likely to be underestimated for two reasons. First, several SA2s from the four large-scale Auckland urban projects, as described in Section 4.3.3, are excluded from the analysis as treatment began prior to 2018. These large-scale urban regeneration projects are likely to have had the largest impact on wellbeing outcomes and their exclusion means urban regeneration treatment effects are likely to be underestimated.

Secondly, many projects were still under development as of 2021, meaning that the full treatment effects of urban regeneration cannot yet be observed. As a result, this research measures the *short run* impacts of urban regeneration on wellbeing outcomes. Additionally, while this study only examines Kāinga Ora-led urban regeneration, the number of new dwellings increased in control areas as well, due to non Kāinga Ora-led urban development (as seen in Table 7 in Section 5.3). That is, we are comparing treated areas with Kāinga Ora-led development against control areas where non-Kāinga Ora development is also taking place.

As a robustness check, Equations (1.1) and (1.2) is also run using Statistical Area Unit 1 (SA1) observations which are smaller than SA2 observations (see Section 4.3.1). Using SA1 as the geographic unit of analysis can help understand if impacts are more localised compared to using SA2. There are 400 treated SA1 observations and 7,940 control SA1 observations. The threshold for high intensity urban regeneration is 25 or more expected dwellings to be built, and low intensity urban regeneration as those expected to build under this 25-dwelling threshold. Of the 400 treated SA1s, 76 are high urban regeneration SA1s (19%) and the remainder 81% are low urban regeneration SA1s. Due to the intensive processing power needed to run staggered DiDs, a random subsample of approximately 25% of control SA1 units are used in the analysis. All treated SA1 observations are used in the regressions.

For readability in the results, the total area-level ATT estimated in Equation (1.2) and cohort area-level ATT estimated in Equation (1.1) will have different notations for the SA2 and SA1-level results. $\hat{v}_g$ denotes the SA2 area-level ATT while $\widehat{w}_g$ denotes the SA1 area-level ATT. Similarly, the SA2 cohort average treatment effect will be denoted as $CATT2_{e,\ell}$ and $\hat{\delta}_{e\ell}$ for its estimator. For the SA1 cohort average treatment effect, this is denoted as $CATT1_{e,\ell}$ and $\hat{\theta}_{e\ell}$ for its estimator.

As described earlier in this section, control SA2s are weighted using entropy balancing. The same variables used for entropy balancing at the SA2-level are also used for SA1 observations except for the share of individuals living in quintile 5. This variable was omitted from entropy balancing as deprivation is defined at the SA1-level, meaning everyone who lives within a particular SA1 is either 100% living in quintile 5 deprivation (the highest deprivation) or 0% living in quintile 5 deprivation.

5.6 Empirical model for individual-level analysis

As with area-level demographic characteristics, characteristics differ for treated and control individuals and therefore individuals are matched based on observable characteristics. Treated and control individuals are those living in treated and control SA2s, respectively, as described in Section 5.1.

Two levels of matching were used to match control to treated individuals. First, a propensity score was calculated for each individual based on age group, ethnicity, gender, partnership status and deprivation for the 2015 to 2017 period (inclusive).[14] Exact one-to-one matching without replacement was used to match control individuals to treated individuals based on their propensity score. Propensity score matching, as opposed to entropy balancing in the area-level analysis, was used due to computational power limitations given the large number of individual-level observations.[15] Second, control individuals were matched to treated individuals based on their mobility. Treated long-term residents are matched to control long-term residents, treated newcomers and leavers are matched to transient control residents and treated residuals are matched to control residuals.

Table 12 presents the covariate balance between the treated and control group based on 2015-2017 demographic characteristics. Column (IV) shows prior to matching, the treated and control group are unbalanced with respects to the proportion of individuals living in the highest deprivation and ethnic composition. Column (X) shows after matching, the treated and control group are balanced in terms of their demographic characteristics.

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[14] Age group at the end of the 2017 period and whether they lived in the highest deprivation at any point between the 2015 to 2017 period.

[15] Entropy balancing provides weights to all control group observations which means all control observations are retained. Exact matching only retains SA2s that are matched, resulting in a much smaller control group compared to matching using entropy balancing.

The decision to implement exact one-to-one matching without replacement, instead of opting for nearest neighbour matching (NNM) or caliper matching, was driven by two computational limitations. First, the computational power required to create the matrix needed for NNM or caliper matching was not feasible. Second, even if higher matching rates were achieved with NNM or caliper methods, running staggered DiDs on the larger matched sample was not possible. As a result, 69% of the treated sample were matched to control individuals (159,422 in column V over 230,967 in column I).[16]

Column (VII) show that the average characteristics of the matched treated group differ from those of the unmatched treated group. Specifically, a smaller proportion of the matched treated group live in high deprivation areas and are Māori or Pacific. The chosen matching method and computational constraints likely result in an underestimation of the individual-level treatment effect of urban regeneration. This underestimation arises because those most likely to benefit from urban regeneration—individuals in the highest deprivation areas—are underrepresented in the matched sample. Even if higher match rates could be obtained with alternative matching methods, computational limits mean regressions could not be run on the full sample. Future research could subset the analysis to those living in high deprivation and are Māori or Pacific.

[16] Match rates for subpopulations were as follows: 74.7% for long-term residents, 87.0% for newcomers, 85.4% for leavers and 45.9% for residuals. Note that the residual population is the largest subpopulation and only 25% of the 45.9% matched residual individuals could be used in the regressions due to computational limits.

Table 12 Covariate balance for individual-level demographic characteristics (2015-2017)

Variable	Unmatched (Full Sample)				Matched (Subsample)					
	I	II	III	IV	V	VI	VII	VIII	IX	X
	T: Mean	C: Mean	SMD (I) – (II)	(I) & (II) balanced	T: Mean	SMD (I) – (V)	(I) & (V) balanced	C: Mean	SMD (V) – (VIII)	(V) & (VIII) balanced
Male	0.50	0.50	0.00	Yes	0.51	-0.01	Yes	0.50	-0.01	Yes
Living in Q5	0.41	0.09	0.32	No	0.16	0.25	No	0.18	0.03	Yes
Legally partnered	0.14	0.14	0.00	Yes	0.13	0.01	Yes	0.14	0.00	Yes
Māori	0.18	0.10	0.08	No	0.13	0.05	Yes	0.13	0.00	Yes
Pacific	0.22	0.06	0.16	No	0.11	0.11	No	0.12	0.02	Yes
Asian	0.25	0.26	-0.01	Yes	0.32	-0.07	No	0.29	-0.03	Yes
MELAA	0.02	0.03	-0.01	Yes	0.03	-0.01	Yes	0.03	0.00	Yes
Other	0.00	0.01	-0.01	Yes	0.00	0.00	Yes	0.00	0.00	Yes
European	0.32	0.55	-0.23	No	0.41	-0.09	No	0.42	0.01	Yes
Aged 0-4	0.08	0.06	0.02	Yes	0.07	0.01	Yes	0.07	0.00	Yes
Aged 5-9	0.09	0.09	0.00	Yes	0.10	-0.01	Yes	0.07	-0.01	Yes
Age 10-14	0.04	0.03	0.01	Yes	0.02	0.02	Yes	0.04	0.02	Yes
Age 15-19	0.07	0.07	0.00	Yes	0.05	0.02	Yes	0.07	0.01	Yes
Age 20-24	0.09	0.09	0.00	Yes	0.10	-0.01	Yes	0.09	-0.01	Yes
Age 25-29	0.10	0.09	0.01	Yes	0.13	-0.03	Yes	0.10	-0.02	Yes
Age 30-34	0.09	0.08	0.01	Yes	0.11	-0.02	Yes	0.09	-0.02	Yes
Age 35-39	0.07	0.07	0.00	Yes	0.08	-0.01	Yes	0.07	-0.01	Yes
Age 40-44	0.06	0.06	0.00	Yes	0.06	0.00	Yes	0.07	0.00	Yes
Age 45-49	0.06	0.07	-0.01	Yes	0.06	0.00	Yes	0.07	0.01	Yes
Age 50-54	0.06	0.06	0.00	Yes	0.05	0.01	Yes	0.06	0.01	Yes
Age 55-59	0.06	0.06	0.00	Yes	0.04	0.02	Yes	0.05	0.01	Yes
Age 60-64	0.04	0.05	-0.01	Yes	0.04	0.00	Yes	0.04	0.01	Yes
Age 65+	0.09	0.13	-0.04	Yes	0.09	0.00	Yes	0.11	0.02	Yes
n	230,967	1,043,607			159,422			532,806		

Source: IDI 2024. T = Treated, C = Control. SMD = Standardized Mean Difference. MELAA = Middle Eastern, Latin American and African. Living in Q5 = living in highest deprivation decile (9,10). Note that balance assessment was performed using the Cobalt/MatchIt packages in R which does not use hypothesis testing such as t-test to assess covariate balance. Instead, standardised mean differences are assessed against a threshold (<0.05) to determine balance in covariates after adjustment. See https://cran.r-project.org/web/packages/cobalt/vignettes/cobalt.html of further information on why t-tests are not used.

The individual-level analysis follows the staggered two-stage difference-in-differences approach from Gardner (2022) to measure the causal impact of urban regeneration on individual-level wellbeing outcomes, rather than the Sun and Abraham (2021) approach. This is because the individual-level analysis has significantly more observations compared to the area-level analysis. Gardner (2022) requires less computational power than Sun and Abraham (2021), which only allowed regressions to be run for up to 5% of treated individuals. The trade-off with Gardner (2022) is that it calculates only the cohort ATT $\delta_{e,\ell}$, but not the overall ATT such as $\hat{v}_g$ from Sun and Abraham (2021).

As mentioned earlier in this section, although methodologies for handling staggered treatment effects differ, they all address the issue of heterogeneity in TWFE models (Callaway, 2023). Therefore, while there may be some quantitative differences between these approaches, they are qualitatively the same. This study adopts the same methodology used by Borbely and Rossi (2023), which uses the Gardner (2022) approach to examine the impact of urban regeneration on crime outcomes. This study extends on Borbely and Rossi (2023) by measuring additional human capital, physical and mental health and safety outcomes using Gardner (2022).

There are two distinct stages for Gardner (2022) – first, cohort and time effects are estimated for control and not-yet-treated observations. In the second stage, average time-specific treatment effects ($\delta_{e,\ell}$) are estimated by comparing treated and control units after removing cohort and time effects. As the first stage of Gardner (2022) removes time and cohort effects, regressing the residualised outcomes in the second stage with all observations yields unbiased treatment effects.

Equation (2.1) presents the first stage estimation of Gardner (2022) and is a reduced from of Equation (1.1) in which $D_{i,t}^{\ell} = 0$, where individuals are never treated or not-yet-treated.

$$Y_{it} = \alpha_i + \lambda_t + \varepsilon_{it} \qquad s.t.\ D_{i,t}^{\ell} = 0 \tag{2.1}$$

Where $i = 1, \dots, N$ individuals and $t = 0, \dots, T$ months between January 2015 – December 2021 (inclusive) and i belongs to the cohort of control and not-yet-treated individuals.

Starting from the left-hand side:

- Y_{it} is the variable of interest for individual i, where the variable of interest is one of the individual-level wellbeing indicators related to education, labour, health, crime and safety wellbeing outcomes defined in Table 3.
- α_i incorporates individual-specific fixed effects to account for unobserved individual heterogeneities.
- λ_t incorporates time-specific fixed effects to account for unobserved time heterogeneities.

Note there are no individual-level covariates as control individuals were matched to treated individuals based on their propensity score as a function of their demographic characteristics.

Equation (2.2) presents the residualised outcome ($\tilde{Y}_{it}$) by subtracting the actual outcome (Y_{it}) and predicted individual ($\hat{\alpha}_i$) and time ($\hat{\lambda}_t$) fixed effects.

(2.2)
$$\tilde{Y}_{it} = Y_{it} - \hat{\alpha}_i - \hat{\lambda}_t \quad s.t.\ D_{i,t}^{\ell} = 0$$

Equation (2.3) is a reduced form of Equation (1.1), with notations referring to individuals rather than SA2. The second stage of Gardner (2022) regresses $\tilde{Y}_{it}$ from Equation (2.2) on $D_{i,t}^{\ell}$ in Equation (2.3).

(2.3)
$$\tilde{Y}_{it} = \sum_{e \notin C} \sum_{\ell \neq -1} \varphi_{e,\ell}\left(1\{E_i = e\} \cdot D_{i,t}^{\ell}\right) + \varepsilon_{it}$$

That is, $i = 1, \dots, N$ individual, $e = 1, \dots, E$ is the cohort of individuals that undergo treatment in the same month where $e \notin C$ (cohort of never-treated individuals). Standard errors are clustered at the individual-level level. $\varphi_{e,\ell}$ is the DiD estimator of interest and estimates the average treatment effect for the cohort of individuals that began treatment at time e, at ℓ periods from time e. Simply, this is the causal difference in wellbeing outcomes for treated individuals that began treatment at the same time, compared to control individuals, having been exposed to treatment for ℓ periods.

Equations (2.1), (2.2) and (2.3) are used to estimate individual-level wellbeing outcomes for the individual subpopulations as described in Table 6. To understand how wellbeing outcomes are distributed among the different subpopulations, the equations are run separately for long-term residents, newcomers, leavers and residual residents compared to their matched control counterparts. The analysis is also split by all population, social housing and non-social housing. For readability in the results, the cohort individual-level ATT estimated in Equation (2.3) will be denoted as $CATTI_{e,\ell}$ to differentiate from the SA2 and SA1-level estimates.

The individual-level analyses are only run for outcomes where there is temporal variation. For example, individual-level results for tertiary educational attainment are omitted because once attainment is achieved, the outcome variable remains 1 permanently. Likewise, significant changes in secondary educational attainment rates are only observable during the December to January period when students complete their schooling and either receive or do not receive their secondary qualification.

6 Results: First Order Effects

This research first examines the first-order effects of housing intensification in treated areas compared to control areas. Given that one of the initiatives of Kāinga Ora-led urban regeneration is to replace single dwellings with multi-unit dwellings, it would be reasonable to expect increased population and dwelling growth in treated areas relative to control areas.

Staggered difference-in-differences (DiD), as described in Section 5, is used to examine first order effects between treated and control areas. The analysis presents the total average treatment effect on the treated (ATT) coefficients, their statistical significance and corresponding confidence intervals. The cohort average treatment effect (CATT) is presented in graphical format. At the SA2-level, the ATT Is denoted as $\hat{\upsilon}_g$ and the CATT denoted as $\hat{\delta}_{e\ell}$. At the SA1-level, this is $\widehat{w}_g$ and $\hat{\theta}_{e\ell}$.

At the SA2-level, results are reported by three UR intensities: all (column I), high (50 or more dwellings in column II) and low (less than 50 dwellings in column III) UR. At the SA1-level, this is reported for all, high (25 or more dwellings) and low (less than 25 dwellings) UR.

6.1 Dwelling growth

Table 13 presents regression results examining dwelling growth for all, high and low UR areas compared to control areas. The SA1 ATT coefficient, $\widehat{w}_g$, in Table 13 (column I) shows the number of dwellings increased by 2.2 in treated SA1s relative to control SA1s and this is statistically significant at the 1% level. Similarly, Figure 15 shows the number of dwellings increased in all treated SA1s relative to control SA1s. While this increase is statistically significant, its economic impact is small, representing only a 0.1% increase from the pre-treatment average of 2,877 dwellings (column I in Table 7). The heterogeneity analysis shows dwellings significantly increased by 3.7 and 1.9 dwellings in high and low UR SA1s, respectively, relative to control SA1s.

There was no significant effect observed at the SA2-level regarding the number of dwellings, regardless of urban regeneration intensity as shown in Table 13 and Figure 14. This result aligns with the descriptive statistics in Table 7 which showed similar dwelling growth rates for treated and control SA2s. The lack of significance at the SA2-level might be attributed to ongoing non-Kāinga Ora urban development occurring in control and treated SA2s.

Figure 16 and Figure 17 show the number of social housing increased in all treated SA2s and SA1s compared to their control counterparts. Table 13 shows social housing significantly increased by 3.1 dwellings in treated SA2s relative to control SA2s. This increase is statistically significant at the 1% level and represents a 3.2% increase from the pre-treatment average of 99 social housing (column I in Table 7). This increase is primarily driven by the increase in social housing in low UR SA2s. Consequently, social housing as share of total dwellings increased by 0.3 percentage points in low UR SA2s. At the SA1 level, social housing significantly increased by 0.6 and 0.8 dwellings for all treated SA1s and low UR SA1s, respectively, compared to control SA1s.

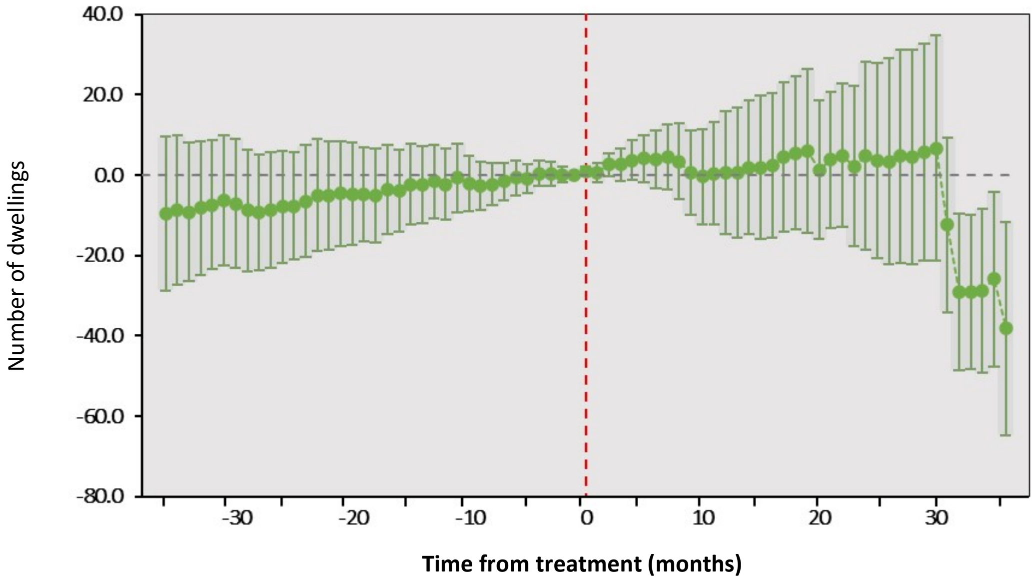
It would be reasonable to expect a greater increase in social housing in high UR areas, as intensification typically involves replacing single dwellings with multi-unit dwellings. However, column II shows no significant increase in the number of social housing dwellings in high UR SA2s. As discussed in Section 5.3, this may be because large-scale developments in high UR SA2s are not yet complete by the end of 2021. Additionally, completed dwellings in high UR SA2s may have only replaced the demolished housing stock during the urban regeneration process, rather than adding net new dwellings.

Table 13 Impact of urban regeneration on dwelling growth

Outcome variable	All UR	High UR	Low UR
SA2 – Dwellings			
Dwellings *(n)*	1.067 [-10.803, 12.938]	-3.770 [-16.048, 8.510]	2.543 [-9.507, 14.593]
Social housing dwellings *(n)*	3.065** [1.118, 5.012]	2.451 [-0.713, 5.615]	3.310*** [1.595, 5.026]
Social housing as % of total dwelling *(percentage points)*	0.300** [0.083, 0.518]	0.181 [-0.360, 0.721]	0.344*** [0.181, 0.507]
SA1 – Dwellings			
Dwellings *(n)*	2.236** [0.679, 3.794]	3.637* [0.450, 6.825]	1.924* [0.268, 3.581]
Social housing dwellings *(n)*	0.616*** [0.267, 0.965]	0.032 [-1.051, 1.114]	0.769*** [0.440, 1.097]
Social housing as % of total dwelling not available at SA1-level due to all values being equal to 0 or 1.			

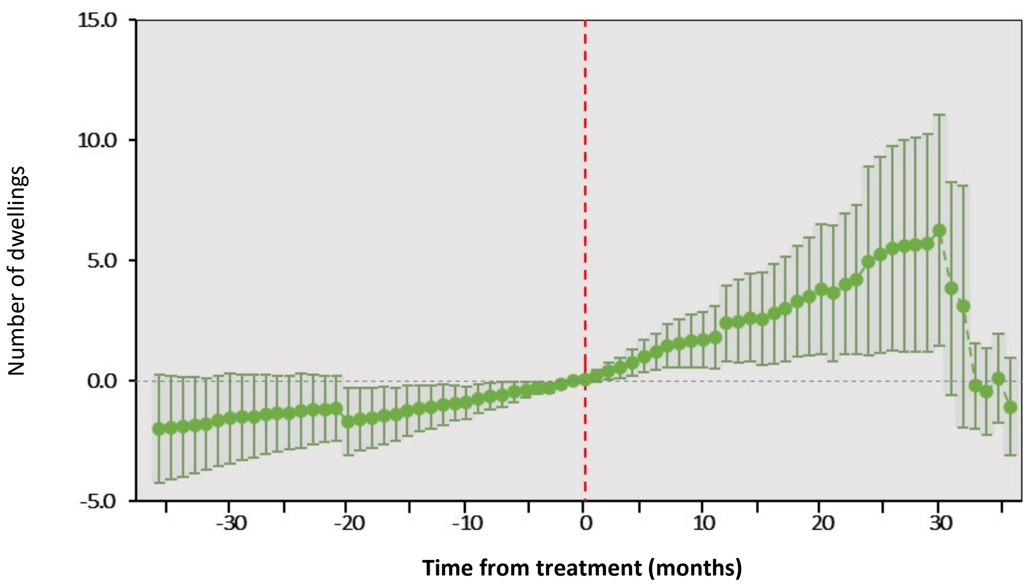
Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\upsilon}_g$ and $\hat{w}_g$, from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05 respectively. 95% confidence intervals in square [] brackets.

Figure 14 DiD - urban regeneration on number of dwellings (SA2, All Dwellings)



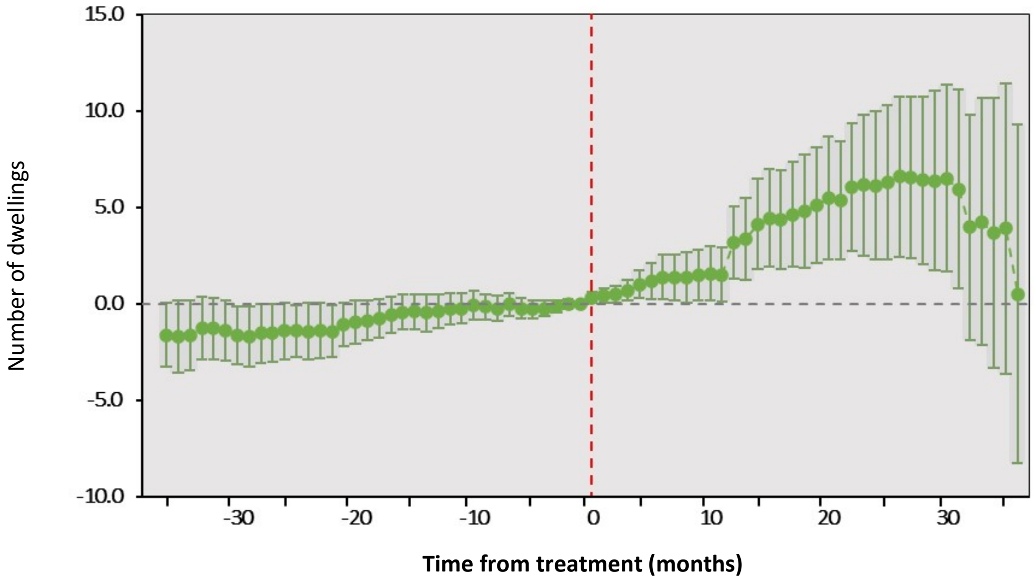
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 15 DiD - urban regeneration on number of dwellings (SA1, All Dwellings)



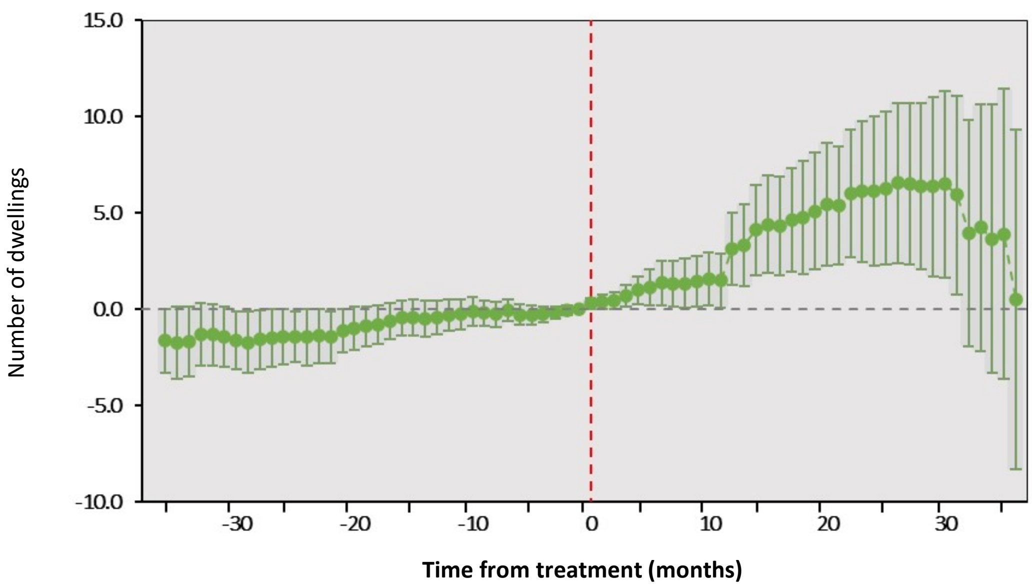
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT1, $\hat{\boldsymbol{\theta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 16 DiD - urban regeneration on number of social housing (SA2, Social Housing Dwellings)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 17 DiD - urban regeneration on number of social housing (SA1, Social Housing Dwellings)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT1, $\hat{\boldsymbol{\theta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

6.2 Population growth

Table 14 presents regression results examining population growth for all, high and low UR areas compared to control areas. The ATT coefficients, $\hat{\upsilon}_g$ and $\hat{w}_g$ in Table 14 (column I) shows no significant difference in population numbers at either the SA2 or SA1 level, compared to control areas, regardless of urban regeneration intensity. This is also further supported in Figure 18 and Figure 19 which show no difference in population over time. This finding is expected, as population growth was similar in both treated and control areas, as discussed in Section 5.3. As a result, there is also no significant difference in household size at either the SA2 or SA1 level.

Table 14 and Figure 20 shows no significant difference in the social housing population when comparing all treated SA2s to control SA2s. Figure 21 shows a significant increase in the social housing population in all treated SA1s, relative to control SA1s. However, the SA1-level ATT point estimate in Table 14 shows no significant difference over time and this is most likely due to only a small number of time periods having significant increases.

The heterogeneity analysis shows the social housing population increased by 16 individuals in low UR SA2s relative to control SA2s, and this is statistically significant at the < 1% level. This represents a 4.7% increase from the pre-treatment average population of 343 social housing residents in low UR SA2s. As a result, social housing as a share of total population increased by 0.3 percentage points. This result aligns with Table 13, which showed a significant increase of 3.3 social housing dwellings in low UR SA2s relative to control SA2s, thus explaining the corresponding increase in the social housing population.

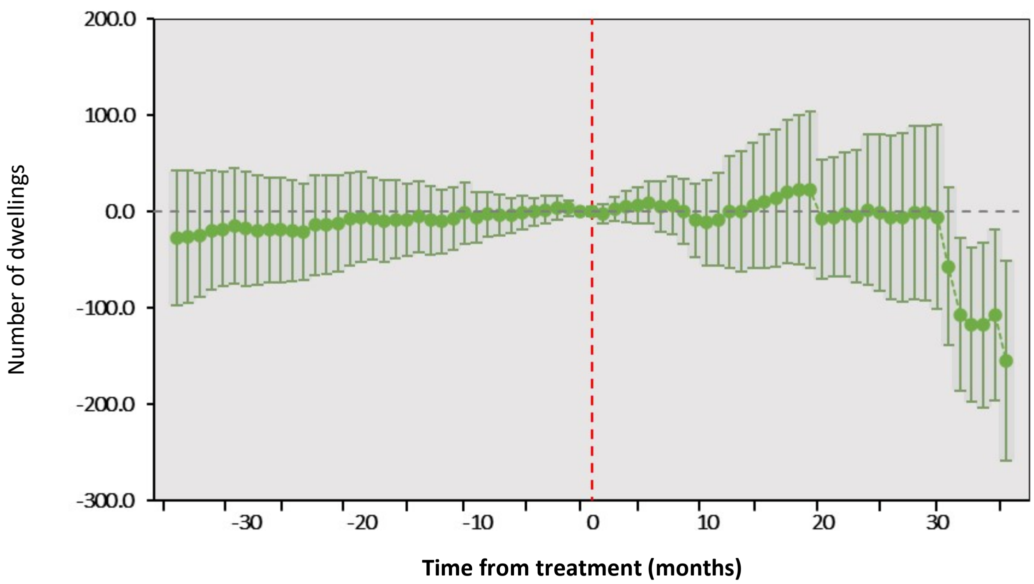
The heterogeneity analysis also shows the social housing population in high UR SA1s decreased by 6 individuals compared to control SA1s, with statistical significance at the 5% level. This decrease is economically small, representing less than 1% of the pre-treatment average of 688 social housing residents. While an increase in the social housing population is expected in high UR areas due to planned developments, the short-term displacement of social housing residents likely explains this decrease. This is because developments in these areas are not yet complete and social housing residents may be displaced to other areas such as low UR or pre-treated areas as part of the urban regeneration process. There, this decrease likely reflects the short run impact of urban regeneration on social housing displacement.

Table 14 Impact of urban regeneration on population growth

Outcome variable	All UR	High UR	Low UR
SA2 – All Population			
Population *(n)*	-4.372 [-48.030, 39.285]	-29.636 [-79.540, 20.278]	4.478 [-37.640, 46.191]
Household size *(population / dwellings)*	-0.014 [-0.038, 0.09]	-0.050 [-0.108, 0.008]	-0.002 [-0.019, 0.014]
SA2 – Social Housing			
Population *(n)*	9.141 [-3.655, 21.938]	-9.373 [-39.232, 20.486]	15.953*** [6.801, 25.106]
Household size *(population / dwellings)*	-0.079* [-0.147, -0.010]	-0.123* [-0.225, -0.021]	-0.070 [-0.147, 0.007]
% of total population *(percentage points)*	0.200 [-0.053, 0.453]	-0.192 [-0.890, 0.506]	0.341*** [0.168, 0.514]
SA1 – All Population			
Population *(n)*	4.835 [-0.279, 9.949]	2.986 [-6.153, 12.125]	5.329 [-0.351, 11.010]
Household size *(population / dwellings)*	-0.056*** [-0.086, -0.026]	0.110** [-0.177, -0.044]	-0.043** [-0.074, -0.013]
SA1 – Social Housing			
Population *(n)*	0.890 [-0.802, 2.582]	-5.971* [-10.941, -1.001]	2.547** [0.917, 4.177]
Household size *(population / dwellings)*	-0.103 [-0.234, 0.028]	0.052 [-0.196, 0.300]	-0.129 [-0.278, 0.020]
Social population as % of total population not available at SA1-level due to all values being equal to 0 or 1.			

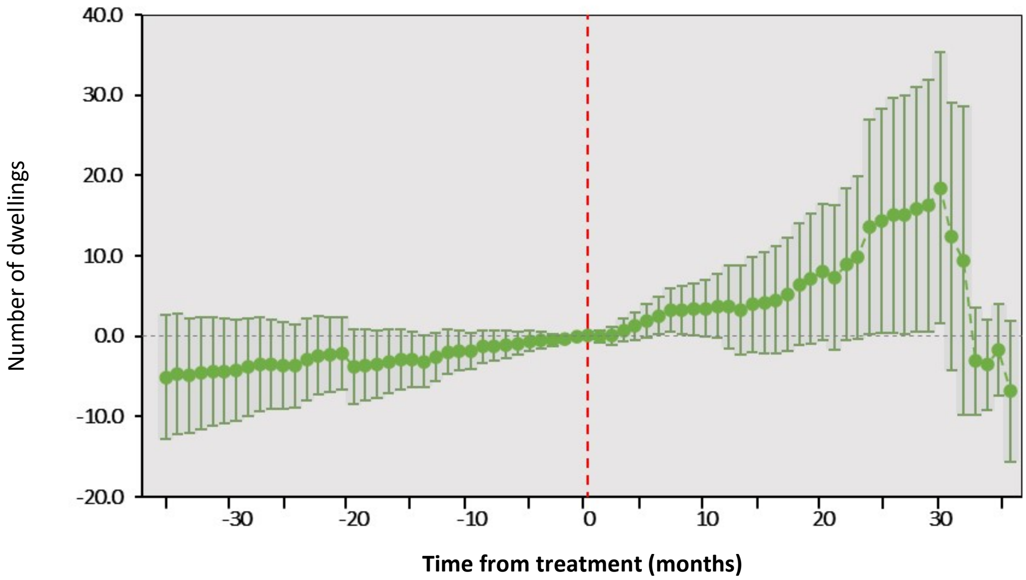
Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\mathbf{v}}_{\mathbf{g}}$ and $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05 respectively. 95% confidence intervals in square [] brackets.

Figure 18 DiD - urban regeneration on population growth (SA2, All Population)



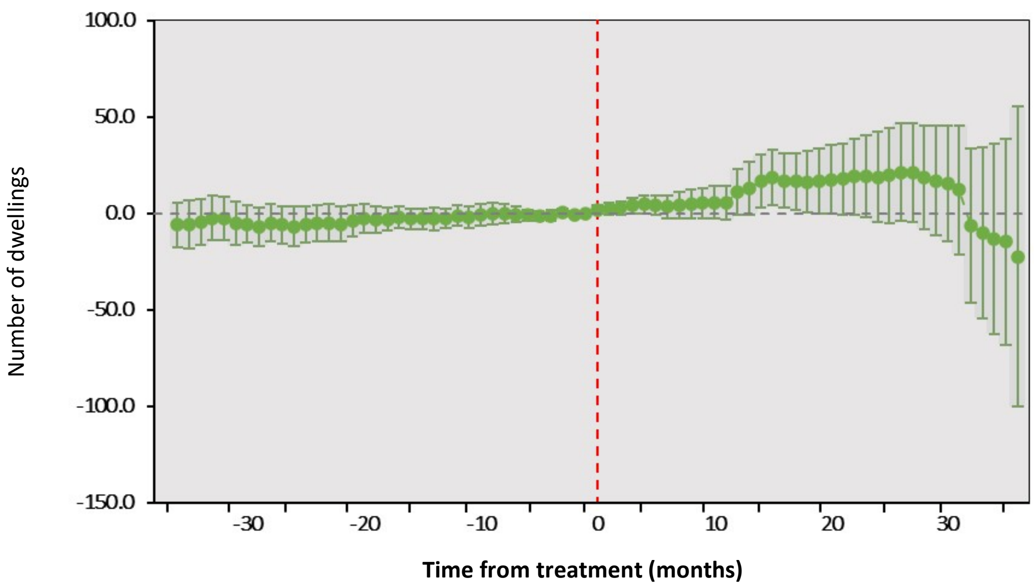
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 19 DiD - urban regeneration on population growth (SA1, All Population)



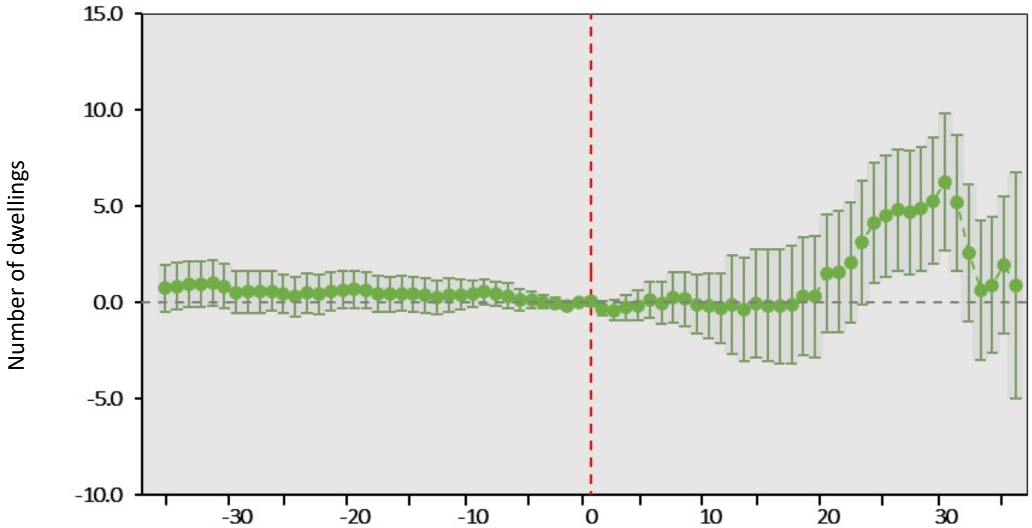
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT1, $\widehat{\boldsymbol{\theta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 20 DiD - urban regeneration on population growth (SA2, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\widehat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 21 DiD - urban regeneration on population growth (SA1, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT1, $\widehat{\boldsymbol{\theta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

6.3 Discussion of first-order effects

The initial first-order effects of urban regeneration are modest with respects to dwelling and population growth. Notably, urban regeneration led to a significant increase in the number of social housing dwellings and population in low UR areas. However, the social housing population significantly decreased in high UR SA1s, likely due to short-term displacement of residents during the regeneration process. There is also no significant difference in the number of social housing dwellings in high UR SA1s – this may be attributable to completed dwellings replacing the demolished housing stock, rather than add to the housing supply, and construction is still ongoing to build the remaining dwellings.

It is important to note that these are short run impacts, as many urban regeneration projects are still incomplete. Consequently, the full impact of urban regeneration cannot yet be observed. Further, non-Kāinga Ora urban development in control and treated areas is likely to underestimate the first-order impacts of Kāinga Ora-led regeneration. Therefore, future analyses should examine dwelling and population growth once Kāinga Ora-led urban regeneration has been fully completed.

While the first-order effects are modest or insignificant, urban regeneration may still have significant impact on wellbeing outcomes. Replacing older homes with new, modern housing is still likely to improve wellbeing for residents. Kāinga Ora urban regeneration initiatives also include improving the existing housing and stock and neighbourhood infrastructure and amenities which can contribute to improved wellbeing outcomes even in the absence of substantial first-order effects.

7 Results: Human Capital

This section provides the descriptive trends and the regression results for short run impacts of urban regeneration (UR) on area- and individual-level human capital outcomes. Given the number of variables examined, each human capital outcome is discussed within its respective subsection.

Each human capital outcome subsection follows the same format. First, as covered in the related literature in Section 2.3.3, the mechanisms in which urban regeneration can impact each human capital indicator are noted. Next, the descriptive portrait shows how wellbeing outcomes have changed over time without adjusting for factors that may contribute to differences in wellbeing outcomes between treated and control areas. For example, differences in wellbeing outcomes may be due to differing ethnic and age compositions, rather than a result of UR. Controlling for these factors helps to delineate the impact of UR on wellbeing outcomes.

Descriptive trends are followed by the total area-level average treatment effect on the treated (ATT) coefficients, their statistical significance and corresponding confidence intervals. At the SA2-level, the ATT Is denoted as $\hat{\upsilon}_g$ and at the SA1-level, this is denoted as $\widehat{w}_g$. The cohort average treatment effect (CATT) for SA2s is presented in graphical format and denoted as $\hat{\delta}_{e\ell}$. Analysis at the SA2- and SA1-level provides insight as to how wellbeing impacts of UR are distributed at the area-level. The area-level regression results examine how human capital outcomes have changed in areas treated by UR, relative to untreated areas, after controlling for characteristics such as population, household size, ethnicity, age, gender and partnership status. At the SA2-level, results are reported by three UR intensities: all (column I), high (50 or more dwellings in column II) and low (less than 50 dwellings in column III) UR. At the SA1-level, this is all, high (25 or more dwellings) and low (less than 25 dwellings) UR. Both SA2- and SA1-level results are presented for three treated populations: overall population, social housing (SH) and non-social housing (NSH).

The individual-level heterogeneity analysis examines wellbeing impacts by subpopulations as described in Table 6 to understand how impacts are distributed at the individual-level. Individual-level results are presented as graphs showing the individual-level time treatment effects for each subpopulation. Treated long-term residents are compared to control long-term residents, treated newcomers and leavers are compared to transient control residents and treated residuals are compared to control residuals. The individual-level results are also presented separately for SH and NSH. As noted in Section 5.6, individual-level ATTs could not be computed due to computational issues. As such, only the individual-level CATT, denoted as $\hat{\varphi}_{e\ell}$, is reported in graphical format in the results.

As noted previously in this thesis, the measurement and impact of UR is likely to be underestimated due to the exclusion of pre-treated SA2s, ongoing treatment and the current period of analysis allowing only for short run impacts to be measured. Therefore, the following results are short run human capital impacts of UR. As most Kāinga Ora-led UR is SH development, the results relate mainly to the impact of SH development.

7.1 Secondary educational attainment

Urban regeneration can potentially improve secondary educational attainment through several mechanisms. New schools may be established to accommodate population growth driven by housing intensification, and these schools could be of higher quality, offering better educational resources and facilities. This can lead to improvements in student achievement and secondary educational attainment. Changes in the population composition, such as higher educated parents moving into regenerated areas, may lead to increased demand for higher-quality education, including attracting more qualified teachers. Community-led initiatives like tutoring services or teaching programs can improve student performance on tests and encourage students to pursue higher levels of education (Batty et al., 2010; Thomson et al., 2006).

New or retrofitted homes can lead to healthier living environments by reducing respiratory illnesses which can impact school attendance (Howden-Chapman et al., 2008; Thomson et al., 2009). Stable housing also provides continuity, which is important for a student's ability to attend school regularly and succeed academically. SH developments may offer children in lower-income families a more stable living situation, reduce disruptions caused by housing insecurity, and improve school attendance and educational attainment (Cole, 2021).

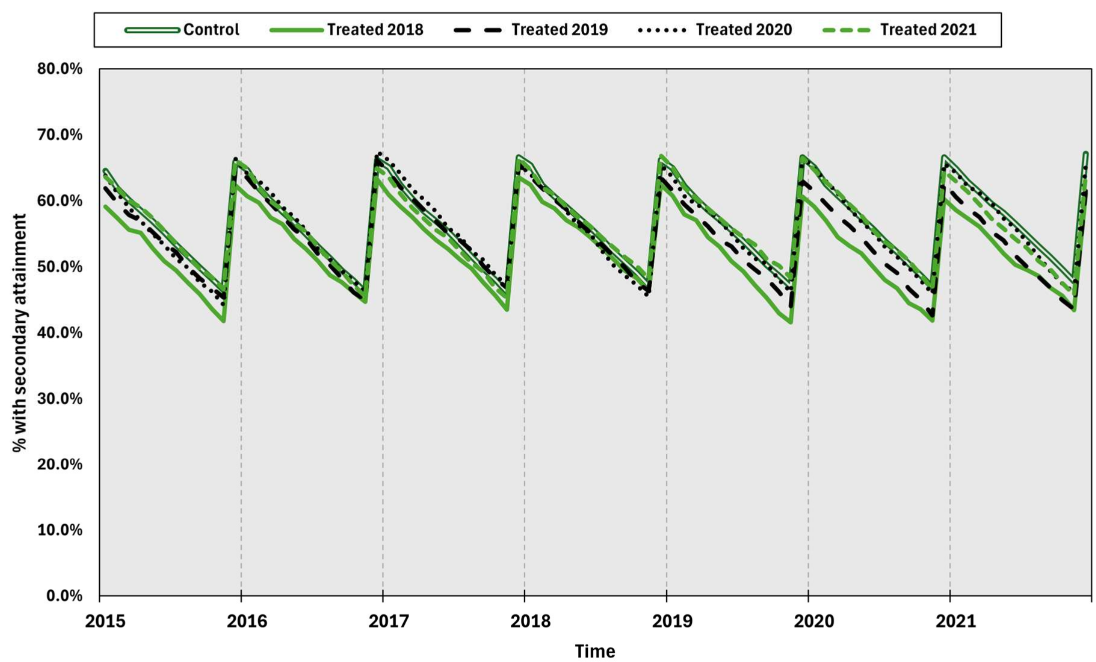
Note that there is no individual-level analysis for secondary educational attainment as there is not enough temporal variation to allow for meaningful inference. Students complete their schooling between December and January, and either receive or do not receive their secondary qualification. Any significant changes to secondary educational attainment rates would only be observed during this December – January period of each year.

7.1.1 Descriptive trends

Figure 22 presents average secondary educational attainment rates for treated SA2s by treatment year and control SA2s from 2015 to 2022. The population of interest are 16- to 19-year-olds (inclusive) who were born in New Zealand or spent at least two years in the New Zealand educational system.[17] The outcome of interest is those who attained at least NCEA Level 2.

Secondary educational attainment is approximately 70% in December–January each year, which corresponds to the period when students complete the school year and either receive or do not receive their secondary qualifications. The declines during the year reflect younger students who have just entered the 16- to 19-year-old age range and have not yet attempted NCEA Level 2. There is little variation between treatment and control SA2s over time, with all SA2s following the same average trend in secondary educational attainment.

Figure 22 Average SA2 secondary attainment by treatment year



Source: IDI 2024. Note: proportion of individuals aged between 16-19 (inclusive) who were born in New Zealand and/or were enrolled in at least two years in secondary institutions in New Zealand and received attainment equivalent to NCEA Level 2.

[17] A two-year threshold in the New Zealand schooling system was used to identify individuals who may not have obtained secondary educational attainment if they did not complete their schooling in New Zealand.

7.1.2 Area-level DiD analysis

Table 15 presents regression results examining secondary educational attainment rates for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 23 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there appears to be decreasing secondary attainment rates over time. The SA2 ATT coefficient $\hat{\upsilon}_g$ in Table 15 (column I) show no impact of UR on secondary educational attainment rates. This is unsurprising given Figure 22 shows secondary attainment rates between treated and control SA2s remain relatively stable over time.

With the exception of low UR SA2s, the heterogeneity analysis finds similar statistically insignificant results. Figure 23 show treated SA2s had similar or even higher rates of secondary educational attainment compared to control SA2s prior to UR. However, secondary attainment rates begin to decrease in the treated group relative to the control group after UR, although the difference is not statistically significant in most time periods. Figure 23 also shows that while secondary educational attainment outcomes for treated SA2s appear to be worsening compared to control SA2s after UR, this is a continuation of a general trend that was evident before UR. It seems, therefore, decreasing secondary educational attainment rates are not linked to UR.

A possible explanation is that school quality in treated and control SA2s were already beginning to diverge prior to UR, resulting in differences in secondary educational attainment rates for treated and control SA2s after UR. The demographic characteristics of treated and control SA2s are virtually identical with respects to factors that may impact secondary educational attainment. However, a potential factor that is not controlled for is diverging school quality. Schools in treated SA2s are likely to be lower decile schools and schools in control SA2s likely to be higher decile schools, as deciles are calculated according to socioeconomic characteristics in a school's catchment. It may have been that school quality diverged between higher and lower decile schools, resulting in the downward trend observed in Figure 23. However, in the long run, it is possible that UR may have positive impacts on secondary educational attainment via improved school quality such as attracting better teaching staff or the construction of new schools in these treated areas.

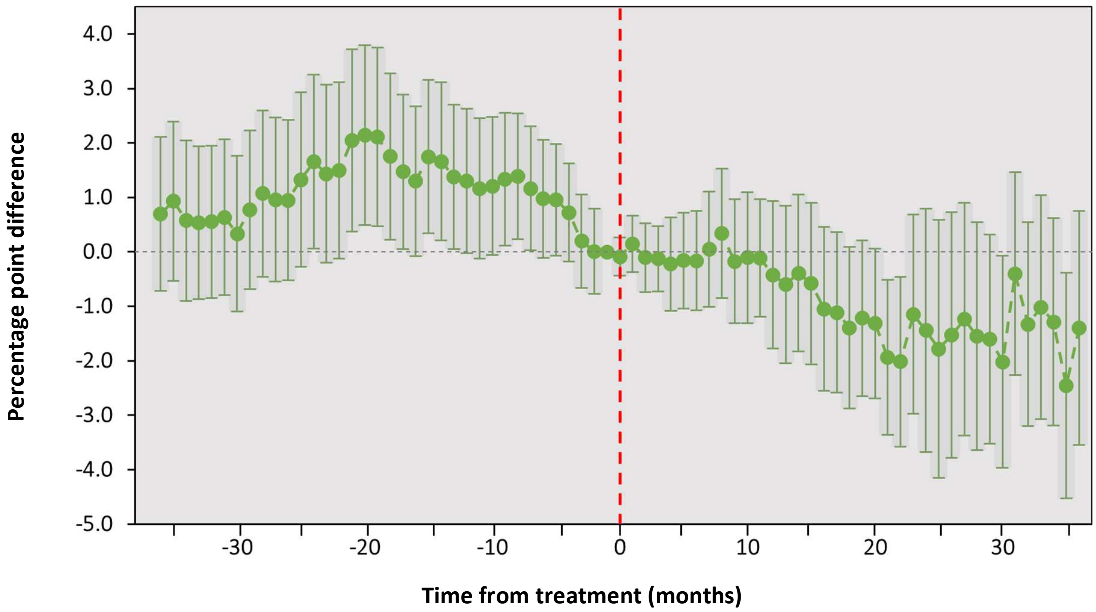
Even if it is the case that there is diverging school quality in treated and control SA2s, the coefficients in Table 15 show the magnitude of this decrease is economically small. A 0.65 percentage point decrease in secondary educational attainment for the overall treated population (column I) is a 0.9% decrease from the average secondary educational attainment rate of 70% observed in Figure 22. Additionally, several coefficients in Table 15 have small confidence intervals. In these instances, the impact of UR is precise enough to rule out large positive or negative impacts. For example, the confidence interval in column I is [-1.54, 0.25] which makes it unlikely that UR increases or decreases secondary educational attainment by more than 2 percentage points for the overall treated population.

Table 15 Impact of urban regeneration on secondary educational attainment

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Secondary educational attainment (percentage point difference)			
All Population	-0.65 [-1.54, 0.25]	0.43 [-1.21, 2.06]	-1.04* [-1.99, -0.08]
Social Housing	-2.15 [-6.41, 2.12]	-1.06 [-3.67, 1.55]	-2.59 [-8.04, 2.86]
Non-Social Housing	-0.68 [-1.71, 0.35]	-0.75 [-3.07, 1.56]	-0.68 [-1.66, 0.30]
SA1 – Secondary educational attainment (percentage point difference)			
All Population	-0.74 [-2.53, 1.04]	-0.86 [-4.04, 2.31]	-0.59 [-2.53, 1.35]
Social Housing	2.92 [-1.07, 6.92]	0.98 [-2.75, 4.70]	3.60 [-1.42, 8.63]
Non-Social Housing	-0.53 [-2.72, 1.66]	0.76 [-4.99, 6.50]	-0.72 [-2.93, 1.50]

Source: IDI 2024. Note UR – urban regeneration. Proportion of individuals aged between 16-19 (inclusive) who were born in New Zealand and/or were enrolled in at least two years in secondary institutions in New Zealand and received attainment equivalent to NCEA Level 2. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ and $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05 respectively. 95% confidence intervals in square [] brackets.

Figure 23 DiD - urban regeneration on secondary educational attainment (SA2, All Population)



Source: IDI 2024. Note: proportion of individuals aged between 16-19 (inclusive) who were born in New Zealand and/or were enrolled in at least two years in secondary institutions in New Zealand and received attainment equivalent to NCEA Level 2). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

7.2 Tertiary educational attainment

UR initiatives that improve tertiary attainment include employment and training hubs which may allow individuals to gain tertiary education or motivate them to go on and complete further education (Batty et al., 2010; Thomson et al., 2006). Improved public transport options, such as new train stations or bus routes in regenerated neighbourhoods, may improve access to tertiary institutions, indirectly supporting higher tertiary attainment levels in those areas (Bull et al., 2015).

However, it is more likely that the potential mechanisms in which UR can improve tertiary educational attainment in treated areas are likely to be driven more by demographic changes than by UR initiatives themselves. Regenerated neighbourhoods with improved housing quality and neighbourhood amenities are likely to attract higher educated individuals. Since UR is still ongoing at the time of analysis, the current results may not yet reflect this population shift. In the short run, however, UR might even reduce tertiary educational attainment rates due to the disruption caused by ongoing development when compared to control areas. These disruptions could motivate some residents to move away, particularly those with higher educational qualifications and greater income, who may have more flexibility in choosing where to live.

As with secondary educational attainment, there is no individual-level analysis for tertiary educational attainment as there is not enough temporal variation to allow for meaningful inference. When an individual receives tertiary educational attainment, they will always have tertiary educational attainment thereafter and therefore there is little temporal variation.

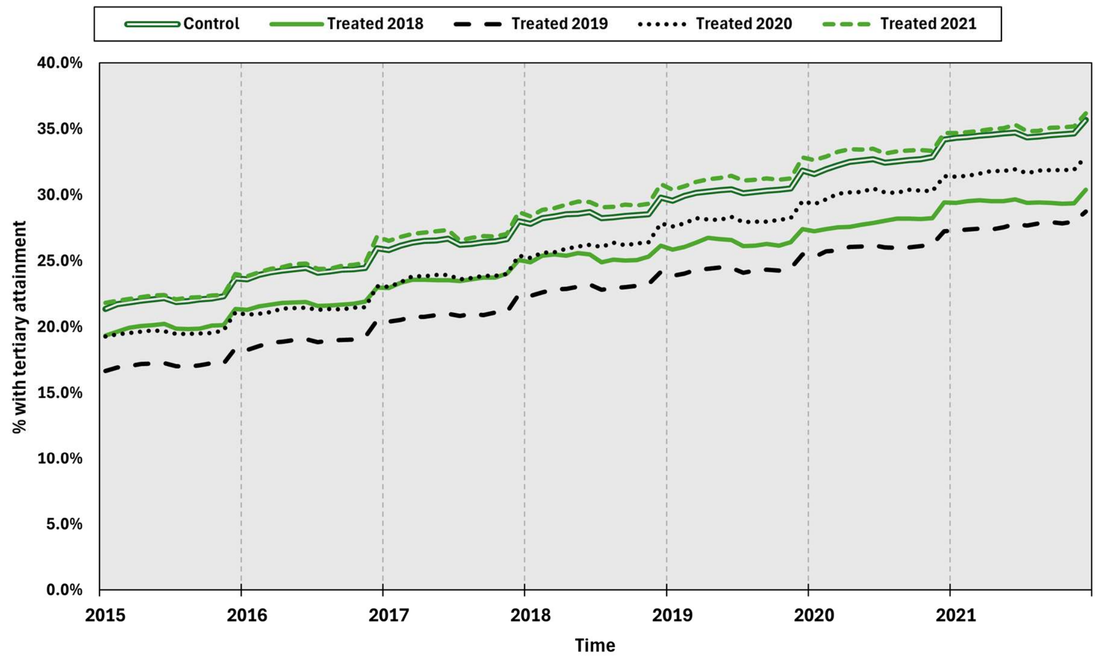
7.2.1 Descriptive trends

Figure 24 presents average tertiary educational attainment for treated SA2s by treatment year and control SA2s from 2015 to 2022. The population of interest are 25-to-64-year-olds (inclusive) who were born in New Zealand or spent at least two years in the educational system.[18] The outcome of interest is those who attained at least a Bachelor's degree.

Tertiary educational attainment steadily rises for all treated and control SA2s between 2015 and 2022. Average tertiary educational attainment rates are similar for SA2s that began treatment in 2021 and for control SA2s. However, for SA2s that started treatment earlier (in 2018 and 2020), tertiary attainment continues to increase but begins to diverge from control areas from 2018 onwards. By the end of 2021, SA2s treated in 2018 and 2020 show an average difference of 2.5 percentage points in tertiary attainment rates, indicating a modest difference in tertiary attainment as UR progresses.

[18] A two-year threshold in the New Zealand schooling system was used to identify individuals who may not have obtained tertiary educational attainment if they did not complete their schooling in New Zealand.

Figure 24 Average SA2 tertiary attainment by treatment year



Source: IDI 2024. Note: proportion of individuals aged between 25-64 (inclusive) who were born in New Zealand and/or spent at least two years in the New Zealand schooling system (either secondary or tertiary) and received a Bachelor's Degree.

7.2.2 Area-level DiD analysis

Table 16 presents regression results examining tertiary educational attainment rates for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 25 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, tertiary attainment rates begin to decrease following UR before recovering 30 months post-treatment. That is, there does appear to some impact of UR on tertiary educational attainment.

The ATT $\hat{\upsilon}_g$ in Table 16 (column I) shows tertiary educational attainment significantly decreased by 0.4 percentage points in treated SA2s compared to control SA2s, and this is statistically significant at the 5% level. Although statistically significant, the impact is economically small and represents a 1.6% decrease from the average pre-treatment tertiary attainment rate. The heterogeneity analysis indicates that this decrease is primarily driven by high UR SA2s, where tertiary attainment decreased by 0.8 percentage points compared to control SA2s and is statistically significant at the 1% level (column II). Figure 24 showed average attainment rates for SA2s treated in 2018 did not increase at the same rate compared to SA2s treated in later years and control SA2s.

Figure 13 in Section 5.1 show approximately 11% of treated SA2s (10 out 88) began treatment in 2018, with five undergoing high UR. As noted in Mohan et al. (2017), areas that receive higher levels of investment are more likely to experience significant change. Conversely, large-scale developments are also likely to experience significant disruptions (Henry et al., 2019). As such, these high UR areas might have experienced significant disruption, prompting higher educated individuals to relocate to other neighbourhoods and deterring others from moving in during ongoing development. Figure 25 indicates this is a negative short run impact of UR as tertiary attainment rates in treated and control SA2s are not significantly different 30 months after UR began. This may indicate that as developments are completed, higher educated individuals move back to these areas.

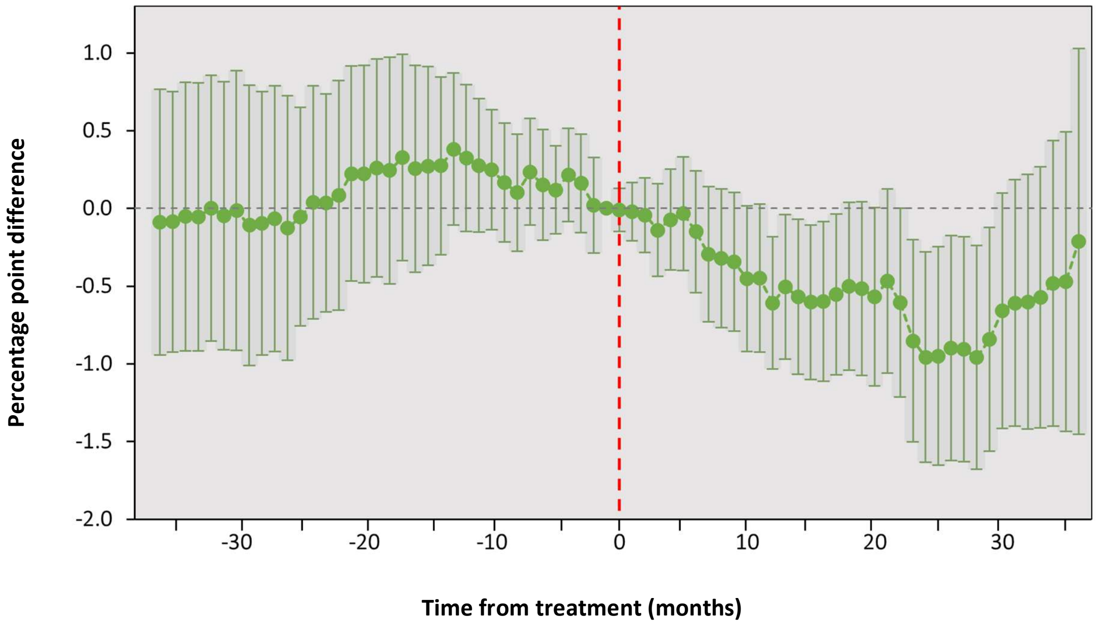
The heterogeneity analysis also shows tertiary educational attainment decreased for SH in low UR SA1s by 1.2 percentage points compared to control SA1s and this is significant at the 5% level. Given most Kāinga Ora-led UR is SH development, this suggests that higher educated SH tenants may have moved from low UR SA1s to SH in control SA1s during the UR process.

Table 16 Impact of urban regeneration on tertiary educational attainment

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Tertiary educational attainment (percentage point difference)			
All Population	-0.42* [-0.81, -0.03]	-0.79** [-1.35, -0.23]	-0.31 [-0.73, 0.12]
Social Housing	-0.95 [-1.97, 0.06]	-0.75 [-1.55, 0.04]	-0.68 [-1.95, 0.59]
Non-Social Housing	-0.38 [-0.80, 0.05]	-0.56 [-1.24, 0.12]	-0.34 [-0.77, 0.10]
SA1 – Tertiary educational attainment (percentage point difference)			
All Population	-0.03 [-0.54, 0.48]	0.04 [-0.98, 1.06]	-0.06 [-0.61, 0.49]
Social Housing	-0.99* [-1.82, -0.16]	-0.08 [-1.14, 0.99]	-1.18* [-2.22, -0.14]
Non-Social Housing	0.14 [-0.45, 0.73]	-0.23 [-1.41, 0.96]	0.28 [-0.35, 0.90]

Source: IDI 2024. Note UR – urban regeneration. Proportion of individuals aged between 25-64 (inclusive) who were born in New Zealand and/or spent at least two years in the New Zealand schooling system (either secondary or tertiary) and received a Bachelor's Degree. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{v}_g$ and $\widehat{w}_g$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05 respectively. 95% confidence intervals in square [] brackets.

Figure 25 DiD - urban regeneration on tertiary educational attainment (SA2, All Population)



Source: IDI 2024. Note: proportion of individuals aged between 25-64 (inclusive) who were born in New Zealand and/or spent at least two years in the New Zealand schooling system (either secondary or tertiary) and received a Bachelor's Degree. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

7.3 Youth not in education, employment, or training rate

UR can improve youths' participation in education, employment, or training through several pathways. First, upgrading public transport and infrastructure can improve access to jobs and education, which is especially important for youth with limited disposable income. Revitalised town centres may also create local employment opportunities, while employment and training hubs can equip youth with the skills necessary to enter the workforce (Batty et al., 2010; Gibbons et al., 2021; Henry et al., 2019; Thomson et al., 2006). In the long term, improved housing stability as part of UR initiatives can provide youth with the security needed to pursue employment or education opportunities.

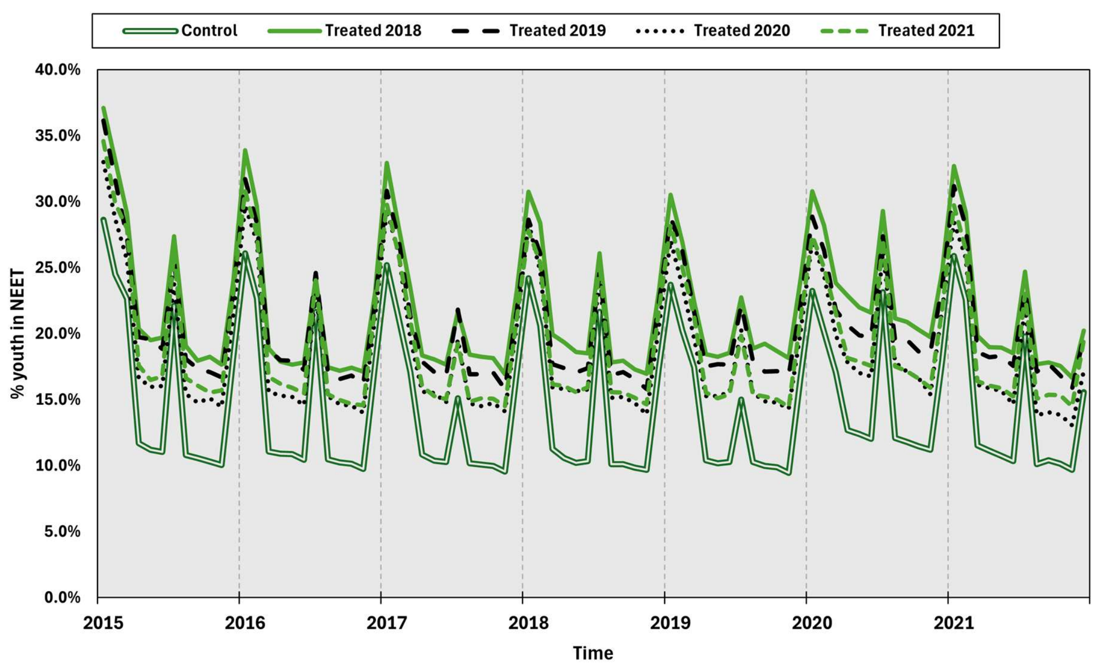
However, UR can also have negative short run impacts on youths' participation in education, employment or training. Disruptions from ongoing construction and development may limit access to transportation and other essential services, making it more difficult for young people to maintain their education or employment (Henry et al., 2019). Additionally, population growth in high UR areas can lead to increased competition for jobs, while the process of moving to regenerated areas may interrupt existing educational or employment opportunities.

7.3.1 Descriptive trends

Figure 26 presents average youth not education, employment or training (NEET) rates for treated SA2s by treatment year and control SA2s from 2015 to 2022. The population of interest are 15- to 24-year-olds (inclusive). The outcome of interest is those not enrolled in any education or training or employed.

While there is some variation in average youth NEET over time, rates largely remain consistent for treated SA2s. Treated SA2s have higher average youth NEET compared to control SA2s. Seasonal peaks are observed between November and February when students are on break from both secondary and tertiary institutions, with a smaller peak occurring in July during the mid-semester break at tertiary institutions. At the end of 2017, the difference in youth NEET between control and treated SA2s ranged between 3.6 to 6.2 percentage points. However, this difference narrows over time as youth NEET rates in control SA2s begin to rise. By the end of 2021, the difference in youth NEET between control and treated SA2s shrank to 1.6 and 4.6 percentage points.

Figure 26 Average SA2 youth NEET by treatment year



Source: IDI 2024. Note: proportion of individuals aged between 15 to 24 (inclusive) not in education, employment, or training (NEET).

7.3.2 Area-level DiD analysis

Table 17 presents regression results examining youth NEET rates for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 27 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on youth NEET. The ATT coefficient $\hat{v}_g$ from Table 17 (column I) show no impact of UR on youth NEET rates at the SA2-level.

The heterogeneity analysis shows significant impacts of UR on youth NEET rates in high UR areas. At the SA2-level, youth NEET significantly increased by 3.5 and 1.4 percentage points for SH and NSH, respectively, relative to control SA2s and this is significant at the < 1% level. The impact is even more pronounced at the local SA1 level, where youth NEET for NSH in high UR SA1s rose by 5.3 percentage points compared to control SA1s, significant at the < 1% level - four times greater than the SA2-level increase (5.3 versus 1.4 percentage points). To contextualise this difference, a 5.3 percentage point rise in average pre-treatment youth NEET represents a 27.1% increase, whereas a 1.4 percentage point rise corresponds to a 7.2% increase.[19]

The ongoing development in high UR SA2s may be challenging for youth with respects to their access to education and employment opportunities, particularly if local job availability is limited. UR initiatives often involve the construction of public transport facilities that could improve access, especially for younger residents who would benefit from affordable transport options However, these facilities are typically completed either during or after urban development, and existing transport options might be temporarily suspended during upgrades. It is unlikely that these facilities are completed and operational in the short run while UR is still in progress.

Additionally, moving can be a disruptive process. With extensive housing and neighbourhood development underway in high UR areas, individuals will start relocating to these regenerated neighbourhoods once they are finished. This movement can disrupt the education and employment patterns of youth, who may choose to leave their current opportunities when they relocate. Individual-level analysis could shed light on whether youth newcomers experience any negative impacts as a result of moving into treated SA2s.

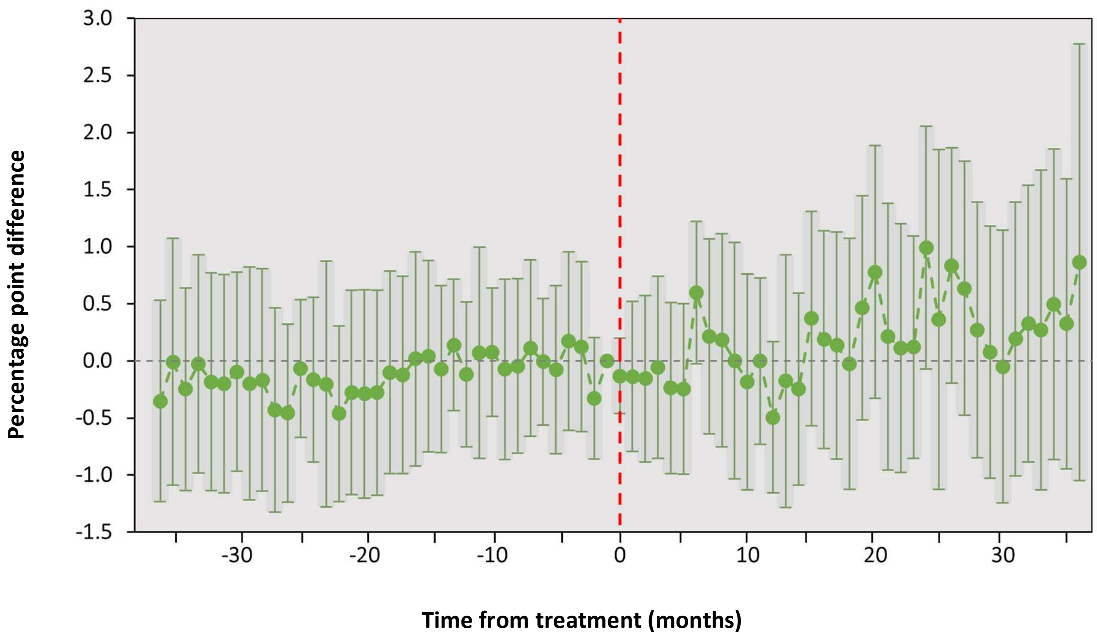
[19] Average taken across all months in 2017 due to seasonality of youth NEET rates.

Table 17 Impact of urban regeneration on youth NEET rates

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Youth not in education, employment, or training (percentage point difference)			
All Population	0.11 [-0.55, 0.76]	1.28*** [0.54, 2.03]	-0.29 [-0.94, 0.35]
Social Housing	1.79 [-0.27, 3.86]	3.47*** [1.78, 5.16]	1.91 [-0.67, 4.49]
Non-Social Housing	0.14 [-0.49, 0.77]	1.39*** [0.64, 2.15]	-0.29 [-0.90, 0.31]
SA1 – Youth not in education, employment, or training (percentage point difference)			
All Population	0.98 [-0.06, 2.03]	3.40*** [1.79, 5.02]	0.43 [-0.74, 1.60]
Social Housing	0.39 [-2.21, 2.99]	0.28 [-2.89, 3.44]	0.28 [-2.89, 3.44]
Non-Social Housing	1.41* [0.08, 2.73]	5.26*** [2.21, 8.30]	0.53 [-0.83, 1.88]

Source: IDI 2024. Note UR – urban regeneration. Proportion of individuals aged between 15 to 24 (inclusive) not in education, employment, or training (NEET). Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\upsilon}_g$ and $\widehat{w}_g$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05 respectively. 95% confidence intervals in square [] brackets.

Figure 27 DiD - urban regeneration on youth NEET rate (SA2, All Population)



Source: IDI 2024. Note: proportion of individuals aged between 15 to 24 (inclusive) not in education, employment, or training (NEET). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{e\ell}$, from Equation (1.1) in Section 5.5.

7.3.3 Individual-level DiD analysis

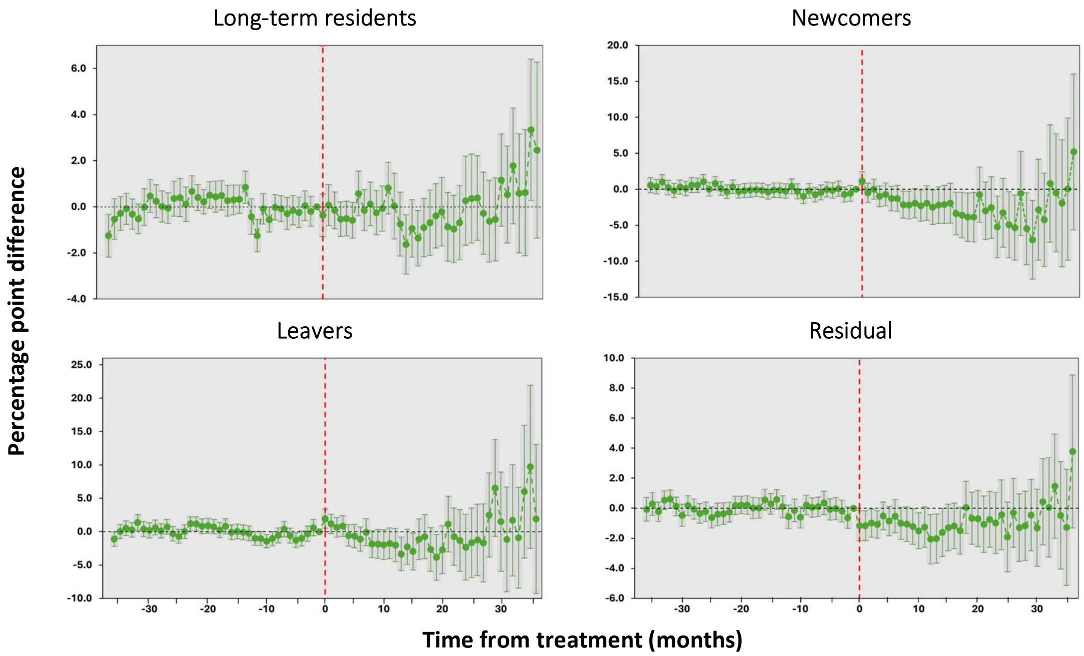
Figure 28 presents individual-level youth NEET regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 29) and NSH (Figure 30).

While the area-level analysis showed a significant increase in youth NEET in high UR areas compared to control areas (as shown in Table 17), the individual-level analysis shows no significant difference in youth NEET for those living in treated areas compared to their control counterparts. This lack of significance may be attributed to the fact that high UR areas comprise only 20% of treated areas, and their small sample size is unlikely to substantially affect overall youth NEET rates.

Although moving can be a disruptive experience that can negatively affects youths' engagement in education and employment, this does not appear to be the case for SH youth moving into treated SA2s. The heterogeneity analysis indicates that youth newcomers in treated SH have significantly lower NEET compared to transient youth in control SH areas (Figure 29). These decreases range between 18 to 36 percentage points two years after their relocation to treated SA2s. That is, significantly more SH youth newcomers are participating in employment, education or training relative to transient youth in control SH.

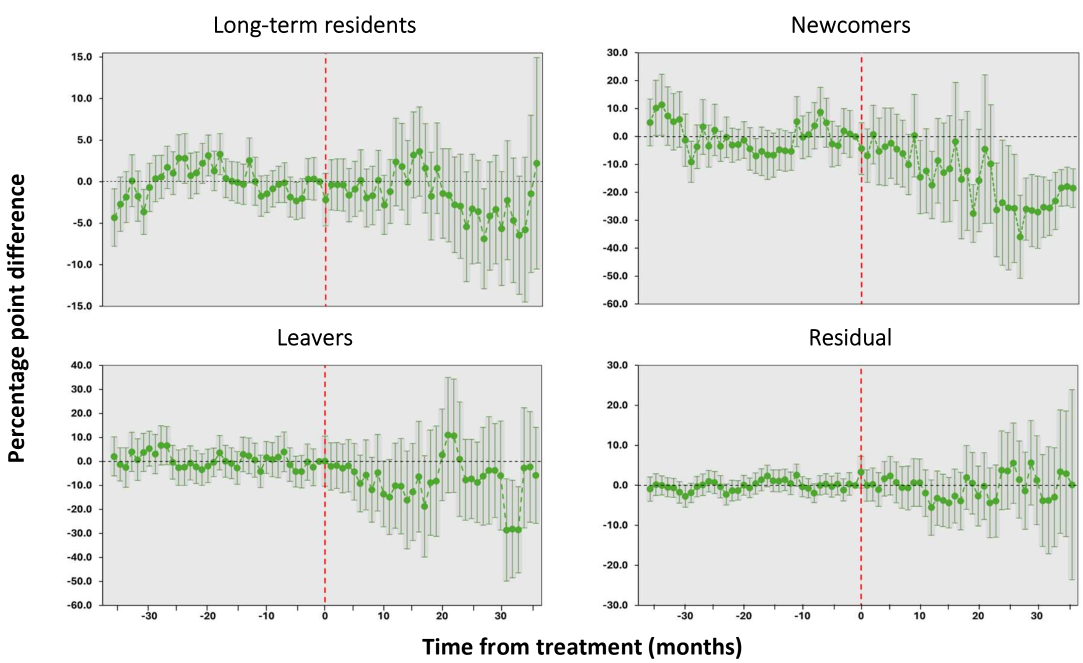
This positive outcome may stem from greater housing stability, which encourages youth to commit to long-term opportunities, improved access to educational and employment resources, or employment and training hubs that improves their skills and employability. While the specific mechanisms behind the lower youth NEET rates remain unclear, the evidence suggests that UR has positive impacts on youth NEET for social housing youth in the short run.

Figure 28 DiD - urban regeneration on youth NEET (Individual, All Population)



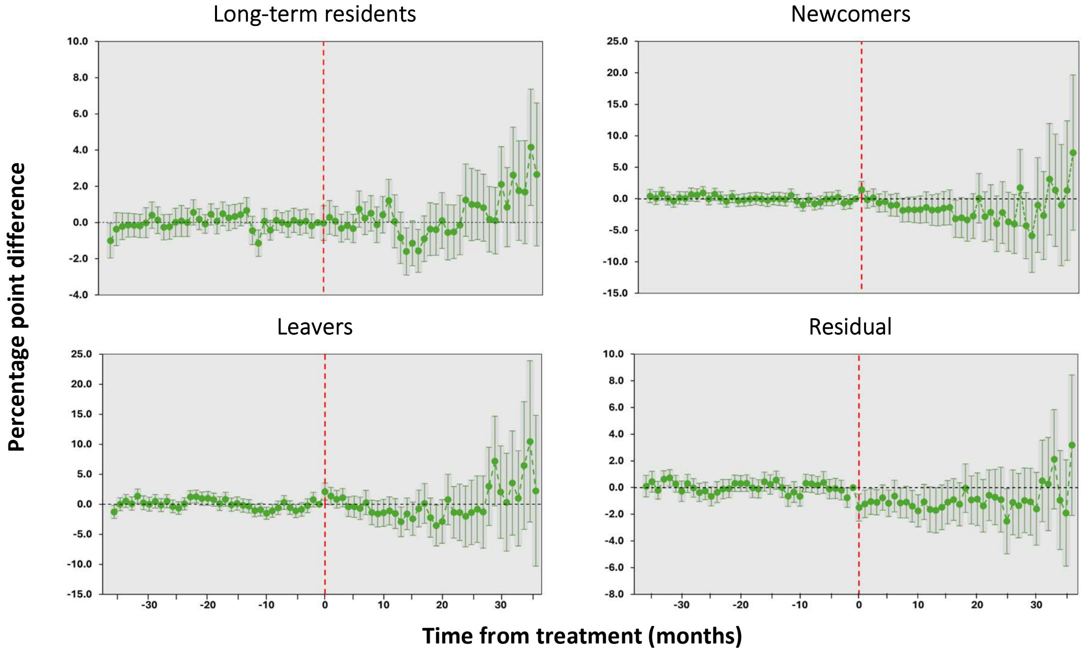
Source: IDI 2024. Note: individuals aged between 15 to 24 (inclusive) not in education, employment, or training (NEET). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 29 DiD - urban regeneration on youth NEET (Individual, Social Housing)



Source: IDI 2024. Note: individuals aged between 15 to 24 (inclusive) not in education, employment, or training (NEET). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 30 DiD - urban regeneration on youth NEET (Individual, Non-Social Housing)



Source: IDI 2024. Note: individuals aged between 15 to 24 (inclusive) not in education, employment, or training (NEET). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{e\ell}$, from Equation (2.3) in Section 5.5.

7.4 Employment rate

There are several mechanisms in which UR has the potential to improve employment opportunities for residents. Employment and training hubs can provide residents with skills that increases their employability or help facilitate job matching (Batty et al., 2010; Henry et al., 2019; Thomson et al., 2006). As mentioned in Section 7.3, revitalising local town centres can create local employment opportunities (Gibbons et al., 2021), while the construction or improvement of public transport facilities can improve access to employment (Bull et al., 2015). Improved housing quality, whether through new builds or retrofitting older properties, can reduce health issues that limit the ability to work (Batty et al., 2010). Further, housing stability may enable residents to secure long-term employment.

It is important to note that the inverse of employment in the analysis is non-employment, as opposed to unemployed or not in the labour force (NILF). The absence of wages and salary for an individual with administrative data does not indicate whether an individual is unemployed or NILF, which is typically only captured in survey data.

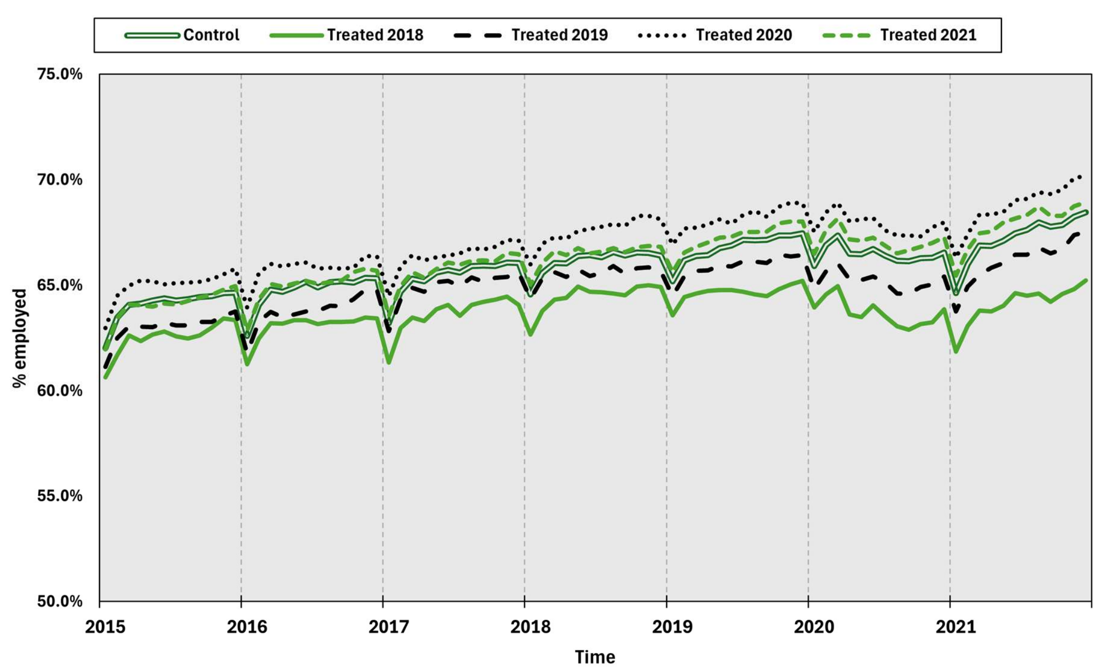
7.4.1 Descriptive trends

Figure 31 to Figure 33 presents average employment rates for treated SA2s by treatment year and control SA2s from 2015 to 2022. The population of interest are those aged between 25 to 64 (inclusive), with the outcome of interest those who are employed. These are presented in total and separately for male and female.

The slight declines in total employment rates observed in January each year correspond with decreases in female employment. Women on casual or hourly paid contracts who are not entitled to holiday pay may be more likely to take January off due to childcare responsibilities during the summer holidays. There is also a slight drop in employment rates around 2021, which is likely to reflect the impact of COVID-19 lockdowns on employment rates, but they recover relatively quickly.

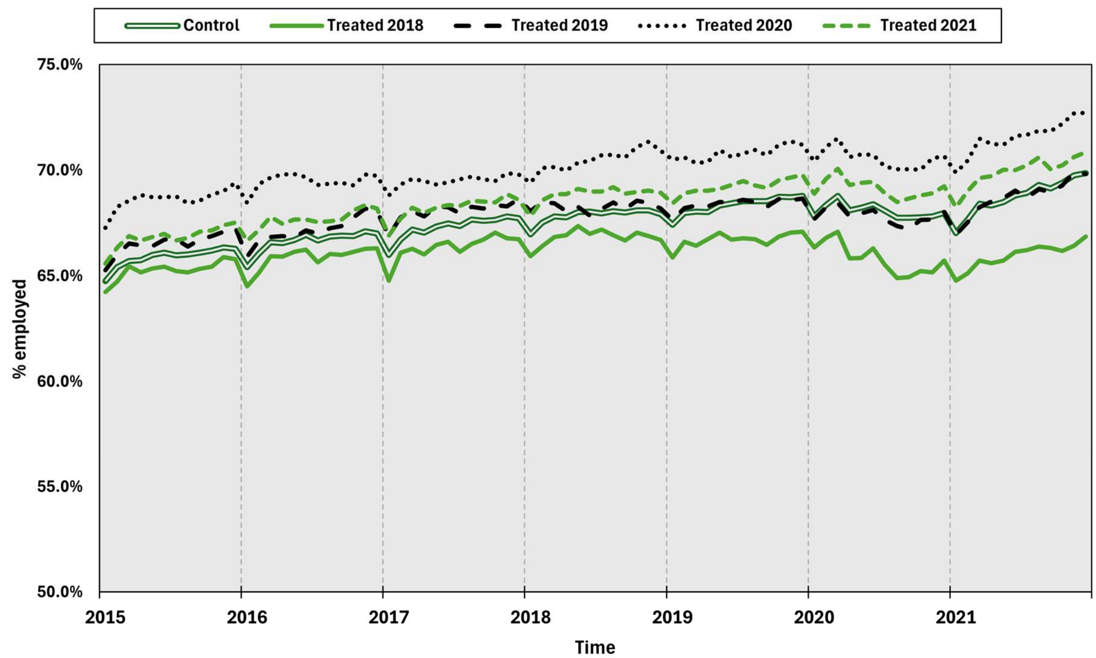
Figure 31 shows average employment rates are highest for SA2s treated in 2020 and lowest for those treated in 2018. Between 2015 and 2017, average employment for SA2s treated in 2020 was around 1 percentage point higher than control SA2s. For SA2s treated in 2018, this was 2 percentage points lower than control SA2s. Employment trends steadily diverge over time. By the end of 2021, average employment for SA2s treated in 2020 was 1.7 percentage points higher than in control SA2s, whereas for those treated in 2018, the average employment rate was 3.2 percentage points lower than that of control SA2s.

Figure 31 Average SA2 total employment rate by treatment year



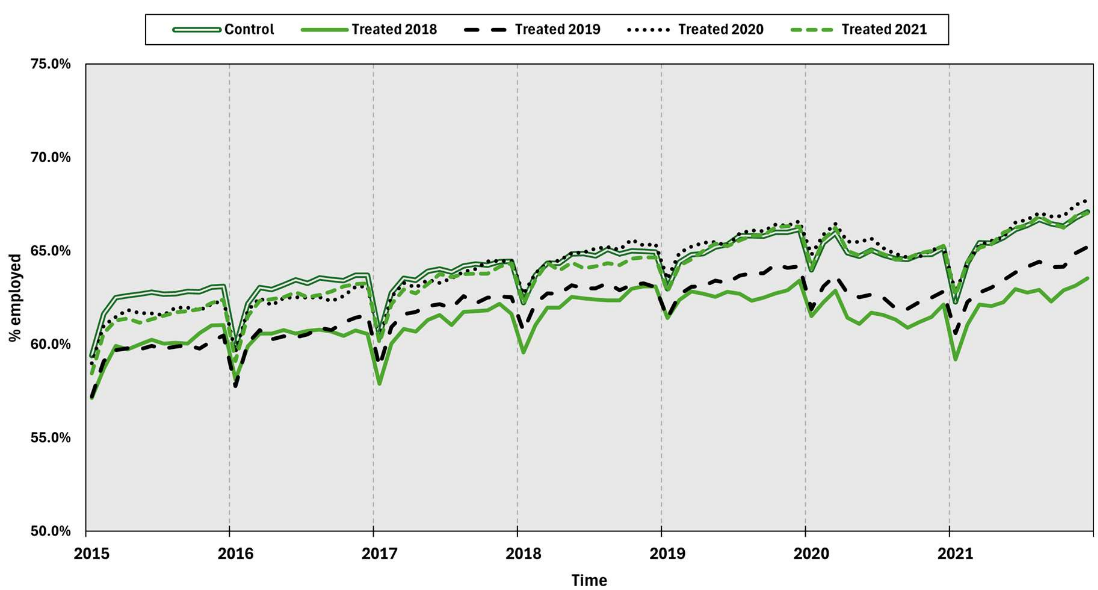
Source: IDI 2024. Note: proportion of individuals aged between 25 to 64 (inclusive) earning wages and salary.

Figure 32 Average SA2 male employment rate by treatment year



Source: IDI 2024. Note: proportion of male individuals aged between 25 to 64 (inclusive) earning wages and salary.

Figure 33 Average SA2 female employment rate by treatment year



Source: IDI 2024. Note: proportion of female individuals aged between 25 to 64 (inclusive) earning wages and salary.

7.4.2 Area-level DiD analysis

Table 18 presents regression results examining employment rates for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 34 to Figure 36 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on total, male and female employment rates.

Although Figure 31 and Figure 32 show descriptive differences in employment rates were widening over time, both the SA2 and SA1 ATT $\hat{v}_g$ and $\hat{w}_g$ shows this difference does not reach statistical significance (column I in Table 18). Additionally, the narrow confidence intervals suggest that UR is unlikely to affect employment rates by more than 1 percentage point across all UR levels.

The heterogeneity analysis shows SH employment decreased by 1.3 percentage points in high UR SA2s (column II in Table 18). Results at the SA1 level show that this decline is localised, with a significant decrease of 1.4 percentage points in employment for SH women in high UR SA1s. This impact, however, is economically small and represents only a 2.2% decrease from the average pre-treatment female employment rate of 62.3%. As shown in Figure 136 in Appendix 7, employment for SH women in high UR SA1s significantly decreased during the first 1.5 years following the onset of UR.

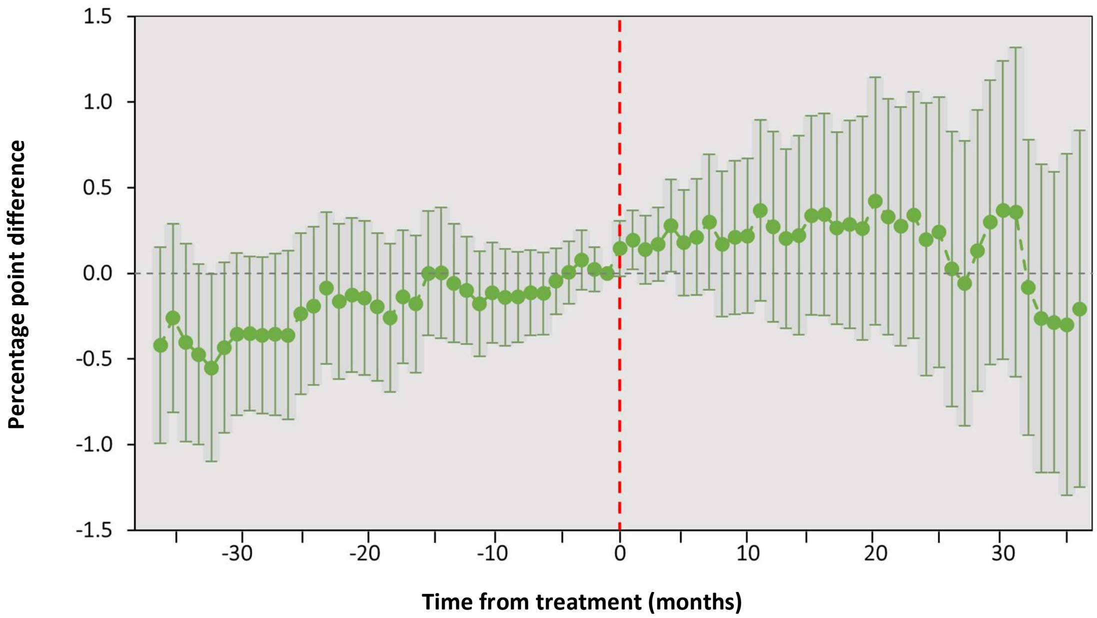
It is possible that large-scale development, especially in high UR SA1s, may have caused some disruption or uncertainty with respects to residents relocating (Bull et al., 2015). Existing tenants living in SH dwellings set to be replaced with multi-unit dwellings may have had uncertainty as to when or where they would be relocated. In the short run, this may make it difficult to continue existing employment or pursue new employment opportunities.

Table 18 Impact of urban regeneration on employment rates

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Total employment rate (percentage point difference)			
All Population	0.22 [-0.24, 0.67]	-0.18 [-0.64, 0.28]	0.36 [-0.14, 0.86]
Social Housing	-0.64 [-1.82, 0.53]	-1.27** [-2.19, -0.34]	-0.30 [-1.74, 1.14]
Non-Social Housing	0.32 [-0.15, 0.79]	0.15 [-0.39, 0.70]	0.38 [-0.10, 0.87]
SA2 – Male employment rate (percentage point difference)			
All Population	0.15 [-0.10, 0.40]	0.03 [-0.28, 0.34]	0.20 [-0.07, 0.47]
Social Housing	-0.13 [-1.16, 0.90]	0.10 [-0.65, 0.86]	-0.22 [-1.55, 1.10]
Non-Social Housing	0.19 [-0.07, 0.45]	0.19 [-0.13, 0.50]	0.19 [-0.07, 0.46]
SA2 – Female employment rate (percentage point difference)			
All Population	0.06 [-0.21, 0.34]	-0.21 [-0.52, 0.10]	0.16 [-0.14, 0.45]
Social Housing	-0.51 [-1.49, 0.47]	-1.37*** [-1.81, -0.92]	-0.08 [-1.01, 0.86]
Non-Social Housing	0.13 [-0.15, 0.42]	-0.03 [-0.39, 0.33]	0.19 [-0.10, 0.49]
SA1 – Total employment rate (percentage point difference)			
All Population	-0.37 [-0.86, 0.13]	0.21 [-0.74, 1.15]	-0.51 [-1.03, 0.02]
Social Housing	-1.75 [-3.75, 0.25]	-0.87 [-2.70, 0.95]	-1.94 [-4.32, 0.45]
Non-Social Housing	0.14 [-0.44, 0.72]	0.51 [-0.89, 1.91]	0.09 [-0.50, 0.69]
SA1 – Male employment rate (percentage point difference)			
All Population	-0.07 [-0.43, 0.28]	-0.07 [-0.72, 0.59]	-0.07 [-0.44, 0.31]
Social Housing	-0.70 [-2.32, 0.93]	0.49 [-0.82, 1.80]	-0.64 [-2.48, 1.20]
Non-Social Housing	0.10 [-0.30, 0.49]	0.31 [-0.48, 1.11]	0.07 [-0.33, 0.48]
SA1 – Female employment rate (percentage point difference)			
All Population	-0.30 [-0.65, 0.06]	0.31 [-0.43, 1.04]	-0.44* [-0.81, -0.07]
Social Housing	-1.05 [-2.45, 0.35]	-1.37* [-2.51, -0.22]	-1.07 [-2.61, 0.46]
Non-Social Housing	0.04 [-0.37, 0.46]	0.19 [-0.82, 1.21]	0.02 [-0.40, 0.44]

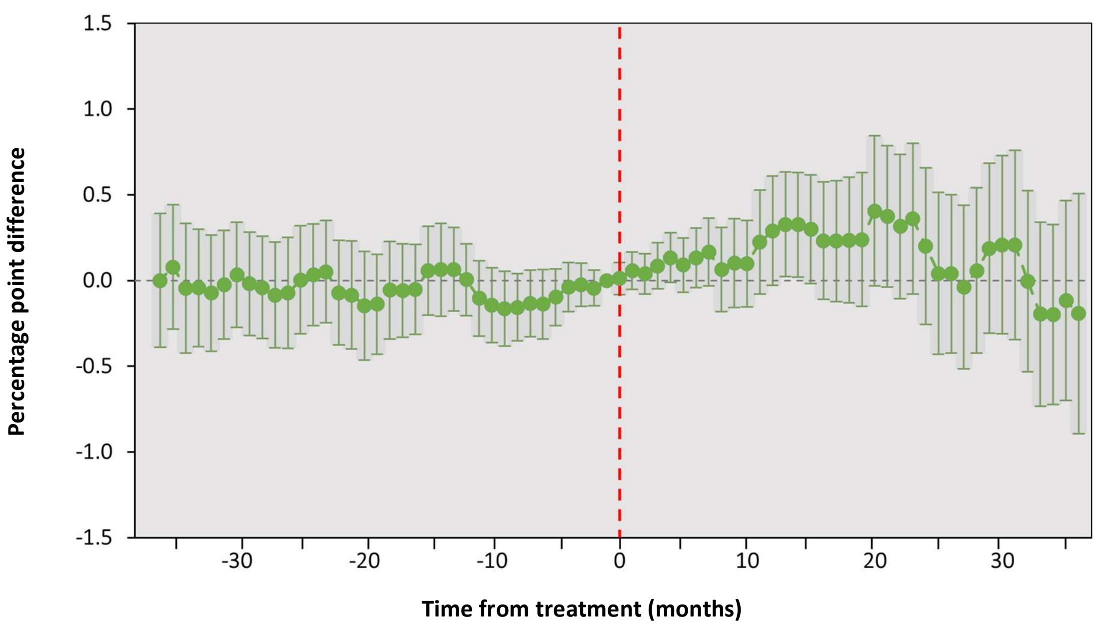
Source: IDI 2024. Note UR – urban regeneration. Proportion of individuals aged between 25 to 64 (inclusive) earning wages and salary. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05 respectively. 95% confidence intervals in square [] brackets.

Figure 34 DiD - urban regeneration on total employment rate (SA2, All Population)



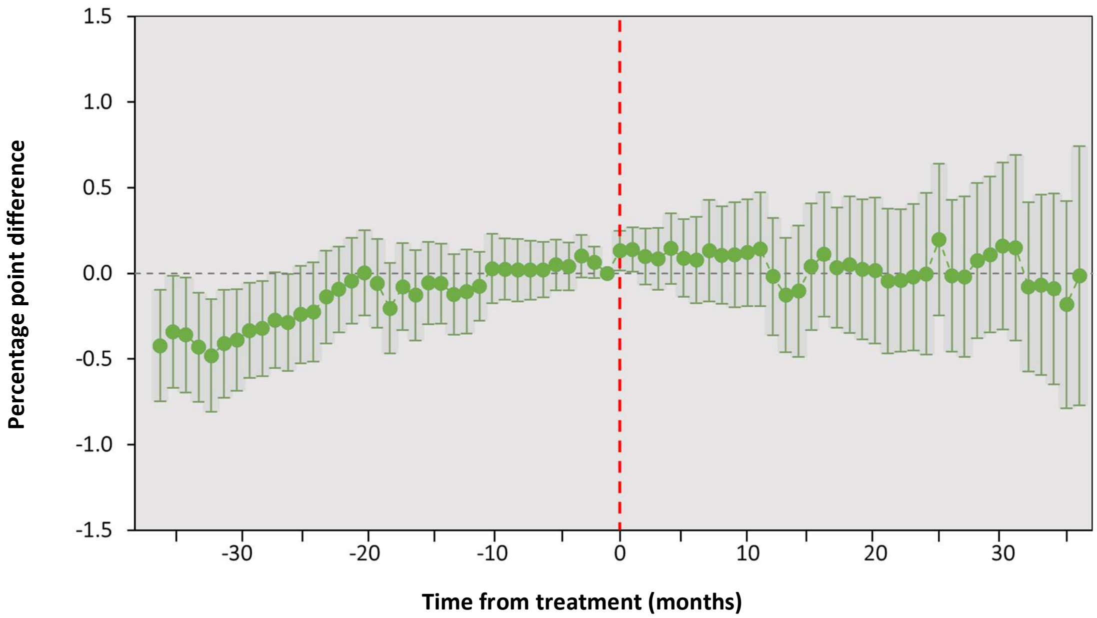
Source: IDI 2024. Note: proportion of individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 35 DiD - urban regeneration on male employment rate (SA2, All Population)



Source: IDI 2024. Note: proportion of male individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 36 DiD - urban regeneration on female employment rate (SA2, All Population)



Source: IDI 2024. Note: proportion of female individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

7.4.3 Individual-level DiD analysis

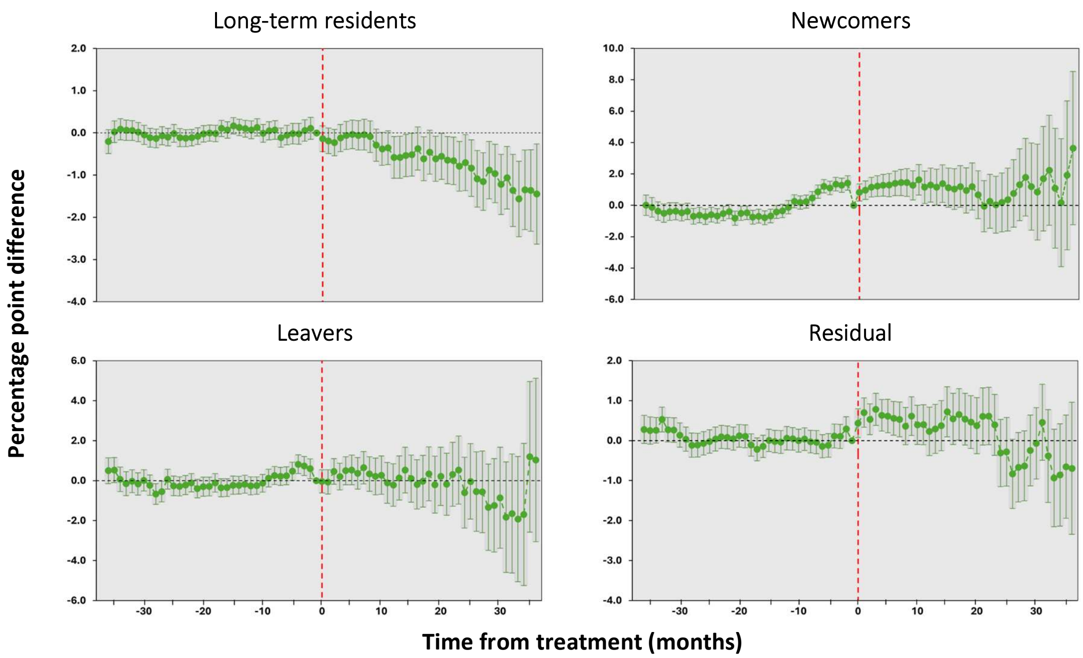
Figure 37 to Figure 39 presents individual-level employment regressions (total, male and female) comparing all treated subpopulations, and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 40 to Figure 42) and NSH (Figure 43 to Figure 45).

The heterogeneity analysis shows employment significantly increased for both NSH male and female newcomers relative to their control counterparts (Figure 44 and Figure 45, respectively). However, their employment was already significantly higher prior to their relocation into treated SA2s. Although this impact is economically small, it is possible that NSH newcomers may have moved to treated areas for reasons related to their employment. For example, UR areas might be centrally located or offer easier access to job opportunities, making them attractive to NSH newcomers.

There are also positive impacts on employment rates for SH male newcomers (Figure 41). Employment rates for SH male newcomers in treated areas significantly increased by 13.9 to 19.1 percentage points between $\ell = 25$ and $\ell = 31$ (relative months from treatment) compared to those in control areas. While this represents a short run impact, the magnitude is economically large, indicating that employment or training hubs may have significantly increased employment for SH male newcomers in the short run.

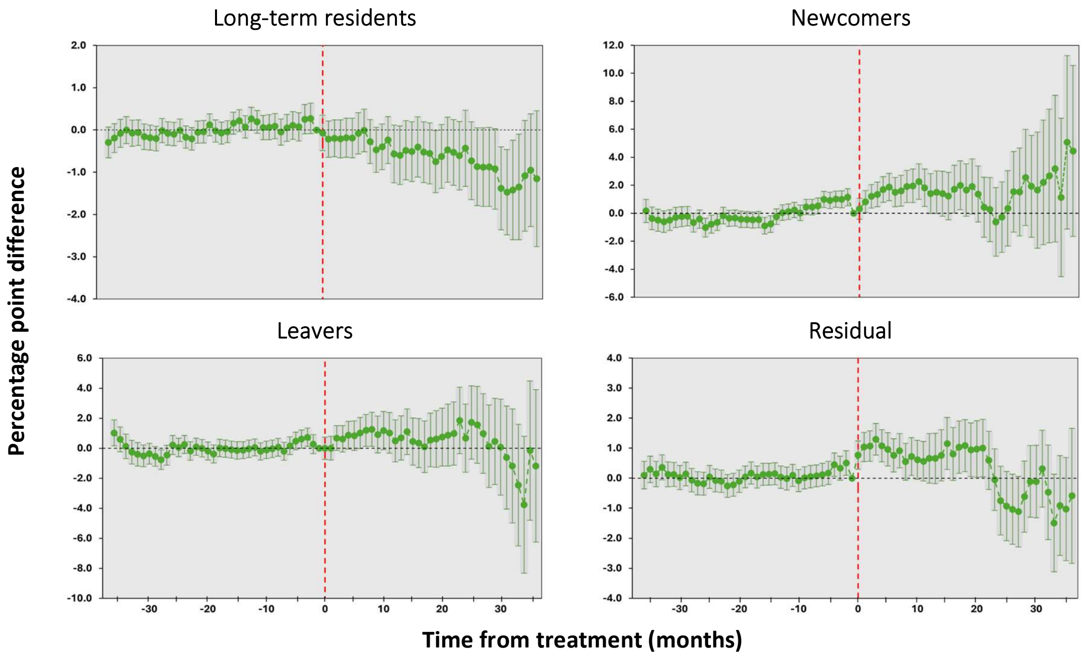
Conversely, Figure 37 shows total employment for treated long-term residents significantly decreased relative to control long-term residents. This decrease begins at $\ell = 12$ (relative months from treatment) and persists even at $\ell = 36$. The heterogeneity analysis shows this is driven mostly by female SH long-term residents relative to their control counterparts (Figure 42). For female SH long-term residents, their employment rate was significantly lower by 3.6 percentage points at $\ell = 14$ and steadily grows to 4.9 percentage points by $\ell = 36$. There is also some impact of UR on male NSH employment – however, the differences are not as large as that for female SH long-term residents (Figure 44). While it is unclear what may be driving lower employment rates for female SH long-term residents, Figure 42 shows this could be a persistent impact that continues in the medium to long run and likely warrants future analysis.

Figure 37 DiD - urban regeneration on total employment rate (Individual, All Population)



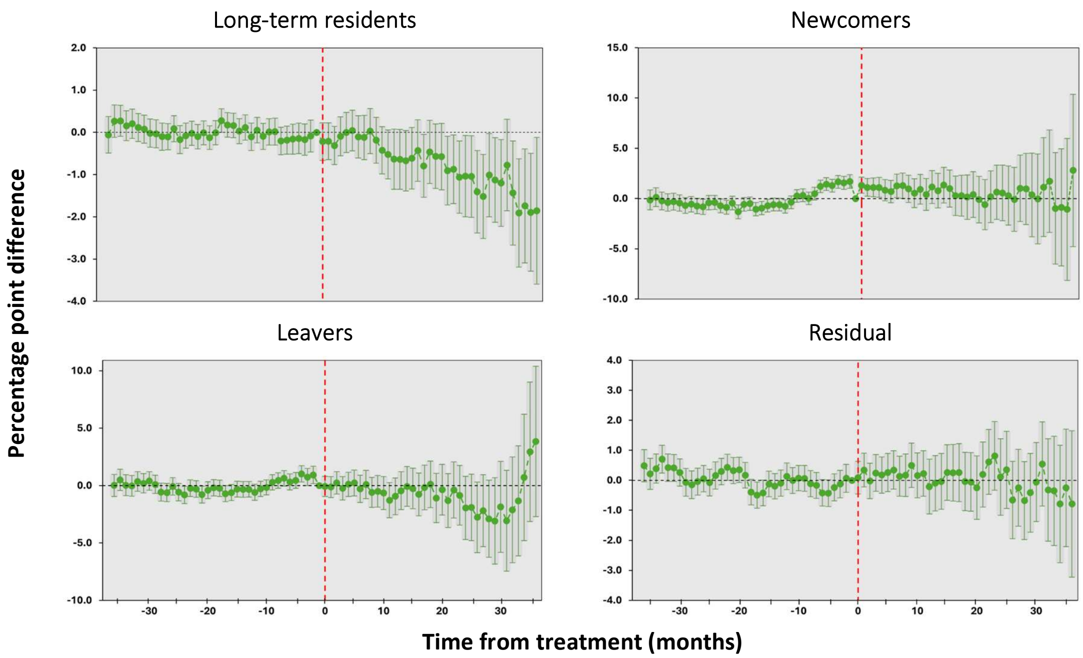
Source: IDI 2024. Note: individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 38 DiD - urban regeneration on male employment rate (Individual, All Population)



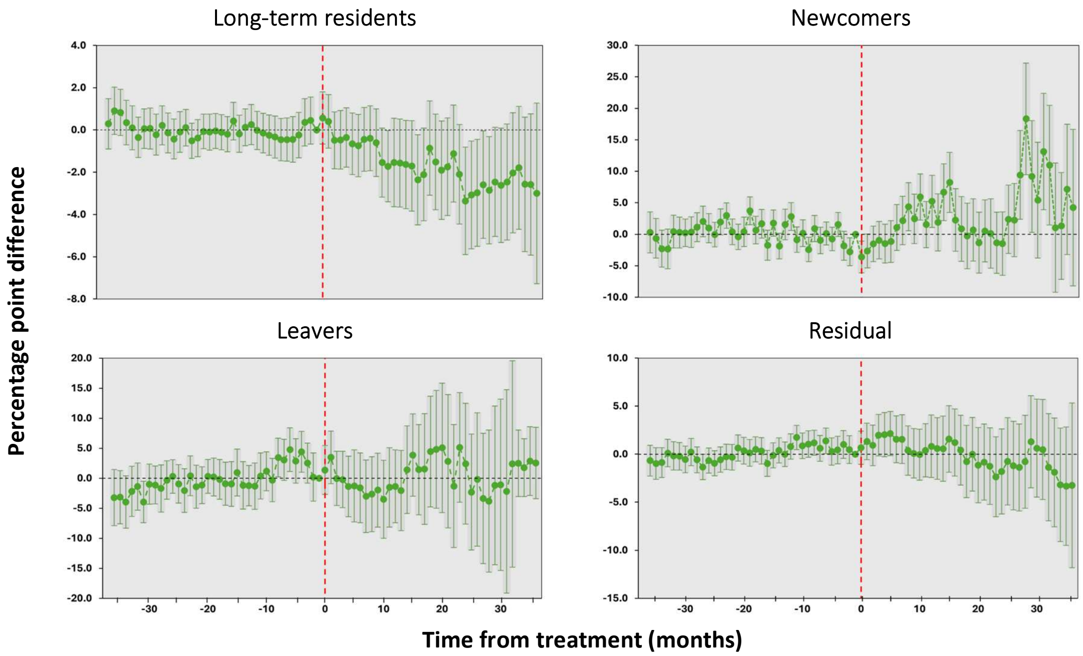
Source: IDI 2024. Note: male individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 39 DiD - urban regeneration on female employment rate (Individual, All Population)



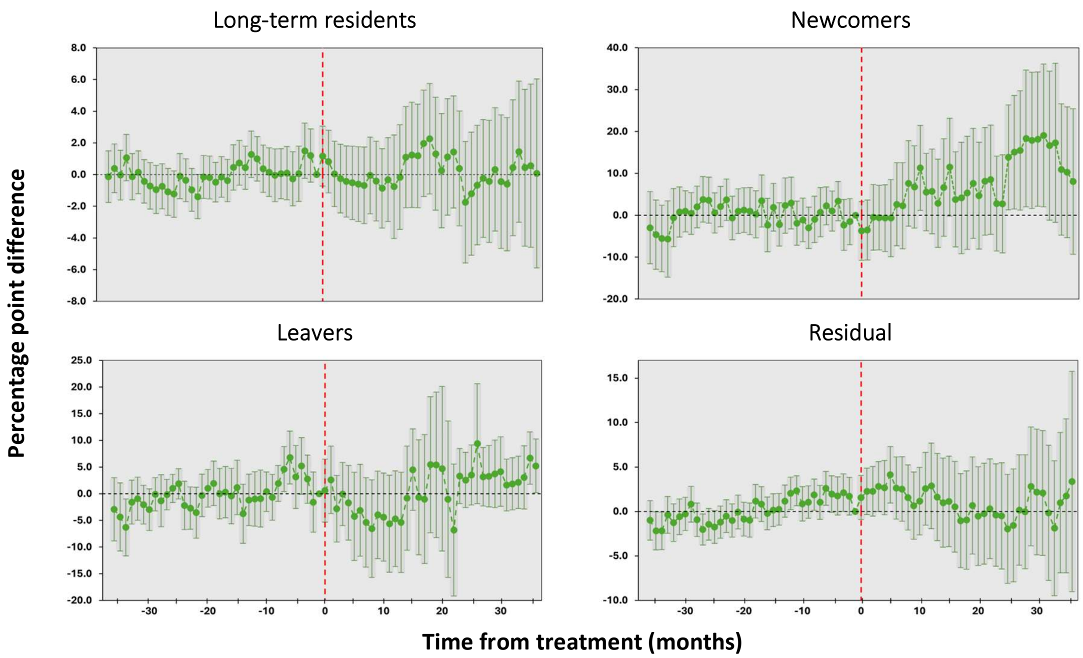
Source: IDI 2024. Note: female individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 40 DiD - urban regeneration on total employment rate (Individual, Social Housing)



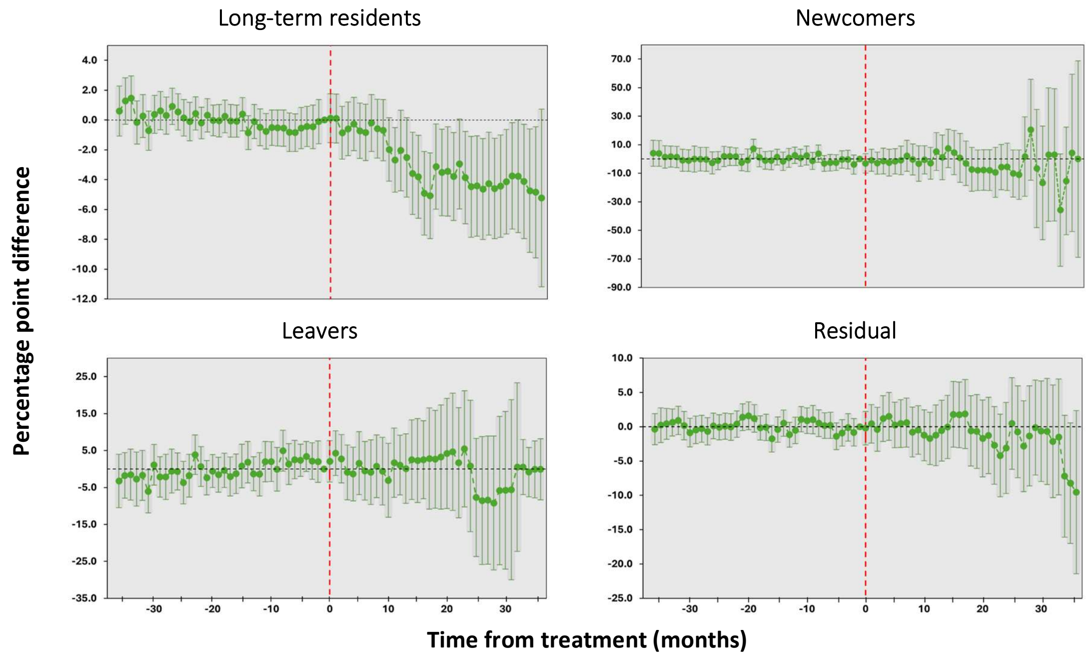
Source: IDI 2024. Note: individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 41 DiD - urban regeneration on male employment rate (Individual, Social Housing)



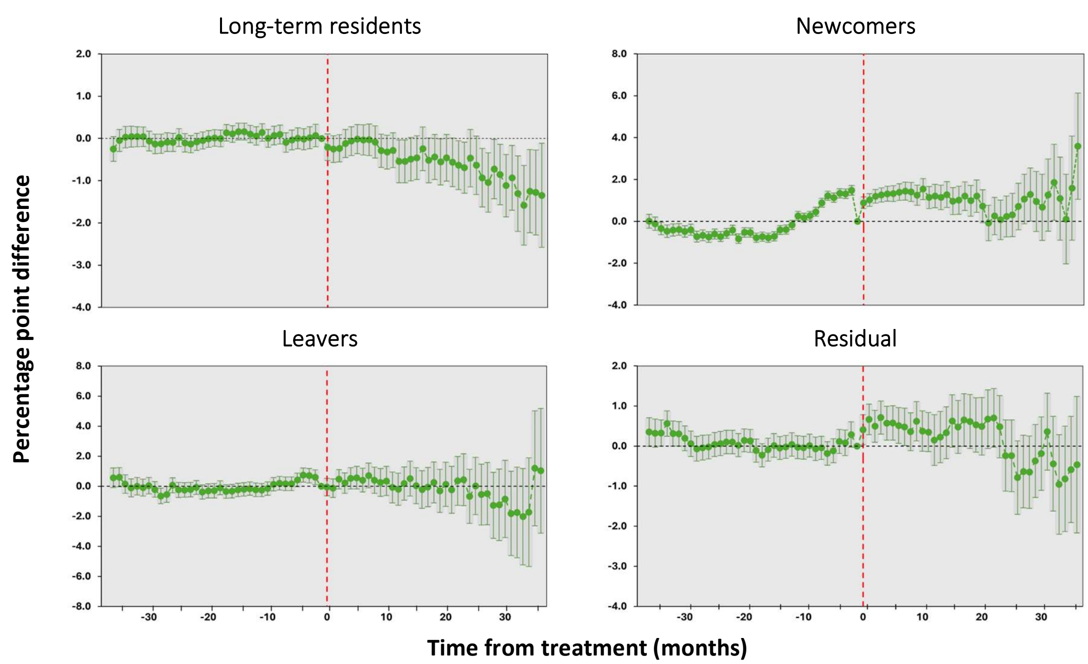
Source: IDI 2024. Note: male individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 42 DiD - urban regeneration on female employment rate (Individual, Social Housing)



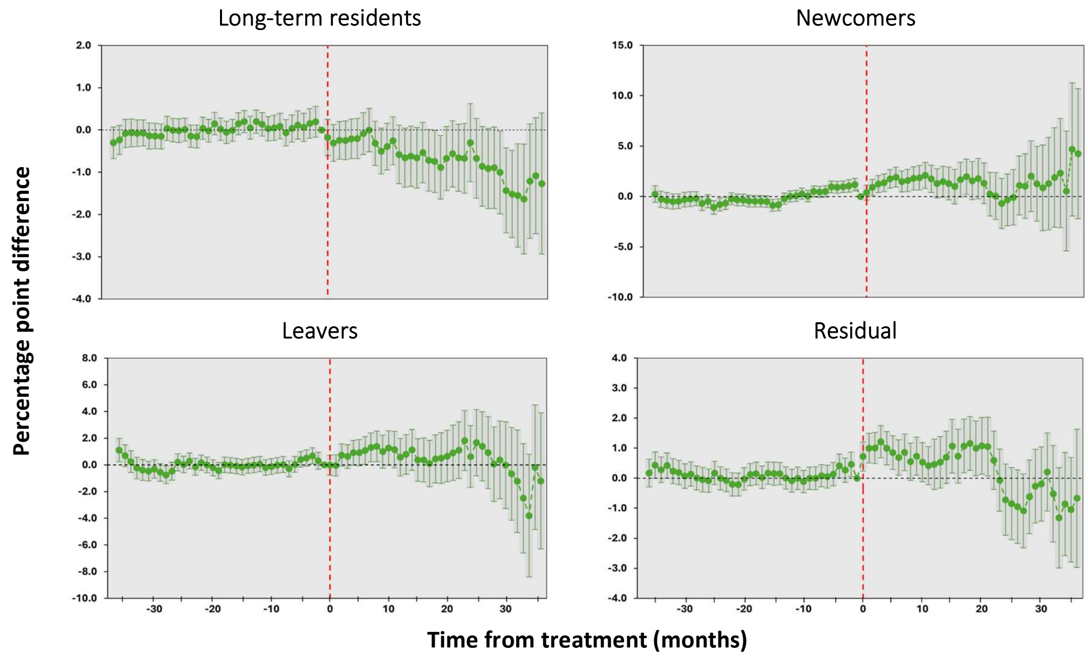
Source: IDI 2024. Note: female individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 43 DiD - urban regeneration on total employment rate (Individual, Non-Social Housing)



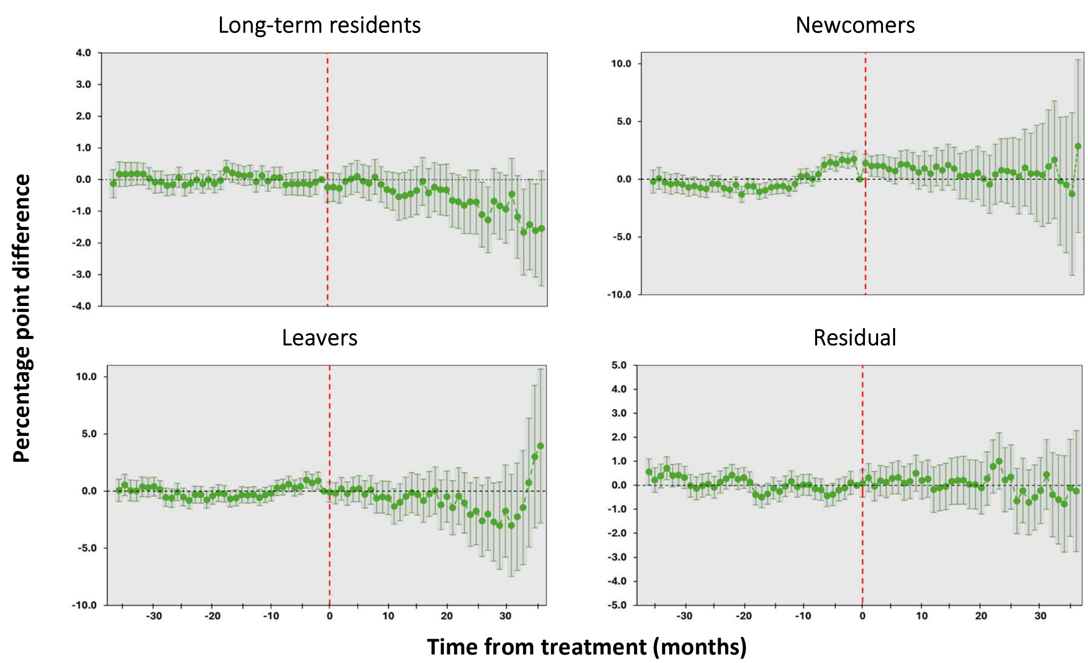
Source: IDI 2024. Note: individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 44 DiD - urban regeneration on male employment rate (Individual, Non-Social Housing)



Source: IDI 2024. Note: male individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 45 DiD - urban regeneration on female employment rate (Individual, Non-Social Housing)



Source: IDI 2024. Note: female individuals aged between 25 to 64 (inclusive) earning wages and salary. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

7.5 Wages and salary

The Wellbeing Outcomes Framework detailed in Section 4.2 measures both average and median wages and salary at the area-level. However, the descriptive statistics and regression results were qualitatively similar for both measures. Therefore, only median wages and salary is presented and discussed for the area-level descriptive trends and regression results.

The mechanisms in which UR has the potential to improve wages and salary are similar to those that improve employment outcomes in Section 7.4. For example, employment and training hubs that upskill residents to improve their employability, and housing stability which can support individuals to maintain continuous employment and pursue opportunities for wage growth. Wages and salary generally increase with educational attainment - those with tertiary educational attainment are likely to have higher earnings trajectories compared to those without tertiary attainment. However, as noted in Section 0, improvements in tertiary educational attainment are likely to be driven by population changes, rather than by UR initiatives themselves.

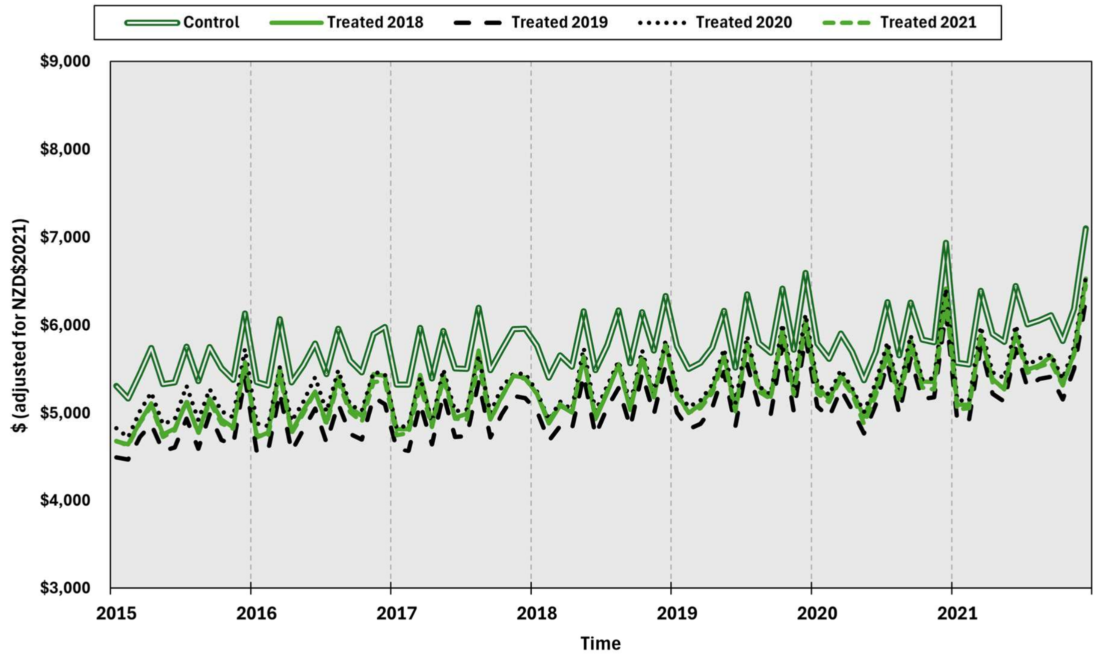
7.5.1 Descriptive trends

Figure 46 to Figure 48 presents median wages and salary ("earnings") for treated SA2s by treatment year and control SA2s from 2015 to 2022. The population of interest are those aged between 25 to 64 (inclusive) who are employed, with the outcome of interest the median earnings for those employed. Results are presented in total and separately for male and female.

Figure 46 shows that while there is some variation in median earnings, all treated SA2s have similar median earnings. Earnings steadily increase over time by similar magnitudes, irrespective of treatment status and gender. Throughout the observation period, control SA2s consistently have higher median earnings than treated SA2s.

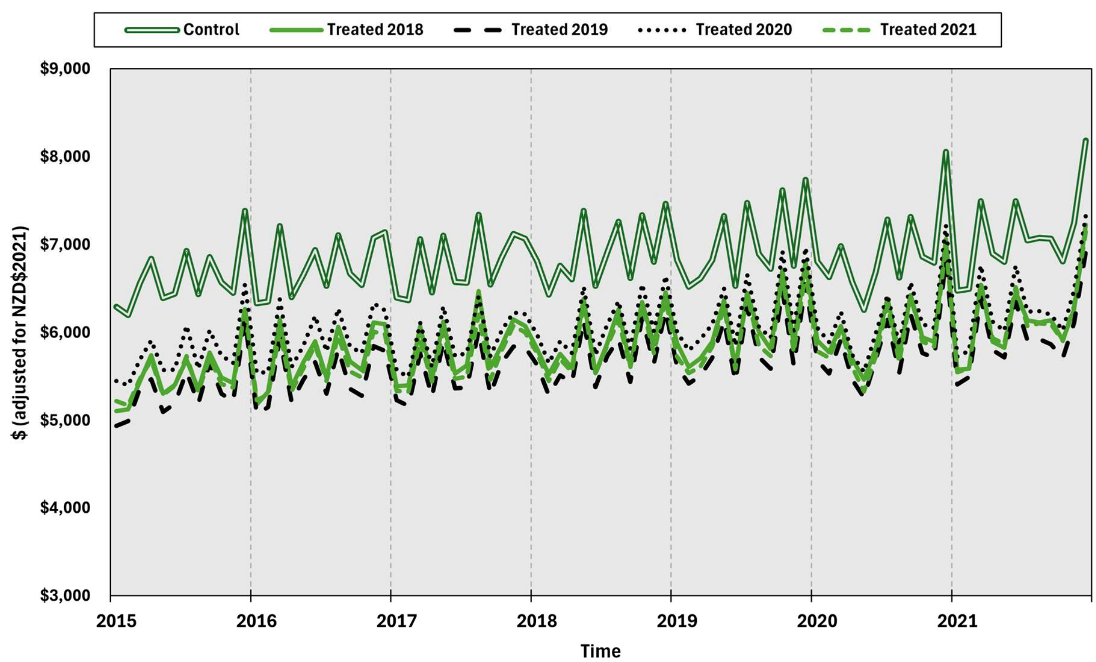
This is also the case when examining earnings separately by gender – however, the difference in female earnings (Figure 48) is smaller than that for male earnings (Figure 47). Prior to treatment, median earnings for men in treated SA2s was $6,030 compared to $7,069 for men in control SA2s. For women, this was $4,701 and $5,039 for treated and control SA2s, respectively. On average, men tend to have higher earnings compared to women due to the gender pay gap and the fact that women often work part-time due to childcare responsibilities. Thus, the results are presented for both genders combined and separately for each gender.

Figure 46 Total SA2 median wages and salary by treatment year



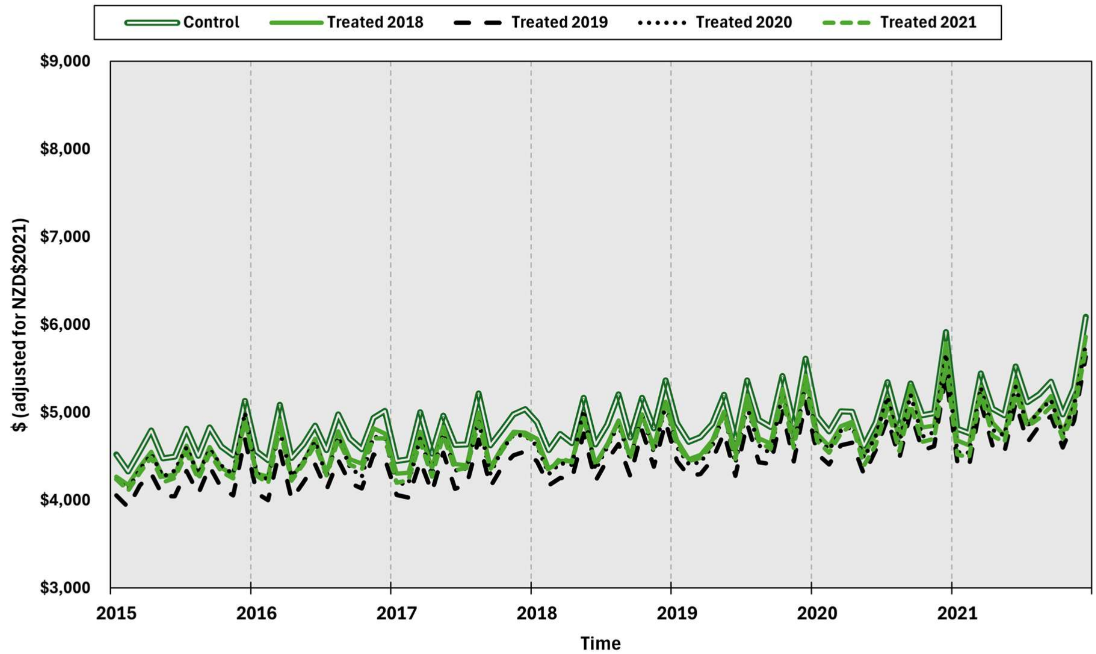
Source: IDI 2024. Note: only includes wages and salary of employed individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021.

Figure 47 Male SA2 median wages and salary by treatment year



Source: IDI 2024. Note: only includes wages and salary of employed male individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021.

Figure 48 Female SA2 median wages and salary by treatment year



Source: IDI 2024. Note: only includes wages and salary of employed female individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021.

7.5.2 Area-level DiD analysis

Table 19 presents regression results examining median earnings for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 49 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is some positive impact of UR on median earnings for women. There was no significant impact of UR on total and male median earnings (Figure 49 and Figure 50, respectively).

The SA2 ATT $\hat{\upsilon}_g$ in Table 19 (column I) show median earnings significantly increased for women by $30 and this is significant at the 10% level (column I). The heterogeneity analysis shows this is driven by NSH women in both high and low UR SA2s – overall, NSH women earned $39 more compared to women in control SA2s and this is statistically significant at the 1% level. While statistically significant, this impact is economically modest—$39 represents less than a 1% increase in pre-treatment median earnings for women.

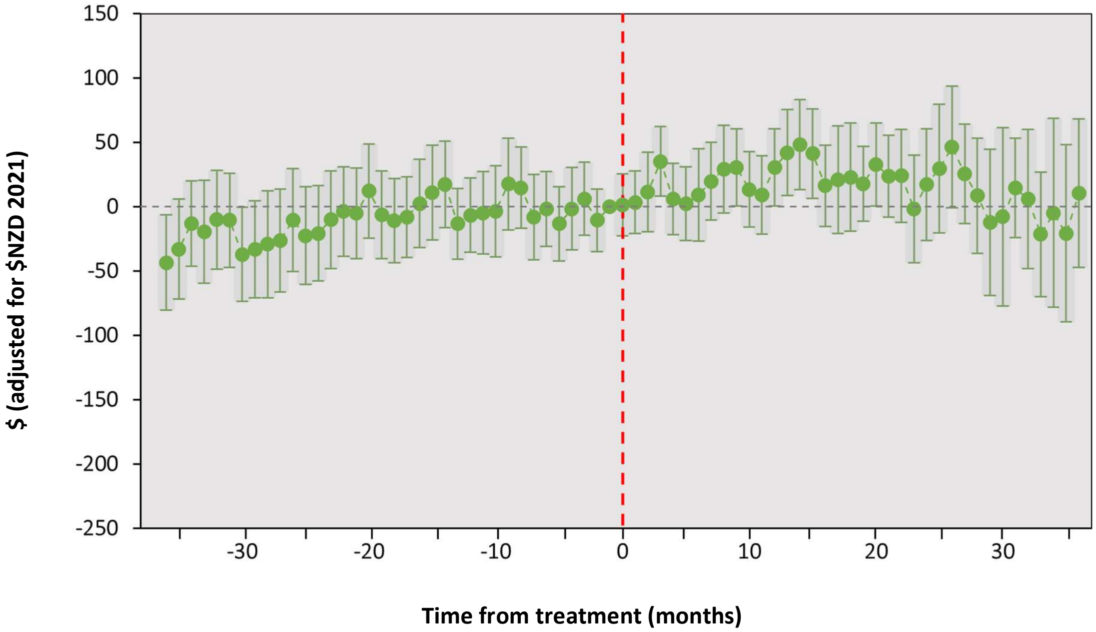
Conversely, median earnings significantly decreased by $122 for SH in high UR SA2s (column II). However, even this decrease is economically small, equating to just a 2.6% decline in pre-treatment median earnings. Overall, while there are some significant impacts of UR on median earnings for women, they are economically small in the short run.

Table 19 Impact of urban regeneration on median wages and salary

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Total median wages and salary (NZD$2021)			
All Population	17.30 [-5.95, 40.56]	-14.01 [-51.67, 23.65]	28.27** [6.90, 49.64]
Social Housing	-25.14 [-138.54, 88.26]	-122.03** [-223.84, -20.22]	8.15 [-124.42, 140.72]
Non-Social Housing	19.43 [-5.43, 44.29]	6.50 [-38.21, 51.22]	24.27* [0.26, 48.28]
SA2 – Male median wages and salary (NZD$2021)			
All Population	-11.67 [-50.34, 27.00]	-31.26 [-83.73, 21.22]	-4.70 [-41.84, 32.45]
Social Housing	-0.99 [-194.82, 192.85]	24.36 [-135.75, 184.47]	2.55 [-232.17, 237.22]
Non-Social Housing	-5.72 [-45.57, 34.13]	-14.95 [-76.00, 46.10]	-1.66 [-39.93, 36.60]
SA2 – Female median wages and salary (NZD$2021)			
All Population	29.88* [4.21, 55.57]	27.69 [-11.76, 67.14]	31.10* [4.86, 57.33]
Social Housing	-85.93 [-231.27, 59.42]	-69.40 [-141.14, 2.34]	-97.88 [-288.45, 92.68]
Non-Social Housing	39.31** [14.88, 63.74]	46.75* [7.35, 86.15]	37.35** [12.04, 62.66]
SA1 – Total median wages and salary (NZD$2021)			
All Population	4.89 [-35.69, 45.47]	-17.46 [-89.24, 54.32]	9.43 [-35.19, 54.04]
Social Housing	-29.02 [-152.81, 94.78]	-64.77 [-179.90, 50.36]	-39.34 [-183.52, 104.84]
Non-Social Housing	5.65 [-46.76, 58.06]	-1.99 [-174.49, 170.52]	7.31 [-40.17, 54.79]
SA1 – Male median wages and salary (NZD$2021)			
All Population	4.12 [-51.45, 59.69]	11.48 [-104.19, 127.15]	3.19 [-55.79, 62.18]
Social Housing	14.04 [-191.58, 219.65]	-76.15 [-306.03, 153.72]	22.35 [-218.56, 263.25]
Non-Social Housing	29.40 [-36.86, 95.66]	122.50* [0.79, 244.21]	10.34 [-60.86, 81.55]
SA1 – Female median wages and salary (NZD$2021)			
All Population	8.77 [-42.65, 60.20]	40.50 [-37.99, 118.99]	-0.08 [-57.83, 57.68]
Social Housing	26.20 [-126.67, 179.06]	71.08 [-138.85, 281.01]	9.62 [-164.45, 183.69]
Non-Social Housing	-39.06 [-108.29, 30.18]	-107.80 [-275.64, 60.06]	-22.72 [-95.86, 50.42]

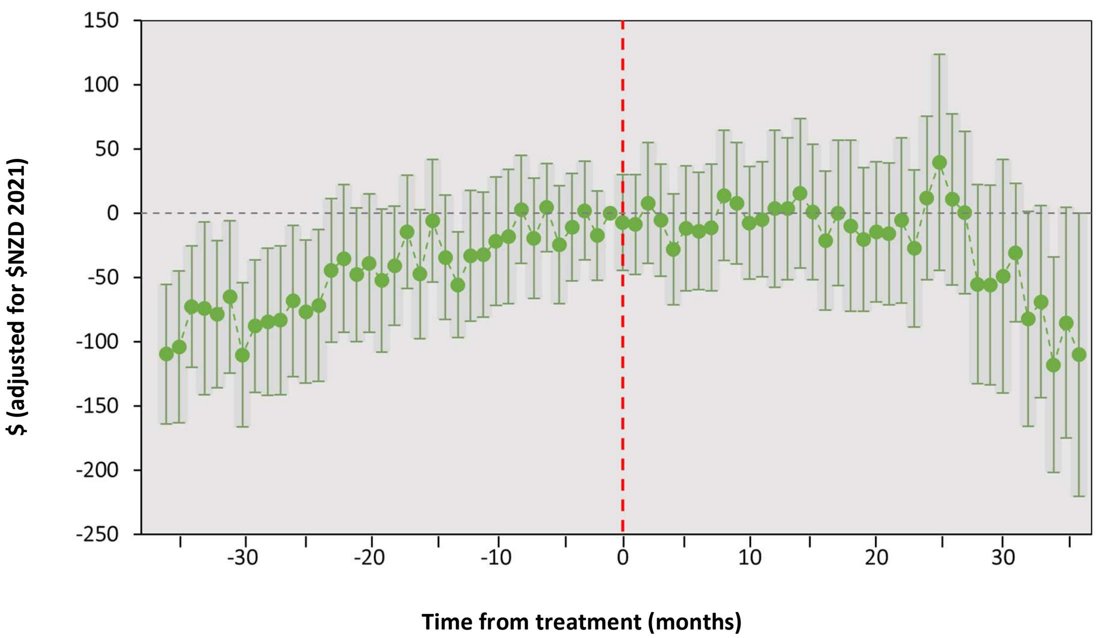
Source: IDI 2024. Note UR – urban regeneration. Only includes wages and salary of employed individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_g$ *and* $\hat{\boldsymbol{w}}_g$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 49 DiD - urban regeneration on total median wages and salary (SA2, All Population)



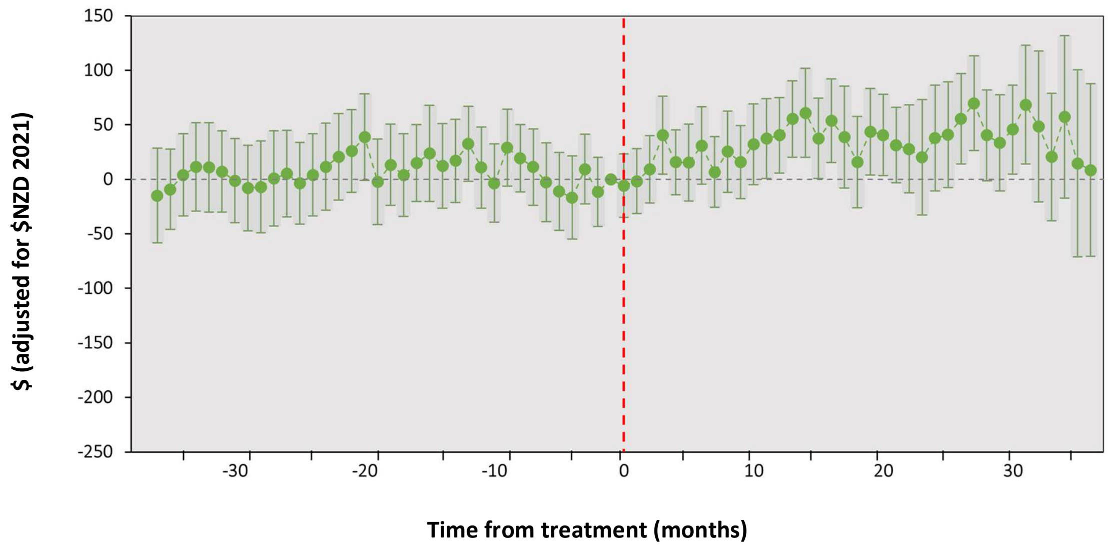
Source: IDI 2024. Note: only includes wages and salary of employed individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\widehat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 50 DiD - urban regeneration on male median wages and salary (SA2, All Population)



Source: IDI 2024. Note: only includes wages and salary of employed men aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\widehat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 51 DiD - urban regeneration on female median wages and salary (SA2, All Population)



Source: IDI 2024. Note: only includes wages and salary of employed women aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{e\ell}$, from Equation (1.1) in Section 5.5.

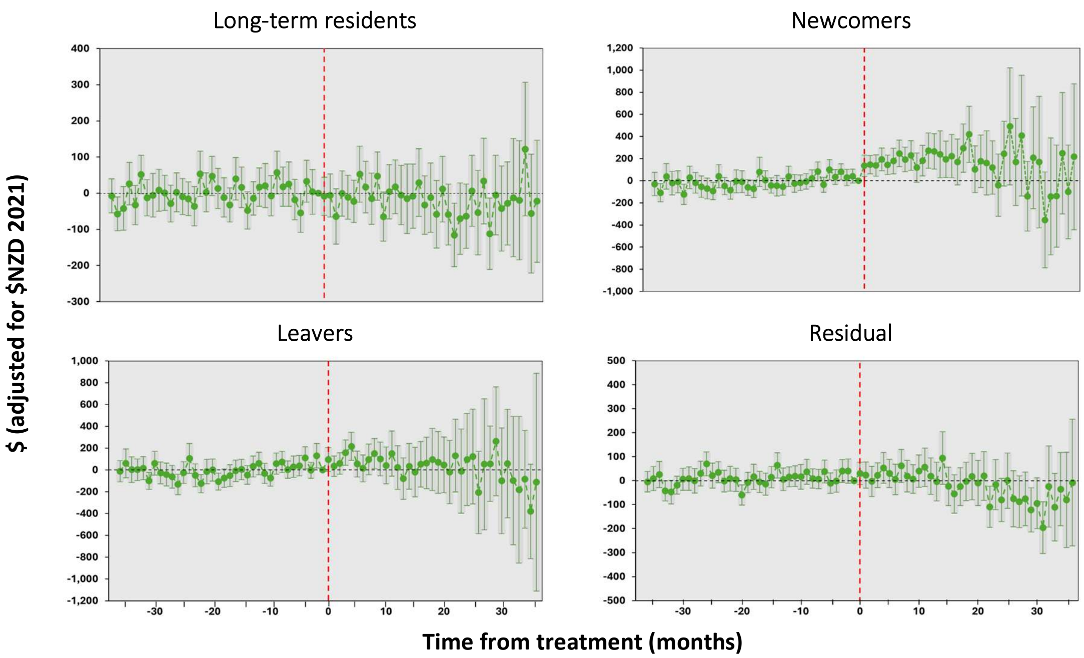
7.5.3 Individual-level analysis

Figure 52 to Figure 54 presents individual-level regressions (total, male and female earnings) comparing all treated subpopulations, and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 55 to Figure 57) and NSH (Figure 58 to Figure 60).

Figure 52 shows newcomers moving into treated SA2s had significantly higher earnings compared to the transient control population. The heterogeneity analysis shows this is primarily driven by NSH male and female newcomers (Figure 59 and Figure 60), whose earnings increased by approximately $293 and $178, respectively, compared to their transient control counterparts. This aligns with findings in Section 7.4 which showed higher employment rates among NSH newcomers in treated SA2s compared to transient control residents. These results suggest that higher earning individuals are moving into regenerated neighbourhoods and may reflect some neighbourhoods beginning to gentrify.

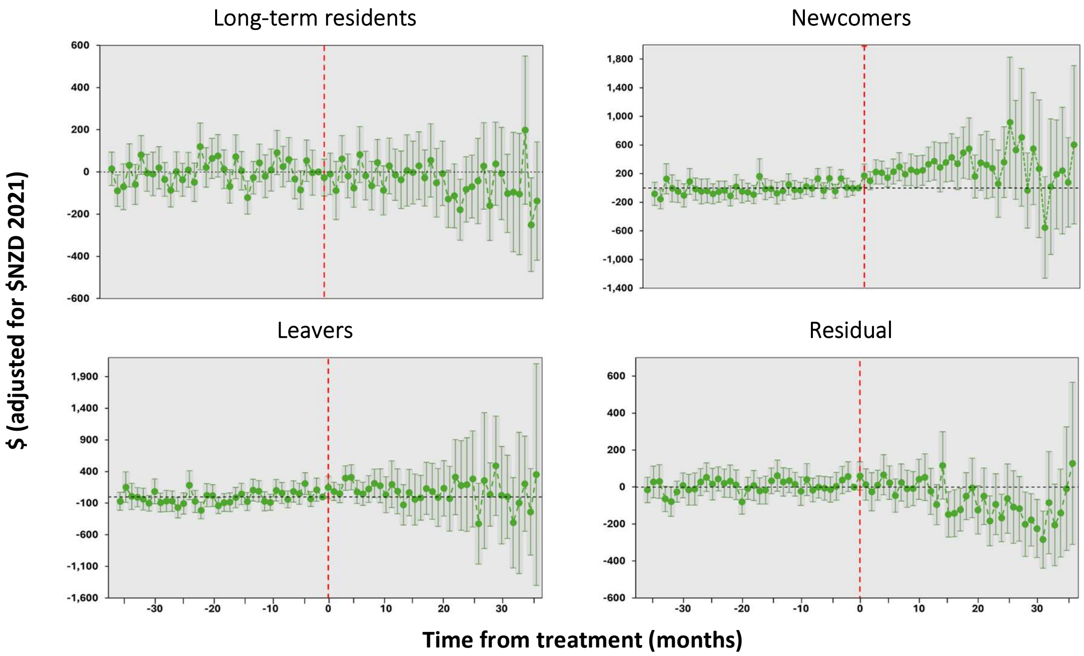
In contrast, Figure 57 shows median earnings significantly decreased over time for female SH newcomers and leavers. The magnitude of this impact is economically large – female SH newcomers and leavers earned, on average, $1,600 less than female SH transient control residents. It is difficult to determine what is driving this significant decrease given transient SH women in treated areas are matched to transient SH women in control areas, meaning characteristics such as vulnerable employment conditions should be the same across both groups. The underlying factors driving this decrease is unclear, but given its short run nature, further analysis is needed to determine whether these impacts persist in the medium to longer run.

Figure 52 DiD - urban regeneration on total wages and salary (Individual, All Population)



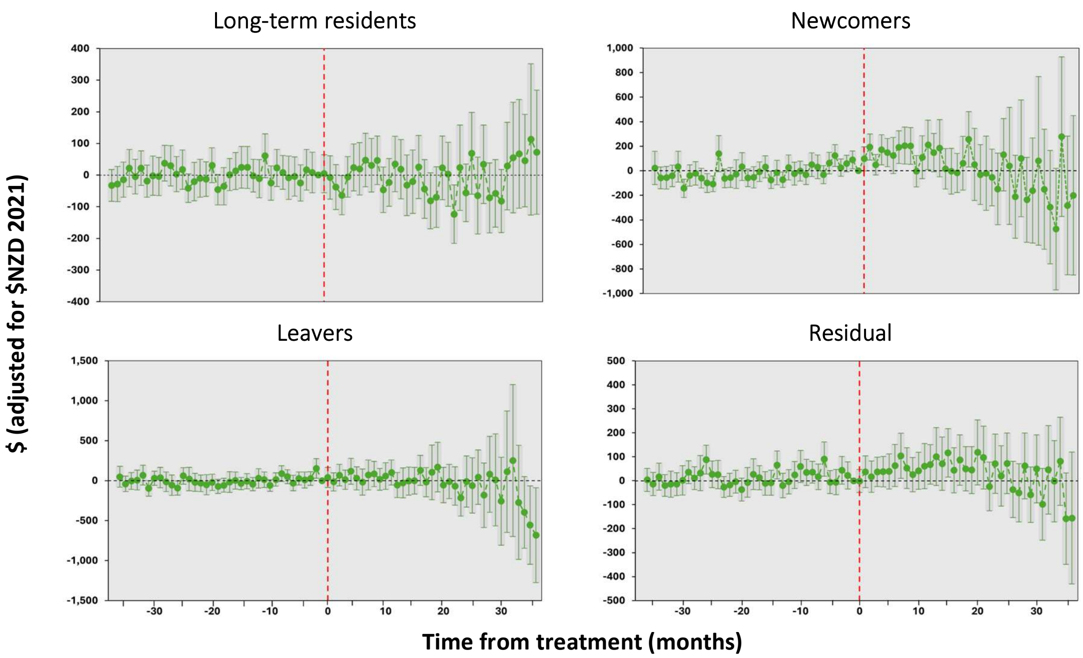
Source: IDI 2024. Note: only includes wages and salary of employed individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 53 DiD - urban regeneration on male wages and salary (Individual, All Population)



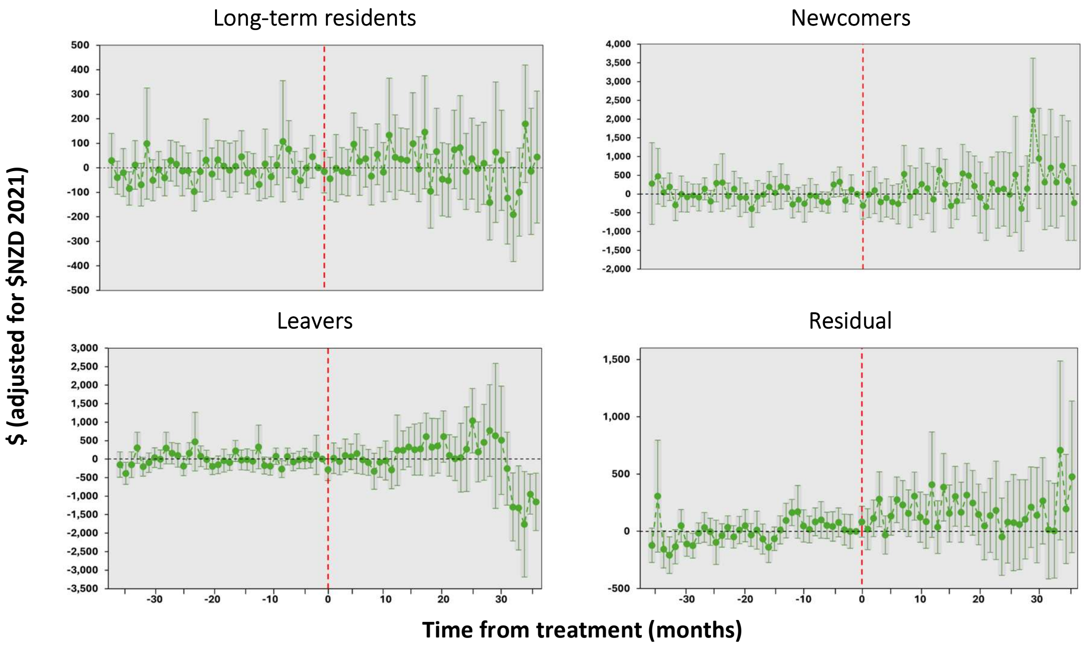
Source: IDI 2024. Note: only includes wages and salary of employed men aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 54 DiD - urban regeneration on female wages and salary (Individual, All Population)



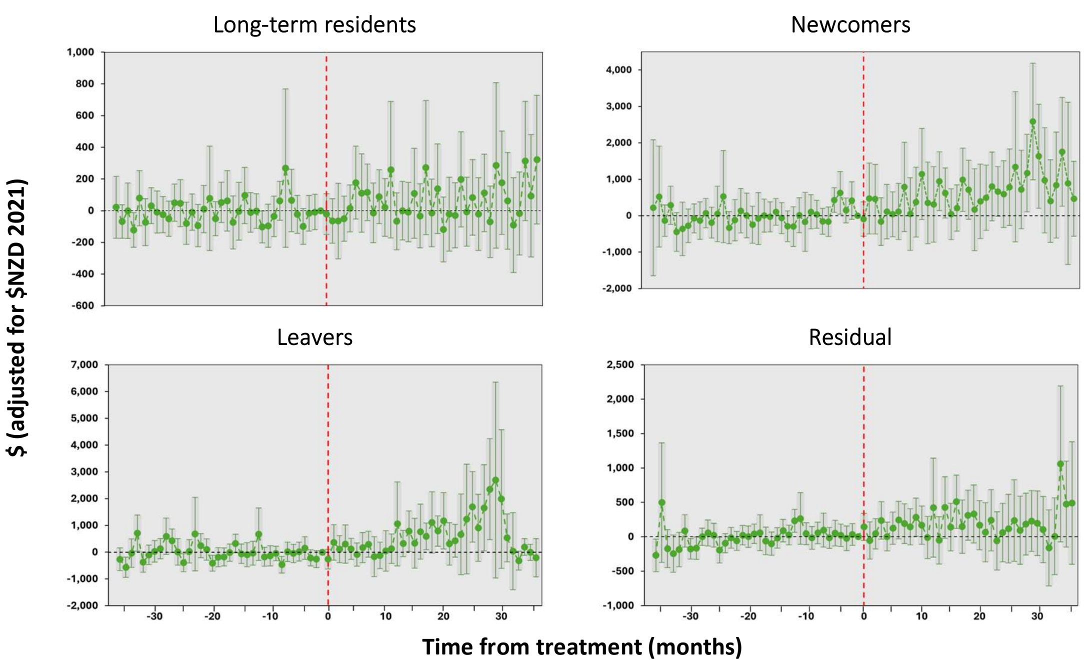
Source: IDI 2024. Note: only includes wages and salary of employed women aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 55 DiD - urban regeneration on total wages and salary (Individual, Social Housing)



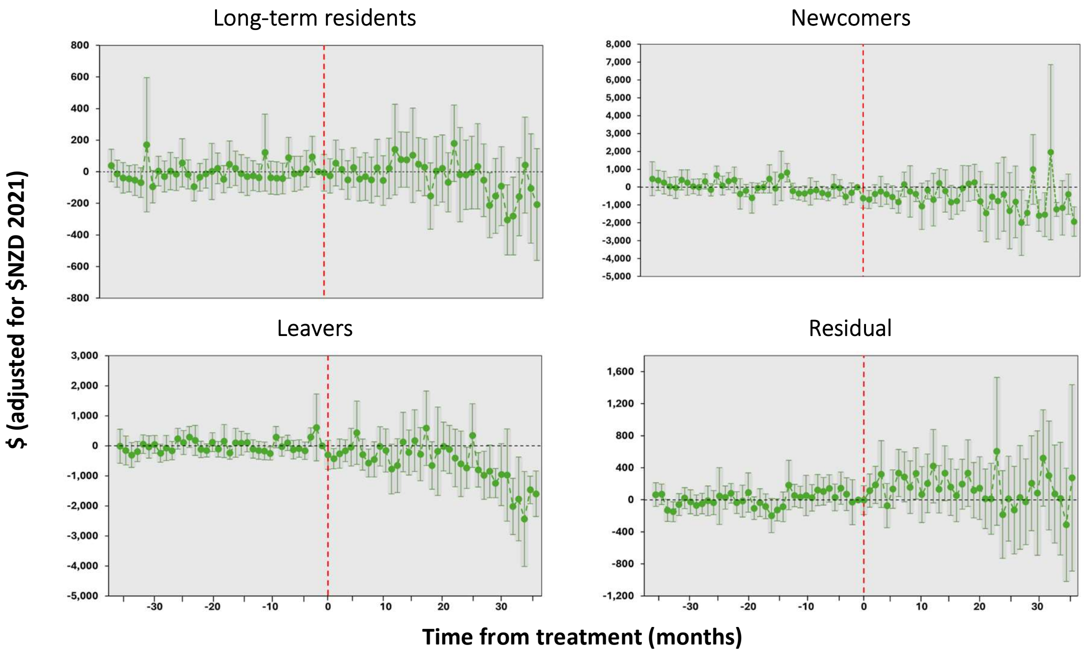
Source: IDI 2024. Note: only includes wages and salary of employed individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 56 DiD - urban regeneration on male wages and salary (Individual, Social Housing)



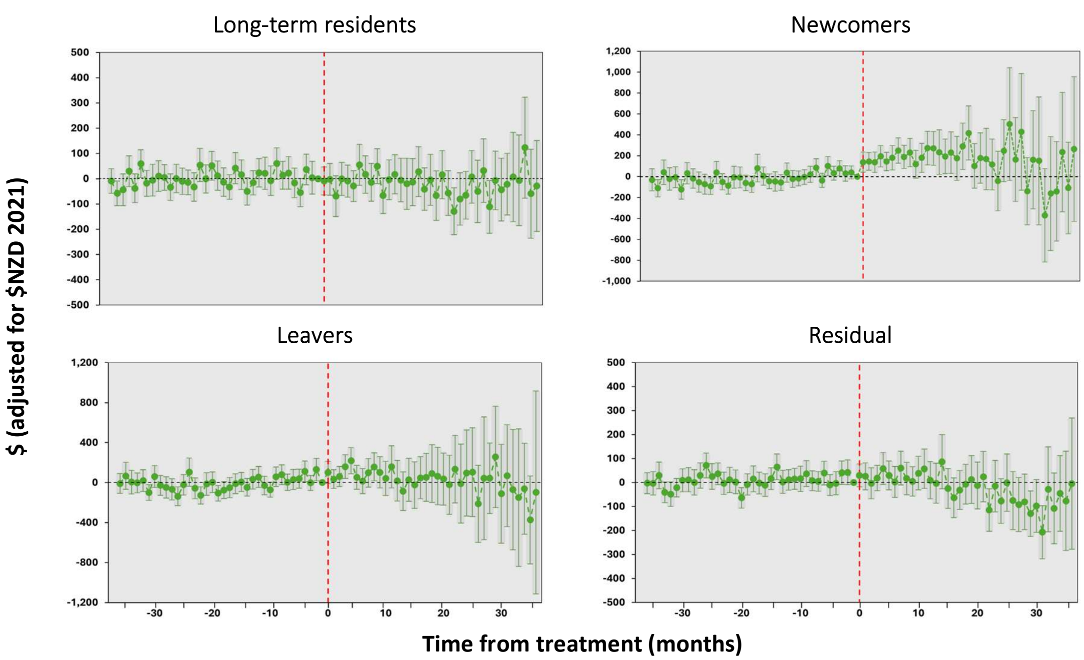
Source: IDI 2024. Note: only includes wages and salary of employed men aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 57 DiD - urban regeneration on female wages and salary (Individual, Social Housing)



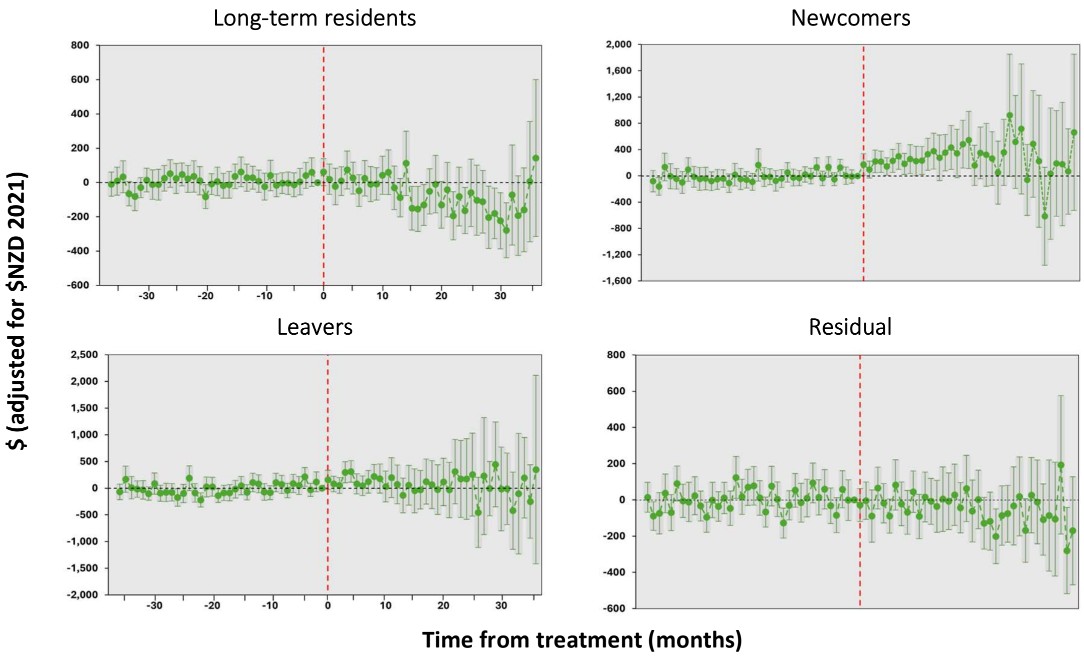
Source: IDI 2024. Note: only includes wages and salary of employed women aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 58 DiD - urban regeneration on total wages and salary (Individual, Non-Social Housing)



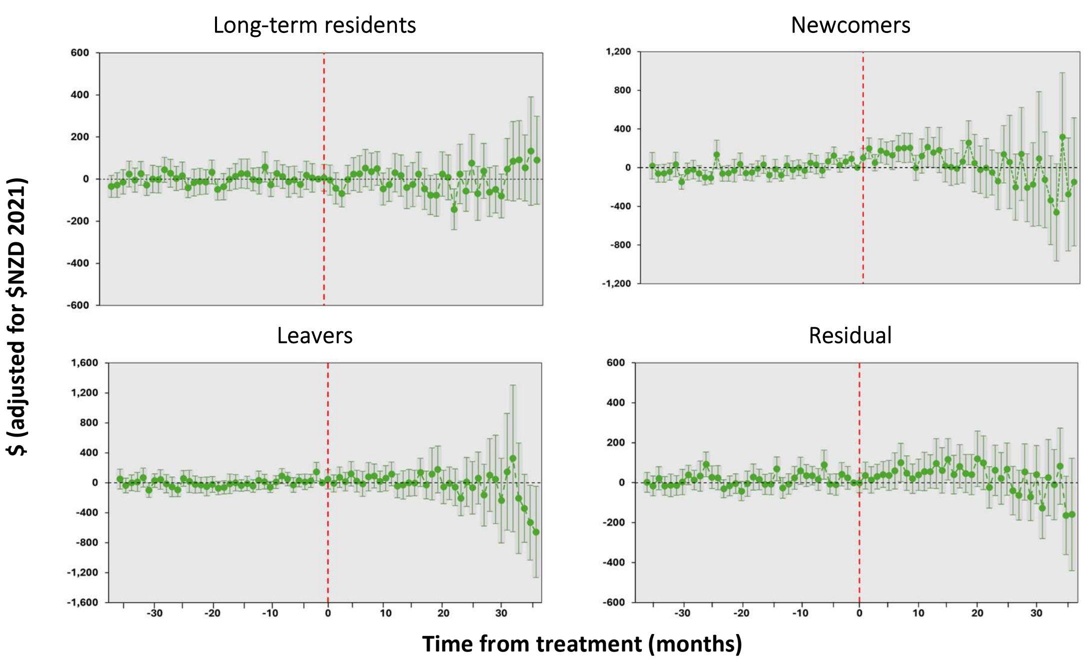
Source: IDI 2024. Note: only includes wages and salary of employed individuals aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 59 DiD - urban regeneration on male wages and salary (Individual, Non-Social Housing)



Source: IDI 2024. Note: only includes wages and salary of employed men aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 60 DiD - urban regeneration on female wages and salary (Individual, Non-Social Housing)



Source: IDI 2024. Note: only includes wages and salary of employed women aged between 25 to 64 (inclusive), adjusted for $NZD 2021. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

7.6 Benefit receipt

UR has the potential to impact benefit receipt through various mechanisms related to human capital and health improvements. All working-age benefits in New Zealand are means-tested – those who earn below a certain threshold qualify for financial assistance for reasons such as unemployment, poor health, disability or sole parental duties.

Improvements in education and employment outcomes as a result of UR may reduce benefit dependency in treated areas by increasing earnings potential (related to Section 0, 7.4 and 7.5), leading to fewer people having to rely on unemployment-related benefits. Improved physical and mental health may reduce the receipt of sickness-related benefits (related to Section 8). Mechanisms such as improved housing (better insulation and heating, reducing respiratory conditions), improved access to primary healthcare (preventing hospitalisations), and housing stability (improving mental wellbeing) can lead to better overall health outcomes and reduce the need for sickness-related benefits.

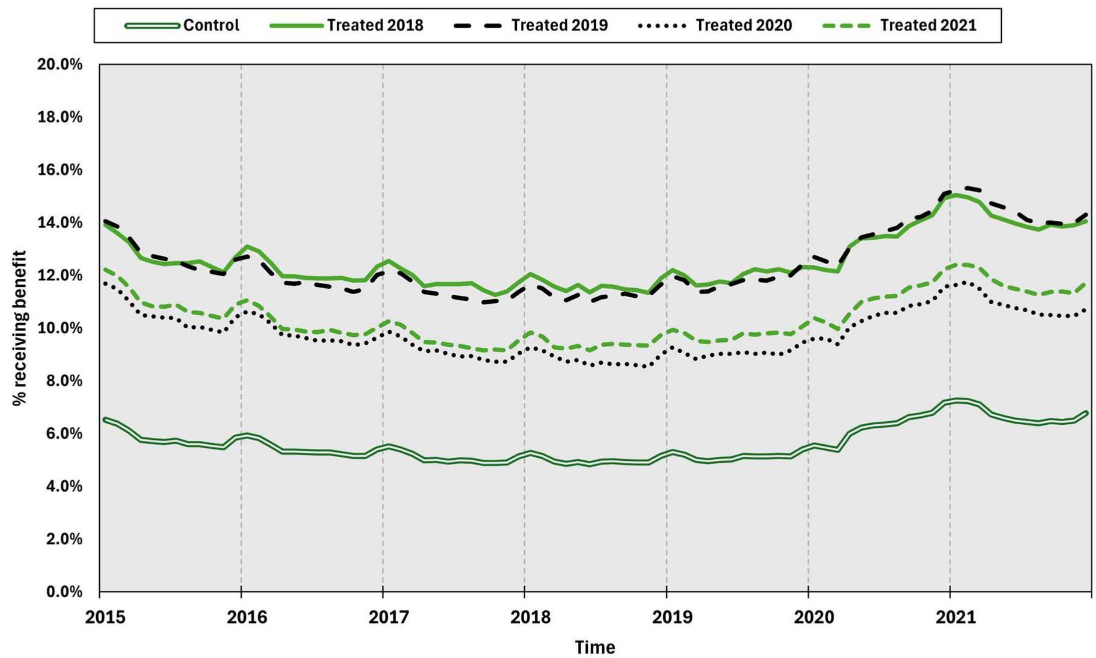
7.6.1 Descriptive trends

Figure 61 and Figure 62 presents average benefit receipt rates for any benefit and unemployment or sickness-related benefit, respectively. These are presented for treated SA2s by treatment year and control SA2s from 2015 to 2022. The population of interest are those aged 15 and above and the outcome of interest are those who receive any benefit and unemployment or sickness-related benefits.

Figure 61 shows clear differences in average benefit receipt among treated and control SA2s. SA2s treated in 2018 and 2019 have the highest rates of benefit receipt, averaging 11.6% at the end of 2017, which is more than twice the rate in control SA2s (5.1%). Later treated SA2s (treated in 2020 and 2021) have slightly lower benefit receipt, averaging 9.3%, but this is still nearly double the rate in control SA2s. Across all SA2s, benefit receipt follows a similar upward trend, peaking during the second COVID-19 lockdown in Auckland at the end of 2021.

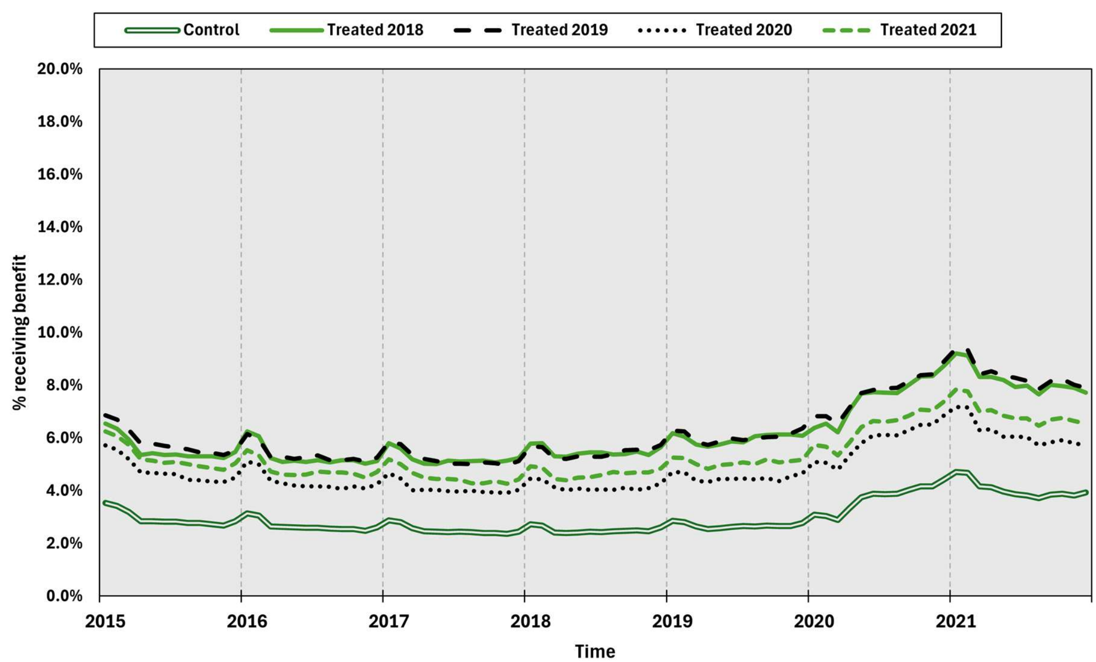
Figure 62 shows similar patterns of unemployment or sickness-related benefit receipt as observed with any benefit receipt. SA2s treated in 2018 and 2019 continue to have higher rates of benefit receipt compared to control SA2s. However, the magnitude of these difference is smaller for unemployment or sickness-related benefits compared to any benefit receipt. At the end of 2017, average unemployment or sickness-related benefit receipt in treated SA2s was between 4.2% and 5.2%, compared to 2.4% in control SA2s.

Figure 61 Average SA2 benefit receipt by treatment year



Source: IDI 2024. Note: proportion of individuals aged 15 and above receiving any benefit.

Figure 62 Average SA2 unemployment or sickness-related benefit receipt by treatment year



Source: IDI 2024. Note: proportion of individuals aged 15 and above and receiving unemployment or sickness-related benefits.

7.6.2 Area-level DiD analysis

Table 20 presents regression results examining benefit receipt rates for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 63 and Figure 64 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on the proportion of those aged 15 and over receiving benefits.

The SA2 and SA1 ATT $\hat{v}_g$ and $\hat{w}_g$ in Table 20 (column I) show there is no impact of UR on either any benefit or unemployment or sickness-related benefit receipt. This aligns with the descriptive statistics, which showed the difference in benefit receipt rates between treated and control SA2s remained mostly unchanged over time.

The SA1 heterogeneity analysis shows mixed results in benefit receipt for SH. For SH in high UR SA1s, benefit receipt decreased by 1.8 percentage points relative to control SA1s and this is significant at the 1% level (column II). This represents a 15.8% to 19.4% decrease in average pre-treatment benefit receipt. Table 20 shows this is partially driven by a significant decrease in unemployment or sickness-related benefit receipt, which decreased by 1.2 percentage points for SH in high UR SA1s.

Conversely, unemployment or sickness-related benefit receipt significantly increased for SH in low UR SA1s by 2.1 percentage points, representing a 50% increase in pre-treatment unemployment or sickness-related benefit receipt. This increase is particularly notable given that no significant differences were found for other outcomes such as youth NEET (Section 7.3), employment (Section 7.4), earnings (Section 7.5) or health (Section 8) for SH in low UR SA1. It is possible that there are negative impacts of UR on health outcomes that cannot be measured by health indicators using administrative data in Section 8.[20] Given the magnitude of this impact, future analysis will be needed to determine if these impacts persist in the longer term.

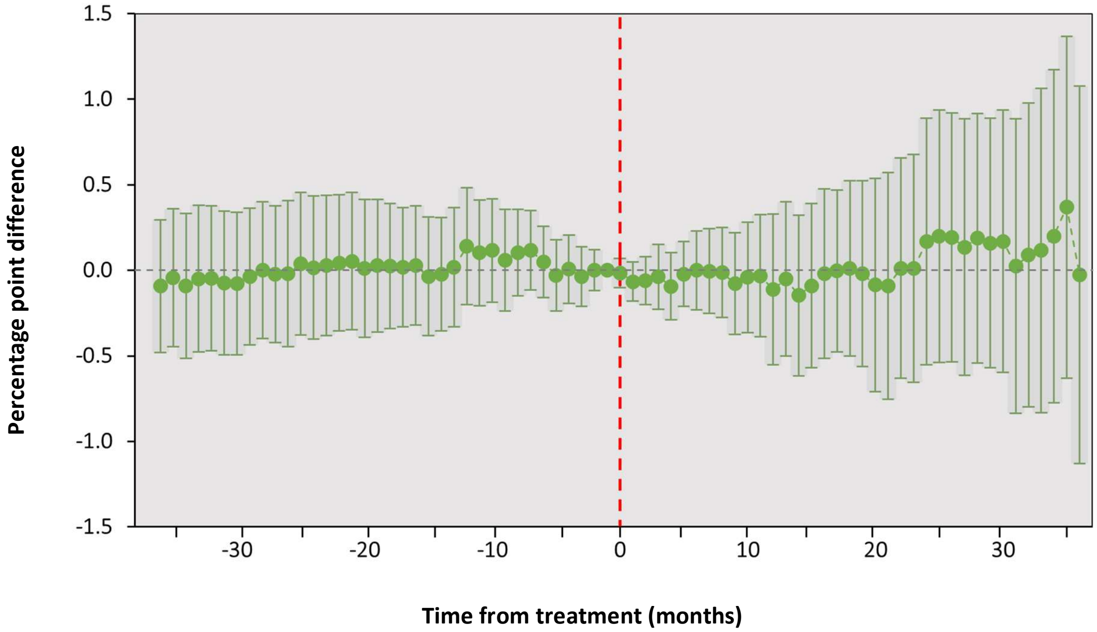
[20] Physical health outcomes are measured by hospital admissions and mental health is mostly measured by pharmaceutical data. For example, individuals with chronic illnesses may not have acute health needs that require hospital care. If these individuals manage their health with their primary care provider, these interactions are not captured in administrative data in the Integrated Data Infrastructure.

Table 20 Impact of urban regeneration on benefit receipt rates

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Benefit receipt (percentage point difference)			
All Population	0.00 [-0.39, 0.38]	0.33 [-0.11, 0.78]	-0.12 [-0.53, 0.29]
Social Housing	0.64 [-0.48, 1.76]	0.02 [-0.93, 0.96]	0.79 [-0.33, 1.90]
Non-Social Housing	-0.05 [-0.43, 0.33]	0.24 [-0.24, 0.71]	-0.15 [-0.53, 0.24]
SA1 – Benefit receipt (percentage point difference)			
All Population	0.21 [-0.13, 0.54]	0.27 [-0.34, 0.88]	0.20 [-0.16, 0.56]
Social Housing	0.47 [-0.75, 1.70]	-1.84** [-3.03, -0.66]	0.91 [-0.49, 2.31]
Non-Social Housing	0.12 [-0.24, 0.47]	0.76 [-0.08, 1.60]	-0.04 [-0.39, 0.31]
SA2 – Unemployment or sickness-related benefit receipt (percentage point difference)			
All Population	0.00 [-0.29, 0.30]	0.37* [0.04, 0.69]	-0.12 [-0.45, 0.20]
Social Housing	1.27** [0.51, 2.03]	0.13 [-0.50, 0.76]	1.51*** [0.85, 2.17]
Non-Social Housing	-0.10 [-0.40, 0.19]	0.21 [-0.13, 0.55]	-0.21 [-0.52, 0.10]
SA1 – Unemployment or sickness-related benefit receipt (percentage point difference)			
All Population	0.17 [-0.12, 0.47]	0.20 [-0.35, 0.76]	0.17 [-0.14, 0.49]
Social Housing	1.55** [0.47, 2.63]	-1.20* [-2.31, -0.08]	2.14*** [0.89, 3.38]
Non-Social Housing	-0.04 [-0.34, 0.25]	0.42 [-0.19, 1.03]	-0.16 [-0.46, 0.14]

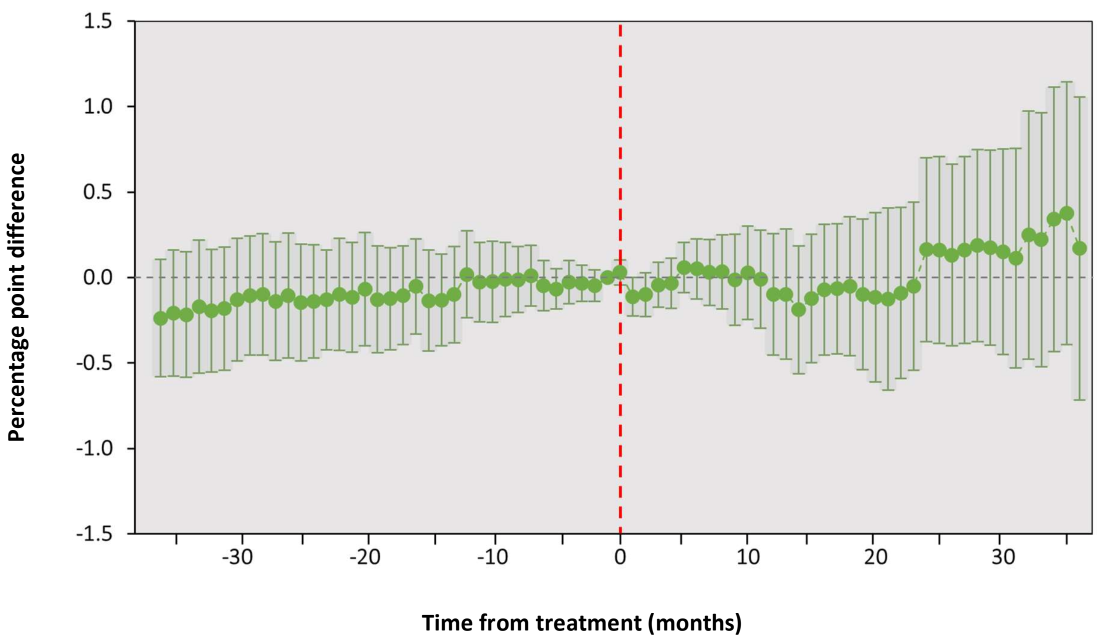
Source: IDI 2024. Note UR – urban regeneration. Proportion of individuals aged 15 and above receiving any benefit or unemployment or sickness-related benefits. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 63 DiD - urban regeneration on benefit receipt rate (SA2, All Population)



Source: IDI 2024. Note: proportion of individuals aged 15 and above receiving any benefit. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 64 DiD - urban regeneration on unemployment or sickness-related benefit receipt (SA2, All Population)



Source: IDI 2024. Note: individuals aged 15 and above receiving unemployment or sickness-related benefits. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

7.6.3 Individual-level analysis

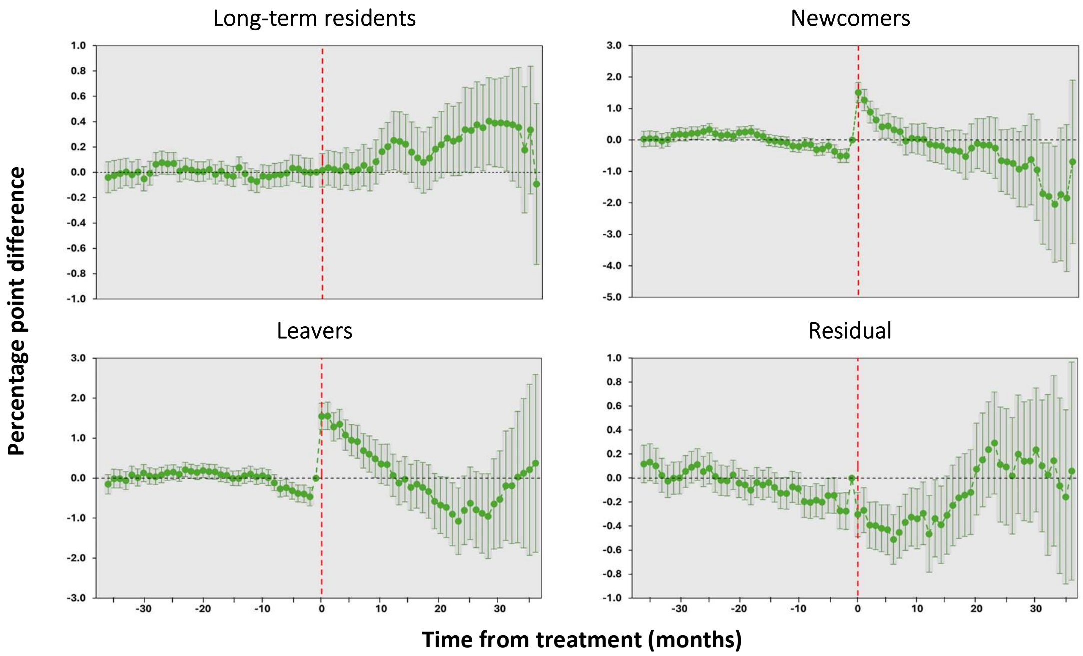
Figure 65 and Figure 68 presents individual-level benefit receipt regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 66 and Figure 69) and NSH (Figure 67 and Figure 70).

The area-level analysis showed a significant increase in unemployment and sickness-related benefit receipt for SH residents in low UR SA1s, which is consistent with higher unemployment and sickness-related benefit receipt observed among residual SH residents between $\ell = 21$ and $\ell = 28$ (relative months from treatment). Given that residual SH residents comprise a large share of SH residents in treated areas (68.7% in column V in Table 10), they largely drive the observed area-level effect. However, this increase in unemployment and sickness-related benefit receipt is short-lived, with no significant difference observed in the following periods.

In the heterogeneity analysis, both SH (Figure 69) and NSH (Figure 70) newcomers had significantly increased unemployment and sickness-related benefit receipt after moving into treated SA2s. Control SA2s may be more expensive to live in, and job losses could motivate NSH individuals to move to treated SA2s if they were more affordable. For SH newcomers, treated SA2s may have better access to healthcare amenities compared to control areas which could motivate individuals receiving sickness-related benefits to move from control areas. Their shift to newer, better-insulated homes in treated SA2s may have also contributed to improved health over time. As a result, their reliance on sickness-related benefits decreased, leading to no significant difference in unemployment and sickness-related benefit receipt compared to their control counterpart in later time periods.

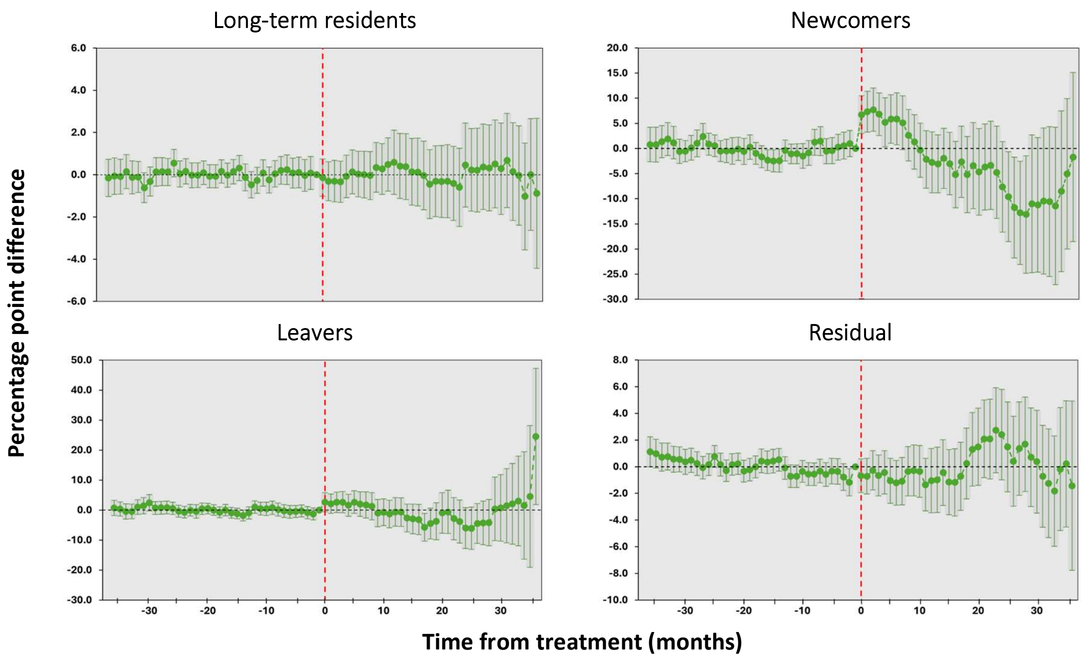
NSH leavers had significantly increased benefit receipt compared to their control counterparts (Figure 70). This may be primarily driven by health-related factors, as opposed to employment, as there was no significant impact of UR on employment for NSH leavers (as discussed in Section 7.4.3). It is possible NSH leavers in poor health may have opted to leave treated SA2s for quieter non-regenerated areas more suited to their health needs.

Figure 65 DiD - urban regeneration on benefit receipt (Individual, All Population)



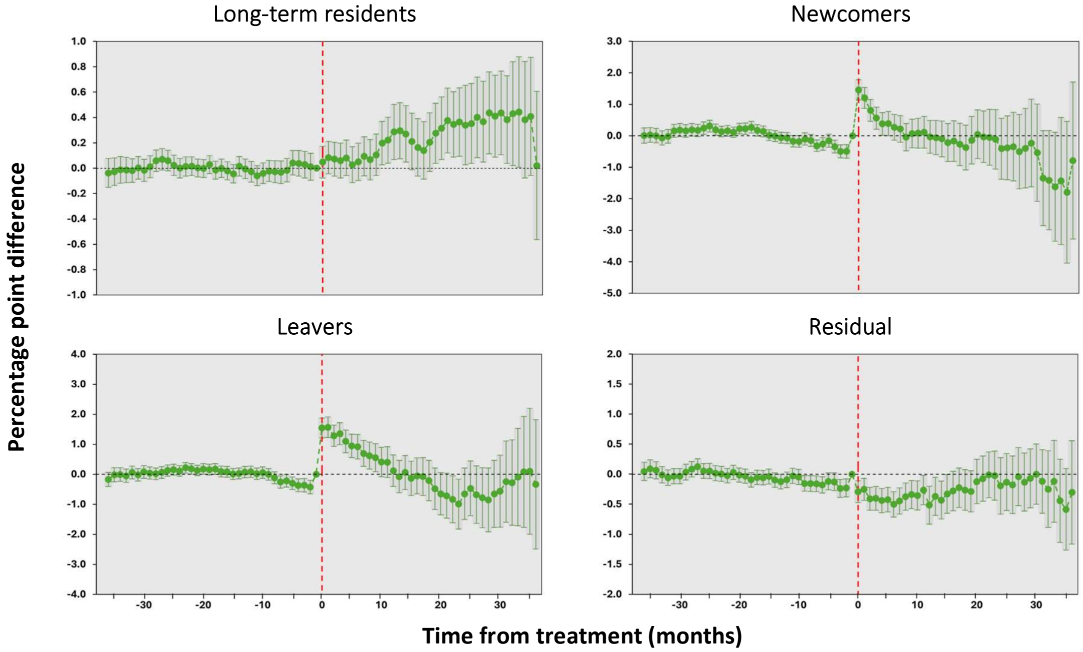
Source: IDI 2024. Note: individuals aged 15 and above receiving any benefit. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 66 DiD - urban regeneration on benefit receipt (Individual, Social Housing)



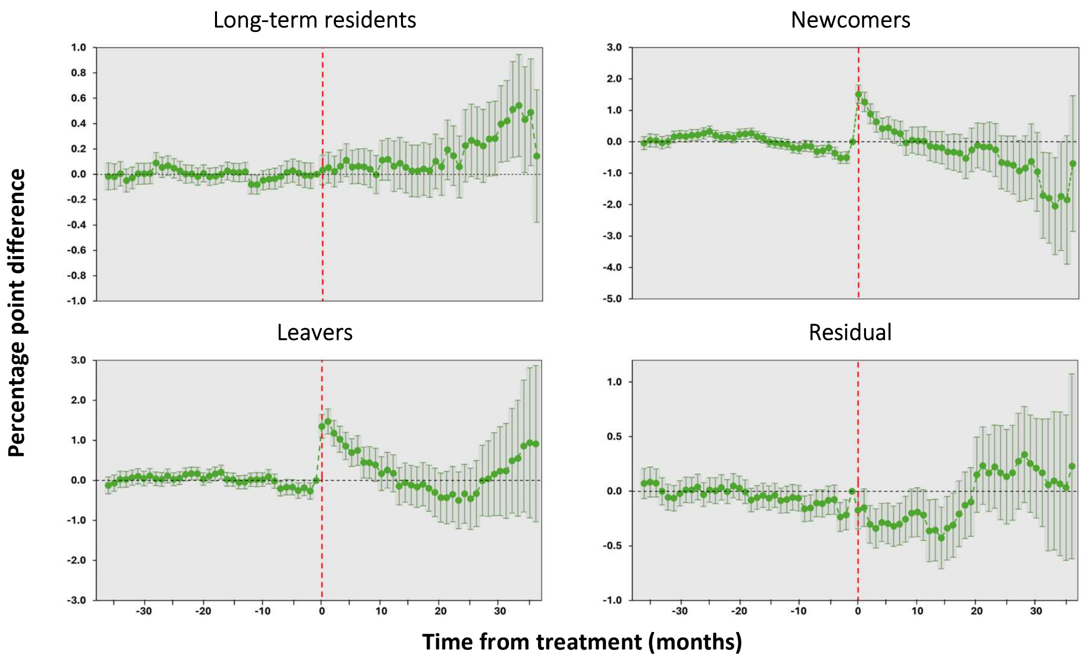
Source: IDI 2024. Note: individuals aged 15 and above receiving any benefit. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 67 DiD - urban regeneration on benefit receipt (individual-level – Non-Social Housing)



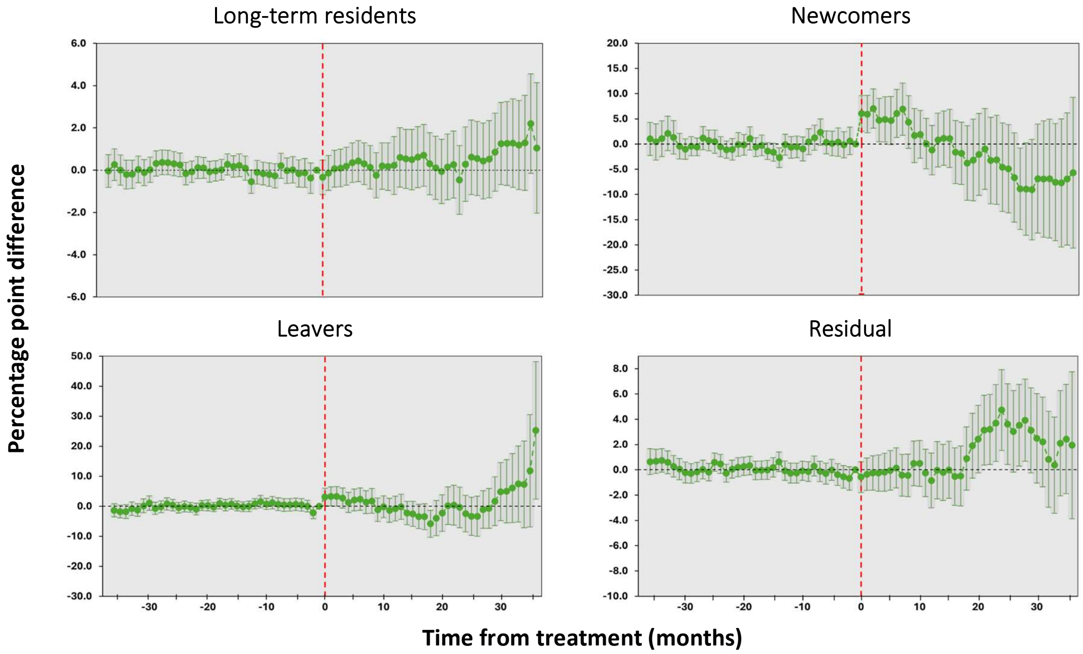
Source: IDI 2024. Note: individuals aged 15 and above receiving any benefit. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 68 DiD - urban regeneration on sickness or unemployment-related benefit receipt (Individual, All Population)



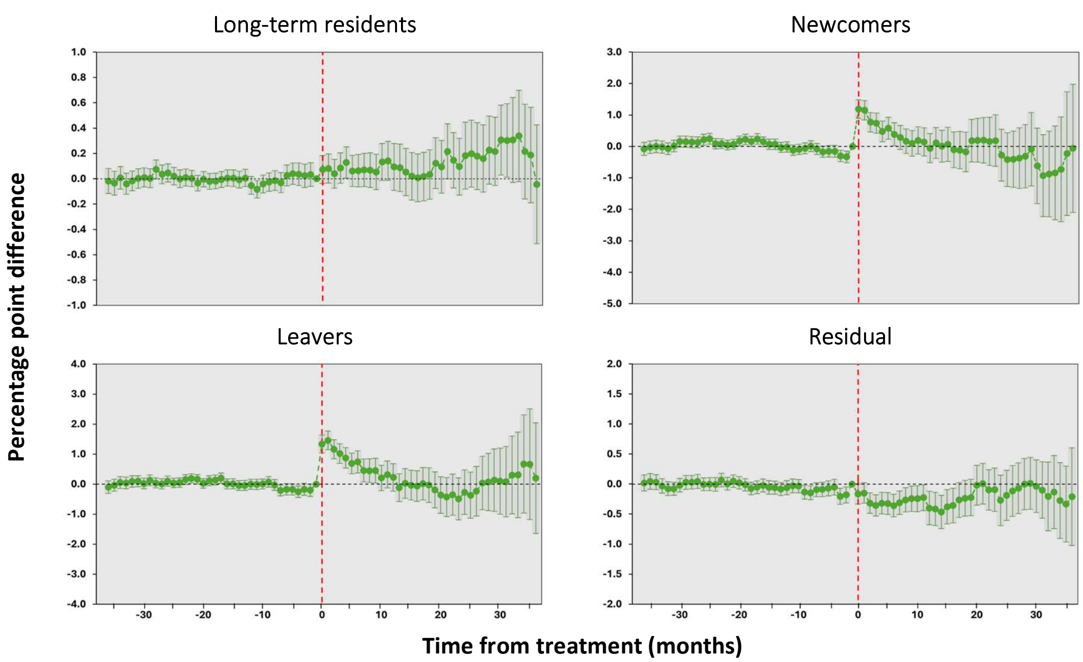
Source: IDI 2024. Note: individuals aged 15 and above receiving unemployment or sickness-related benefits. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 69 DiD - urban regeneration on sickness or unemployment-related benefit receipt (Individual, Social Housing)



Source: IDI 2024. Note: individuals aged 15 and above receiving unemployment or sickness-related benefits. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 70 DiD - urban regeneration on sickness or unemployment-related benefit receipt (Individual, Non-Social Housing)



Source: IDI 2024. Note: individuals aged 15 and above receiving unemployment or sickness-related benefits. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

8 Results: Physical and Mental Health

This section provides the descriptive trends and the regression results for short run impacts of urban regeneration (UR) on area- and individual-level physical and mental health outcomes. Given the number of variables examined, each physical and mental health outcome is discussed within its respective subsection.

Each physical and mental health outcome subsection follows the same format. First, as covered in the related literature in Section 2.3.4 the mechanisms in which urban regeneration can impact each physical and mental health outcome are discussed. Next, the descriptive portrait shows how wellbeing outcomes have changed over time without adjusting for factors that may contribute to differences in wellbeing outcomes between treated and control areas. For example, differences in wellbeing outcomes may be due to differing ethnic and age compositions, rather than a result of UR. Controlling for these factors helps to delineate the impact of UR on wellbeing outcomes.

Descriptive trends are followed by the total area-level average treatment effect on the treated (ATT) coefficients, their statistical significance and corresponding confidence intervals. At the SA2-level, the ATT Is denoted as $\hat{\upsilon}_g$ and at the SA1-level, this is denoted as $\widehat{w}_g$. The cohort average treatment effect (CATT) for SA2s is presented in graphical format and denoted as $\hat{\delta}_{e\ell}$. Analysis at the SA2- and SA1-level provides insight as to how wellbeing impacts of UR are distributed at the area-level. The area-level regression results examine how physical and mental health outcomes have changed in areas treated by UR, relative to untreated areas, after controlling for characteristics such as population, household size, ethnicity, age, gender and partnership status. At the SA2-level, results are reported by three UR intensities: all (column I), high (50 or more dwellings in column II) and low (less than 50 dwellings in column III) UR. At the SA1-level, this is all, high (25 or more dwellings) and low (less than 25 dwellings) UR. Both SA2- and SA1-level results are presented for three treated populations: overall population, social housing (SH) and non-social housing (NSH).

The individual-level heterogeneity analysis examines wellbeing impacts by subpopulations as described in Table 6 to understand how impacts are distributed at the individual-level. Individual-level results are presented as graphs showing the individual-level time treatment effects for each subpopulation. Treated long-term residents are compared to control long-term residents, treated newcomers and leavers are compared to transient control residents and treated residuals are compared to control residuals. The individual-level results are also presented separately for SH and NSH. As noted in Section 5.6, individual-level ATTs could not be computed due to computational issues. As such, only the individual-level CATT, denoted as $\hat{\varphi}_{e\ell}$, is reported in graphical format in the results.

As noted previously in this thesis, the measurement and impact of UR is likely to be underestimated due to the exclusion of pre-treated SA2s, ongoing treatment and the current period of analysis allowing only for short run impacts to be measured. Therefore, the following results are short run physical and mental health impacts of UR. As most Kāinga Ora-led UR is SH development, the results relate mainly to the impact of SH development.

8.1 Emergency department admissions

Primary care data was not available for this research as it is not stored within the Integrated Data Infrastructure – therefore, emergency department (ED) admissions serve as a proxy for the availability and use of local primary care facilities (see Dasgupta and Pacheco (2019)). People who frequently visit their primary care providers are more likely to address health concerns early before they are acute enough to require emergency care. ED admissions are also closely linked to accidents and injuries as described in Section 9, as individuals may present to ED because of their accident or injury.

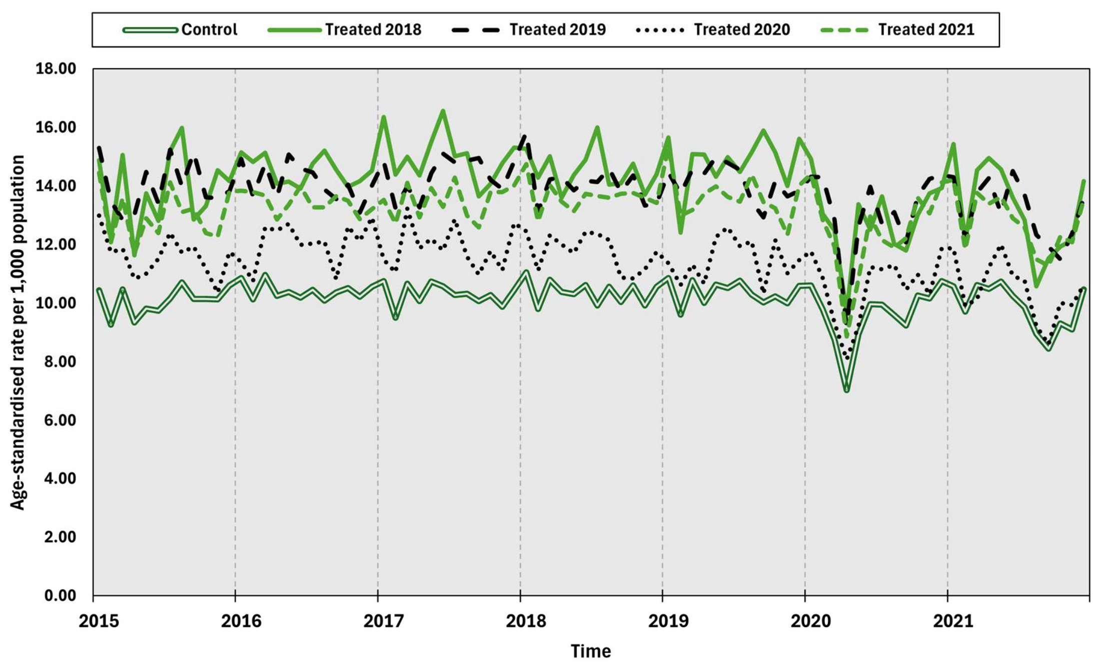
Housing intensification and population growth resulting from UR can increase demand for primary healthcare services in regenerated areas. This growing demand may stimulate an increase in the supply of primary care services or encourage competition among existing providers, leading to more affordable and accessible healthcare. Lower costs and shorter wait times could motivate individuals to seek care from their primary provider more frequently, potentially reducing the need for ED visits. Conversely, if primary healthcare services fail to keep pace with the expanding population, it could result in service shortages. This would drive more individuals to rely on EDs for healthcare, increasing the burden on emergency services.

8.1.1 Descriptive trends

Figure 71 presents average emergency department admissions age-standardised rate per 1,000 population ("ED admissions") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Age-standardised rates are calculated based on ED admissions for those aged 15 and above.

While there is some variation in the average ED admissions trend, admissions appear mostly unchanged for treated SA2s before 2018. At the end of 2017, treated SA2s had an average of 14.2 admissions, while control SA2s had a lower rate of 10.4 admissions. There is notable decrease in ED admissions across all SA2s in early 2022 due to COVID-19 restrictions. New Zealand had low COVID-related admissions during the pandemic (Public Health Agency, 2022). However, public health restrictions meant non-essential workers stayed home, and public movement was limited, reducing incidents like workplace and road accidents that typically require ED visits (Section 9.6 and 9.8, respectively). ED admissions do recover, though at a slightly lower rate compared to pre-pandemic levels. By the end of 2021, the difference between treated and control SA2s appears to have narrowed, with SA2s areas averaging 13.0 ED admissions and control SA2s at 10.5 admissions.

Figure 71 Average SA2 ED admissions by treatment year



Source: IDI 2024. Note: age-standardised rate includes only individuals aged 15 and above.

8.1.2 Area-level DiD analysis

Table 21 presents regression results examining ED admissions for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 72 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on ED admissions. While the descriptive trends in Figure 71 showed the difference in ED admissions between treated and control SA2s was beginning to close over time, Table 22 shows this difference is not statistically significant ($\hat{v}_g$ and $\hat{w}_g$ in column I).

The heterogeneity analysis shows ED admissions significantly decreased for SH and NSH in treated SA2s by 3.2 and 0.9 admissions, respectively, relative to control SA2s and this is statistically significant at the 5% level (column II in Table 21). These reductions, representing a 22.5% and 6.3% decrease from pre-treatment levels, suggest that improved access to or quality of primary healthcare services in high UR SA2s could be contributing to better health outcomes.

However, the SA1 level results diverge from the SA2 level. For SH residents in high UR SA1s, ED admissions significantly increased by 5.8 admissions – a 40.8% rise from pre-treatment averages – and is significant at the 1% level. This suggests that in the short run, primary care infrastructure may have not kept pace with population growth, leading to more frequent ED visits.

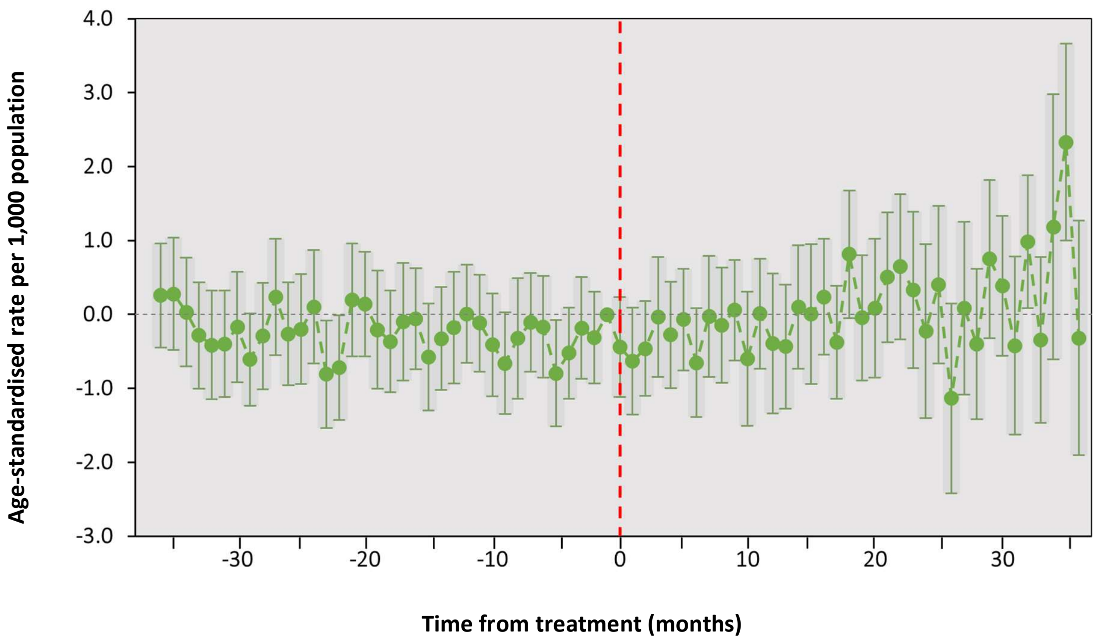
In the medium to long term, UR may help reduce ED admissions by improving primary healthcare accessibility and quality. However, it can have negative short run impacts on ED admissions if the existing primary care infrastructure does not keep up with population growth. This can create shortages in primary care and push people to have to present to ED instead which may appear to be the case as shown in Table 21.

Table 21 Impact of urban regeneration on ED admissions

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Emergency department admissions (age-standardised rate per 1,000 population)			
All Population	-0.072 [-0.673, 0.529]	-0.480 [-1.477, 0.517]	0.078 [-0.503, 0.658]
Social Housing	-3.303 [-9.054, 2.448]	-3.181* [-6.112, -0.251]	-3.345 [-11.021, 4.330]
Non-Social Housing	-0.100 [-0.722, 0.522]	-0.923* [-1.746, -0.100]	0.196 [-0.376, 0.769]
SA1 – Emergency department admissions (age-standardised rate per 1,000 population)			
All Population	0.488 [-0.770, 1.756]	2.062 [-0.670, 4.794]	0.095 [-1.222, 1.413]
Social Housing	2.240 [-0.541, 5.022]	5.779** [2.014, 9.545]	1.509 [-1.761, 4.778]
Non-Social Housing	0.166 [-1.344, 1.676]	0.316 [-4.345, 4.978]	0.109 [-1.282, 1.499]

Source: IDI 2024. Note UR – urban regeneration. Age-standardised rate includes only individuals aged 15 and above. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 72 DiD - urban regeneration on ED admissions (SA2, All Population)



Source: IDI 2024. Note: age-standardised rate includes only individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

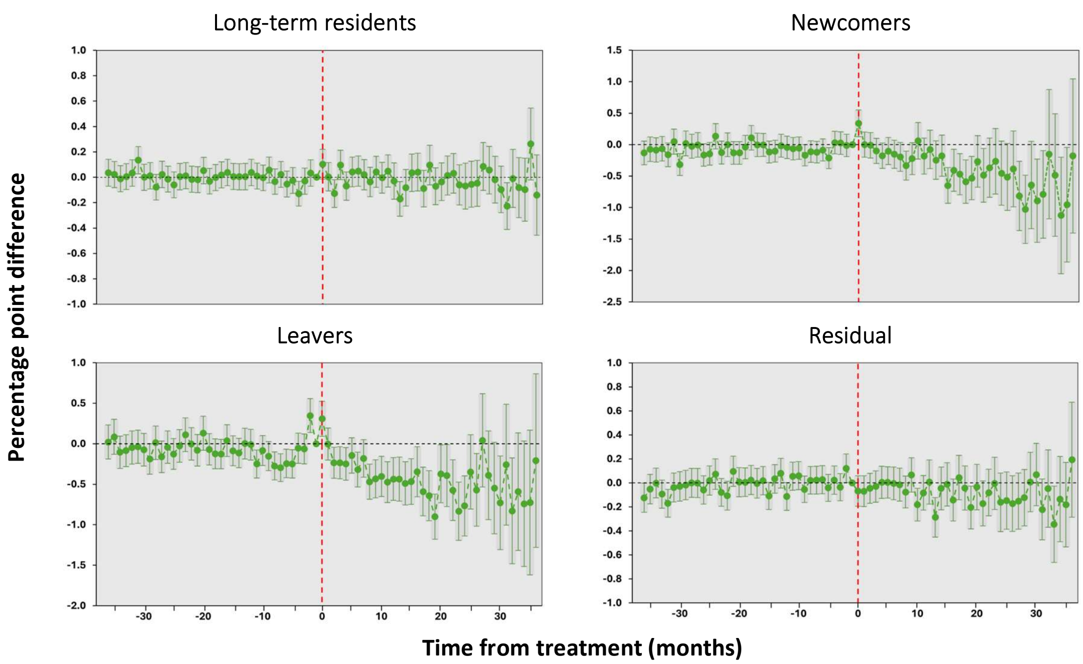
8.1.3 Individual-level DiD analysis

Figure 73 presents individual-level ED admission regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 74) and NSH (Figure 75).

While the area-level showed ED admissions significantly decreased (increased) for SH in high UR SA2s (SA1s), the individual-level analysis shows there is economically small or no significant impact of UR on ED admissions. This may be because high UR areas comprise only 20% of treated areas, and therefore their small sample size is unlikely to influence overall ED admissions.

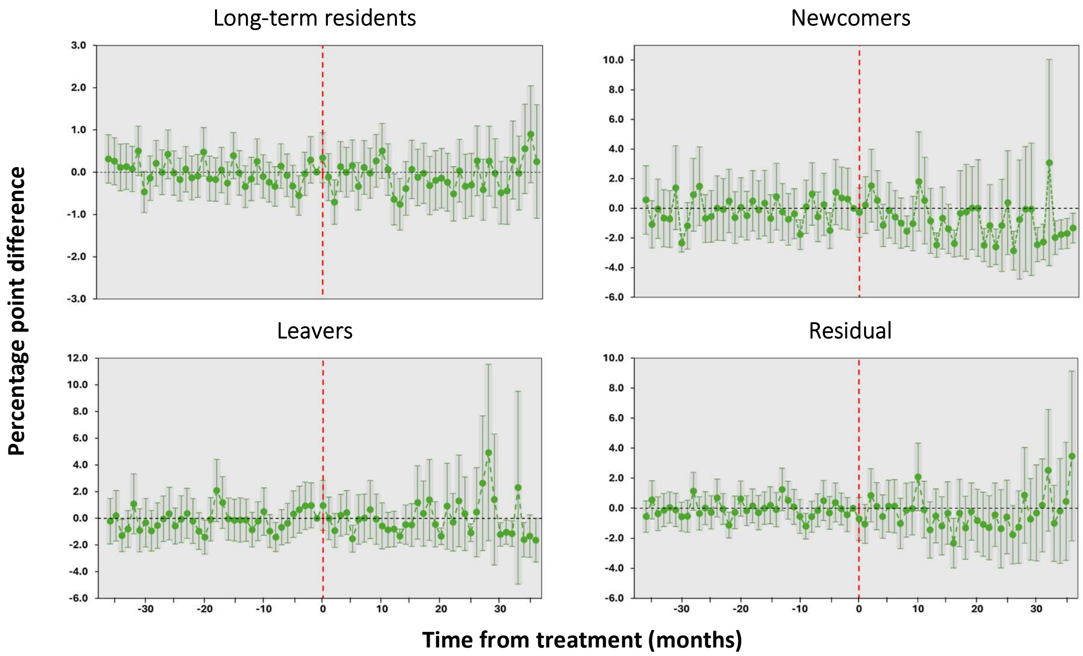
The heterogeneity analysis shows ED admissions significantly decreased for both newcomers and leavers. However, the magnitude of impact is economically small and represents only a reduction of 0.1 to 0.3 ED admissions.

Figure 73 DiD - urban regeneration on ED admissions (Individual, All Population)



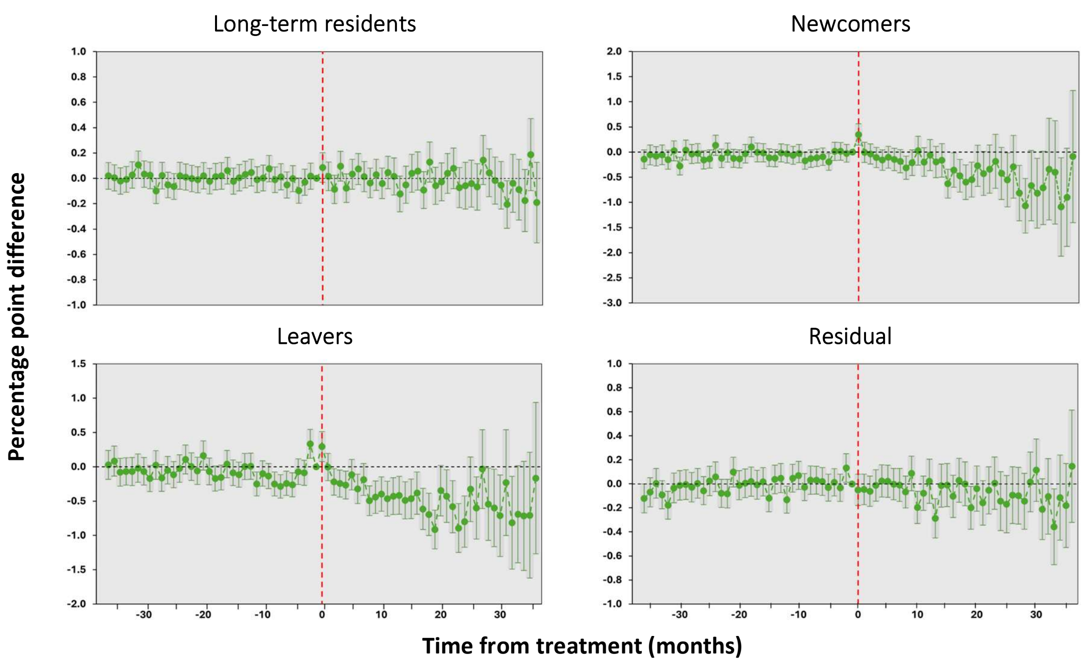
Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 74 DiD - urban regeneration on ED admissions (Individual, Social Housing)



Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 75 DiD - urban regeneration on ED admissions (Individual, Non-Social Housing)



Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

8.2 Cardiovascular disease-related hospitalisations

The association between UR and improved cardiovascular health is discussed frequently in the literature. UR can improve cardiovascular health by promoting physical activity through the development of walkable neighbourhoods, cycling infrastructure, and access to public transport (Badland et al., 2017; Bull et al., 2015; Giles-Corti et al., 2012). Designing neighbourhoods to be within walking distance of local amenities, schools, and transport hubs, along with increasing the number of green spaces, parks and walking and cycling paths, encourages residents to walk more and rely less on cars.

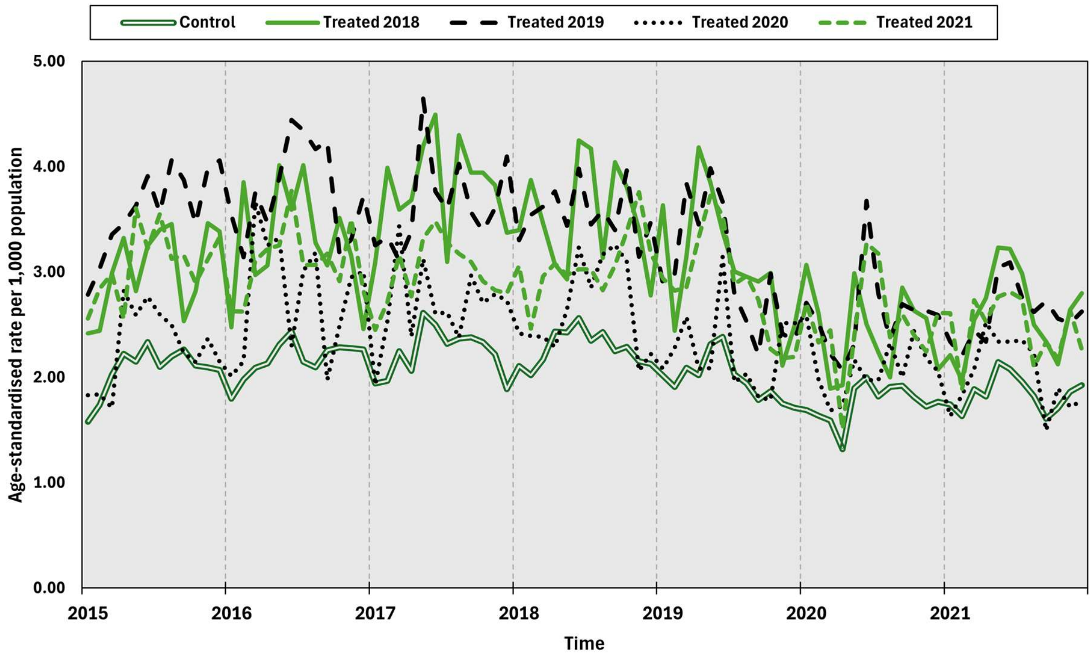
However, in the short run, UR can have adverse impacts on cardiovascular health due to the disruptions caused by ongoing construction. Large-scale development projects can take several years to complete, leading to stress and uncertainty for residents (Henry et al., 2019), and may also reduce the walkability of neighbourhoods due to ongoing road closures and construction sites.

8.2.1 Descriptive trends

Figure 76 presents average cardiovascular disease-related admissions age-standardised rate per 1,000 population ("CVD admissions") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Age-standardised rates are calculated based on CVD admissions for those aged 30 and above.

Differences in CVD admissions between treated and control SA2s fluctuate over time. Between 2015 to 2018, treated SA2s generally have higher CVD admissions (3.3 admissions) compared to control SA2s (1.9 admissions). CVD admissions for both treated and control SA2s begin to decline between mid-2019 and early 2020. This decrease may partially be attributable to COVID-19 public health restrictions that limited access to non-essential services. Following the pandemic, average CVD admissions recover to mid-2019 averages, and the difference in average CVD admissions between treated and control SA2s begins to narrow. By the end of 2021, average CVD admissions were 2.4 for treated SA2s and 1.9 for control SA2s.

Figure 76 Average SA2 CVD admissions by treatment year



Source: IDI 2024. Note: age-standardised rate includes only individuals aged 30 and above.

8.2.2 Area-level DiD analysis

Table 22 presents regression results examining CVD admissions for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 77 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on CVD admissions. While it appeared that differences in CVD admissions between treated and control SA2s was closing (Figure 76), the SA2 and SA1 ATT $\hat{\upsilon}_g$ and $\widehat{w}_g$ in Table 22 (column I) show this difference is not statistically significant.

The heterogeneity analysis shows CVD admissions significantly decreased by 2.2 admissions for SH in high UR SA2s, relative to control SA2s, and this is significant at the 5% level. The impact of this is economically large - a 2.2 decrease in CVD admissions represents a 67.7% decrease in average pre-treatment CVD admissions. Consistent with the SA2 result, the SA1 coefficient for high UR SA1 is also negative but the point estimate is not significant at the 5% level.

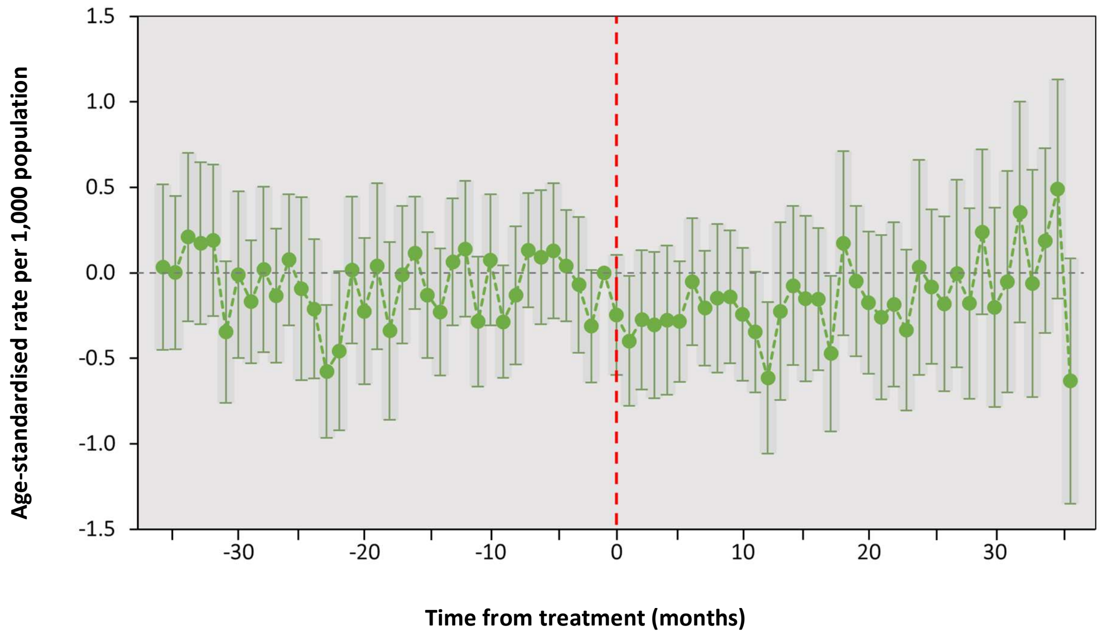
As noted earlier in this section, the literature highlights a positive association between UR and cardiovascular health, emphasising the design of walkable neighbourhoods, active transport options, and green spaces that encourage physical activity. Increased exercise and improved physical health can lead to better cardiovascular health, thereby reducing the likelihood of residents requiring CVD admissions. Section 8.1 also noted significantly lower ED admissions for SH residents in high UR SA2s, indicating an overall positive impact of UR on physical health for SH residents.

Table 22 Impact of urban regeneration on CVD admissions

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Cardiovascular disease-related (CVD) admissions (age-standardised rate per 1,000 population)			
All Population	0.188 [-0.466, 0.091]	-0.296 [-0.643, 0.052]	-0.153 [-0.434, 0.129]
Social Housing	-1.117 [-2.344, 0.019]	-2.213* [-3.943, -0.484]	-0.621 [-2.160, 0.918]
Non-Social Housing	-0.182 [-0.466, 0.102]	-0.435 [-0.960, 0.089]	-0.096 [-0.362, 0.171]
SA1 – Cardiovascular disease-related (CVD) admissions (age-standardised rate per 1,000 population)			
All Population	0.218 [-0.524, 0.960]	0.218 [-1.317, 1.752]	0.211 [-0.587, 1.009]
Social Housing	0.550 [-0.690, 1.790]	-1.239 [-3.543, 1.064]	0.903 [-0.286, 2.093]
Non-Social Housing	0.101 [-0.768, 0.970]	0.676 [-1.750, 3.102]	-0.019 [-0.875, 0.838]

Source: IDI 2024. UR – urban regeneration. Age-standardised rate includes only individuals aged 30 and above. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 77 DiD - urban regeneration on CVD admissions (SA2, All Population)



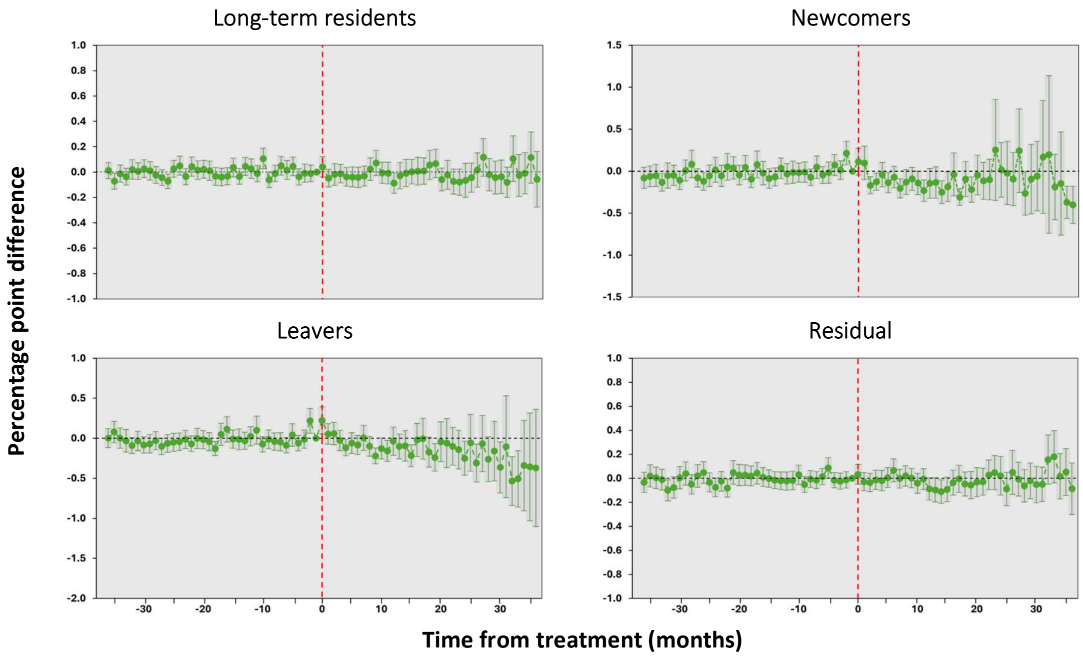
Source: IDI 2024. Note: age-standardised rate includes only individuals aged 30 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

8.2.3 Individual-level DiD analysis

Figure 78 presents individual-level CVD-related admission regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 79) and NSH (Figure 80).

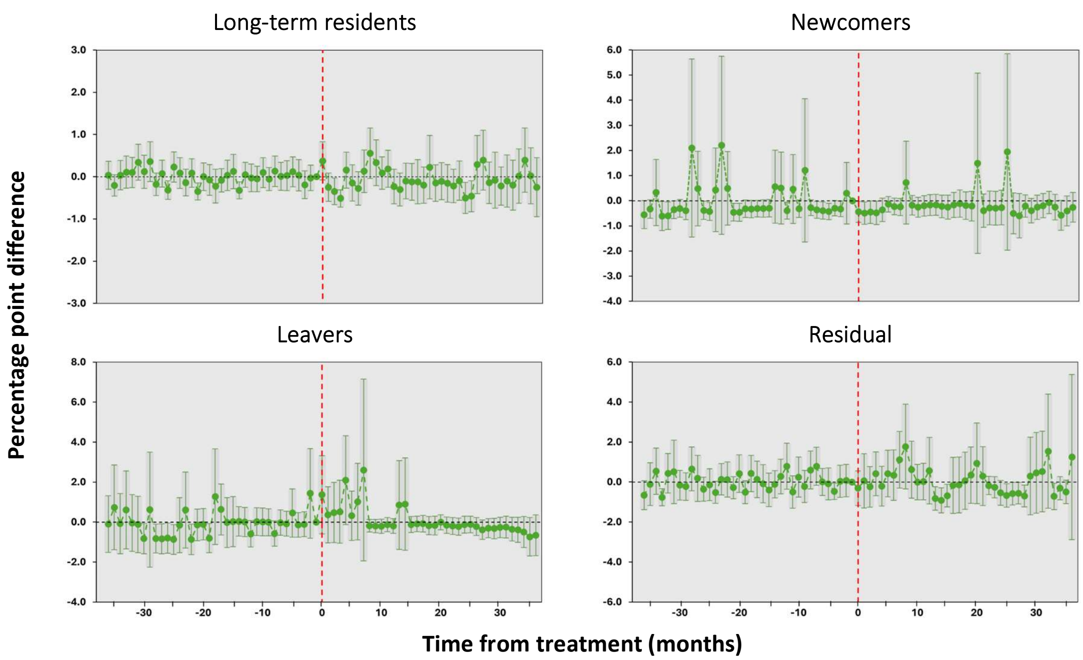
The area-level results showed no impact of UR on CVD admissions, except for SH in high UR SA2s. This finding aligns with the individual-level results, which show only economically small impacts of UR on CVD admissions. Where significant, CVD admissions were only significantly lower for treated residents by half a percentage point. While UR initiatives have potential positive impacts on cardiovascular health, the short run analysis indicate that there is generally no significant impact of UR on CVD admissions by different subpopulations.

Figure 78 DiD - urban regeneration on CVD admissions (Individual, All Population)



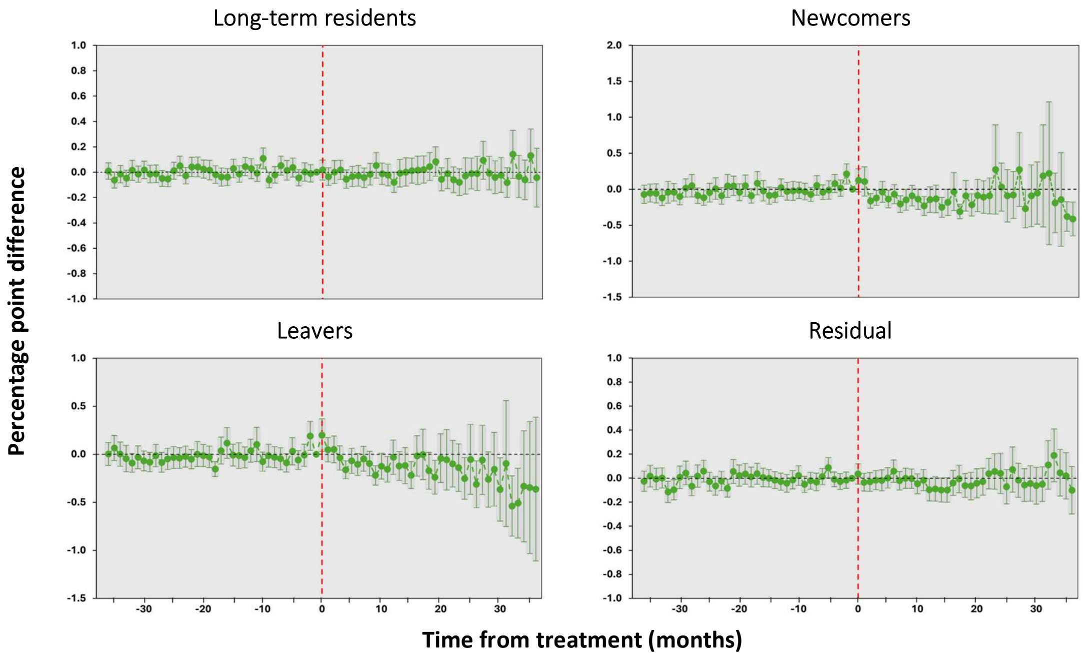
Source: IDI 2024. Note: individuals aged 30 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 79 DiD - urban regeneration on CVD admissions (Individual, Social Housing)



Source: IDI 2024. Note: individuals aged 30 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 80 DiD - urban regeneration on CVD admissions (Individual, Non-Social Housing)



Source: IDI 2024. Note: individuals aged 30 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

8.3 Respiratory-related admissions

New homes constructed as part of UR developments tend to be better insulated and warmer, which can help reduce the likelihood of respiratory-related hospital admissions (Egan et al., 2015). Additionally, older homes may be retrofitted with better insulation that can help improve respiratory health (Barton et al., 2007; Howden-Chapman et al., 2008; Thomson et al., 2009). Smoking cessation services also play a role in promoting better respiratory health (Batty et al., 2010).

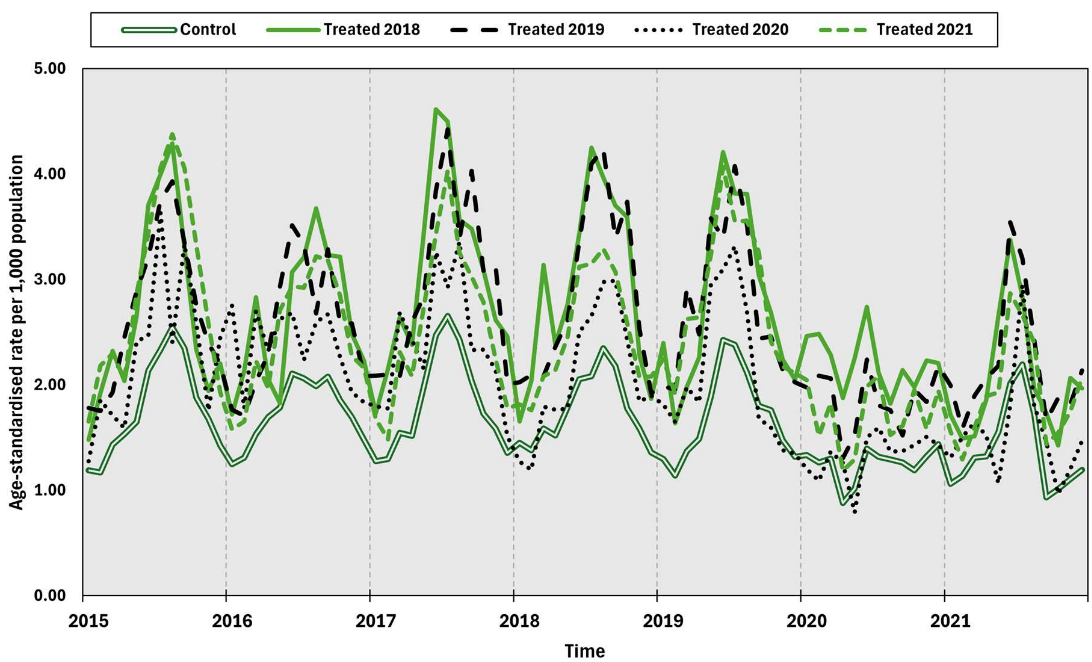
However, housing intensification often leads to an increase in local population density and the amenities available in the neighbourhood. Many respiratory diseases are communicable, so a more crowded environment can increase transmission risk, making it harder for individuals to maintain social distance (Howden-Chapman et al., 2021). Further, population growth can lead to an increase in traffic, potentially increasing air pollution levels over time. In the short run, ongoing construction activities can also contribute to increased air pollution, which may negatively affect respiratory health (Badland et al., 2017).

8.3.1 Descriptive trends

Figure 81 presents average respiratory-related admissions age-standardised rate per 1,000 population ("respiratory admissions") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Age-standardised rates are calculated based on respiratory admissions for all ages.

There are spikes in respiratory admissions between June and July each year, aligning with the winter months when respiratory-related illnesses typically increase. Prior to the COVID-19 pandemic in 2020, average respiratory admissions during the winter period were 3.9 for treated SA2s and 2.7 for control SA2s. Following the COVID-19 pandemic, average respiratory admissions decreased for all SA2s and remained lower than pre-COVID levels. During the 2021 winter period, average respiratory admissions were 2.9 for treated SA2s and 2.1 for control SA2s.

Figure 81 Average SA2 respiratory admissions by treatment year



Source: IDI 2024.

8.3.2 Area-level DiD analysis

Table 23 presents regression results examining respiratory admissions for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 82 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on respiratory admissions.

The SA1 ATT $\widehat{w}_g$ in Table 23 (column I) show respiratory admissions increased by 0.6 admissions in treated SA1s, relative to control SA1s, and this is significant at the 5% level. The heterogeneity analysis shows this increase is driven by both SH and NSH, with respiratory admissions significantly increasing by 0.8 admissions relative to control SA1s. The magnitude of this impact is relatively large, representing a 20.6% increase in average pre-treatment winter respiratory admissions.

In low UR areas, fewer dwellings are being constructed which means that older housing stock may not be replaced with newer, warmer homes. The number of new homes built in low UR areas may not make any meaningful difference in improving respiratory health, especially if control areas also have ongoing non-Kāinga Ora development as seen in Section 5.3. Even if there are improvements in low UR areas, it may be the case that respiratory health is improving faster in control SA1s relative to low UR SA1s.

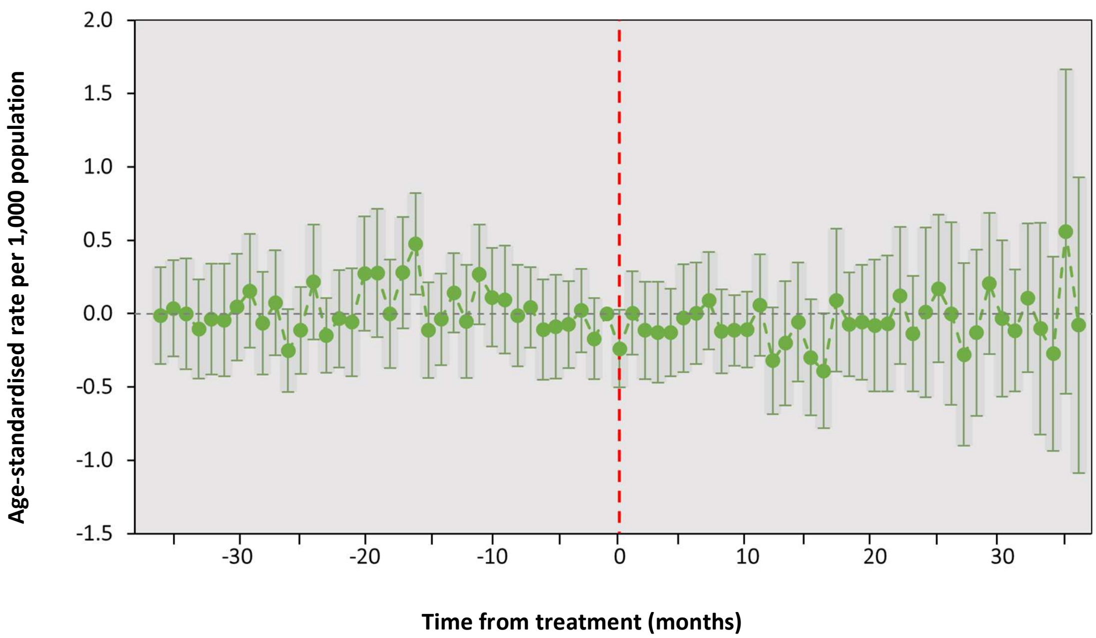
Column II in Table 23 shows respiratory admissions decreased by 3.2 admissions for SH in high UR SA2s. The magnitude of this impact is economically large – a 3.2 reduction in respiratory admissions represents an 82.5% decrease in average pre-treatment admissions during the winter period. It appears large-scale urban development in high UR SA2s have positive impacts on respiratory health for SH. This improvement may be attributable to the construction of new, warmer dwellings and the replacement of older homes as part of UR initiatives, as found in the literature (Barton et al., 2007; Egan et al., 2015; Howden-Chapman et al., 2008; Thomson et al., 2009). This trend is consistent with findings regarding ED (Section 8.1) and CVD admissions (Section 8.2). Overall, it seems that both respiratory health and general physical health are improving for SH in high UR SA2s.

Table 23 Impact of urban regeneration on respiratory admissions

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Respiratory-related admissions (age-standardised rate per 1,000 population)			
All Population	-0.075 [-0.355, 0.205]	-0.488 [-1.142, 0.165]	0.069 [-0.133, 0.270]
Social Housing	-0.878 [-1.827, 0.070]	-3.177** [-5.201, -1.152]	-0.043 [-1.056, 0.970]
Non-Social Housing	0.047 [-0.247, 0.341]	-0.251 [-0.942, 0.440]	0.148 [-0.048, 0.345]
SA1 – Respiratory-related admissions (age-standardised rate per 1,000 population)			
All Population	0.570* [0.028, 1.111]	-0.434 [-2.033, 1.165]	0.803** [0.291, 1.314]
Social Housing	0.120 [-1.103, 1.342]	-1.564 [-4.375, 1.247]	0.565 [-0.743, 1.873]
Non-Social Housing	0.714** [0.236, 1.192]	0.182 [-0.936, 1.299]	0.833*** [0.339, 1.328]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 82 DiD - urban regeneration on respiratory admissions (SA2, All Population)



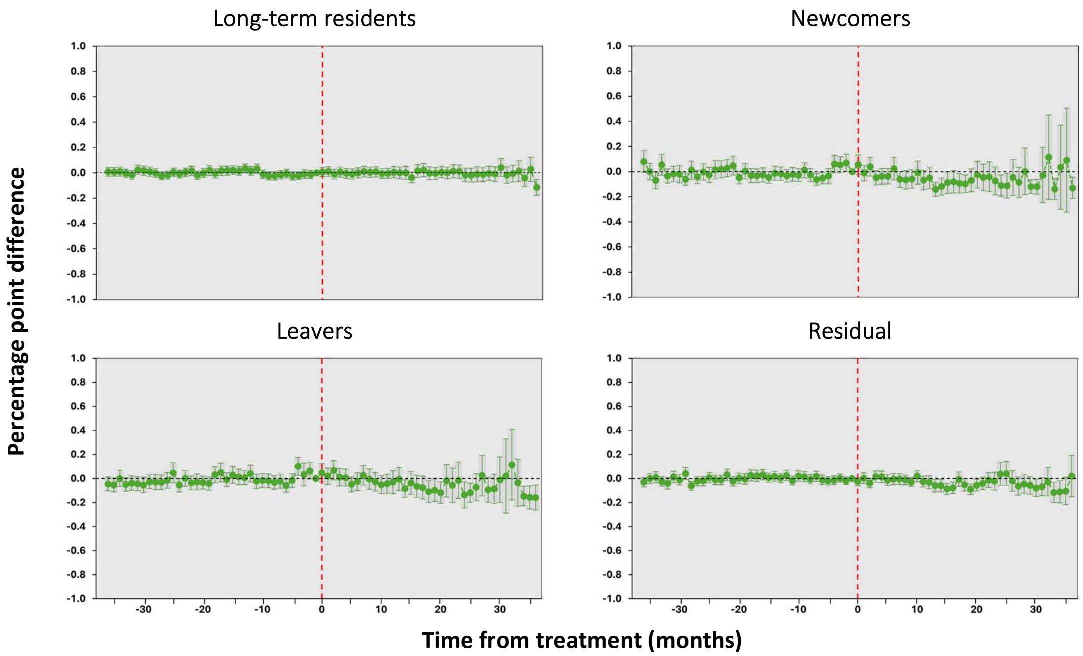
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

8.3.3 Individual-level DiD analysis

Figure 83 presents individual-level respiratory admission regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 84) and NSH (Figure 85).

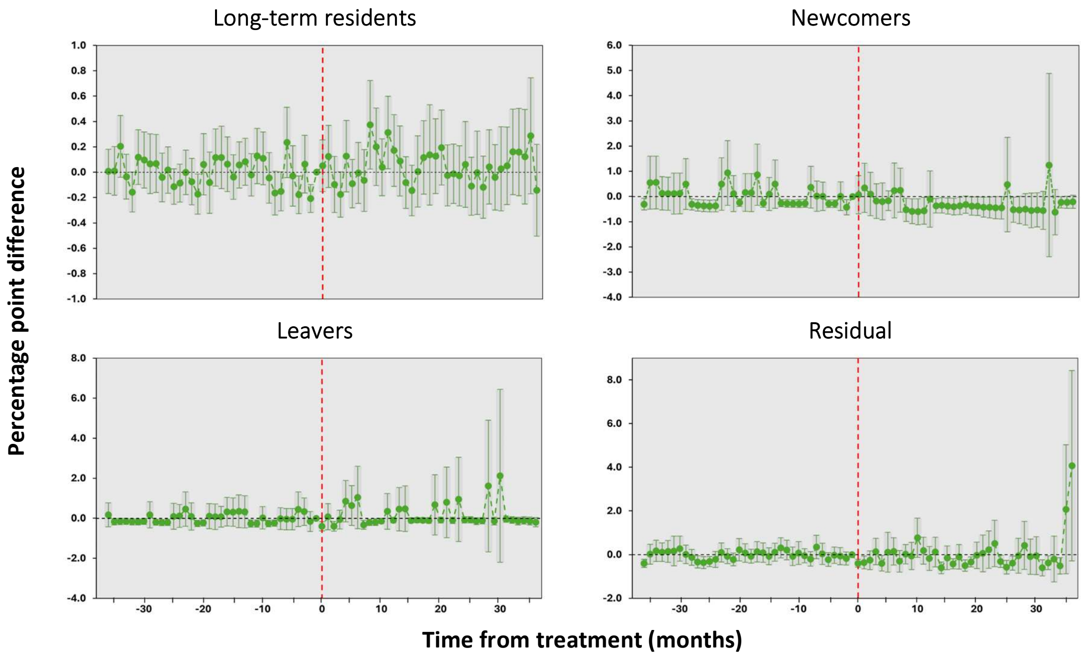
Similar to findings for ED (Section 8.1) and CVD (Section 8.2) admissions, there seems to be mostly no impact of UR on respiratory admissions. Although there is some variation in treatment effects, the differences are not statistically significant across most time periods, and the magnitude of the impact on respiratory-related admissions is economically small.

Figure 83 DiD - urban regeneration on respiratory admissions (Individual, All Population)



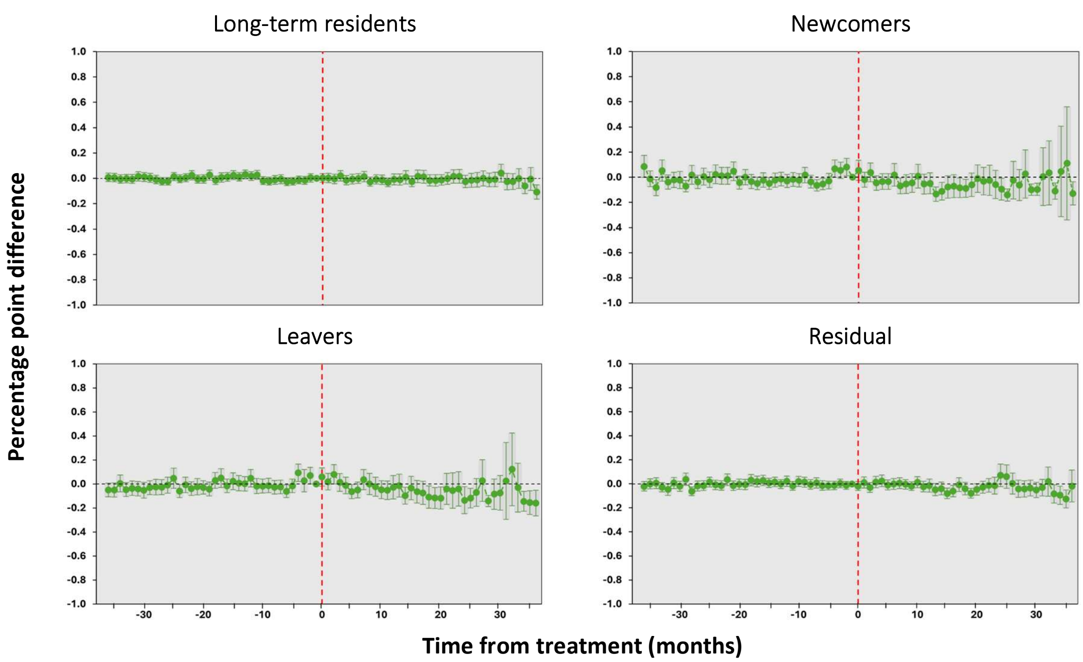
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e}\boldsymbol{\ell}}$, from Equation (2.3) in Section 5.5.

Figure 84 DiD - urban regeneration on respiratory admissions (Individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 85 DiD - urban regeneration on respiratory admissions (Individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

8.4 Mental health

The quality of residential environments, including both the home and neighbourhood, can significantly impact people's mental health. Related to Sections 8.2 and 8.3, regenerated areas with better quality homes, improved neighbourhood aesthetic and increased green spaces can positively impact mental health. By improving and increasing the housing supply, residents have more options as to where they live which can alleviate stressors associated with lower-quality housing and housing instability. Housing stability also fosters the formation of local communities and support networks, which are beneficial for mental health (Cole, 2021).

Conversely, UR can have negative impacts on mental health. Given that most Kāinga Ora-led UR projects focus on SH, this may adversely affect NSH residents who oppose these developments. As noted earlier in Section 2.2.4 and 5.2.1, SH developments often encounter resistance due to concerns about antisocial behaviour from SH tenants, fears that high concentrations of SH developments could devalue neighbourhoods and increased crime rates.

The literature indicates that residents living in high-density housing may experience a greater mental health burden if UR prioritises the construction of additional homes without simultaneously improving neighbourhood amenities such as green spaces (Berglund et al., 2017; Giles-Corti et al., 2012). A lack of these areas—whether due to high-density housing that lacks garden spaces or developments that overlook environmental considerations—can lead to residents spending more time indoors, negatively impacting their mental health.

In the short run, ongoing development can create significant uncertainty and disruption for residents (Egan et al., 2013; Henry et al., 2019). Residents may need to temporarily or permanently relocated, which can disband local communities and support networks (Cole, 2021; Egan et al., 2015; Henry et al., 2019; Ade Kearns & Whitley, 2020). Residents may also have to deal with continuous construction noise and disruptions which can negatively impact their mental health (Badland et al., 2017; Henry et al., 2019).

8.4.1 Descriptive trends

Figure 86 presents average mental healthcare utilisation age-standardised rate per 1,000 population ("mental health utilisation") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Age-standardised rates are calculated based on individuals aged 15 and above utilising mental health services each month.[21]

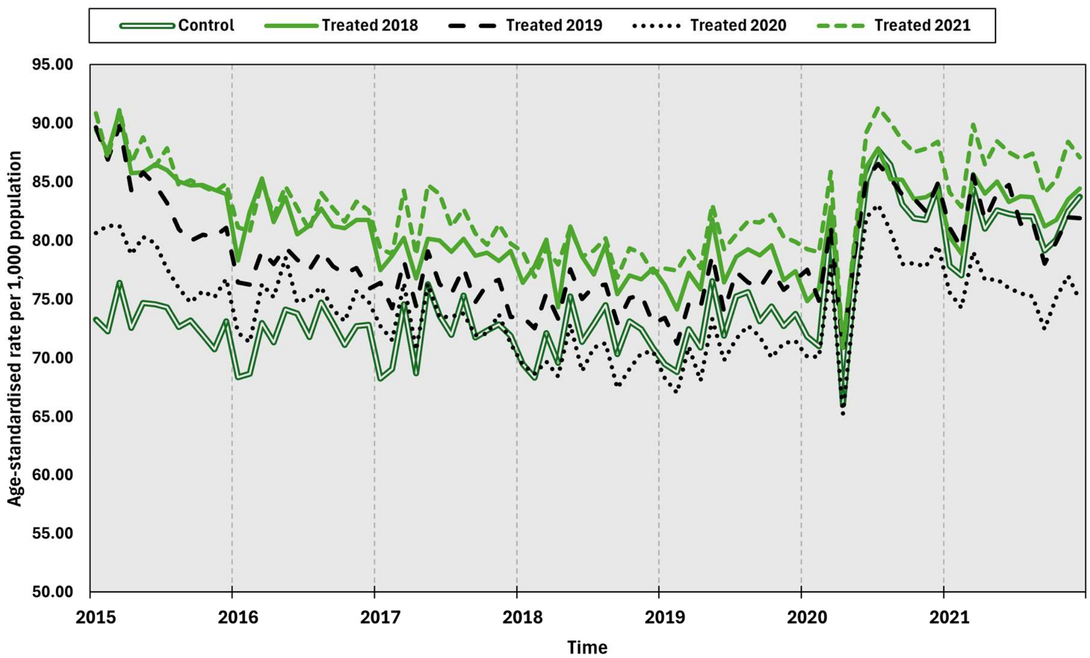
Between 2015 and 2017, the gap in mental health utilisation between treated and control SA2s narrows over time. By the end of 2017, average mental health utilisations were 75.9 for treated SA2s and 71.9 for control SA2s. Mental health utilisation remains relatively stable until early 2020, when the COVID-19 pandemic caused a sharp decline in service use. After the pandemic, there was a significant rebound in average mental health utilisation across all SA2s, higher than pre-pandemic levels. By the end of 2021, SA2s treated in 2020 have much lower average mental health utilisation compared to control SA2s, with rates of 74.9 and 83.7, respectively. For SA2s treated in other years, the average utilisation rate was 84.5 by the end of 2021.

Figure 87 presents average self-harm events (including self-harm that results in death) age-standardised rate per 1,000 population ("self-harm events") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Age-standardised rates are calculated based on self-harm events for those aged 15 and above. Self-harm is one extreme outcome of poor mental health and the mechanisms by which UR affects self-harm align with those that may lead to negative mental health outcomes.

It is worth noting that the incidence of self-harm events is relatively low. On average, there were 0.5 self-harm events per month for every 1,000 individuals at the end of 2017. This translates to an average of 2.5 self-harm events per month for every 5,000 individuals aged 15 and above.

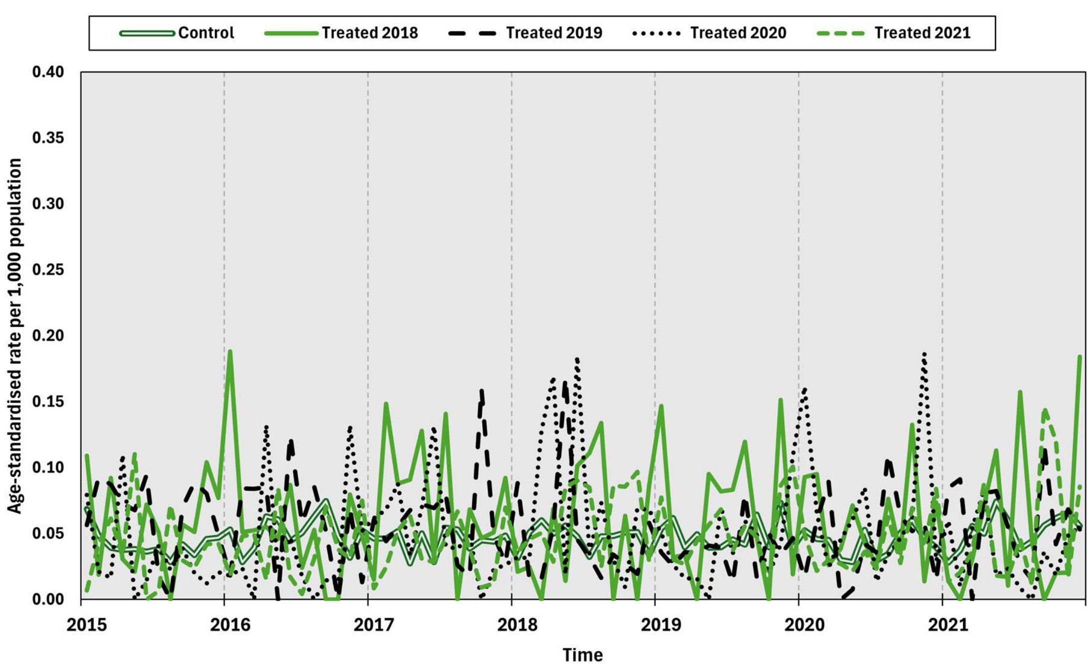
[21] Mental health utilisation includes receiving mental health related pharmaceuticals, referred to secondary mental health services and admitted into hospital for mental health reasons.

Figure 86 Average SA2 mental health utilisation by treatment year



Source: IDI 2024. Note: age-standardised rate includes only individuals aged 15 and above.

Figure 87 Average SA2 self-harm events by treatment year



Source: IDI 2024. Note: age-standardised rate includes only individuals aged 15 and above.

8.4.2 Area-level DiD analysis

Table 22 presents regression results examining mental health utilisations and self-harm events for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 88 and Figure 89 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on mental health utilisations or self-harm events. This is further evidenced both the SA2 and SA1 ATT $\hat{v}_g$ and $\hat{w}_g$ in Table 24 (column I) which show no impact of UR on mental health and self-harm events.

The heterogeneity analysis shows a significant increase in mental health utilisation for SH in high UR SA2s, which increased by 8.6 utilisations relative to control SA2s, significant at the < 1% level. This represents an 11.3% increase in average pre-treatment mental health utilisation. Additionally, self-harm events for SH in high UR SA2s also significantly increased by 0.3 events compared to control SA2s. Although the magnitude of this increase appears economically small, it reflects a 55.5% rise in average pre-treatment self-harm events. For SH in low UR SA2s, self-harm events also increased significantly by 0.06 events relative to control SA2s, marking a 111.1% increase in average pre-treatment self-harm events.

The ongoing development in high UR SA2s may have negative mental health impacts, particularly for SH residents who are most likely to be affected by these changes. Given that most housing intensification is related to the redevelopment of SH, SH tenants may face being displaced themselves or have their communities disbanded if other residents are displaced (Cole, 2021; Egan et al., 2015; Henry et al., 2019; Ade Kearns & Whitley, 2020). Additionally, Henry et al. (2019) found urban regeneration caused anxiety for residents during the redevelopment process.

The SA1 point estimate indicates that mental health utilisation for SH in high UR SA1s is not significantly different from that of control SA1s, suggesting that the notably higher mental utilisation may be primarily driven by SH in SA1s that are not treated. Completed developments can provide stable housing for vulnerable residents facing housing instability. However, other SH residents in untreated SA1s (within treated SA2s) may be negatively impacted if they are at risk of displacement, lose their community support and local networks, and face uncertainty and disruption from UR which can increase their mental health burden.

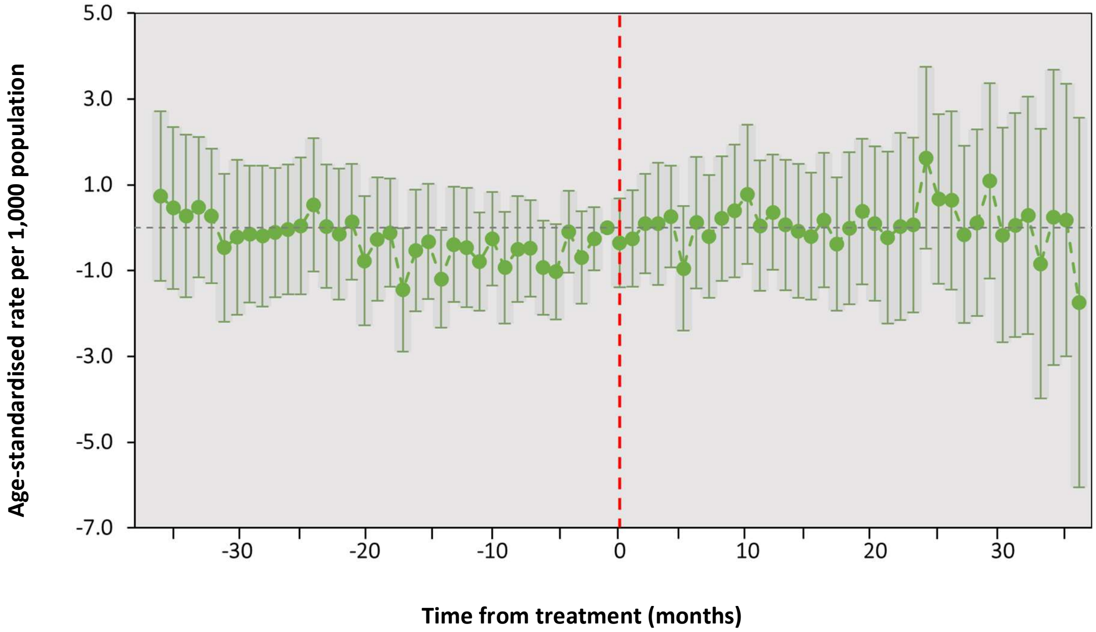
Mental health utilisation for NSH was also of interest in the heterogeneity analysis, given SH developments are often met with resistance from NSH residents (see Section 2.2.4 and Section 5.2.1). However, Table 24 shows no significant difference in mental health utilisation for NSH in treated areas relative to control areas. Additionally, the confidence intervals for NSH ATT coefficients are relatively large – there is a lot of variation in NSH mental health utilisation among treated SA2s. That is, there is no clear indication that mental health utilisation for NSH in treated areas is improving or getting worse relative to control areas.

Table 24 Impact of urban regeneration on mental health utilisation

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Mental healthcare utilisation (age-standardised rate per 1,000 population)			
All Population	0.072 [-1.101, 1.244]	2.463* [0.341, 4.585]	-0.755 [-1.906, 0.396]
Social Housing	1.269 [-5.318, 7.855]	8.593*** [3.641, 13.546]	-1.955 [-10.481, 6.571]
Non-Social Housing	0.024 [-1.193, 1.241]	1.829 [-0.419, 4.076]	-0.582 [-1.790, 0.626]
SA1 – Mental healthcare utilisation (age-standardised rate per 1,000 population)			
All Population	0.902 [-1.171, 2.976]	1.956 [-2.459, 6.370]	0.752 [-1.419, 2.923]
Social Housing	1.118 [-1.079, 3.316]	1.185 [-3.127, 5.497]	1.332 [-1.120, 3.784]
Non-Social Housing	1.119 [-0.958, 3.197]	2.431 [-2.403, 7.264]	0.881 [-1.257, 3.020]
SA2 – Self-harm events (including self-harm resulting in death) (age-standardised rate per 1,000 population)			
All Population	0.016 [-0.010, 0.041]	0.026 [-0.018, 0.070]	0.012 [-0.015, 0.040]
Social Housing	0.051*** [0.029, 0.073]	0.034*** [0.016, 0.052]	0.059*** [0.031, 0.087]
Non-Social Housing	0.011 [-0.021, 0.042]	0.013 [-0.056, 0.082]	0.010 [-0.021, 0.040]
SA1 – Self-harm events (including self-harm resulting in death) (age-standardised rate per 1,000 population)			
All Population	0.014 [-0.039, 0.067]	0.037* [0.007, 0.067]	0.009 [-0.054, 0.072]
Social Housing	0.010 [-0.047, 0.066]	0.031 [-0.001, 0.063]	0.006 [-0.061, 0.073]
Non-Social Housing	0.014 [-0.039, 0.067]	0.039* [0.008, 0.070]	0.009 [-0.054, 0.072]

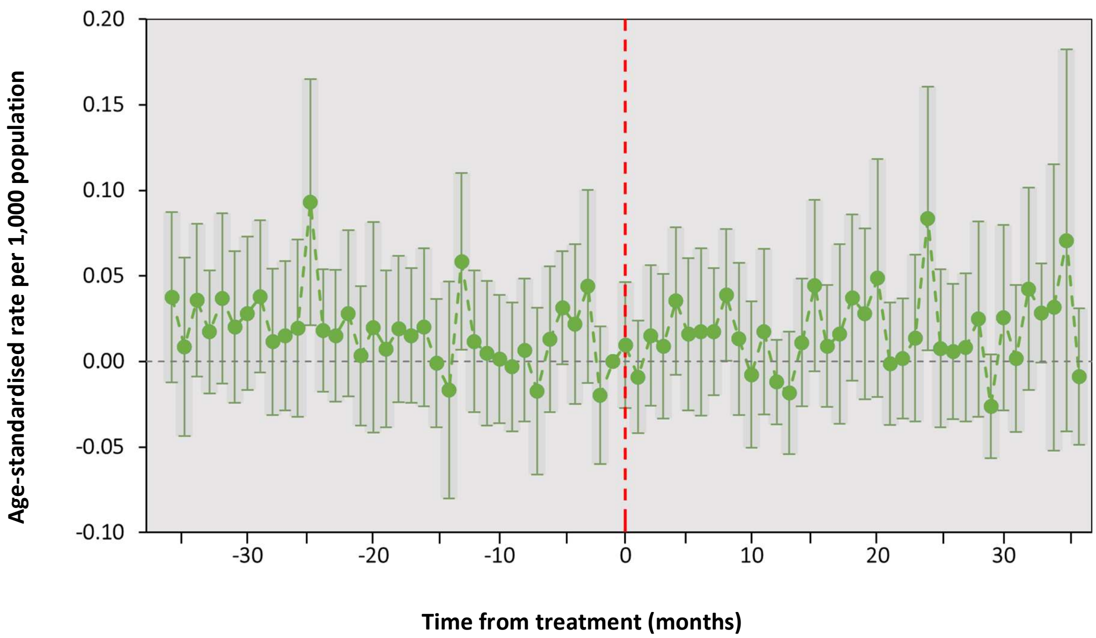
Source: IDI 2024. Note UR – urban regeneration. Age-standardised rate includes only individuals aged 15 and above. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 88 DiD - urban regeneration on mental health utilisation (SA2, All Population)



Source: IDI 2024. Note: age-standardised rate includes only individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 89 DiD - urban regeneration on self-harm events (SA2, All Population)



Source: IDI 2024. Note: age-standardised rate includes only individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

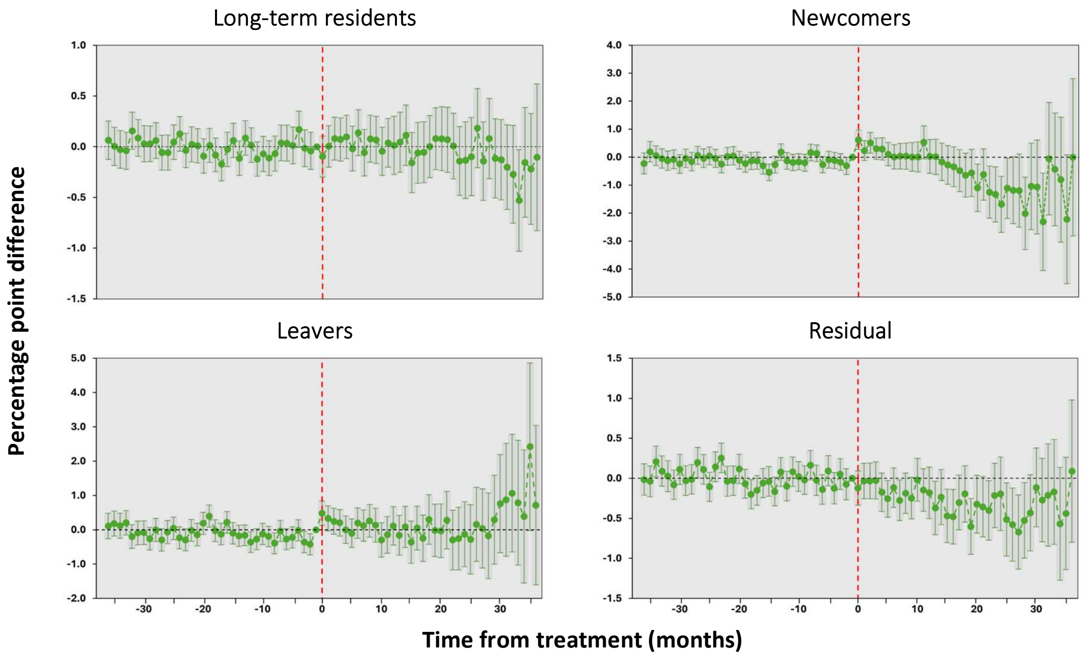
8.4.3 Individual-level DiD analysis

Figure 90 and Figure 93 presents individual-level mental health utilisation and self-harm event regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately NSH (Figure 91 and Figure 94) and NSH (Figure 92 and Figure 95).

The mental health utilisation of NSH long-term residents and leavers in treated SA2s is of particular interest to the individual-level results (as noted in Section 5.2.2), to help understand the characteristics of individuals who remain in treated areas and individuals moving into and out of treated areas. The individual-level heterogeneity analysis shows the mental health utilisation of NSH long-term residents in treated SA2s is not significantly different to those in control SA2s (Figure 92). This indicates that long-term residents living near SH developments do not experience a greater mental health burden compared to long-term residents living in control areas with no SH developments. Similarly, no significant difference was observed for NSH leavers, indicating that their reasons for moving were not linked to a higher mental health burden associated with living near SH developments.

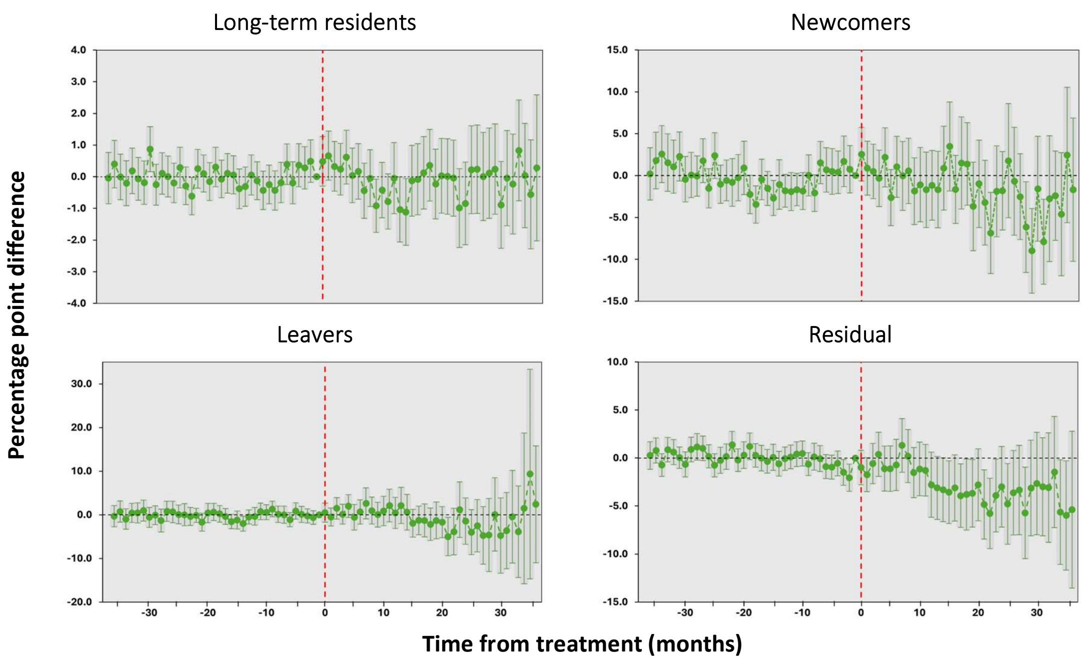
The individual-level analysis offers limited insights regarding significant impacts of UR on self-harm events across different subpopulations. In cases where differences are significant, such as for NSH newcomers in Figure 95, the magnitude of these impacts are very small and not greater than 0.01 percentage points.

Figure 90 DiD - urban regeneration on mental health utilisation (Individual, All Population)



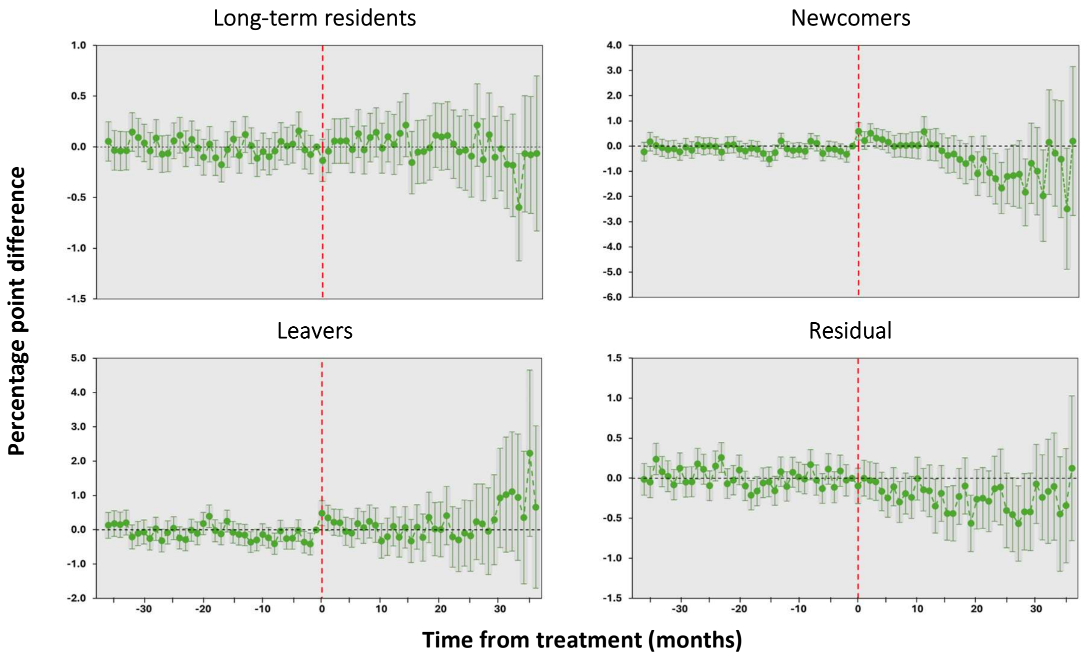
Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 91 DiD - urban regeneration on mental health utilisation (Individual, Social Housing)



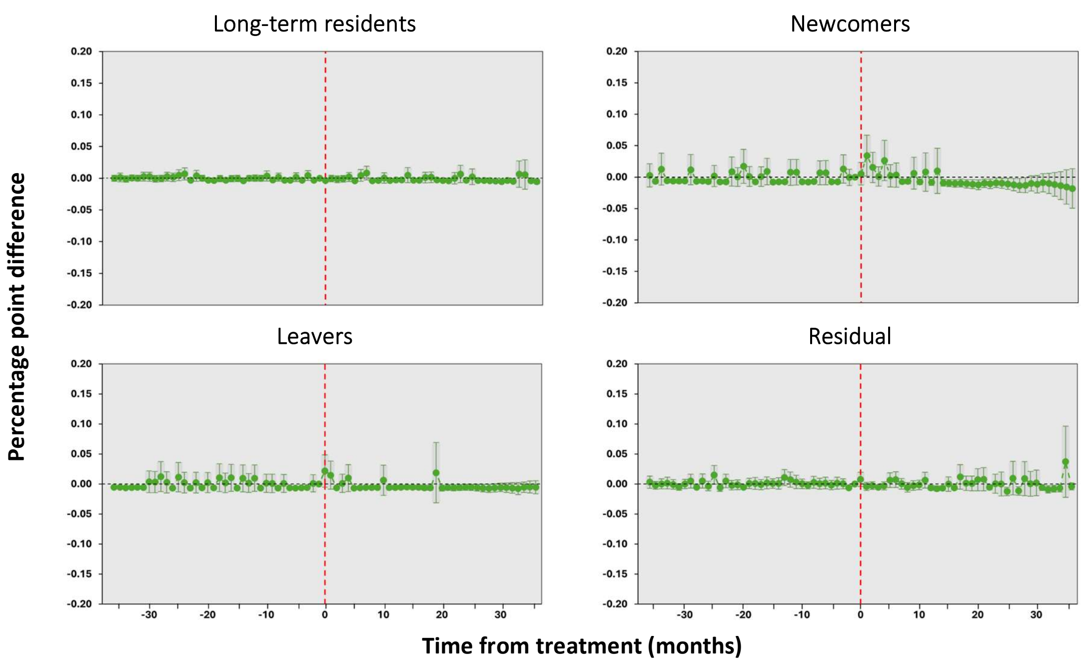
Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 92 DiD - urban regeneration on mental health utilisation (Individual, Non-Social Housing)



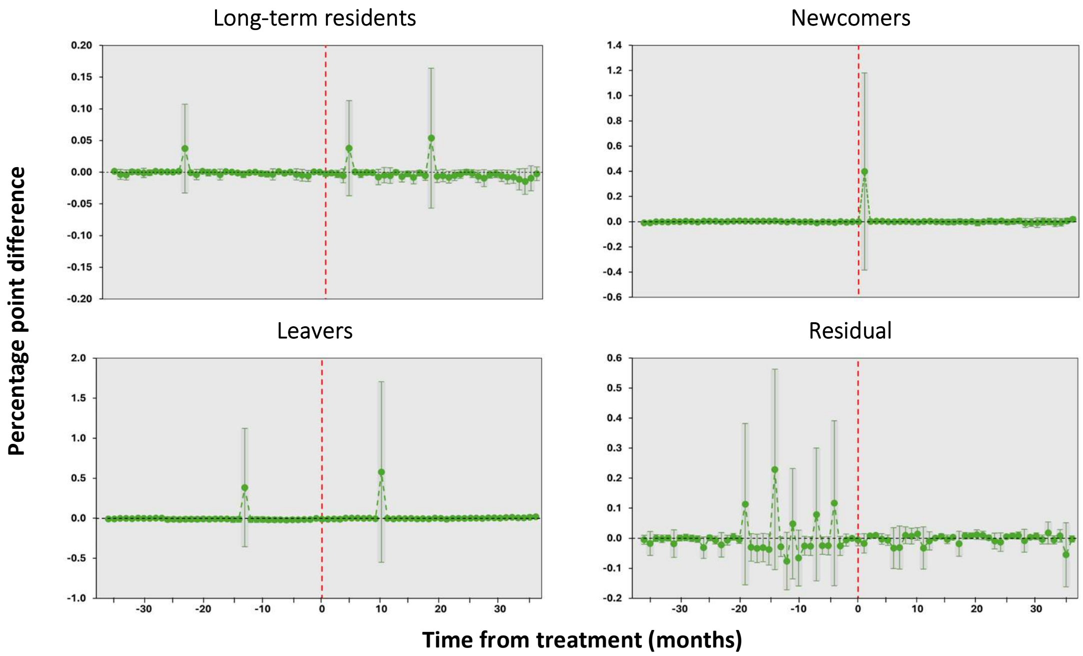
Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 93 DiD - urban regeneration on self-harm events (Individual, All Population)



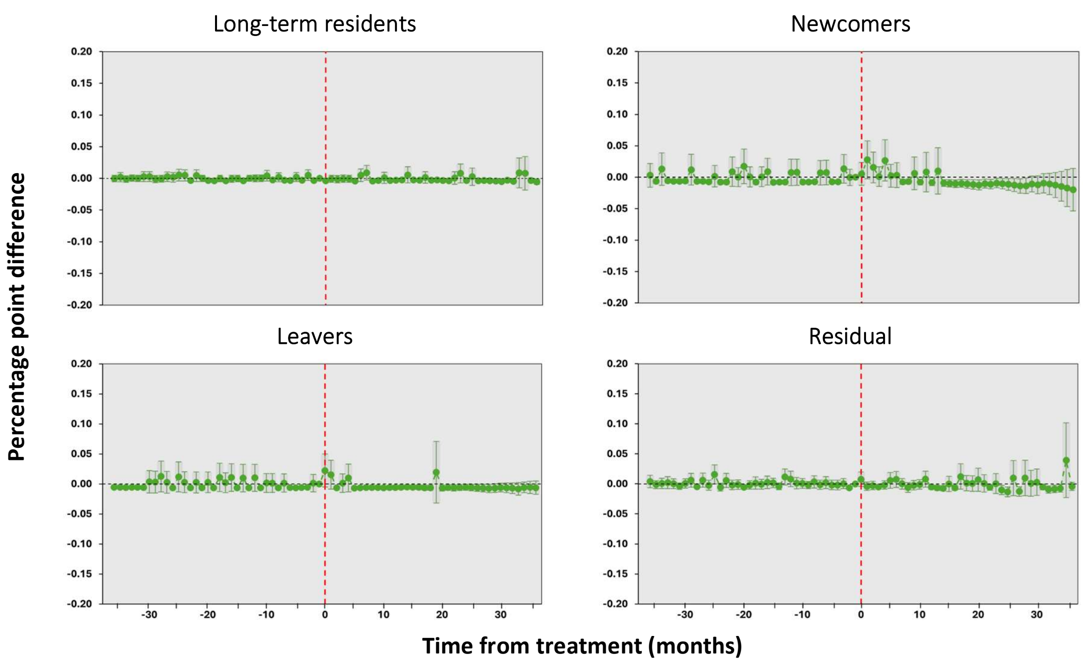
Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 94 DiD - urban regeneration on self-harm events (Individual, Social Housing)



Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 95 DiD - urban regeneration on self-harm events (Individual, Non-Social Housing)



Source: IDI 2024. Note: individuals aged 15 and above. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

9 Results: Crime and Safety

This section provides the descriptive trends and the regression results for short run impacts of urban regeneration (UR) on area- and individual-level crime and safety outcomes. Given the number of variables examined, each crime and safety outcome is discussed within its respective subsection.

Each crime and safety outcome subsection follows the same format. First, as covered in the related literature in Section 2.3.5, the mechanisms in which urban regeneration can impact each crime and safety indicator are discussed. Next, the descriptive portrait shows how wellbeing outcomes have changed over time without adjusting for factors that may contribute to differences in wellbeing outcomes between treated and control areas. For example, differences in wellbeing outcomes may be due to differing ethnic and age compositions, rather than a result of UR. Controlling for these factors helps to delineate the impact of UR on wellbeing outcomes.

Descriptive trends are followed by the total area-level average treatment effect on the treated (ATT) coefficients, their statistical significance and corresponding confidence intervals. At the SA2-level, the ATT Is denoted as $\hat{\upsilon}_g$ and at the SA1-level, this is denoted as $\widehat{w}_g$. The cohort average treatment effect (CATT) for SA2s is presented in graphical format and denoted as $\hat{\delta}_{e\ell}$. Analysis at the SA2- and SA1-level provides insight as to how wellbeing impacts of UR are distributed at the area-level. The area-level regression results examine how crime and safety outcomes have changed in areas treated by UR, relative to untreated areas, after controlling for characteristics such as population, household size, ethnicity, age, gender and partnership status. At the SA2-level, results are reported by three UR intensities: all (column I), high (50 or more dwellings in column II) and low (less than 50 dwellings in column III) UR. At the SA1-level, this is all, high (25 or more dwellings) and low (less than 25 dwellings) UR. Both SA2- and SA1-level results are presented for three treated populations: overall population, social housing (SH) and non-social housing (NSH).

The individual-level heterogeneity analysis examines wellbeing impacts by subpopulations as described in Table 6 to understand how impacts are distributed at the individual-level. Individual-level results are presented as graphs showing the individual-level time treatment effects for each subpopulation. Treated long-term residents are compared to control long-term residents, treated newcomers and leavers are compared to transient control residents and treated residuals are compared to control residuals. The individual-level results are also presented separately for SH and NSH. As noted in Section 5.6, individual-level ATTs could not be computed due to computational issues. As such, only the individual-level CATT, denoted as $\hat{\varphi}_{e\ell}$, is reported in graphical format in the results.

As noted previously in this thesis, the measurement and impact of UR is likely to be underestimated due to the exclusion of pre-treated SA2s, ongoing treatment and the current period of analysis allowing only for short run impacts to be measured. Therefore, the following results are short run crime and safety impacts of UR. As most Kāinga Ora-led UR is SH development, the results relate mainly to the impact of SH development.

All descriptive statistics for abduction and kidnapping victimisations were suppressed due to small incidence rates. Given the small incidence rates, no meaningful inferences could be made with respects to the regression results. Therefore, no results are presented for abduction and kidnapping victimisations.

9.1 Family violence victimisations

UR may reduce family violence, and overall crime victimisations, through several mechanisms. Initiatives may include enhanced police presence and neighbourhood warden schemes which can reduce the incidence of crime (Batty et al., 2010). Improved neighbourhood aesthetics—such as better street lighting and less public disorder—can contribute to a perception of safety and limit opportunities for criminal activity (Batty et al., 2010; Bull et al., 2015). Increased housing density and mixed-tenure neighbourhoods can discourage crime by encouraging natural surveillance, making it more likely that criminal activity will be observed and reported (Badland et al., 2017; Bull et al., 2015).

However, higher housing density can also contribute to elevated crime rates, as the increased number of people in a concentrated area may provide more opportunities for criminal activity (Badland et al., 2017; Bull et al., 2015). In the short run, areas undergoing construction and development may feel abandoned as people move out which may attract criminals and increase crime (Henry et al., 2019). Displacement of residents may disband local communities and support networks, which may have deterred crime within the local community if residents actively reported incidents or because natural surveillance is more effective when there are more people are in an area. Additionally, displacement of residents may also just displace perpetrators of crime to other areas (Borbely & Rossi, 2023). This may reduce local crime rates, but overall neighbourhood crime rates may remain unchanged.

While increased police presence may reduce crime occurrence, it can also lead to increased reporting of crime, meaning actual crime rates might remain unchanged but reported victimisations have increased. Additionally, this study does not record the location of the victimisations. In the case of family violence, which typically occurs in the home, lower recorded victimisations might indicate an improvement in family violence victimisations. It may instead indicate that residents are spending more time away from home due to factors like construction or noise, reducing their exposure to potential victimisation.

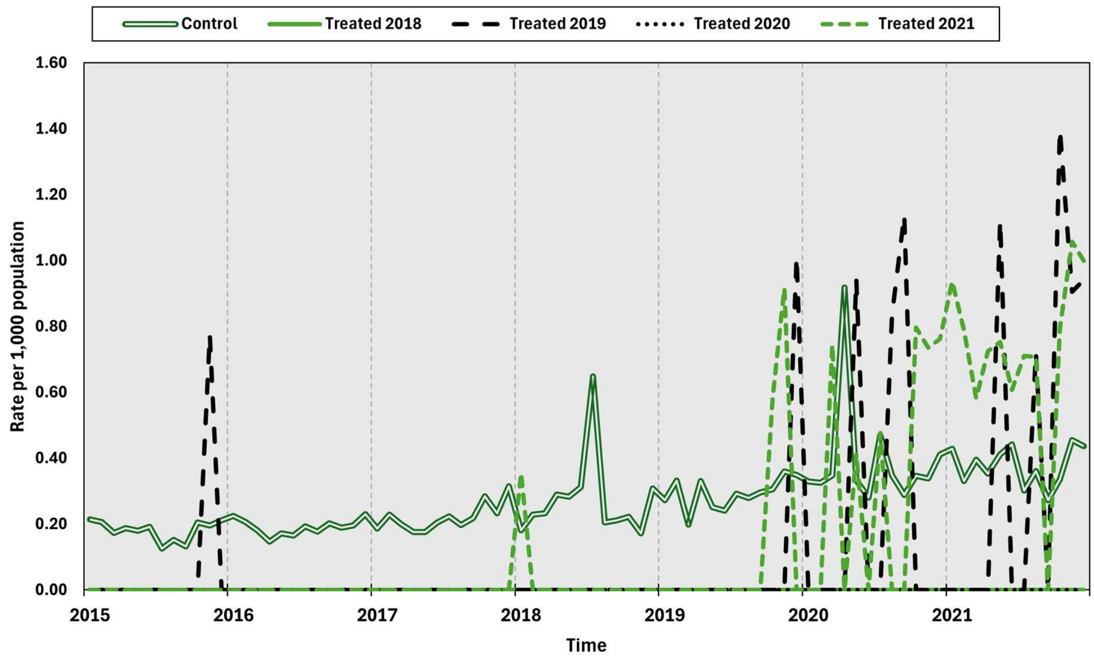
9.1.1 Descriptive trends

Figure 96 presents average family violence victimisation rates per 1,000 population ("family violence victimisations") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of family violence victimisations per 1,000 population. All family violence victimisations for SA2s treated in 2018 and 2020, as well as pre-2020 data for SA2s treated in 2019 and 2021 were suppressed due to Stats NZ suppression rules for confidentiality.[22]

For the cohort of treated SA2s, only two pre-treatment averages for family violence victimisations were available – 0.8 victimisations in November 2015 and 0.4 victimisations in January 2018. Post-treatment, family violence victimisations in treated SA2s rose to 0.7 by mid-2020 and further increased to 1.0 by the end of 2021. In contrast, for control SA2s, the average number of family violence victimisations increased from 0.2 in January 2018 to 0.4 in December 2021.

[22] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero crime victimisations are suppressed.

Figure 96 Average SA2 family violence victimisations by treatment year



Source: IDI 2024. Note all observations for the ‘Treated – 2018’ and ‘Treated – 2020’ series and some observations for other ‘Treated’ series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

9.1.2 Area-level DiD analysis

Table 25 presents regression results examining family violence victimisations for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 97 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on family violence victimisations. The SA2 and SA1 ATT $\hat{v}_g$ and $\hat{w}_g$ in Table 25 (column I) further confirms there is no significant impact of UR on family violence victimisations in treated areas relative to control areas.

The heterogeneity analysis shows family violence victimisations significantly increased by 1.2 victimisations for SH in low UR SA2s relative to control SA2s, and this is statistically significant at the < 1% level. The magnitude of this increase is economically large, representing a substantial 150% and 300% increase based on 0.8 and 0.4 victimisations, respectively. As shown in Figure 137 in Appendix 7, this significant increase is predominantly driven by significantly higher family violence victimisations at $\ell = 18$ (relative months from treatment).

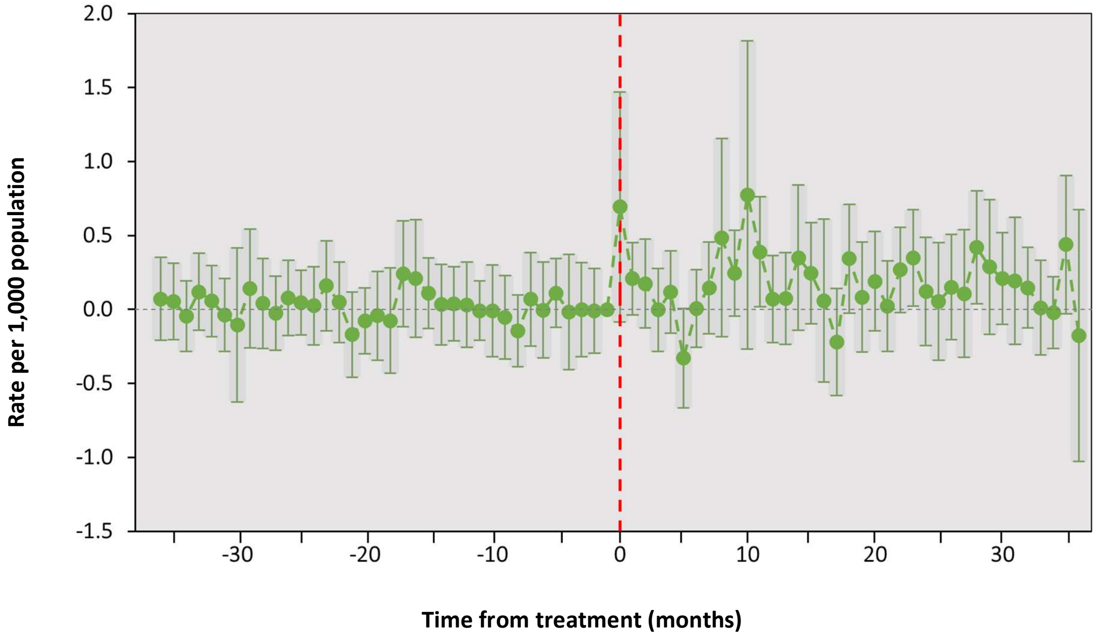
There is no corresponding impact for SH in low UR SA1s which suggests that the significant increase in family violence victimisations is occurring in untreated SA1s, within the boundaries of a treated SA2. There are two potential explanations for this – first, UR may have simply displaced SH residents from low UR SA1s to untreated SA1s (within a treated SA2), shifting —rather than reducing—family violence victimisations (as in Borbely and Rossi (2023)). Second, increased policing in low UR areas might be detecting more family violence incidents, without a change in the actual occurrence of violence, thereby increasing the recorded victimisations in low UR SA2s.

Table 25 Impact of urban regeneration on family violence victimisations

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Family violence victimisations (rate per 1,000 population)			
All Population	0.198 [-0.011, 0.406]	0.149 [-0.138, 0.436]	0.216 [-0.033, 0.465]
Social Housing	0.984*** [0.515, 1.453]	0.236 [-0.393, 0.865]	1.202*** [0.634, 1.770]
Non-Social Housing	0.176 [-0.038, 0.391]	0.216 [-0.089, 0.521]	0.164 [-0.093, 0.421]
SA1 – Family violence victimisations (rate per 1,000 population)			
All Population	-0.012 [-0.329, 0.304]	0.243 [-0.287, 0.773]	-0.066 [-0.412, 0.279]
Social Housing	0.715 [-0.332, 1.762]	0.592 [-0.039, 1.492]	0.730 [-0.528, 1.989]
Non-Social Housing	-0.067 [-0.340, 0.206]	0.221 [-0.266, 0.708]	0.730 [-0.528, 1.989]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{v}_g$ and $\hat{w}_g$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 97 DiD - urban regeneration on family violence victimisations (SA2, All Population)



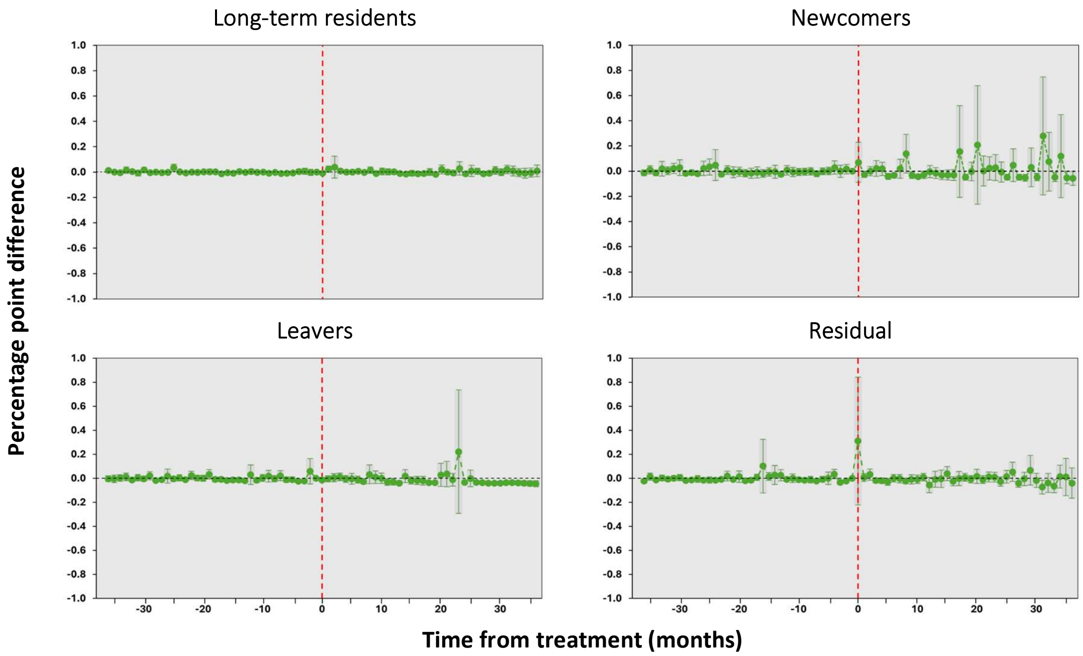
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.1.3 Individual-level DiD analysis

Figure 98 presents individual-level family violence victimisation regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 99) and NSH (Figure 100).

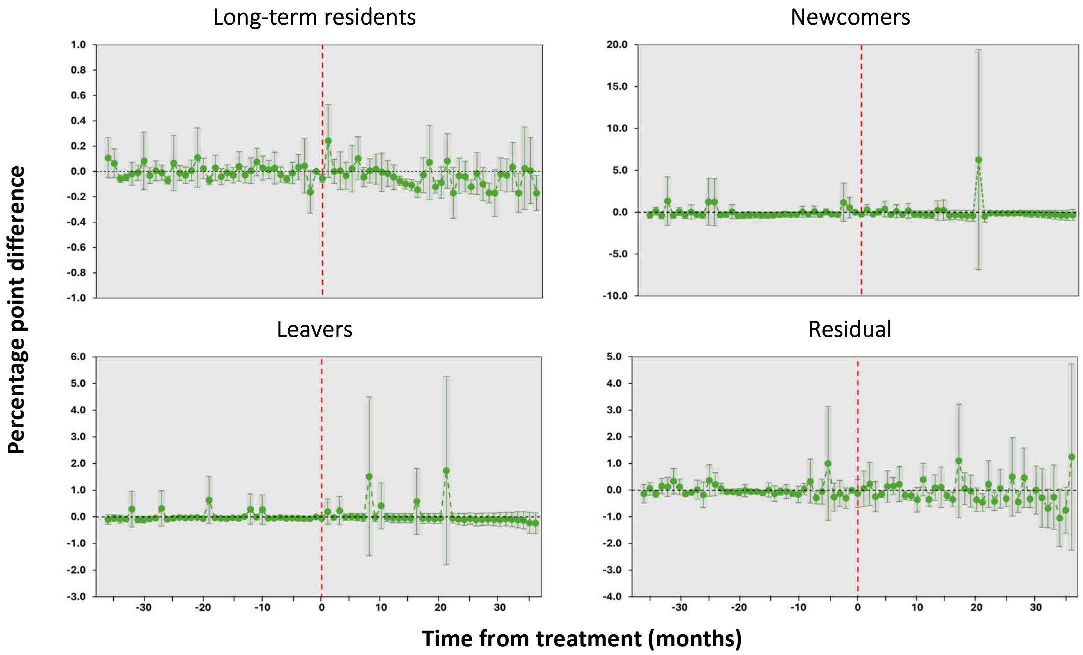
The individual-level findings align with the area-level analysis and show no impact of UR on family violence victimisations in the short run. While the area-level results found a significant increase of 1.2 victimisations for SH residents in low UR SA2s, the individual-level heterogeneity analysis reveals no significant differences between SH subpopulations and their control counterparts (Figure 99).

Figure 98 DiD - urban regeneration on family violence victimisations (Individual, All Population)



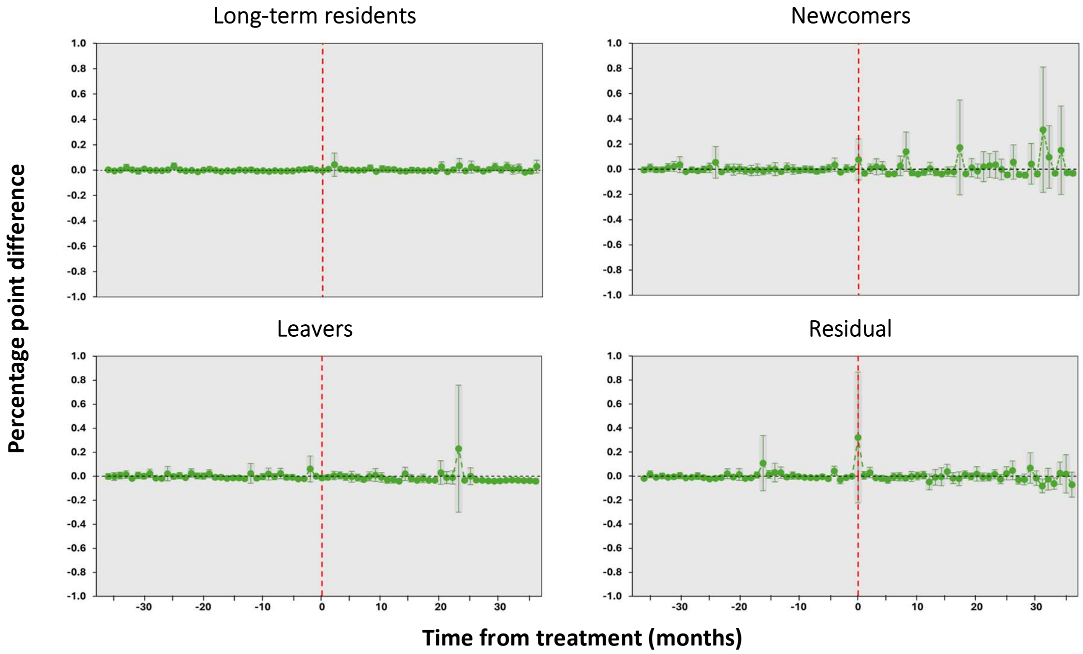
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 99 DiD - urban regeneration on family violence victimisations (Individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 100 DiD - urban regeneration on family violence victimisations (Individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

9.2 Assault victimisations

The mechanisms by which UR may reduce assault victimisations are similar to those for family violence, as described in Section 9.1. That is, increased police presence, neighbourhood warden schemes, increased density and mixed tenure and improved neighbourhood aesthetics may discourage or reduce the occurrence of crime.

However, as described in Section 9.1, higher density can also increase population levels, potentially leading to a rise in crime rates. Additionally, during ongoing construction, areas might experience a temporary increase in crime as they become less populated and local communities are disbanded. Another possibility is that crime is merely displaced from one area to another, rather than being reduced. Further, while increased police presence can help deter crime, it might also lead to more crimes being reported, even if the actual incidence remains unchanged.

Assaults, unlike family violence, can occur in various locations and involve a wider range of perpetrators. Assault victimisations are of interest in this study, as they can be indicative of antisocial behaviour particularly in areas undergoing SH development (see Section 2.2.4 and 5.2.1). If SH tenants are perceived as more likely to commit crimes such as assaults or theft, then treated areas would expect an increase in victimisations in compared to control areas.

It is important note that this study does not measure whether an assault was perpetrated by SH or NSH tenants – it only records whether the victim lived in SH or NSH at the time of the assault. The study also does not specify the location of the assault, meaning it is unclear if victimisations occurred within the residents' SA2 or elsewhere. Residents who spend more time away from home due to noise or construction may have less exposure to becoming victims of assaults.

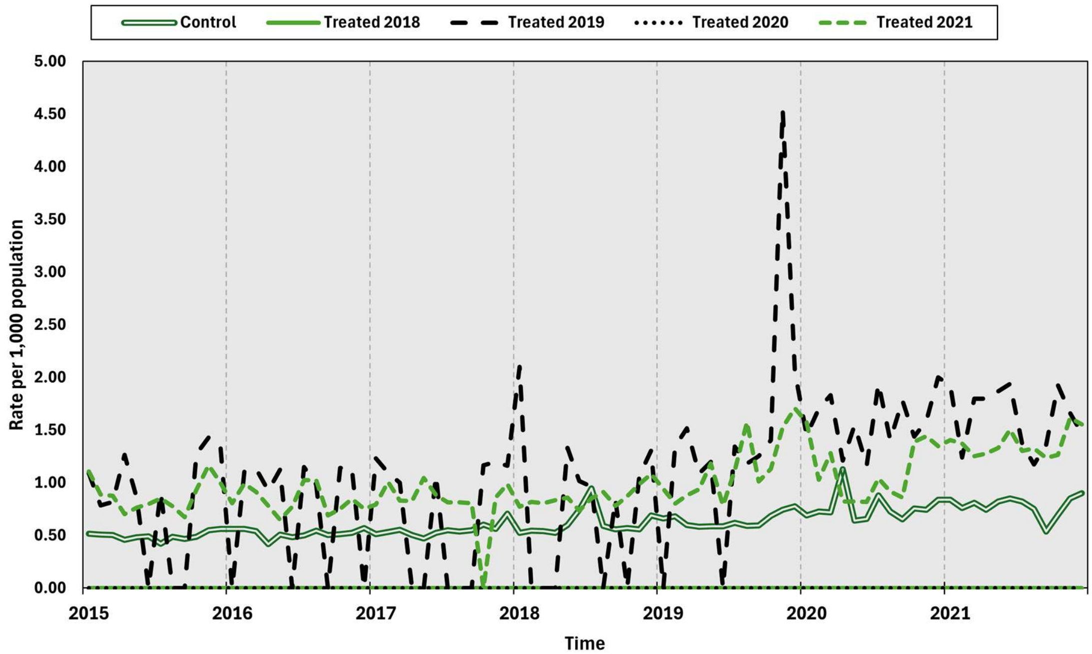
9.2.1 Descriptive trends

Figure 101 presents average assault victimisation rates per 1,000 population ("assault victimisations") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of assault victimisations per 1,000 population. Assault victimisations for SA2s treated in 2018 and 2020 were suppressed due to Stats NZ suppression rules for confidentiality.[23]

Between 2015 and 2017, there are some fluctuations in assault victimisations between treated and control SA2s. However, trends remained generally stable, with treated SA2s consistently showing higher victimisation rates compared to control areas. At the end of 2017, treated SA2s reported an average of 1.1 assault victimisations, while control SA2s had 0.7. Average assault victimisations gradually increase for treated SA2s, with SA2s treated in 2019 experiencing an extremely large spike at the end of 2019 of 4.6 victimisations. This quickly recovers – however, assault victimisations remain higher in treated SA2s compared to control SA2s. At the end of 2021, average assault victimisations were 1.5 and 0.9 for treated and control SA2s, respectively.

[23] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero crime victimisations are suppressed.

Figure 101 Average SA2 assault victimisations by treatment year



Source: IDI 2024. Note all observations for the 'Treated – 2018' and 'Treated – 2020' series and some observations for other 'Treated' series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

9.2.2 Area-level DiD analysis

Table 26 presents regression results comparing assault victimisations for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 102 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on assault victimisations. The SA2 and SA1 ATT $\hat{\upsilon}_g$ and $\widehat{w}_g$ in Table 26 (column I) further confirm there is no significant impact of UR on assault victimisations in treated areas relative to control areas.

The heterogeneity analysis shows assault victimisations significantly increased by 1.3 victimisations in low UR SA2s relative to control SA2s, and this is significant at the 1% level. This increase is of a similar magnitude to that observed for family violence victimisations in Section 9.1 for SH in low UR SA2s. As with family violence victimisations, assault victimisations were significantly higher at $\ell = 18$ (relative months from treatment). Given the overlap of family violence offences classified as assault—such as domestic male-on-female assault—this suggests a substantial number of assault victimisations may be related to family violence (further detail on offence codes provided in Appendix 6).

It is likely that assaults are occurring in untreated SA1s (within a treated SA2), as there is no corresponding increase in assault victimisations for SH in low UR SA1s. This could be due to urban regeneration displacing assault victimisations from treated SA1s to untreated SA1s (Borbely & Rossi, 2023), or from increased policing that increases the detection of assault victimisations.

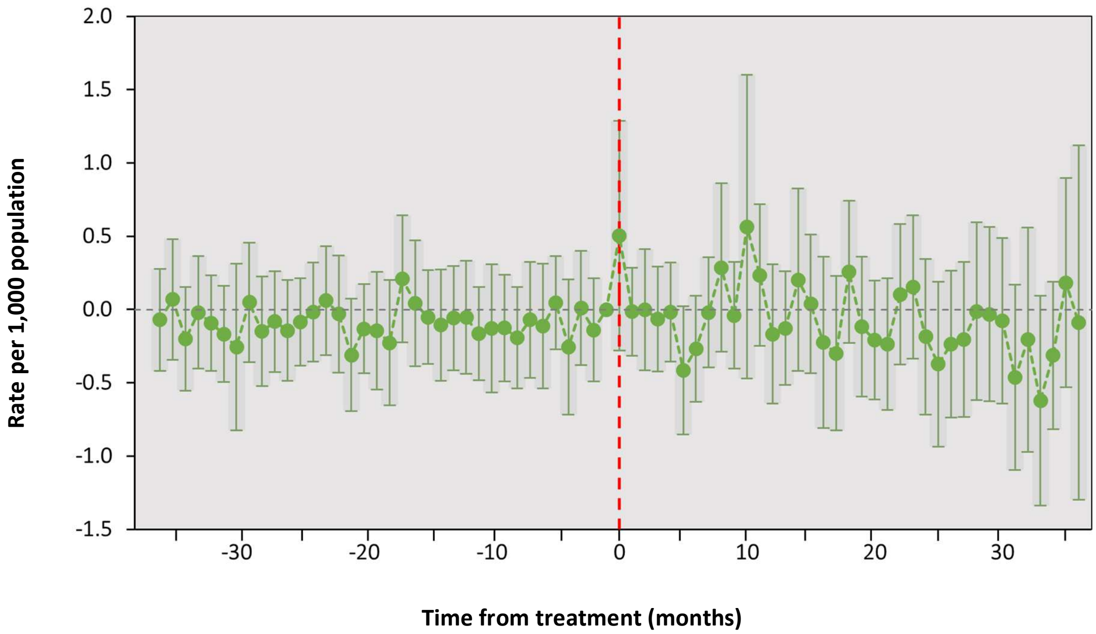
The heterogeneity analysis shows that there was no significant difference in assault victimisations for NSH residents in treated areas compared to control areas. As discussed in Section 2.2.4 and 5.2.1, this finding is particularly relevant to this study, as NSH residents may have concerns about antisocial behaviour stemming from increased SH development. Further analysis assessing medium- to long-term assault victimisations will be needed to determine if this situation changes as UR developments are completed.

Table 26 Impact of urban regeneration on assault victimisations

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Assault victimisations (rate per 1,000 population)			
All Population	-0.027 [-0.323, 0.269]	-0.509 [-1.310, 0.292]	0.144 [0.126, 0.413]
Social Housing	0.967** [0.305, 1.630]	-0.063 [-0.832, 0.706]	1.256** [0.416, 2.095]
Non-Social Housing	-0.092 [-0.460, 0.277]	-0.558 [-1.696, 0.580]	0.074 [-0.205, 0.353]
SA1 – Assault victimisations (rate per 1,000 population)			
All Population	-0.178 [-0.647, 0.291]	0.341 [-0.413, 1.096]	-0.295 [-0.815, 0.226]
Social Housing	0.814 [-0.503, 2.131]	0.781 [-1.630, 1.739]	-0.264 [-0.728, 0.200]
Non-Social Housing	-0.222 [-0.713, 0.269]	0.014 [-1.329, 1.358]	0.799 [-0.774, 2.371]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 102 DiD - urban regeneration on assault victimisations (SA2, All Population)



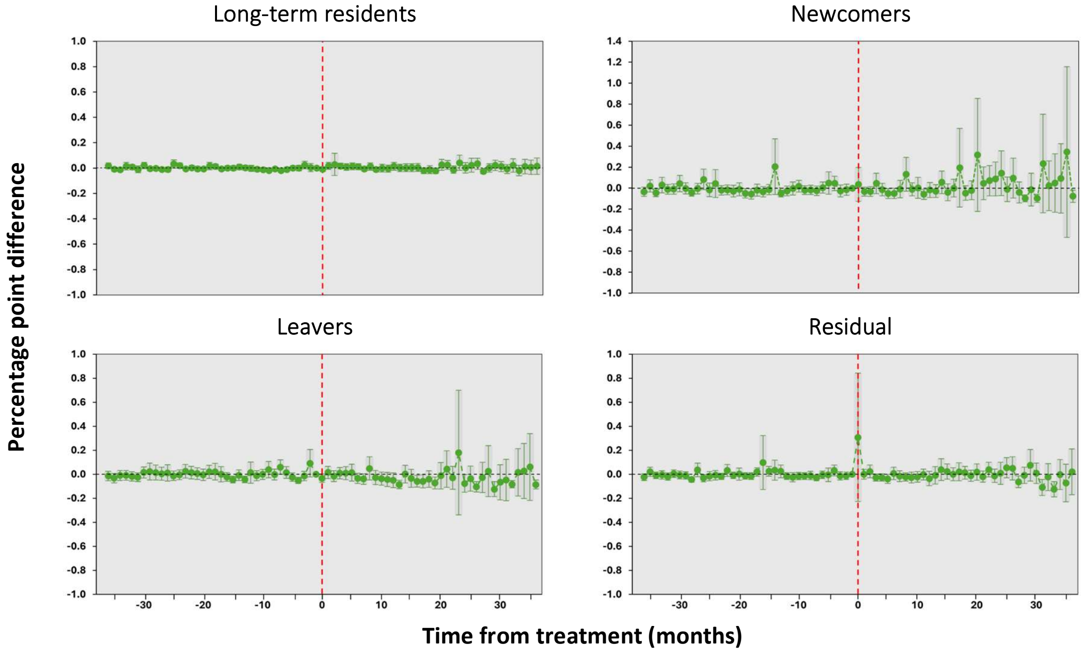
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\widehat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.2.3 Individual-level DiD analysis

Figure 103 presents individual-level assault victimisation regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 104) and NSH (Figure 105).

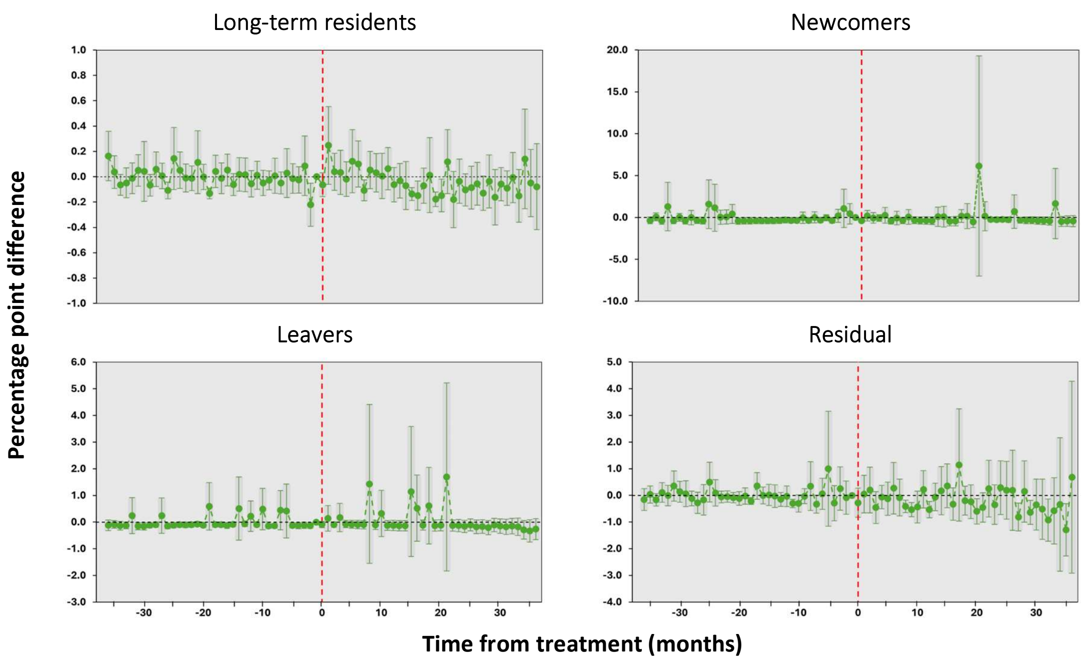
The individual-level analysis indicates that UR has little to no impact on assault victimisations for both SH and NSH residents. While some treatment effects are observed, these differences are not statistically significant for most time periods. Where significant, the magnitude of the impact on assault victimisations is economically small.

Figure 103 DiD - urban regeneration on assault victimisations (Individual, All Population)



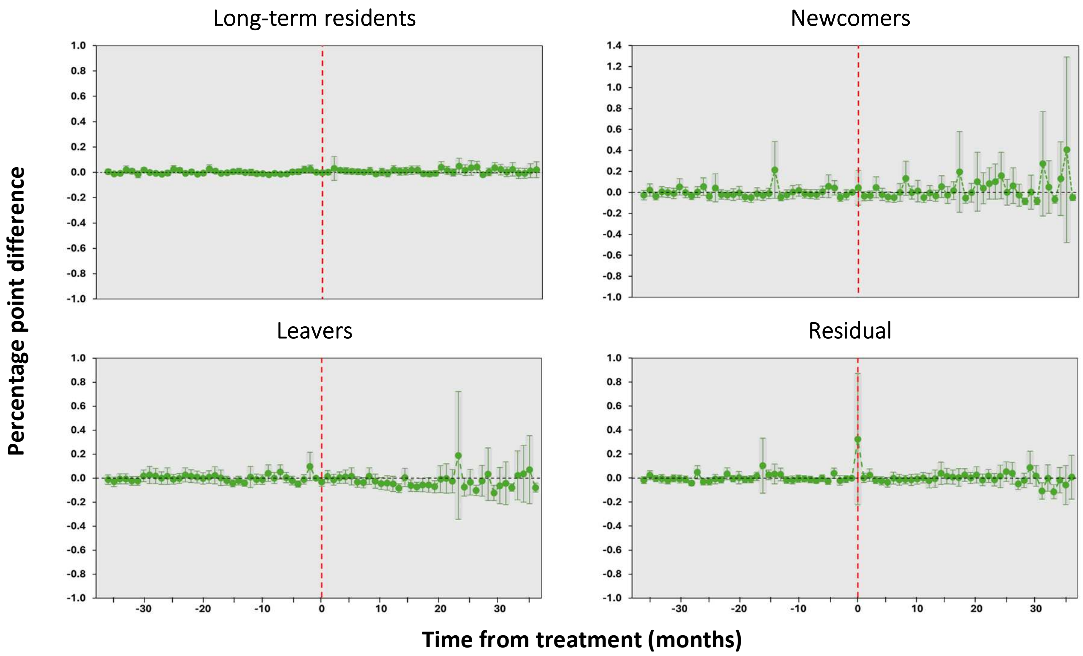
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 104 DiD - urban regeneration on assault victimisations (Individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 105 DiD - urban regeneration on assault victimisations (Individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

9.3 Sexual assault victimisations

The mechanisms by which UR may reduce sexual assault victimisations are similar to those for family violence, as described in Section 9.1. That is, increased police presence, neighbourhood warden schemes, increased density and mixed tenure and improved neighbourhood aesthetics may discourage or reduce the occurrence of crime.

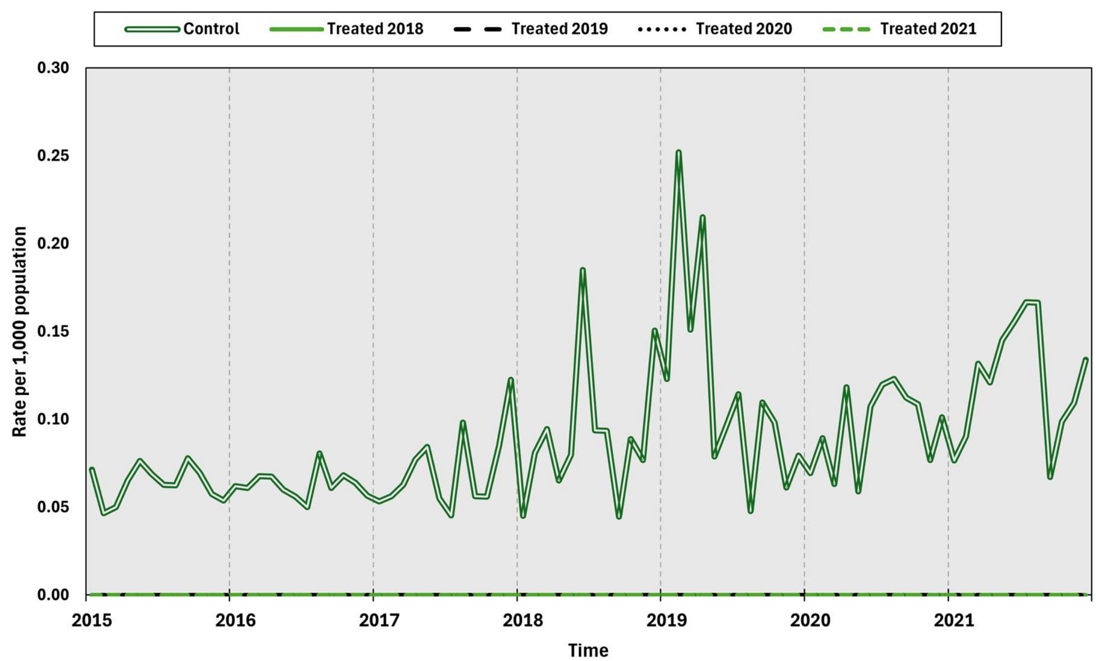
However, as described in Section 9.1, higher density can also increase population levels, potentially leading to a rise in crime rates. Additionally, during ongoing construction, areas might experience a temporary increase in crime as they become less populated and local communities are disbanded. Another possibility is that crime is merely displaced from one area to another, rather than being reduced. Furthermore, while increased police presence can help deter crime, it might also lead to more crimes being reported, even if the actual incidence remains unchanged.

9.3.1 Descriptive trends

Figure 106 presents average sexual assault victimisation rates per 1,000 population ("sexual assault victimisations") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of sexual assault victimisations per 1,000 population. All victimisations for treated SA2s were suppressed due to Stats NZ suppression rules for confidentiality.[24]

The figure shows the incidence of sexual assault victimisations for control SA2s is relatively low, averaging 0.1 victimisations between 2018 and 2021. There is a noticeable upward trend in average sexual assault victimisations over time for control SA2s, with significant spikes in victimisation rates observed between 2018 and 2019.

Figure 106 Average SA2 sexual assault victimisations by treatment year



Source: IDI 2024. Note all observations for all 'Treated' series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

[24] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero crime victimisations are suppressed.

9.3.2 Area-level DiD analysis

Table 27 presents regression results examining sexual assault victimisations for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 107 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on sexual assault victimisations. The SA2 and SA1 ATT $\hat{v}_g$ and $\hat{w}_g$ in Table 27 (column I) show no impact of UR on sexual assault victimisations in treated areas, relative to control areas.

The heterogeneity analysis shows mixed impacts of UR on sexual assault victimisations. There is a significant increase of 0.3 victimisations for SH residents in low UR SA2s compared to control SA2s, which is statistically significant at the 5% level. Although no pre-treatment averages are available for treated SA2s, this represents a 300% increase in average sexual assault victimisations for control SA2s. Unlike family violence (Section 9.1) and assaults (Section 9.2), sexual assault victimisations did not significantly increase at $\ell = 18$ (relative months from treatment) and therefore not likely to be related to this period of significantly higher victimisations.

There is no corresponding impact at the SA1 level for SH in low UR SA1s which suggests sexual assaults are likely occurring in untreated SA1s (within a treated SA2). This pattern aligns with the findings for family violence (Section 9.1) and assault (Section 9.2) victimisations, suggesting that UR may be displacing sexual assault victimisations (Borbely & Rossi, 2023) from treated SA1s to untreated SA1s (within a treated SA2), or that increased policing is resulting in more sexual assault victimisations being detected.

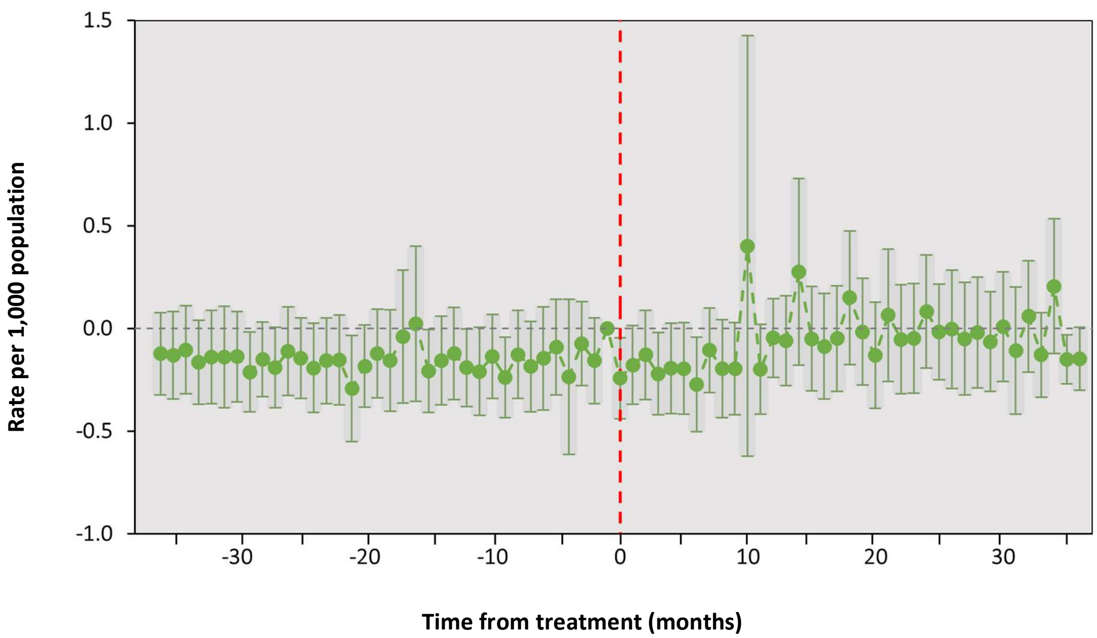
The heterogeneity also shows sexual assault victimisations significantly decreased by 0.3 victimisations for NSH in high UR SA2s relative to control SA2s. This decrease is of the same magnitude but in the opposite direction as the increase observed for SH in low UR SA2s, representing a 300% decrease in average sexual assault victimisations for control SA2s. Areas that receive higher levels of investment are more likely to experience significant change (Mohan et al., 2017). As such, high UR neighbourhoods are likely to benefit from large-scale developments, such as improved aesthetics, increased policing, and enhanced natural surveillance, which may help minimise unsafe areas where sexual assaults could occur.

Table 27 Impact of urban regeneration on sexual assault victimisations

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Sexual assault victimisations (rate per 1,000 population)			
All Population	-0.077 [-0.253, 0.098]	-0.331** [-0.555, -0.106]	0.012 [-0.208, 0.232]
Social Housing	0.257* [0.051, 0.464]	-0.011 [-0.283, 0.260]	0.312** [0.084, 0.541]
Non-Social Housing	-0.098 [-0.295, 0.100]	-0.323* [-0.618, -0.028]	-0.018 [-0.260, 0.224]
SA1 – Sexual assault victimisations (rate per 1,000 population)			
All Population	-0.001 [-0.202, 0.200]	-0.013 [-0.301, 0.200]	0.004 [-0.197, 0.205]
Social Housing	0.216 [-0.018, 0.449]	0.334 [-0.027, 0.695]	-0.023 [-0.239, 0.193]
Non-Social Housing	-0.031 [-0.244, 0.181]	-0.056 [-0.359, 0.247]	0.184 [-0.057, 0.425]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 107 DiD - urban regeneration on sexual assault victimisations (SA2, All Population)

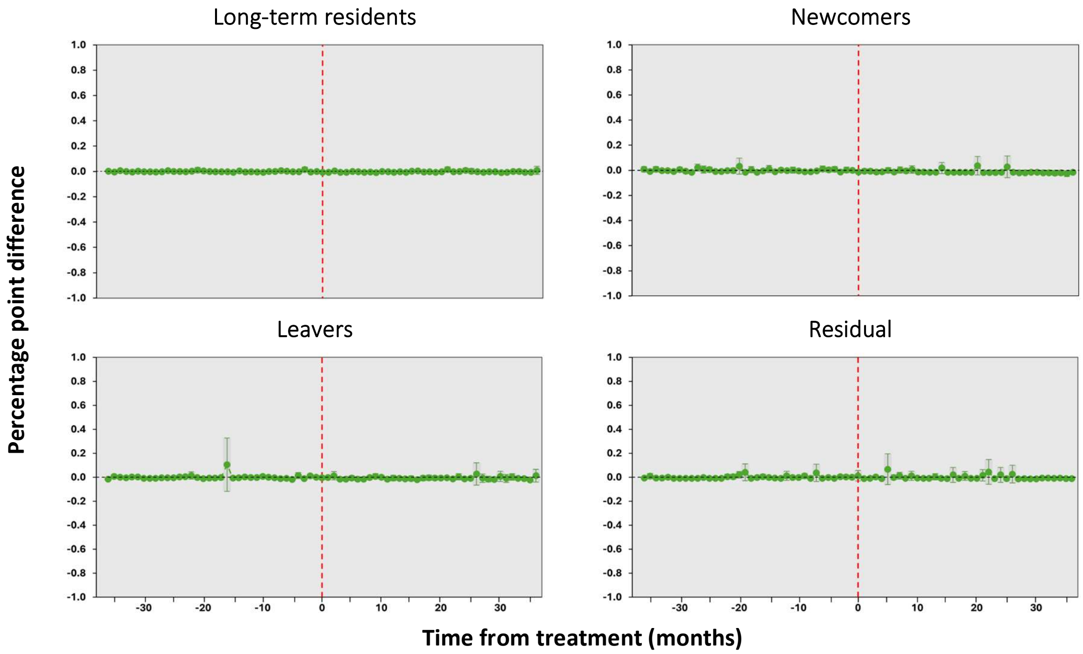


Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.3.3 Individual-level DiD analysis

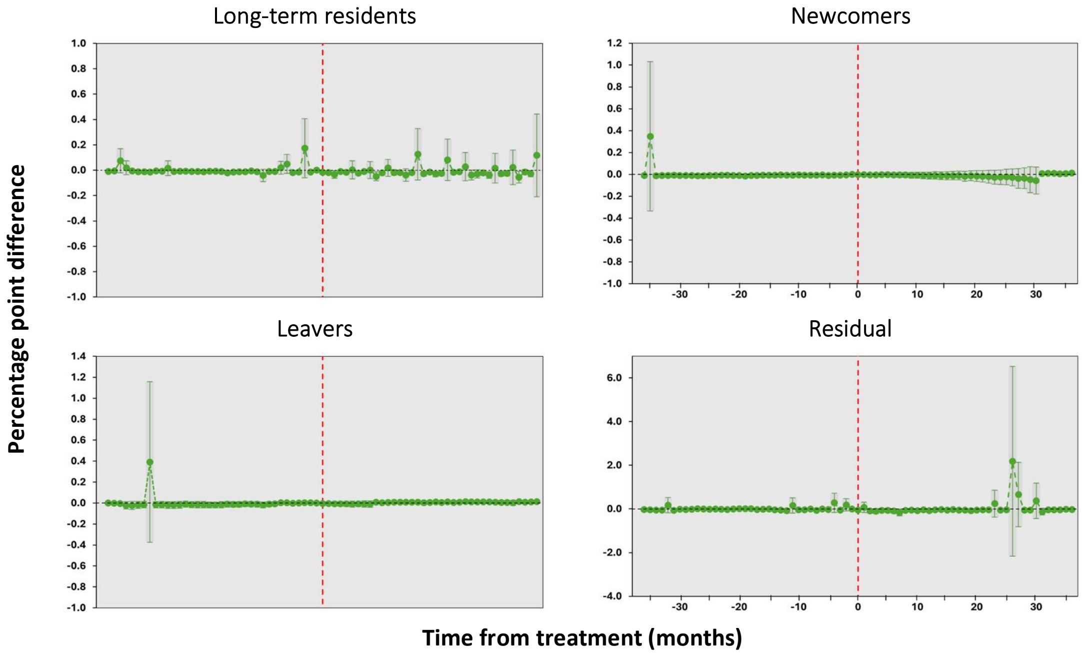
Figure 108 presents individual-level sexual assault victimisation regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 109) and NSH (Figure 110). Given the relatively low incidence rate of sexual assault victimisations, the individual-level analysis shows no impact of UR on sexual assault victimisations by different subpopulations.

Figure 108 DiD - urban regeneration on sexual assault victimisations (Individual, All Population)



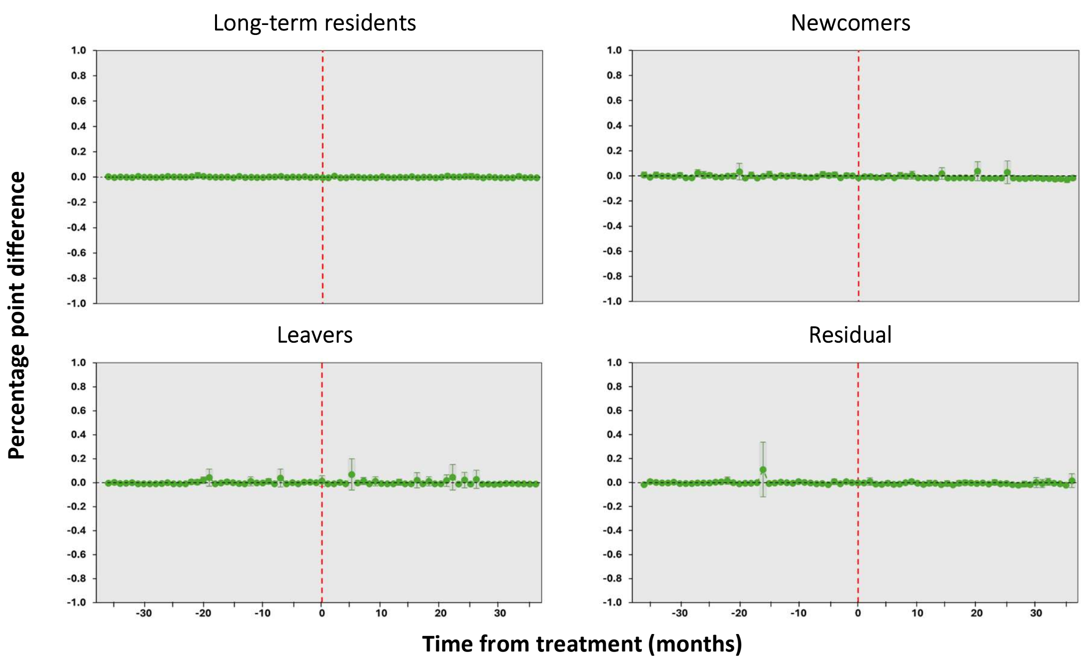
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 109 DiD - urban regeneration on sexual assault victimisations (Individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 110 DiD - urban regeneration on sexual assault victimisations (Individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

9.4 Theft victimisations

The mechanisms by which UR may reduce theft victimisations are similar to those for family violence, as described in Section 9.1. That is, increased police presence, neighbourhood warden schemes, increased density and mixed tenure and improved neighbourhood aesthetics may discourage or reduce the occurrence of crime.

However, as described in Section 9.1, higher density can also increase population levels, potentially leading to a rise in crime rates. Additionally, during ongoing construction, areas might experience a temporary increase in crime as they become less populated and local communities are disbanded. Another possibility is that crime is merely displaced from one area to another, rather than being reduced. Furthermore, while increased police presence can help deter crime, it might also lead to more crimes being reported, even if the actual incidence remains unchanged.

As with assault victimisations, examining theft victimisations is of interest in this study, as they can be indicative of antisocial behaviour particularly in areas undergoing SH development (see Section 2.2.4 and 5.2.1). If SH tenants are perceived as more likely to commit crimes such as assaults or theft, then treated areas would expect an increase in victimisations compared to control areas.

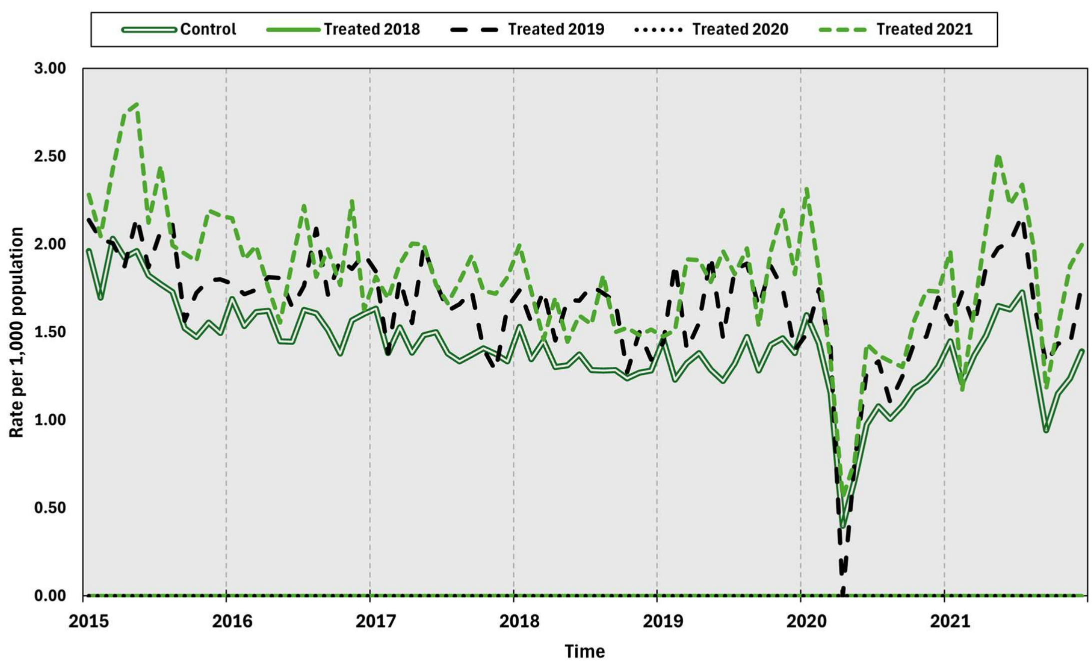
It is important to note that this study does not record if theft is perpetrated by SH or NSH, only if the victim was living in SH or not at the time of victimisation. Additionally, this study does not record where the victimisation took place, for example, if victimisations took place within the resident SA2 or elsewhere. Residents who spend more time away from home due to construction or noise may have less exposure to being potential theft victims.

9.4.1 Descriptive trends

Figure 111 presents average theft victimisation rates per 1,000 population ("theft victimisations") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of theft victimisations per 1,000 population. All average theft victimisations for SA2s treated in 2018 and 2020 were suppressed due to Stats NZ suppression rules for confidentiality.[25]

Between 2015 and 2017, average theft victimisations steadily declined for both treated and control SA2s. At the end of 2017, average theft victimisations were 1.7 for treated SA2s and 1.3 for control SA2s. Victimisations sharply fall during the COVID-19 pandemic in 2020, followed by a recovery to pre-COVID levels. By the end of 2021, average theft victimisations marginally exceeded pre-treatment averages, reaching 1.9 for treated SA2s and 1.4 for control SA2s.

Figure 111 Average SA2 theft victimisations by treatment year



Source: IDI 2024. Note all observations for the 'Treated – 2018' and 'Treated – 2020' series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

[25] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero crime victimisations are suppressed.

9.4.2 Area-level DiD analysis

Table 28 presents regression results examining theft victimisations for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 112 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on theft victimisations. The SA2 and SA1 ATT $\hat{\upsilon}_g$ and $\widehat{w}_g$ in Table 28 (column I) further confirm there is no impact of UR on theft victimisations in treated areas, relative to control areas.

The heterogeneity analysis identifies two populations significantly impacted by UR - all residents in high UR SA1s and SH in low UR areas. Theft victimisations significantly increased for both SH (by 1.5 victimisations) and NSH residents (by 0.8 victimisations) in high UR SA1s compared to control SA1s. The magnitude of these increases is economically large, representing an 86.8% and 49.2% increase in average pre-treatment theft victimisations, respectively.

As shown in Figure 138 in Appendix 7, theft victimisations were already significantly higher in high UR SA1s relative to control SA1s, indicating that theft may have already been a common issue in these areas prior to UR. Victimisations continued to remain significantly higher in the two years following UR, with SH experiencing a greater frequency and magnitude of theft victimisations compared to NSH. Theft victimisations in high UR SA1s were not significantly different to control SA1s from $\ell = 24$ onwards (relative months from treatment).

Given that Kāinga Ora-led urban regeneration primarily focuses on increasing SH, residents in SH may be more vulnerable to antisocial behaviours from other SH residents due to their closer proximity to one another compared to NSH residents. Additionally, characteristics of high UR SA1s may have made them more appealing targets for theft, such as inadequate lighting, abandoned houses, and fewer neighbourhood amenities, alongside lower policing levels before and during construction (Henry et al., 2019).

Once developments are complete and residents return to improved homes, neighbourhoods with better amenities and increased policing, there may be a reduction in theft victimisations (Batty et al., 2010; Bull et al., 2015). Alternatively, the higher density of people in these areas could simply lead to increased crime rates (Batty et al., 2010; Bull et al., 2015). Further analysis assessing medium to long-term theft victimisations is needed to see which is the case.

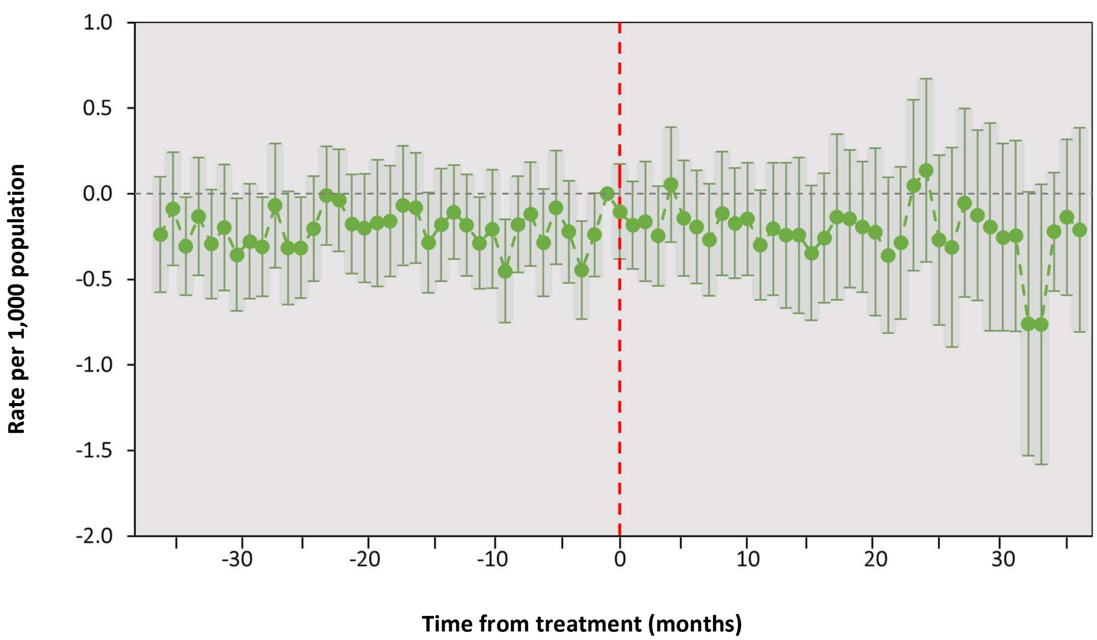
The heterogeneity analysis also shows a significant increase in theft victimisations for SH in low UR areas compared to control areas. Low UR areas have less development compared to high UR areas and may not benefit from UR to the same extent that residents in high UR areas do. There is less SH being built, which may not result in many neighbourhood amenities being built or improved.

Table 28 Impact of urban regeneration on theft victimisations

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Theft victimisations (rate per 1,000 population)			
All Population	-0.194 [-0.515, 0.127]	-0.893 [-1.935, 0.150]	0.055 [-0.152, 0.263]
Social Housing	0.944*** [0.507, 1.381]	0.793** [0.207, 1.379]	0.992*** [0.462, 1.523]
Non-Social Housing	-0.339 [-0.749, 0.071]	-1.347 [-2.777, 0.083]	0.021 [-0.182, 0.225]
SA1 – Theft victimisations (rate per 1,000 population)			
All Population	0.257 [-0.062, 0.576]	0.783* [0.136, 1.429]	0.131 [-0.222, 0.484]
Social Housing	0.952*** [0.392, 1.511]	1.465*** [0.976, 1.954]	0.818* [0.141, 1.494]
Non-Social Housing	0.125 [-0.259, 0.510]	0.845* [0.093, 1.598]	-0.039 [-0.470, 0.391]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 112 DiD - urban regeneration on theft victimisations (SA2,All Population)

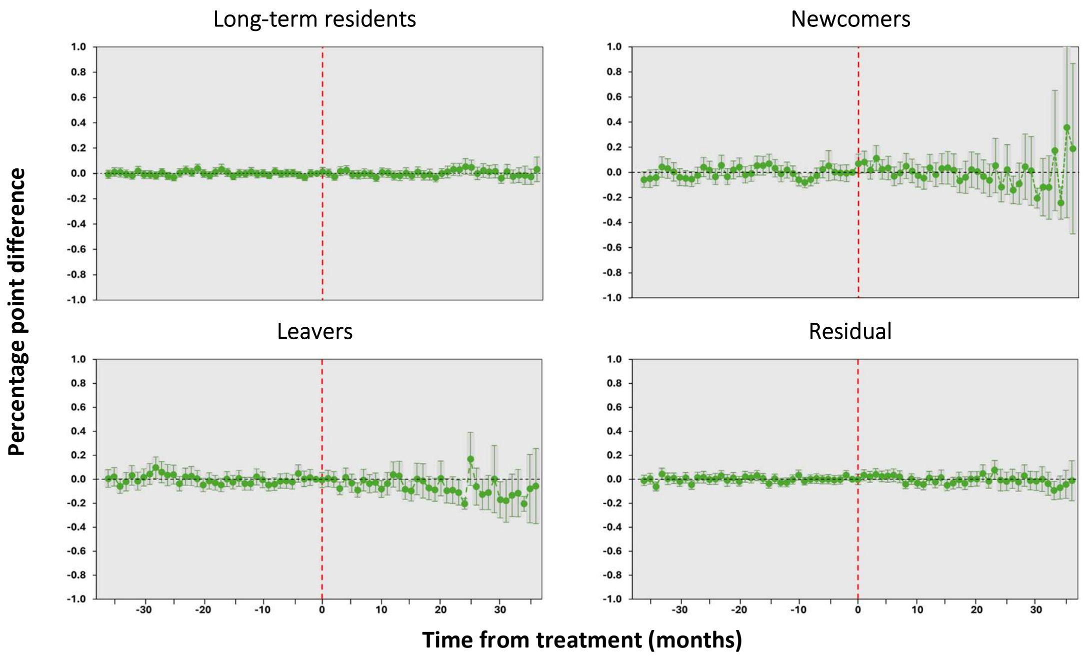


Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.4.3 Individual-level DiD analysis

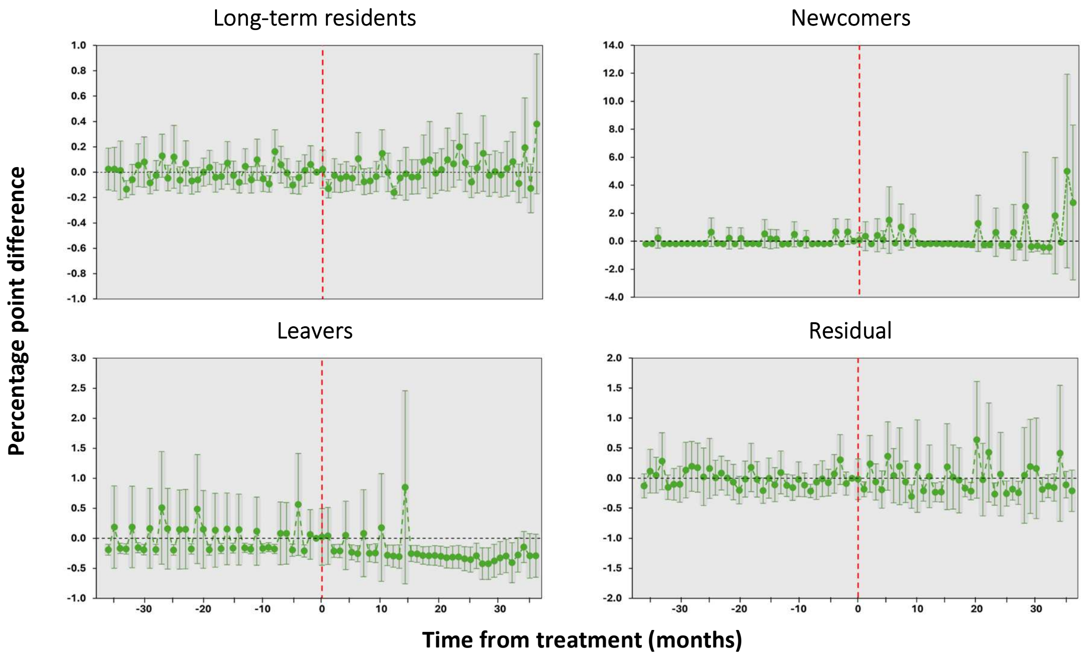
Figure 113 presents individual-level theft victimisation regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 114) and NSH (Figure 115). The area-level heterogeneity analysis showed significant differences in theft victimisation rates. However, there is little to no impacts observed with respects to theft victimisations at the individual-level.

Figure 113 DiD - urban regeneration on theft victimisations (Individual, All Population)



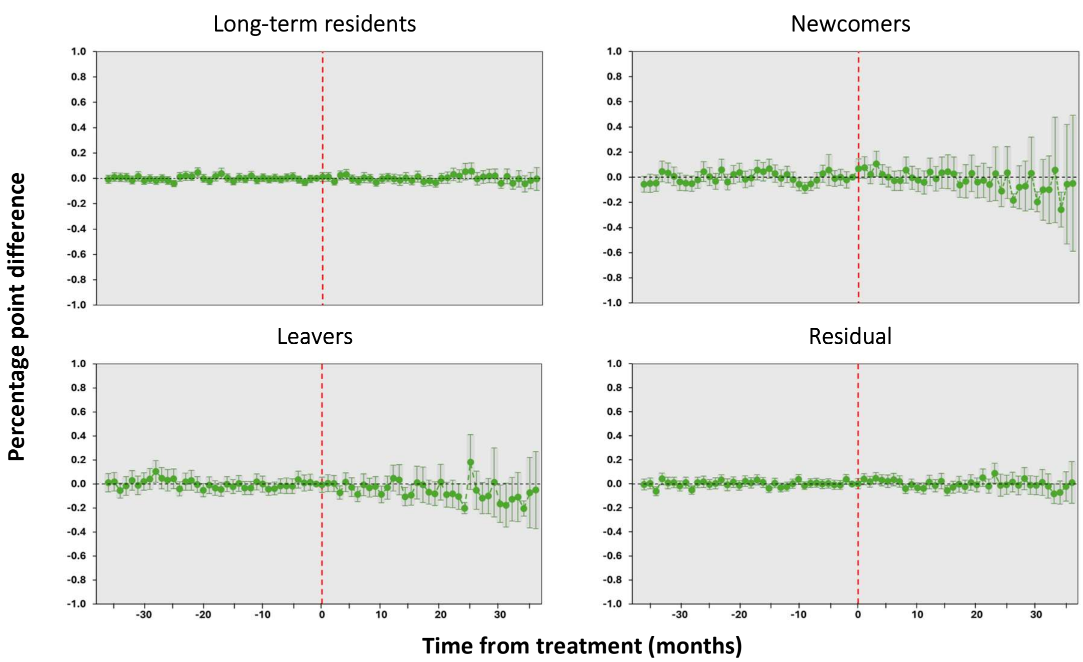
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 114 DiD - urban regeneration on theft victimisations (Individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 115 DiD - urban regeneration on theft victimisations (Individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

9.5 Robbery and extortion victimisations

The mechanisms by which UR may reduce robbery and extortion ("robbery") victimisations are similar to those for family violence, as described in Section 9.1. That is, increased police presence, neighbourhood warden schemes, increased density and mixed tenure and improved neighbourhood aesthetics may discourage or reduce the occurrence of crime.

However, as described in Section 9.1, higher density can also increase population levels, potentially leading to a rise in crime rates. Additionally, during ongoing construction, areas might experience a temporary increase in crime as they become less populated and local communities are disbanded. Another possibility is that crime is merely displaced from one area to another, rather than being reduced. Furthermore, while increased police presence can help deter crime, it might also lead to more crimes being reported, even if the actual incidence remains unchanged.

As with assault victimisations, examining robbery victimisations is of interest in this study, as they can be indicative of antisocial behaviour particularly in areas undergoing SH development (see Section 2.2.4 and 5.2.1). If SH tenants are perceived as more likely to commit crimes such as robberies, then treated areas would expect an increase in victimisations compared to control areas.

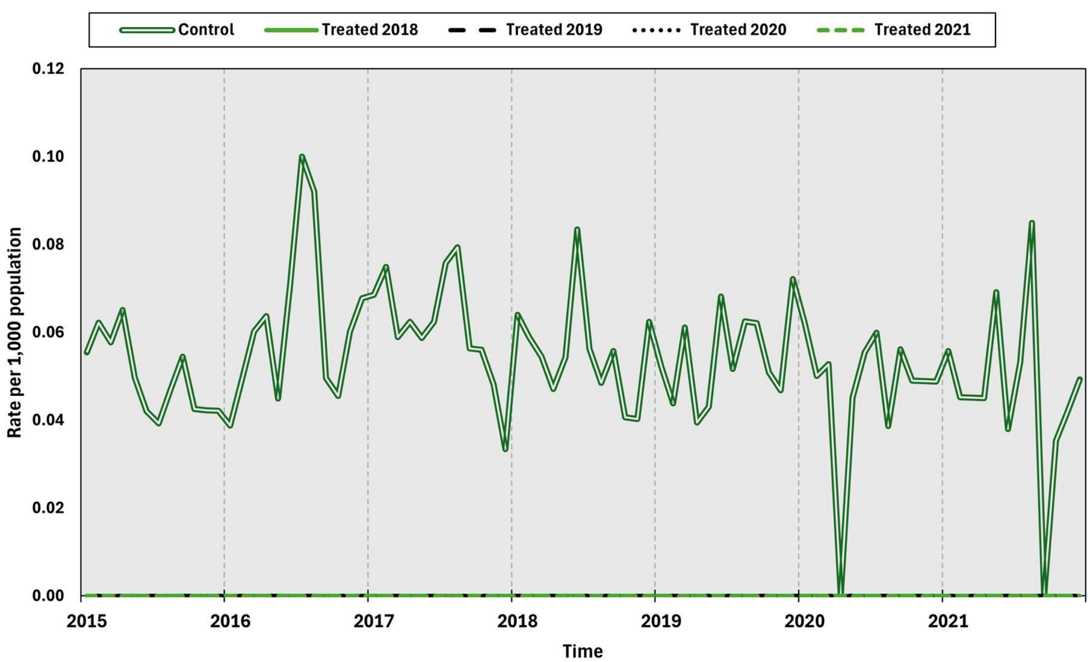
It is important to note that this study does not record if a robbery is perpetrated by SH or NSH, only if the victim was living in SH or not at the time of victimisation. Additionally, this study does not record where the victimisation took place, for example, if victimisations took place within the resident SA2 or elsewhere. Residents who spend more time away from home due to construction or noise may have less exposure to being potential robbery victims.

9.5.1 Descriptive trends

Figure 116 presents average robbery and extortion victimisation rates per 1,000 population ("robbery victimisations") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of robbery and extortion victimisations per 1,000 population. All victimisations for treated SA2s were suppressed due to Stats NZ suppression rules for confidentiality.[26]

The figure shows the incidence of robbery victimisations for control SA2s is relatively low, averaging 0.05 victimisations between 2018 and 2021. Over time, average robbery victimisations for control SA1s remain mostly stable, with noticeable dips in average victimisations occurring during the COVID-19 restrictions in early 2020 and towards the end of 2021.

Figure 116 Average SA2 robbery victimisations by treatment year



Source: IDI 2024. Note all observations for all 'Treated' series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

[26] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero crime victimisations are suppressed.

9.5.2 Area-level DiD analysis

Table 29 presents regression results examining robbery victimisations for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 117 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on robbery victimisations. The SA2 and SA1 ATT $\hat{\upsilon}_g$ and $\widehat{w}_g$ in Table 29 (column I) show no impact of UR on robbery victimisations in treated areas, relative to control areas.

Similarly, as with theft victimisations, the heterogeneity analysis shows there are two populations significantly impacted by UR – all residents in high UR SA1s and SH in low UR areas. Relative to control SA1s, robbery victimisations significantly increased by 0.06 for SH in high UR SA1s, 0.05 for SH in low UR SA1s, and 0.1 for NSH residents. Although no pre-treatment averages were available for treated SA2s, these increases reflect a 100% to 200% rise in average robbery victimisations for control SA2s.

Unlike theft victimisations, robbery victimisations were not significantly different for these populations in the pre-treatment period, with significant differences only appearing in the post-treatment period. As shown in Figure 139 in Appendix 7, robbery victimisations for NSH were only significantly higher within the first 6 months after the onset of UR. In contrast, Figure 140 shows robbery victimisations were significantly higher for SH between $\ell = 10$ and $\ell = 26$ (relative months from treatment).

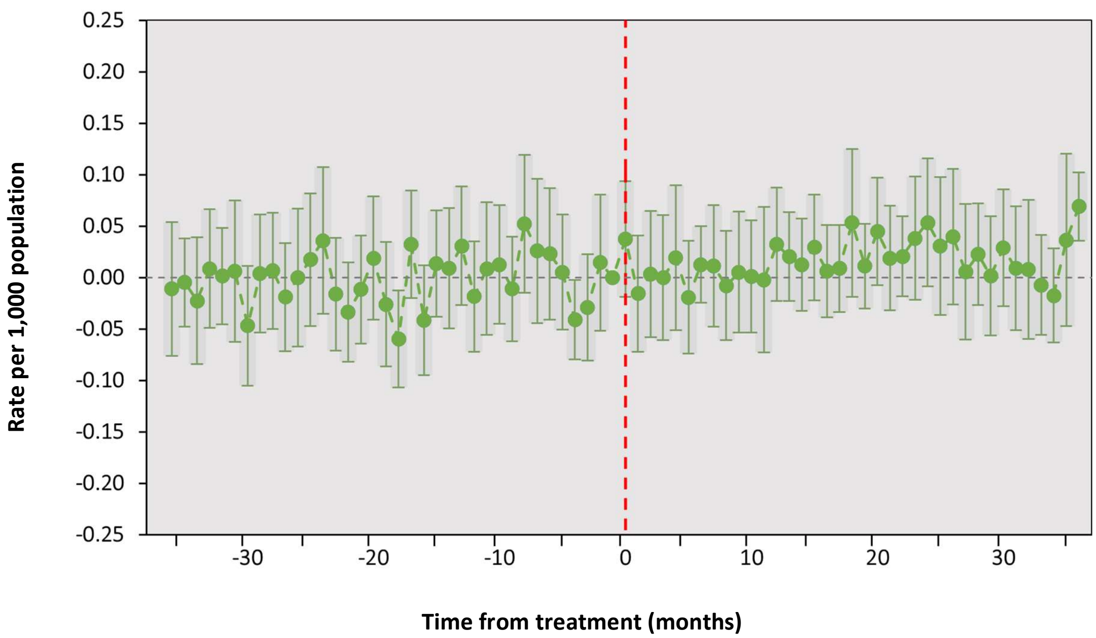
Areas with new SH developments may attract potential robbers, as higher density areas typically have more people and potential victims (Badland et al., 2017; Bull et al., 2015). Initially, NSH may have been targeted, prompting them to implement preventive measures against future robberies. However, once developments were completed, robbers may have shifted their focus to SH in these new developments. This ongoing increase in robbery victimisations raises concerns that newly established SH developments may be targets for criminal activity. Further medium- to long-term analysis is essential to determine whether this pattern of robbery victimisations persists in the future.

Table 29 Impact of urban regeneration on robbery victimisations

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Robbery and extortion victimisations (rate per 1,000 population)			
All Population	0.014 [-0.018, 0.046]	-0.029 [-0.101, 0.044]	0.029 [-0.002, 0.059]
Social Housing	0.025 [-0.017, 0.067]	-0.006 [-0.091, 0.079]	0.038 [-0.010, 0.085]
Non-Social Housing	0.019 [-0.017, 0.055]	-0.009 [-0.097, 0.080]	0.029 [-0.003, 0.060]
SA1 – Robbery and extortion victimisations (rate per 1,000 population)			
All Population	0.041 [-0.011, 0.093]	0.081*** [0.047, 0.115]	0.031 [-0.030, 0.093]
Social Housing	0.053** [0.020, 0.085]	0.060** [0.015, 0.104]	0.050** [0.015, 0.086]
Non-Social Housing	0.044 [-0.010, 0.098]	0.103*** [0.053, 0.153]	0.030 [-0.034, 0.094]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 117 DiD - urban regeneration on robbery victimisations (SA2, All Population)

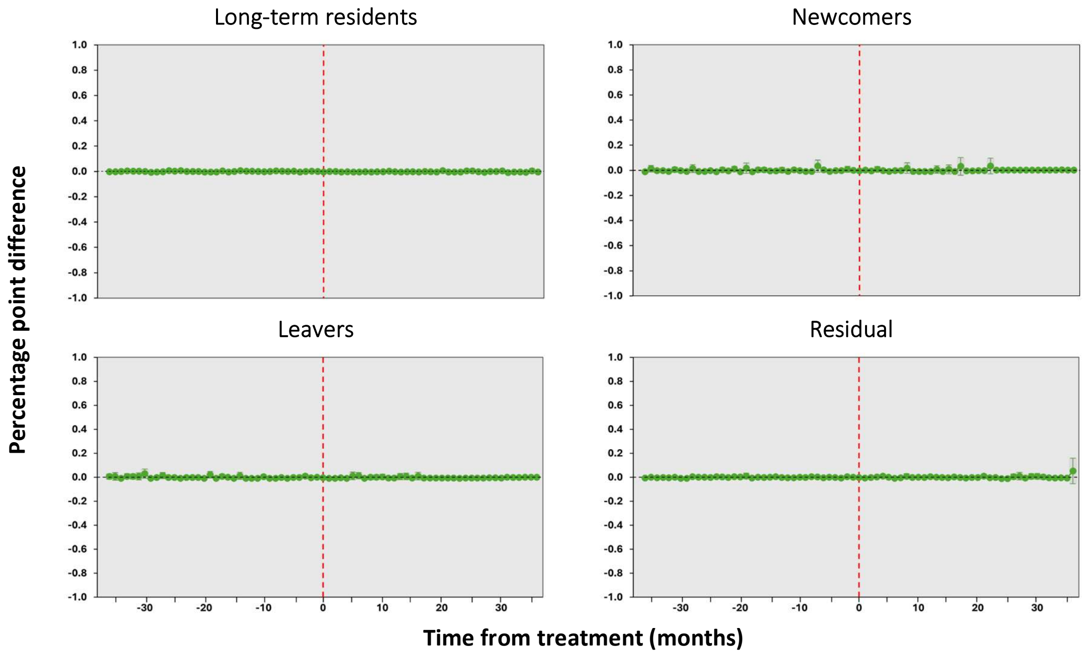


Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.5.3 Individual-level DiD analysis

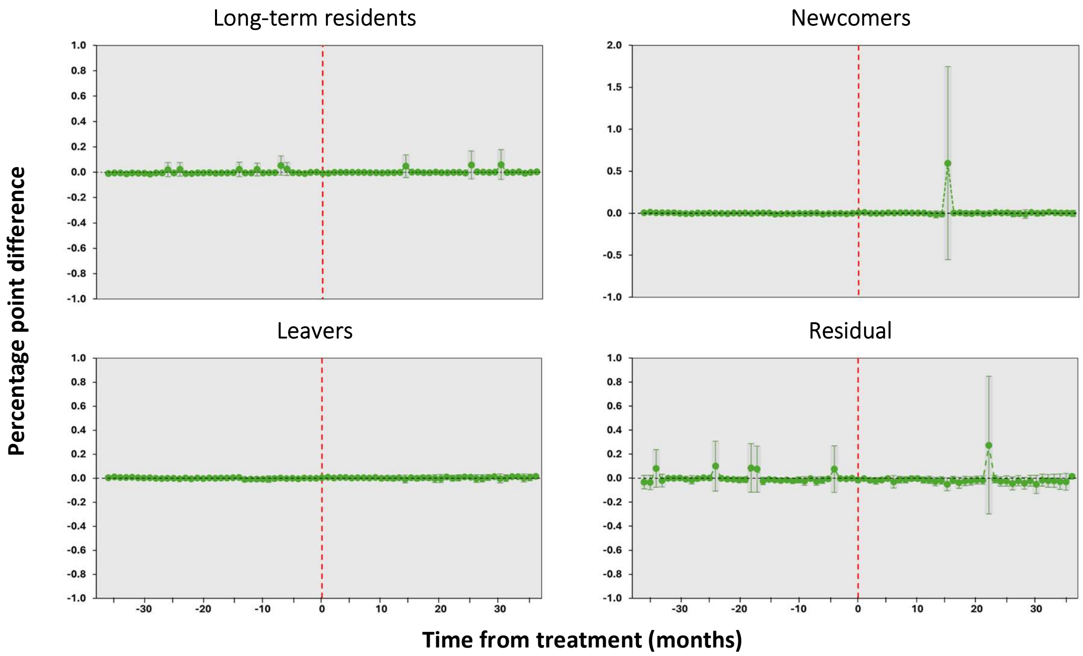
Figure 118 presents individual-level robbery victimisation regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 119) and NSH (Figure 120). Given the relatively low incidence rate of robbery victimisations, the individual-level analysis shows no impact of UR on robbery victimisations by different subpopulations.

Figure 118 DiD - urban regeneration on robbery victimisations (Individual, All Population)



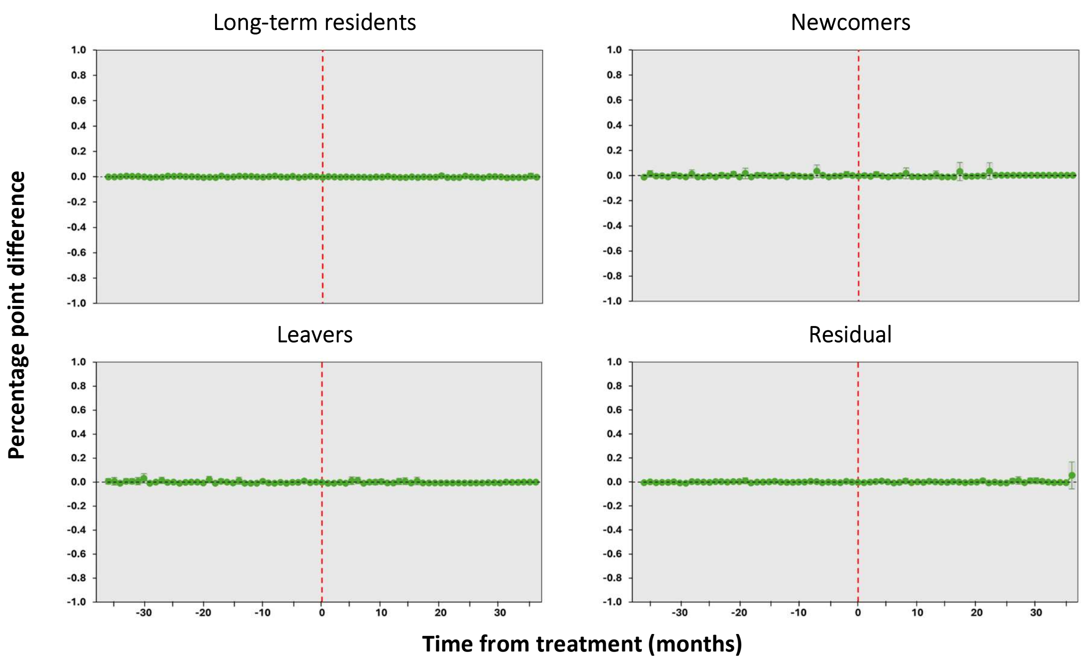
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 119 DiD - urban regeneration robbery victimisations (Individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 120 DiD - urban regeneration on robbery victimisations (Individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

9.6 Work-related accidents and injuries

Stressors outside the workplace can significantly affect the likelihood of workplace accidents. High levels of stress can lead to poor health and negatively impact concentration and information processing, increasing the risk of errors that result in workplace injuries. UR can improve work-related accidents and injuries by alleviating stressors that hinder safe work practices. The mechanisms through which UR achieves this are similar to those discussed for mental health (Section 8.4) and respiratory-related admissions (Section 8.3).

By increasing the housing supply, UR provides residents with more options for housing stability and opportunities to build local support networks. This can help reduce stress and anxiety, which in turn can increase concentration at work. Similarly, as in Section 8.3, warmer and better-insulated homes can lower the incidence of respiratory illnesses, allowing individuals to work more effectively and take fewer sick days off work.

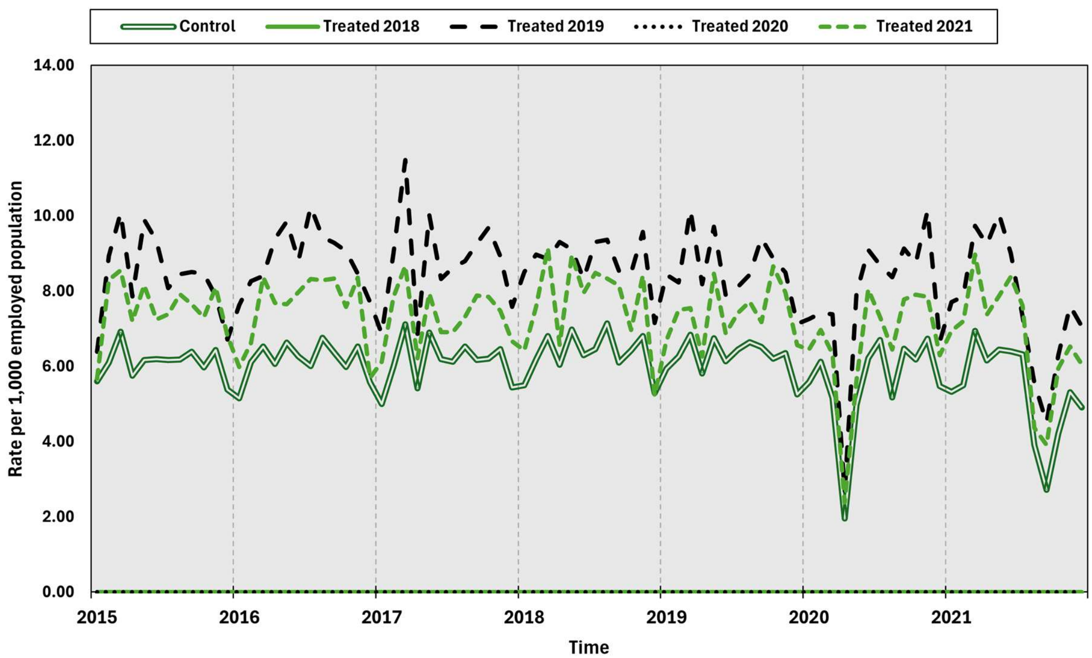
However, UR may also have negative impacts on work-related accidents and injuries by introducing short-term stressors that affect concentration. Related to mental health in Section 8.4, residents may need to temporarily or permanently relocate, which can be disruptive and create uncertainty. The disbanding of local communities can add to this disruption and uncertainty, while continuous construction noise and disturbances may interfere with sleep patterns and relaxation at home. Consequently, tired and stressed individuals may find it challenging to maintain focus and safety in the workplace, which may lead to accidents.

9.6.1 Descriptive trends

Figure 121 presents workplace accidents and injuries rate per 1,000 employed population ("workplace accidents") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of workplace accidents per 1,000 employed population aged between 25 to 64 (inclusive). All workplace accidents for SA2s treated in 2018 and 2020 were suppressed due to Stats NZ suppression rules for confidentiality.[27]

Excluding the two COVID-19 lockdown periods, average workplace accident rates remain relatively stable over time for both treated and control SA2s. However, treated SA2s generally exhibit higher average workplace accident rates compared to control SA2s. At the end of 2017, the average workplace accident rate was 7.1 for treated SA2s and 5.4 for control SA2s.

Figure 121 Average SA2 workplace accidents by treatment year



Source: IDI 2024. Note: rate per 1,000 employed individuals aged between 25 to 64 (inclusive) and all observations for the 'Treated – 2018' and 'Treated – 2020' series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

[27] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero accidents are suppressed.

9.6.2 Area-level DiD analysis

Table 30 presents regression results examining workplace accidents for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 121 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on workplace accidents.

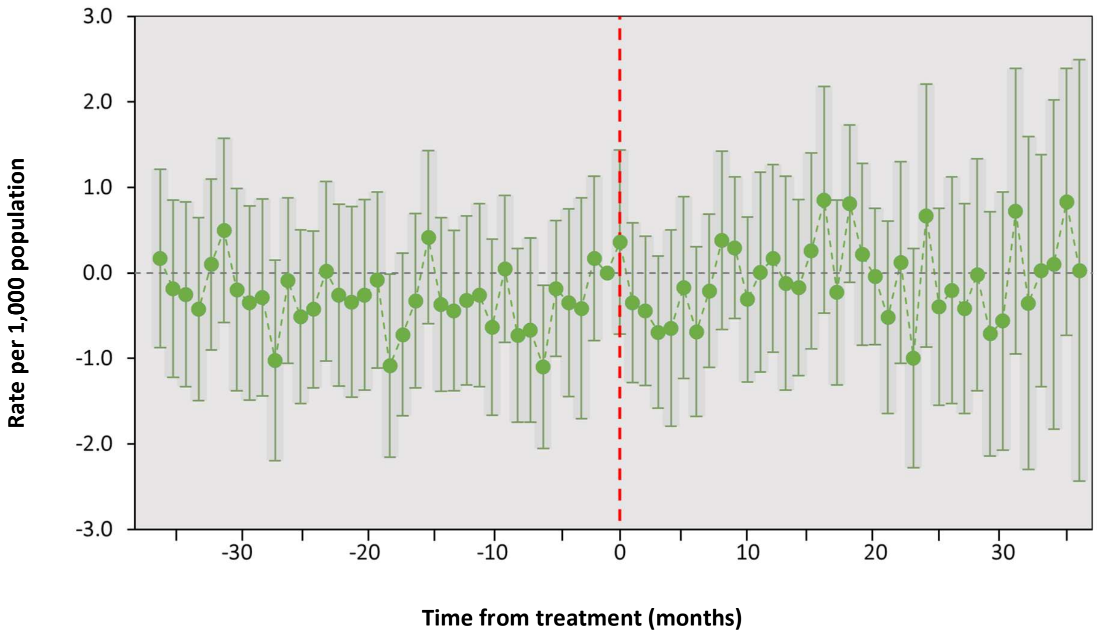
The SA2 and SA1 ATT $\hat{\upsilon}_g$ and $\widehat{w}_g$ coefficients in Table 30 (column I) further confirm there is no impact of UR on workplace accidents in treated areas, relative to control areas. Similarly, the heterogeneity analysis also shows no impact of UR on workplace accidents. While there is the potential for UR to positively impact workplace accidents by alleviating stressors outside of work, this does not appear to be the case in the short run. Further analysis in the medium to longer run is needed to see if this changes once developments are complete.

Table 30 Impact of urban regeneration on workplace accidents

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Work-related accidents and injuries (rate per 1,000 employed population)			
All Population	-0.102 [-0.847, 0.643]	-0.582 [-2.566, 1.403]	0.068 [-0.532, 0.669]
Social Housing	-2.823 [-5.764, 0.118]	-6.544 [-14.471, 1.382]	-1.565 [-3.938, 0.807]
Non-Social Housing	-0.241 [-0.957, 0.474]	-0.731 [-2.417, 0.955]	-0.068 [-0.736, 0.601]
SA2 – Work-related accidents and injuries (rate per 1,000 employed population)			
All Population	-0.244 [-1.639, 1.151]	-0.643 [-3.380, 2.093]	-0.139 [-1.638, 1.361]
Social Housing	-0.867 [-7.292, 5.558]	-1.820 [-7.767, 4.127]	-0.351 [-7.963, 7.261]
Non-Social Housing	0.100 [-1.399, 1.598]	0.713 [-2.933, 4.359]	-0.065 [-1.649, 1.519]

Source: IDI 2024. Note UR – urban regeneration. Rate per 1,000 employed individuals aged between 25 to 64 (inclusive)**.** Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{\upsilon}}_g$ *and* $\widehat{\boldsymbol{w}}_g$*,* in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 122 DiD - urban regeneration on workplace accidents (SA2, All Population)



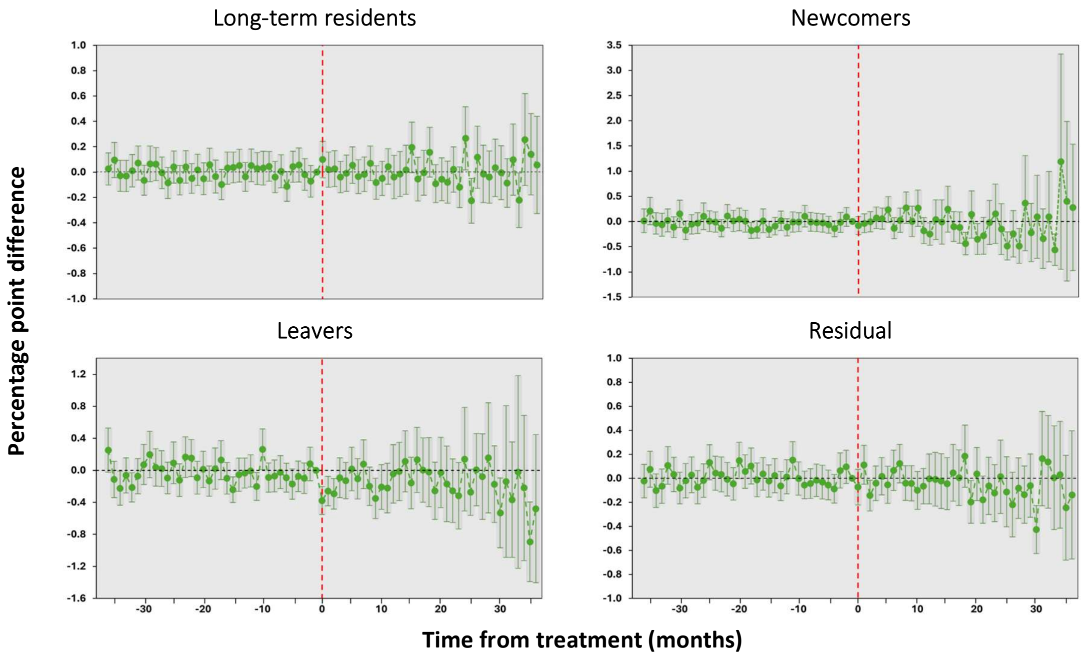
Source: IDI 2024. Note: rate per 1,000 employed individuals aged between 25 to 64 (inclusive). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.6.3 Individual-level DiD analysis

Figure 123 presents individual-level workplace accident regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 124) and NSH (Figure 125). Consistent with the area-level analysis, the individual-level analysis indicates no impact of UR on workplace accidents (Figure 123).

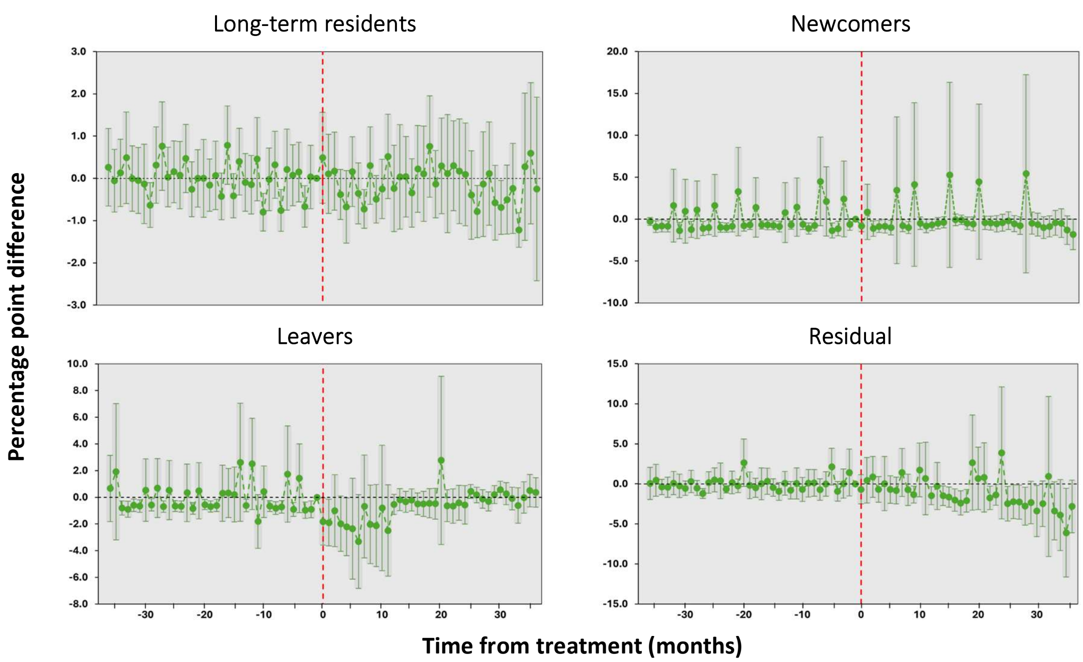
The heterogeneity analysis shows a significant decrease in workplace accidents for SH residual residents living in treated areas compared to SH residual residents in control areas (Figure 124). Specifically, workplace accidents decreased by between 1.5 and 6.1 percentage points for SH residual residents relative to their control counterparts. While statistically significant, this reduction translates to a maximum of 0.4 fewer accidents from the average pre-treatment workplace accident rate, which represents an economically small decrease in workplace accidents.

Figure 123 DiD - urban regeneration on workplace accidents (Individual, All Population)



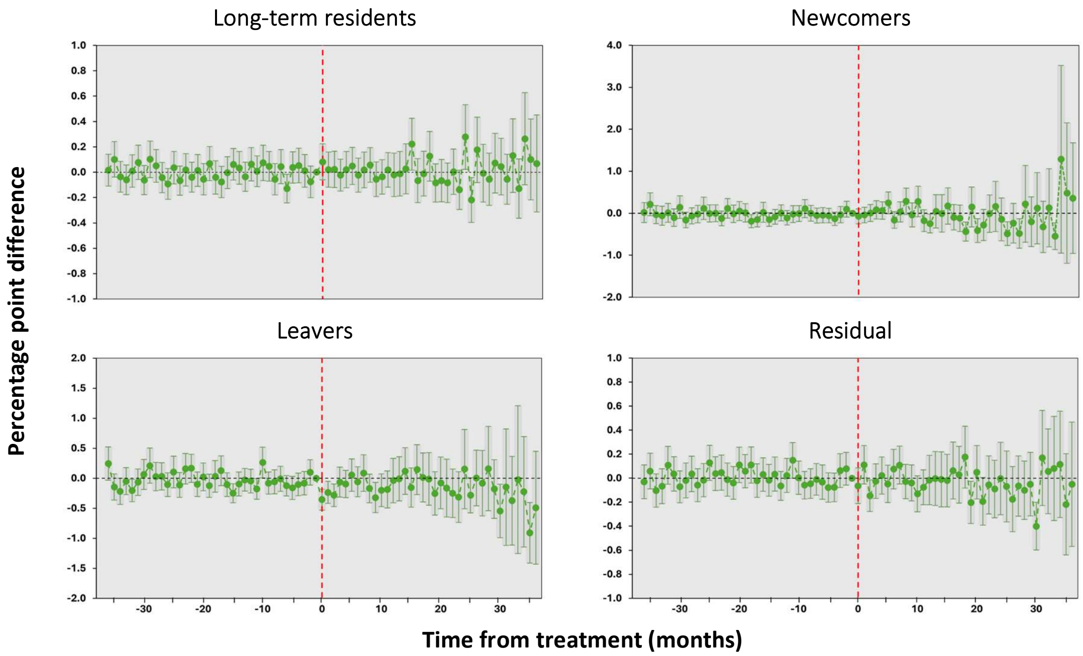
Source: IDI 2024. Note: includes employed individuals aged between 25 to 64 (inclusive). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 124 DiD - urban regeneration on workplace accidents (Individual, Social Housing)



Source: IDI 2024. Note: includes employed individuals aged between 25 to 64 (inclusive). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\varphi}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 125 DiD - urban regeneration workplace accidents (Individual, Non-Social Housing)



Source: IDI 2024. Note: includes employed individuals aged between 25 to 64 (inclusive). Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\widehat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

9.7 Home-related accidents and injuries

Home is the environment where people spend much of their time. Various injury hazards are commonly found in older homes, including unsafe electrical wiring, inadequate lighting, uneven or slippery floors, and unsecured carpets. UR can positively impact home-related accidents and injuries by improving existing homes or replacing older dwellings with new, safer homes, which may result in fewer injuries (Keall et al., 2015; Keall et al., 2021).

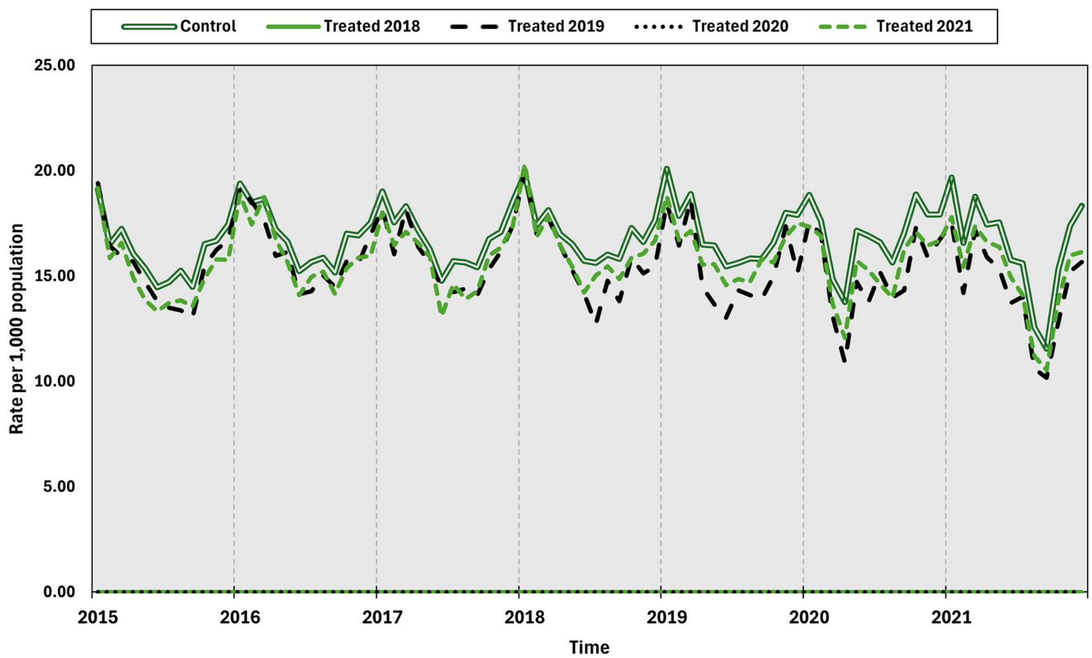
However, it is also possible that home accidents could increase as a result of UR. Housing intensification typically involves replacing single dwelling with multi-unit dwellings, such as townhouses and walk-up apartments (as described in Section 2.2.1). This increases the number of stairs required to access dwellings (such as walk-up apartments) or to move within dwellings (such as townhouses) which can increase the likelihood of accidents.

9.7.1 Descriptive trends

Figure 126 presents home accidents and injuries rate per 1,000 population ("home accidents") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of home accidents per 1,000 population. All home accidents for SA2s treated in 2018 and 2020 were suppressed due to Stats NZ suppression rules for confidentiality.[28]

The figure shows, on average, home accidents are similar for treated and control SA2s. At the end of 2017, the average rates were 17.3 for treated SA2s and 18.5 for control SA2s. The two noticeable dips in average home accidents correspond to the COVID-19 lockdowns in early 2020 and late 2021. However, average home accident rates recover and remain relatively consistent with pre-COVID levels.

Figure 126 Average SA2 home accidents by treatment year



Source: IDI 2024. Note all observations for the 'Treated – 2018' and 'Treated – 2020' series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

[28] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero accidents are suppressed.

9.7.2 Area-level DiD analysis

Table 31 presents regression results examining home accidents for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 127 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there is no significant impact of UR on home accidents. The SA2 and SA1 ATT $\hat{\upsilon}_g$ and $\widehat{w}_g$ in Table 31 (column I) show no impact of UR on home accidents in treated areas, relative to control areas.

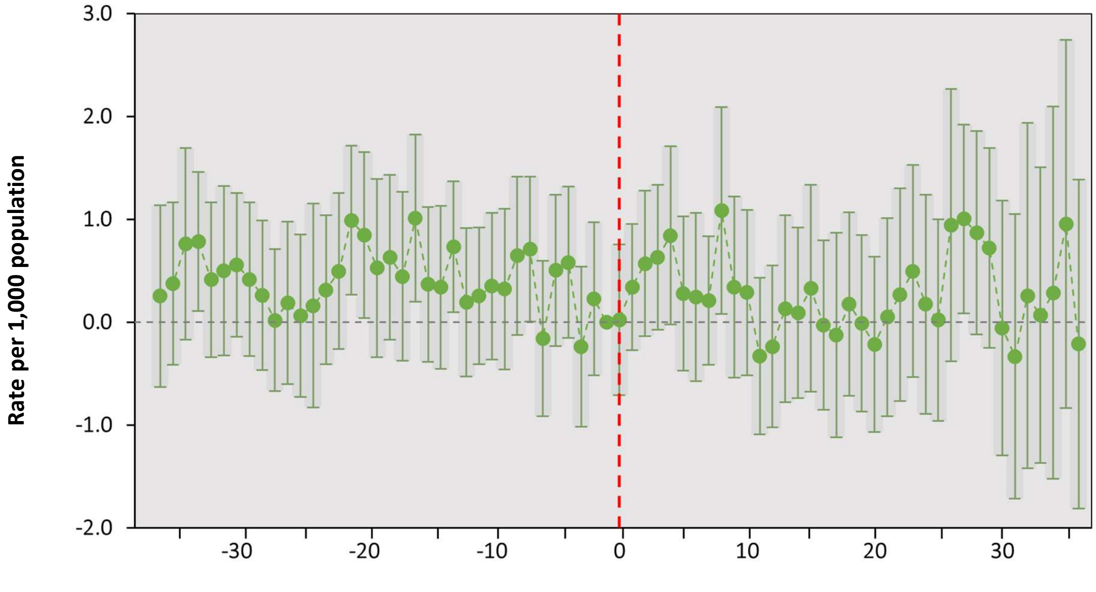
The heterogeneity analysis shows a significant increase of 4.2 home accidents for SH residents in high UR SA1s compared to control SA1s, which is statistically significant at the < 1% level. Unsurprisingly, there is no corresponding impact at the SA2-level as the impact of UR on home accidents should primarily affect residents in homes directly constructed through UR initiatives and unlikely to have spillover impacts at the neighbourhood level. While housing intensification can improve home safety by replacing older, potentially hazardous dwellings with newer ones, the increase in multi-unit dwellings such as townhouses and walk-up apartments can introduce more stairs compared to single-level homes. These housing typologies can increase the risk of falls and slips at home, leading to increased home accident rates.

Table 31 Impact of urban regeneration on home accidents

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Home-related accidents and injuries (rate per 1,000 population)			
All Population	0.289 [-0.328, 0.905]	-0.069 [-0.941, 0.804]	0.421 [-0.272, 1.113]
Social Housing	-0.167 [-5.631, 5.297]	0.064 [-2.513, 2.640]	-0.197 [-7.302, 6.909]
Non-Social Housing	0.204 [-0.412, 0.819]	-0.312 [-1.223, 0.600]	0.389 [-0.289, 1.067]
SA12 – Home-related accidents and injuries (rate per 1,000 population)			
All Population	0.136 [-1.005, 1.276]	1.665 [-0.970, 4.300]	-0.227 [-1.443, 0.989]
Social Housing	-2.403 [-6.764, 1.958]	4.202*** [1.768, 6.635]	-4.005 [-9.337, 1.326]
Non-Social Housing	0.068 [-1.359, 1.495]	1.037 [-3.024, 5.097]	-0.197 [-1.597, 1.204]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{\upsilon}}_{\boldsymbol{g}}$ *and* $\widehat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 127 DiD - urban regeneration on home accidents (SA2, All Population)



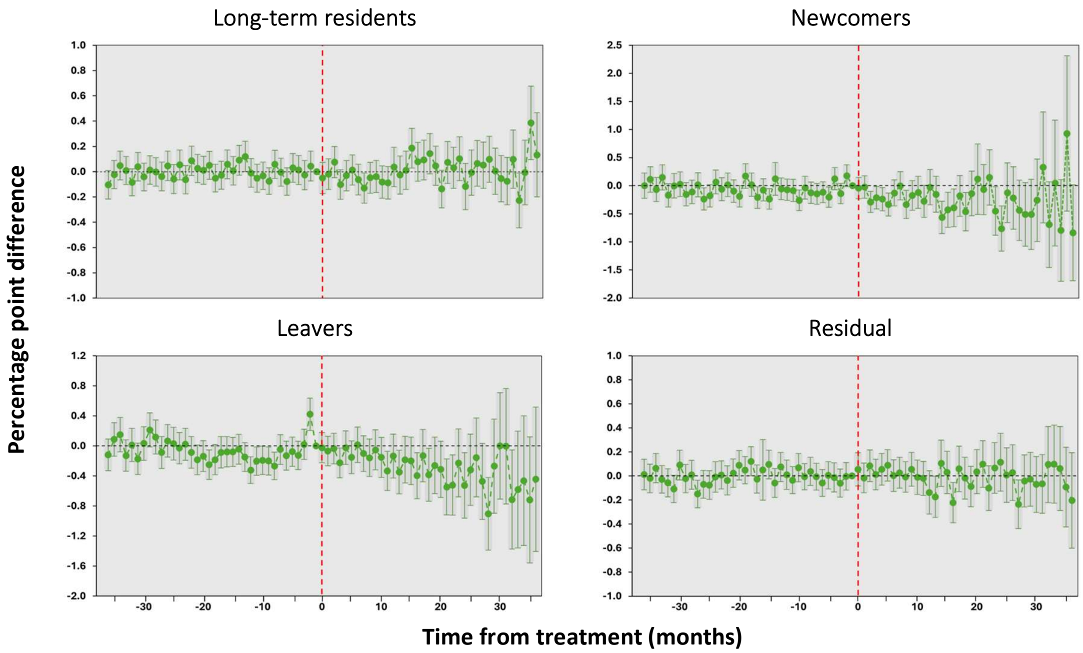
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.7.3 Individual-level DiD analysis

Figure 128 presents individual-level home accident regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 129) and NSH (Figure 130).

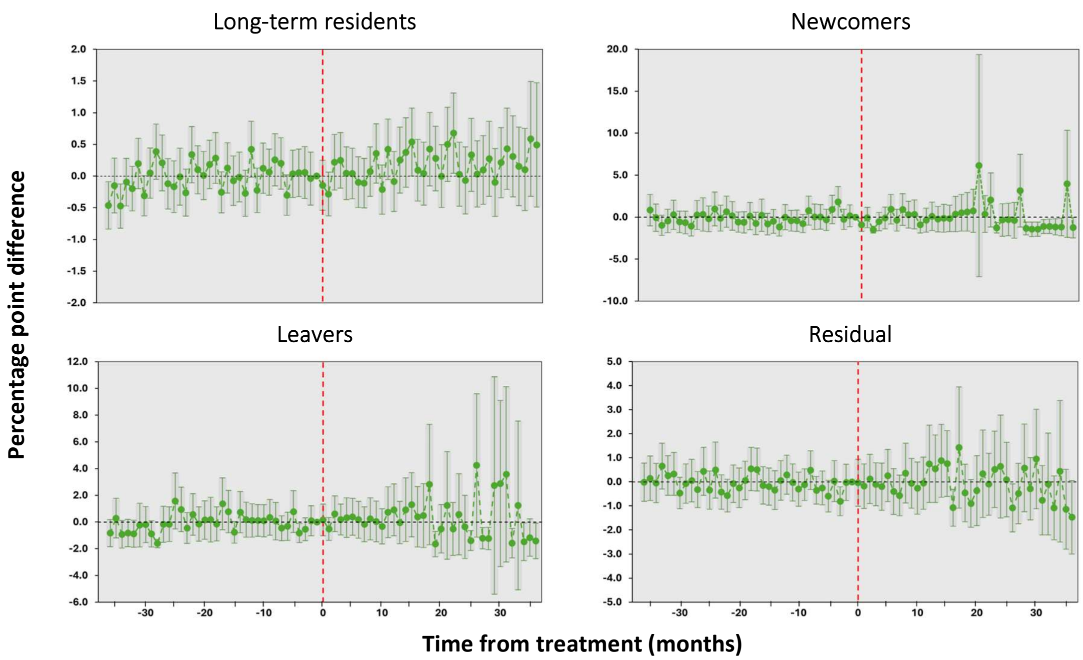
While the area-level showed home accidents significantly increased for SH in high UR SA2s, the individual-level analysis shows there is economically small or no significant impact of UR on home accidents. This may be because high UR areas comprise only 20% of treated areas, and therefore their small sample size is unlikely to influence overall home accidents. While some treatment effects are observed, the differences are not statistically significant for most time periods. In instances where significant impacts are noted, the magnitude of impact on home accidents is economically small.

Figure 128 DiD - urban regeneration on home accidents (individual, All Population)



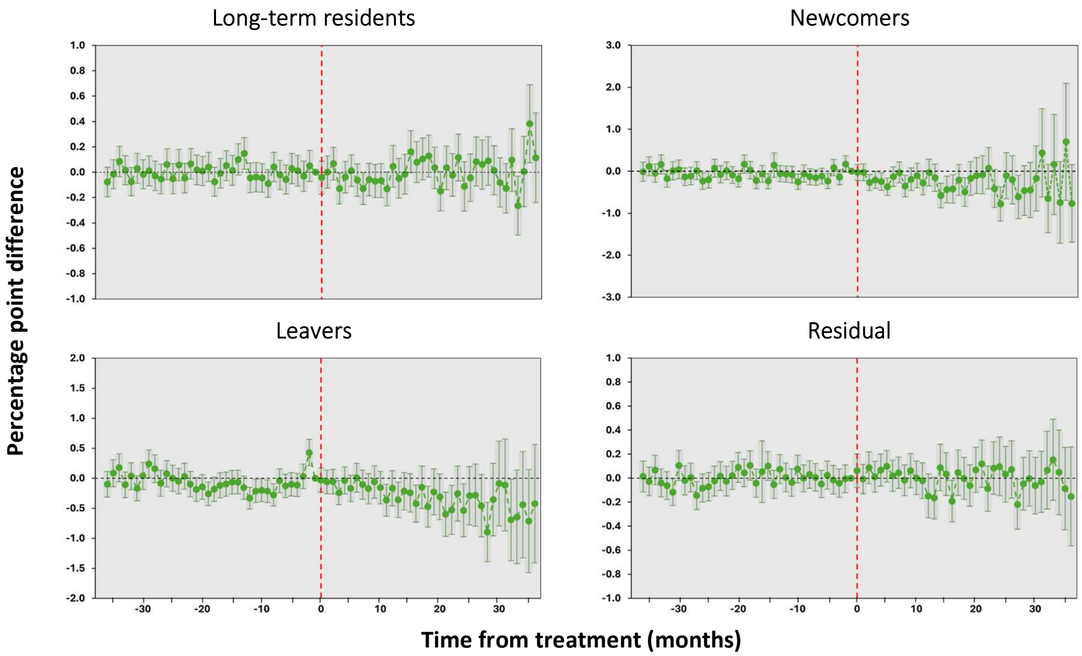
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 129 DiD - urban regeneration on home accidents (individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{e\ell}$, from Equation (2.3) in Section 5.5.

Figure 130 DiD - urban regeneration on home accidents (individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

9.8 Road-related accidents and injuries

Housing intensification through UR can promote higher density living and improve public transport infrastructure, which can lead to several potential benefits with respects road safety. Increased density can encourage residents to adopt more active modes of transport, such as walking and cycling (related to Section 8.2), thereby reducing car dependency and potentially decreasing road accidents. Additionally, having local amenities within close proximity means shorter car trips, which could result in slower vehicle speeds and lower accident rates (Giles-Corti et al., 2012). The introduction of new walking and cycling pathways can also create clear boundaries for different modes of transportation, further reducing the likelihood of accidents (Bull et al., 2015).

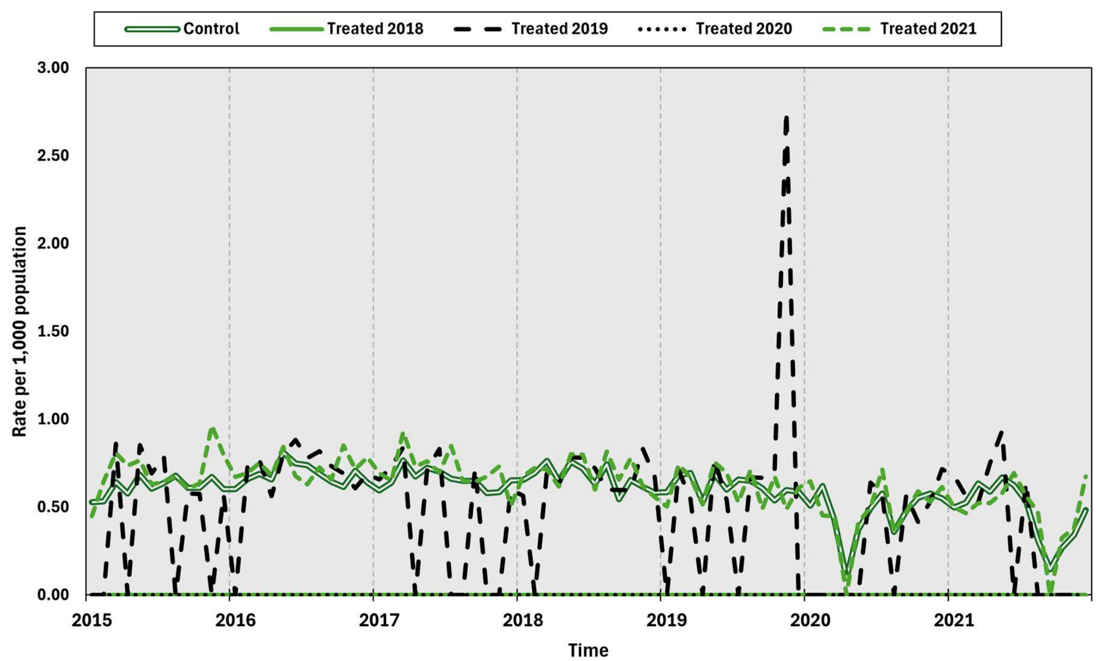
However, high density areas can also lead to increased traffic volumes if they do not sufficiently reduce car dependency (Giles-Corti et al., 2012). If public transport facilities are not adequately developed or lack comprehensive coverage, residents may continue to rely on their cars, thereby increasing the risk of road accidents. In the short run, ongoing construction related to UR can create hazardous road conditions, restrict access, and necessitate diversions that may inadvertently increase the likelihood of accidents.

9.8.1 Descriptive trends

Figure 131 presents road accidents and injuries rate per 1,000 population ("road accidents") for treated SA2s by treatment year and control SA2s from 2015 to 2022. Rates are calculated as the number of road accidents per 1,000 population. All average road accidents for SA2s treated in 2018 and 2020 were suppressed due to Stats NZ suppression rules for confidentiality.[29]

Between 2015 and 2017, average road accidents were similar for both treated (0.55 accidents) and control SA2s (0.65 accidents). Starting in 2018, there is a gradual decline in road accidents for both groups, although there was a significant spike for SA2s treated in 2019, reaching an average of 2.8 accidents during this period. Average road accidents drop during the two COVID-19 lockdown periods in early 2020 and the end of 2021 where driving was restricted unless travelling for essential services. However, road accidents recover to pre-COVID levels once restrictions had lifted.

Figure 131 Average SA2 road accidents by treatment year by treatment year



Source: IDI 2024. Note all observations for the 'Treated – 2018' and 'Treated – 2020' series and some observations for other 'Treated' series are equal to zero as values have been suppressed according to Stats NZ confidentiality rules.

[29] Stats NZ confidentiality rule requires each month to have at least 20 non-zero observations. Therefore, months with less than 20 SA2s reporting non-zero accidents are suppressed.

9.8.2 Area-level DiD analysis

Table 32 presents regression results examining road accidents for the treated population (and respective subpopulations) against all those living in control areas, with results shown separately for high and low UR. Figure 132 shows when comparing all treated SA2s to control SA2s, after controlling for population, household size, age, ethnicity, gender and partnership status, there appears to be some significant impact of UR on road accidents. However, the SA2 and SA1 ATT $\hat{v}_g$ and $\hat{w}_g$ in Table 32 (column I) show there is no impact of UR on road accidents.

The heterogeneity analysis also road accidents significantly increased for SH residents, with an increase of 0.40 accidents in high UR SA1s and 0.52 accidents in low UR SA1s relative to control SA1s. The magnitude of these impacts is economically large, amounting to a 72.1% and 93.7% increase in the average pre-treatment road accidents, respectively. This is a highly localised impact – SH residents moving into new developments may face increased risks if road and public transport infrastructure have not adapted to accommodate the increased population density.

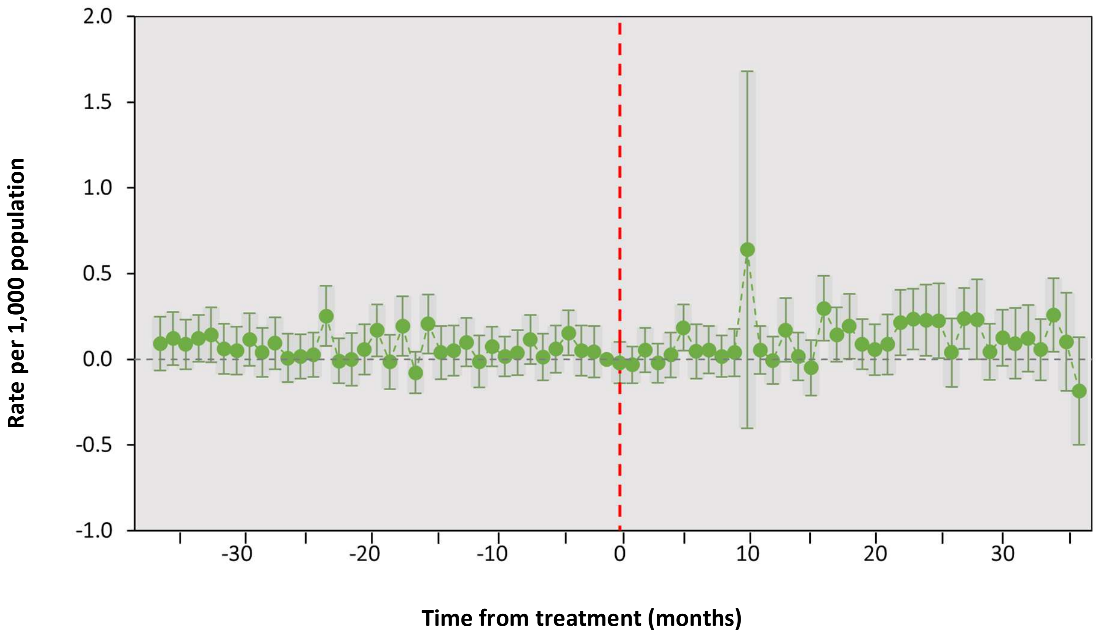
The heterogeneity analysis shows road accidents increased by 0.15 accidents for NSH in low UR SA2s, representing a 27.0% increase in the pre-treatment average of 0.55 accidents. There is no corresponding impact for NSH at the SA1-level, indicating that these accidents may be occurring in untreated SA1s (within the boundaries of a treated SA2). It is therefore unclear if road accidents are related to UR initiatives.

Table 32 Impact of urban regeneration on road accidents

Outcome variable	All UR (I)	High UR (II)	Low UR (III)
SA2 – Road-related accidents and injuries (rate per 1,000 population)			
All Population	0.106 [-0.002, 0.214]	-0.072 [-0.259, 0.114]	0.169** [0.054, 0.285]
Social Housing	0.118 [-0.224, 0.461]	-0.428 [-0.944, 0.089]	0.297 [-0.106, 0.700]
Non-Social Housing	0.126* [0.010, 0.241]	0.059 [-0.114, 0.231]	0.150* [0.026, 0.273]
SA1 – Road-related accidents and injuries (rate per 1,000 population)			
All Population	0.181 [-0.004, 0.365]	0.096 [-0.202, 0.393]	0.201 [-0.005, 0.408]
Social Housing	0.505*** [0.244, 0.767]	0.400* [0.093, 0.707]	0.519*** [0.220, 0.818]
Non-Social Housing	0.152 [-0.055, 0.360]	0.158 [-0.108, 0.424]	0.151 [-0.091, 0.392]

Source: IDI 2024. Note UR – urban regeneration. Estimates refer to the estimated SA2 and SA1 ATT, $\hat{\boldsymbol{v}}_{\boldsymbol{g}}$ *and* $\hat{\boldsymbol{w}}_{\boldsymbol{g}}$, in the post-treatment period from Equation (1.2) in Section 5.5. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively. 95% confidence intervals in square [] brackets.

Figure 132 DiD - urban regeneration on road accidents (SA2, All Population)

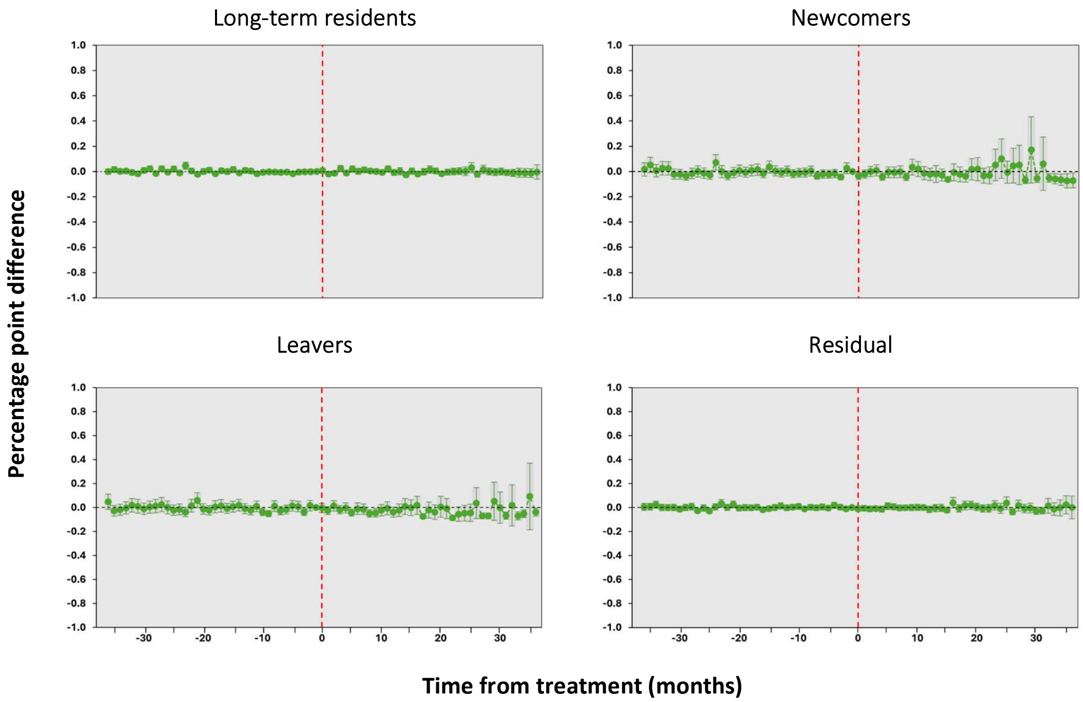


Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

9.8.3 Individual-level DiD analysis

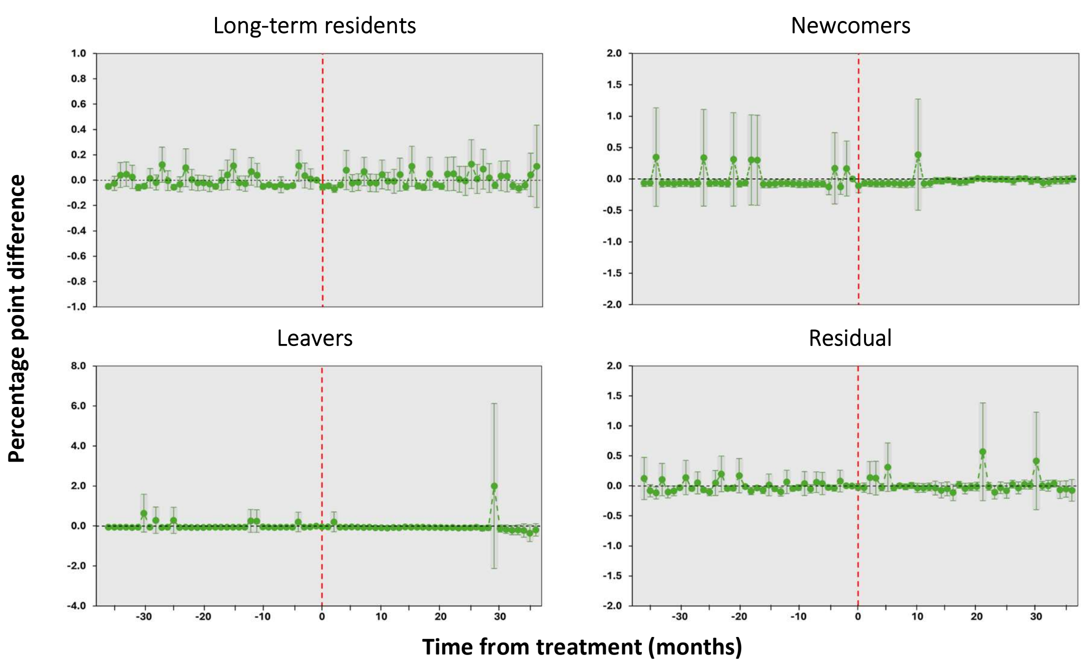
Figure 133 presents individual-level road accident regressions comparing all treated subpopulations and their respective counterparts as described in Table 6. These are presented separately for SH (Figure 134) and NSH (Figure 135). While the area-level analysis showed there is some impact of UR on road accidents, the individual-level results show no statistically significant differences in road accidents.

Figure 133 DiD - urban regeneration on road accidents (Individual, All Population)



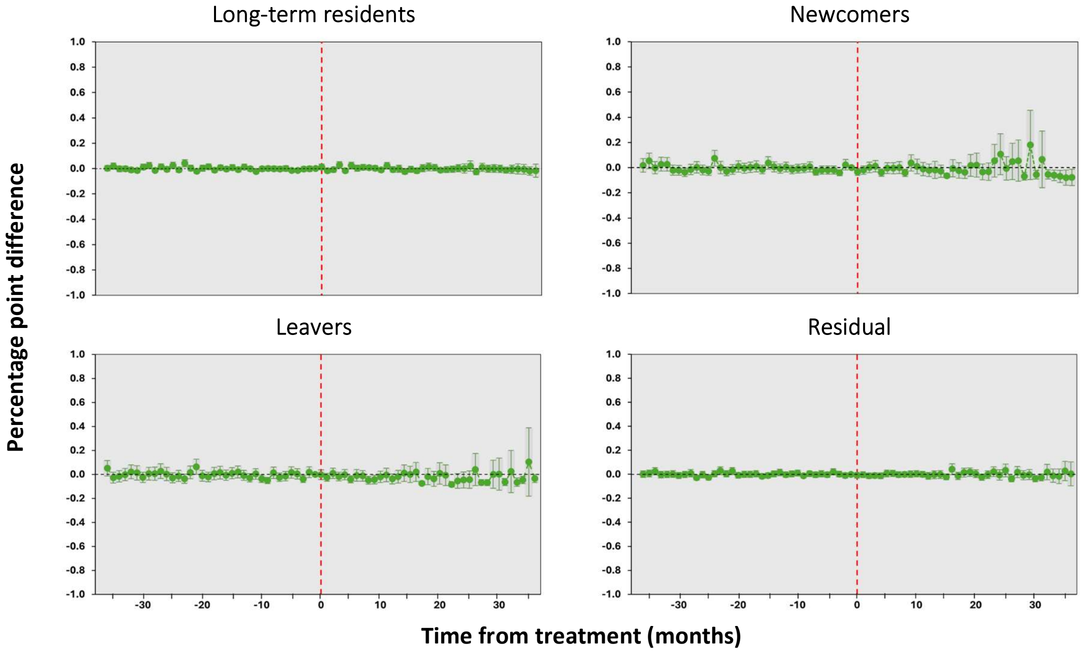
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 134 DiD - urban regeneration on road accidents (Individual, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

Figure 135 DiD - urban regeneration on road accidents (Individual, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATTI, $\hat{\boldsymbol{\varphi}}_{\boldsymbol{e\ell}}$, from Equation (2.3) in Section 5.5.

10 Discussion

The purpose of this study is to evaluate the short run wellbeing impacts of urban regeneration in New Zealand using population-wide administrative data. The impact of urban regeneration on area-level wellbeing outcomes are summarised in tabular format for human capital (Table 33), physical and mental health (Table 34) and crime and safety (Table 35) outcomes, presented for all populations and urban regeneration intensities. Positive (negative) impacts of urban regeneration are highlighted in green (orange) and populated with their respective significance levels while blank cells are no significant impacts.

The area-level analysis broadly shows no short run impact of urban regeneration on wellbeing outcomes for the full treated population. This is in line with similar studies that examine wellbeing impacts of urban regeneration using difference-in-differences, which found no significant impact of urban regeneration on health (Mohan et al., 2017) and crime (Borbely & Rossi, 2023) in Northern Ireland and Scotland. The heterogeneity analysis shows there is some short run impact of urban regeneration on wellbeing outcomes, namely for residents living in high urban regeneration areas and social housing residents. These results are to be expected given treatment effects of Kāinga Ora-led urban regeneration are likely to be stronger where 1) there are high levels of urban regeneration and that 2) most dwellings developed by urban regeneration are social housing.

While Kāinga Ora-led urban regeneration aims to improve wellbeing not just for social housing residents, but all residents living in regenerated neighbourhoods, this does not appear to be the case in the short run. The negative short run impacts of urban regeneration on wellbeing outcomes may be attributable to factors like ongoing construction, displacement, and increased uncertainty which might contribute to a lack of immediate positive impacts for residents, particularly in areas with high regeneration activity. There are either no impacts or negative short run impacts of urban regeneration on human capital, mental health, crime and safety outcomes. However, positive health outcomes are reported for social housing residents in high urban regeneration areas, with significant decreases in emergency department, cardiovascular and respiratory-related admissions.

It is important to note that urban regeneration projects are often long-term undertakings, and at the end of the analysis period, many developments were still in progress. As such, the full impact of urban regeneration has not yet been fully assessed. Studies like A Kearns et al. (2020) find no impact of urban regeneration on outcomes where development was still ongoing. This supports the findings in this study, where short run outcomes of urban regeneration showed limited or even negative wellbeing impacts.

However, it is likely that longer-term impacts will point towards more positive outcomes once urban regeneration projects are complete. Key factors such as better-quality housing, improved local amenities and infrastructure will be available to residents once urban regeneration is completed, potentially improving their wellbeing over time. Therefore, future analysis is needed to examine the medium to long term impacts once developments are complete to assess the full impact of urban regeneration initiatives.

As detailed in Section 2.2.4 and 5.2.1, it was of relevance to this study to examine wellbeing outcomes for non-social housing residents living in neighbourhoods with social housing development, given the opposition expressed by non-social housing residents towards social housing developments in their neighbourhood. Drivers for these sentiments include fear of antisocial behaviour from social housing tenants, the potential for neighbourhoods to be devalued from high concentration of social housing developments and increased crime rates (Cole, 2021; Kāinga Ora, 2021; Olssen et al., 2010; Saville-Smith et al., 2015).

Individuals with higher educational attainment or earnings generally have more choices about where they choose to live. If neighbourhoods are devalued from high concentration of social housing developments, then these individuals would be less likely to move into regenerated neighbourhoods. We would expect to see regenerated neighbourhoods to have residents with decreased tertiary attainment, increased benefit receipt and decreased employment and earnings compared to areas with no social housing development. However, the area-level results show no significant difference in employment and benefit receipt in treated neighbourhoods relative to control neighbourhoods. Tertiary educational attainment only marginally decreased in treated areas, and women in treated areas had increased earnings compared to women in control areas.

If social housing tenants are perceived as more likely to commit crimes such as assaults, theft or robberies, then treated areas would expect an increase in victimisations compared to control areas. It is worth noting the victimisation data only identifies whether the victim lived in social housing at the time of the victimisation. It does not record if the perpetrator lived in social housing at the time of the crime, nor does it indicate where the crime took place. Thus, victimisations as measured in this research cannot directly link increased victimisations to antisocial behaviours of social housing tenants or if they occurred in a victim's SA2 of residence.

Assault victimisations significantly increased for social housing residents in low urban regeneration areas, with no significant difference found for non-social housing residents. In high urban regeneration areas, both social and non-social housing residents experienced significant increases in theft and robbery victimisations compared to control areas. While non-social housing residents experienced increased robbery victimisations during the first six months following urban regeneration, social housing residents continued to experience significantly increased victimisations for almost two years post urban regeneration. Additionally, the frequency and magnitude of theft victimisations for social housing was greater than that of non-social housing, which might reflect their closer proximity to other social housing tenants in high-density developments and their increased exposure to antisocial behaviour.

The negative short run impacts of urban regeneration on theft and robbery may also be attributable to neighbourhood factors such as poor lighting, derelict buildings, or low policing in high urban regeneration areas. These conditions could worsen during ongoing construction as more buildings are demolished, making way for new development, and residents are relocated during the urban regeneration process. This would likely make these areas easier targets for theft and robbery.

Once urban regeneration is finished and infrastructure and amenities are completed—such as better street lighting, enhanced police presence, and newly built housing—these negative impacts are expected to improve, potentially reducing future crime rates. While increased population density resulting from urban regeneration may lead to higher reporting of crime, it can also increase opportunities for crime due to the higher concentration of residents. Therefore, further analysis which incorporates social housing status of perpetrators and location of victimisations is needed once urban regeneration developments are complete.

The individual-level analysis showed mixed and modest impacts of urban regeneration on wellbeing outcomes across different subpopulations. Where impacts were statistically significant, they were economically small, and this may be in part due to incomplete treatment effects where urban regeneration was still ongoing at the time of analysis. This study assessed outcomes for long-term residents to understand if wellbeing improved for existing residents who lived in regenerated areas prior to urban regeneration. However, the individual-level results show there is little difference in their wellbeing outcomes after urban regeneration. That is, in the short run, urban regeneration has neither improved nor worsened wellbeing outcomes for long-term residents.

Following urban regeneration, regenerated neighbourhoods may become gentrified neighbourhoods, as gentrification typically occurs in historically deprived areas that are centrally located and well-serviced by local amenities (Brummet & Reed, 2019). Assessing outcomes for newcomers helps to understand whether regenerated areas are attracting individuals with better outcomes and thereby gentrifying neighbourhoods. The individual-level analysis showed non-social housing newcomers moving from control to treated areas had significantly increased employment and earnings compared to non-social housing transient residents in control areas. However, they also had significantly increased benefit receipt. That is, the incoming population of newcomers include both worse-off and better-off individuals and therefore it is not clear whether this points towards gentrification.

Urban regeneration can voluntarily and involuntarily displace residents from treated areas, which may impact area-level wellbeing. Some non-social housing residents may choose to leave areas where social housing is expected to increase. If these residents have better wellbeing outcomes compared to those who remain in treated areas, area-level wellbeing outcomes would decrease following their departure. On the other hand, social housing residents might be involuntarily displaced if their homes are demolished as part of the regeneration process. Similarly, disadvantaged non-social housing residents may be priced out of neighbourhoods that are beginning to gentrify and becoming more attractive to live in. If these displaced residents have poorer wellbeing outcomes, their departure could improve area-level wellbeing for treated areas. However, the individual-level analysis shows there is no, or economically small, impacts of urban regeneration on wellbeing outcomes for leavers, irrespective of social housing status.

Closing the discussion on the causal impact of urban regeneration on wellbeing outcomes requires reflecting on the choice of counterfactual. A key challenge lies in identifying what would have happened to regenerated areas in the absence of Kāinga Ora-led urban regeneration. The descriptive statistics in Section 5.3 and first order effects in Section 6 show population and dwellings increased in control areas, suggesting urban development occurs in some control areas regardless of Kāinga Ora involvement. The empirical strategy used in this study compares treated areas to control areas that did not experience Kāinga Ora-led urban regeneration. However, alternative counterfactuals may be that treated areas remain undeveloped in the absence of Kāinga Ora-led urban regeneration, or they would have undergone development led by non-Kāinga Ora developers.

Had the analysis focused only on control areas with no development at all, the estimated impacts of urban regeneration might have appeared larger, as the comparison would be between developed and completely undeveloped areas. Alternatively, selecting control areas with comparable levels of non-Kāinga Ora-led development would likely yield smaller impacts and isolate the specific contributions of Kāinga Ora's interventions, such as social housing development (which is recorded in the housing intensification data) and neighbourhood improvements (which is not recorded in the housing intensification data). While it is unclear which counterfactual is most appropriate, it is important to note that the choice of control areas is likely to significantly influence the estimated impacts of urban regeneration.

Table 33 Area-level human capital outcomes summary

Human capital outcomes	SA2			SA1		
All Population *Social housing* *Non-social housing*	All UR	High UR	Low UR	All UR	High UR	Low UR
Secondary educational attainment			*			
Social housing						
Non-social housing						
Tertiary educational attainment	*	**				
Social housing				*		*
Non-social housing						
Youth not in education, employment or training		***			***	
Social housing		***				
Non-social housing		***		*	***	
Total employment rate						
Social housing		**				
Non-social housing						
Male employment rate						
Social housing						
Non-social housing						
Female employment rate						*
Social housing		***			*	
Non-social housing						
Total median wages & salary			**			
Social housing		**				
Non-social housing			*			
Male median wages & salary						
Social housing						
Non-social housing					*	
Female median wages & salary	*		*			
Social housing						
Non-social housing	**	*	**			
Benefit receipt						
Social housing					**	
Non-social housing						
Unemployment or sickness-related benefit receipt		*				
Social housing	**		***	**	*	***
Non-social housing						

Source: IDI 2024. UR = urban regeneration. Table displays the significance level for the total average treatment effect on the treated (ATT) coefficients at the SA2 ($\hat{v}_g$) and SA1 ($\hat{w}_g$) level. Orange cells are negative impacts of UR, green cells are positive impacts of UR, blank cells are no significant impacts of UR. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively.

Table 34 Area-level physical and mental health outcomes summary

Physical and mental health outcomes	SA2			SA1		
All Population	All UR	High UR	Low UR	All UR	High UR	Low UR
Social housing						
Non-social housing						
Emergency department admissions						
Social housing		*			**	
Non-social housing		*				
Cardiovascular disease-related admissions						
Social housing		*				
Non-social housing						
Respiratory-related admissions				*		**
Social housing		**				
Non-social housing				**		***
Mental health utilisation		*				
Social housing		***				
Non-social housing						
Self-harm events					*	
Social housing	***	***	***			
Non-social housing					*	

Source: IDI 2024. UR = urban regeneration. Table displays the significance level for the total average treatment effect on the treated (ATT) coefficients at the SA2 ($\hat{\upsilon}_g$) and SA1 ($\hat{w}_g$) *level.* Orange cells are negative impacts of UR, green cells are positive impacts of UR, blank cells are no significant impacts of UR. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively.

Table 35 Area-level crime and safety outcomes summary

Crime and safety outcomes	SA2			SA1		
All Population	All UR	High UR	Low UR	All UR	High UR	Low UR
Social housing						
Non-social housing						
Family violence victimisations						
Social housing	***		***			
Non-social housing						
Assault victimisations						
Social housing	**		**			
Non-social housing						
Sexual assault victimisations		**				
Social housing	*		**			
Non-social housing		*				
Theft victimisations					*	
Social housing	***	**	***	***	***	***
Non-social housing					*	
Robbery victimisations					***	
Social housing				**	**	**
Non-social housing					***	
Workplace-related accidents and injuries						
Social housing						
Non-social housing						
Home-related accidents and injuries						
Social housing					***	
Non-social housing						
Road-related accidents and injuries			**			
Social housing				***	*	***
Non-social housing	*		*			

Source: IDI 2024. UR = urban regeneration. Table displays the significance level for the total average treatment effect on the treated (ATT) coefficients at the SA2 ($\hat{\upsilon}_g$) and SA1 ($\hat{w}_g$) *level.* Orange cells are negative impacts of UR, green cells are positive impacts of UR, blank cells are no significant impacts of UR. Significance stars ***, ** and * indicate p-values of < 0.001, < 0.01 and < 0.05, respectively.

11 Conclusion

New Zealand faces substantial housing challenges including persistent housing shortages, rising housing costs, poor quality stock and overcrowding issues. Urban regeneration has the potential to positively impact long-term wellbeing through the provision of housing, improving the quality of the current housing stock, providing shared community spaces and building active transport options to support access to employment, amenities and services. Housing intensification is the main policy tool used by Kāinga Ora to deliver its urban regeneration initiatives. However, there is limited research examining the social return-on-investment of urban regeneration developments in New Zealand. Considering the substantial monetary investment into housing-led urban regeneration, it is important to understand how these developments impact wellbeing outcomes for residents living in areas being developed.

There is a small but growing body of research that seeks to establish causal links between urban regeneration and wellbeing outcomes using administrative data and robust econometric techniques. This research aimed to contribute to the literature by first, developing a robust framework and method to measure population-wide wellbeing indicators using administrative data and secondly, using this framework to measure the short-run wellbeing impacts of urban regeneration in New Zealand. These research aims were met in this thesis by developing the Wellbeing Outcomes Framework to measure wellbeing with administrative data across human capital, physical and mental health and crime and safety outcomes. This framework is used to causally evaluate the short run wellbeing impacts of housing intensification in New Zealand, using Kāinga Ora housing intensification data and administrative data from the Stats NZ Integrated Data Infrastructure. The findings of this thesis provide an empirical evidence base to help guide current and future housing developments.

The empirical models in this research employ staggered difference-in-differences modelling to account for differences in urban regeneration timing among regenerated neighbourhoods. Matching methodologies are used to match treated areas and individuals to their non-treated counterparts, allowing for unbiased causal estimates of the impact urban regeneration on wellbeing outcomes. Using administrative data allows for longitudinal analysis of wellbeing impacts for nearly the entire affected population, which has not yet been fully explored in the literature.

The large sample sizes used in this study provide sufficient statistical power to conduct heterogeneity analyses by area-level and individual-level characteristics, which is often challenging with survey data. This is particularly important, given urban regeneration is an area-level treatment for which the wellbeing impacts are likely to be unevenly distributed among individuals living in regenerated areas. This allowed for separate analyses to assess wellbeing outcomes for social housing, non-social housing residents, long-term residents, newcomers and leavers.

The results broadly show no short run impact of urban regeneration on area-level wellbeing outcomes. This aligns with the results found in Mohan et al. (2017) and Borbely and Rossi (2023) who found no impact of urban regeneration on wellbeing in Scotland and Northern Ireland, respectively. While most outcomes were insignificant, stronger impacts were observed for residents living in high urban regeneration areas and social housing residents. This is to be expected as these two populations are most likely to be affected by Kāinga Ora-led urban regeneration. In the short run, urban regeneration appears to have positive impacts on neighbourhood-level physical health but negative impacts on mental health. Additionally, there are negative short run impacts of urban regeneration on local theft and robbery victimisations. This serves as a useful starting point for policymakers to understand how individuals and communities are impacted by large housing-led policies using robust evaluation methods.

This research is not without its limitations. As noted previously in this thesis, urban regeneration is still ongoing at the end of the analysis period and not enough time has yet elapsed to allow for medium to long-term analysis of wellbeing outcomes. Therefore, the short run impacts may reflect negative impacts of ongoing disruption and possible displacement of residents during urban regeneration. Secondly, computational constraints meant not all individuals living in highly deprived areas could be matched in the individual-level analysis. The excluded individuals are skewed towards those who are likely to benefit the most from urban regeneration initiatives and their exclusion likely underestimates the impact of urban regeneration. Therefore, future analysis is needed to examine longer term impacts of urban regeneration once developments are complete, especially for individuals living in highly deprived areas. The Wellbeing Outcomes Framework developed in this study means longer-term wellbeing impacts of urban regeneration can be readily examined once more time has elapsed.

There is future scope for analysis that will better delineate the treatment effects of urban regeneration on wellbeing outcomes. First, there is emerging literature related to spatial difference-in-differences which capture geographic spillover effects of treatment - see Butts (2023) and Borbely and Rossi (2023). This thesis uses SA2 as the geographic unit to capture potential spillover effects of urban regeneration. However, these spatial models can accommodate smaller geographic units such as SA1 or meshblocks with 'rings' extending outwards. These rings represent varying distances and allows the model to measure how urban regeneration impacts wellbeing outcomes the further away rings are from the treatment unit. This allows for spillover effects to be captured more precisely.

Second, the area-level analysis showed high urban regeneration areas and social housing populations were most impacted by urban regeneration. There was minimal impact at the individual-level which was expected as individuals living in social housing and/or high urban regeneration comprised only a small share of the overall treated population. The future scope of work could subset the analysis to individuals residing in high urban regeneration and/or social housing to better understand how wellbeing impacts are distributed at the individual-level.

Third, future analyses could explore different counterfactual scenarios for areas regenerated by Kāinga Ora. As there is considerable urban development occurring in control areas that are not led by Kāinga Ora, it would be interesting to compare wellbeing outcomes between Kāinga Ora-led developments and areas developed by non-Kāinga Ora agencies. By matching treated areas to control areas with similar rates of dwelling growth, future studies can specifically assess the impacts of Kāinga Ora-led urban regeneration. Publicly available building consent data or administrative address data in the Integrated Data Infrastructure could be used for this matching process. Comparing treated areas to control areas, where there is no urban development at all, would provide insight into how wellbeing outcomes differ between developed and undeveloped areas. This would allow researchers to better assess the overall benefits of urban development.

To conclude, this research uses the Wellbeing Outcomes Framework developed in this study to evaluate the short run wellbeing impacts of urban regeneration using administrative data. While the framework was specifically applied to urban regeneration in this study, it is designed to allow for broader application in any policy setting which aims to measure wellbeing outcomes. This can be used in conjunction with quasi-experimental methods, such as difference-in-differences as used in this study, to evaluate the impact of policies over time. This opens the door for future policy evaluations using a robust framework and methodology to provide an evidence-based approach to understanding policy impacts.

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Appendix 1 Living Standards Framework

Table 36 Living Standards Framework indicators

Domain	Indicators	Units	Data source
Health	Healthy life expectancy	Number of years that a person under 1 year old can expect to live in good health, taking into account mortality and disability	OECD Health Statistics
	Health status	% of adults reporting good or very good health	New Zealand Health Survey, Ministry of Health
	Mental health	% of adults with high levels of psychological distress	New Zealand Health Survey, Ministry of Health
	Suicide rate	Deaths caused by intentional self-harm, age-standardised rate per 100,000 population	Mortality Collection, Ministry of Health
	Unmet health needs	% of children aged under 15 with unmet need for GP due to cost in the past 12 months	New Zealand Health Survey, Ministry of Health
Knowledge and skills	Educational attainment (tertiary)	% of adults aged between 25 and over with a Bachelor's degree or higher qualification	Household Labour Force Survey
	Educational attainment (upper secondary)	% of adults aged between 25 and over with at least an upper secondary education (equivalent to NCEA Level 2)	Household Labour Force Survey
	Cognitive skills at age 15	Programme for International Student Assessment (PISA) mean score for reading, mathematics and science	PISA; Ministry of Education
	Regular school attendance	% of school students attending regularly	Education Counts, Ministry of Education
Cultural capability and belonging	Ability to express identity	% of people who said it was easy or very easy to express their identity in New Zealand	General Social Survey
	Sense of belonging to New Zealand	Percentage of adults with a score of 7/10 or higher for sense of belonging to New Zealand	General Social Survey
	Arts participation	% of people who have participated in at least one art form in the last 12 months	New Zealanders and the Arts Survey, Creative New Zealand
	Te reo Māori speakers	% of people who can converse about a lot of everyday things in te reo Māori	Census, Stats NZ
	Māori connection to marae	% of Māori adults who feel strongly or very strongly connected with their ancestral marae	Te Kupenga, Stats NZ
	Multilingualism	Average number of languages spoken	Census, Stats NZ
Work, care and volunteering	Unemployment rate	% of labour force who are unemployed	Household Labour Force Survey
	Employment rate	% of adults (aged 15+) who are employed	Household Labour Force Survey
	Median hourly earnings	Median hourly earnings for people in paid employment	Household Labour Force Survey
	Youth NEET rate	% of young people aged 15-24 not in education, employment or training (NEET)	Household Labour Force Survey
	Hours worked	Average actual weekly hours worked by employed adults	Household Labour Force Survey

	Unpaid work	Average hours per day spent doing unpaid work (for own household, other household, or an organisation)	Time Use Survey, Stats NZ
	Volunteering	% of adults who reported having done voluntary work in the previous four weeks	General Social Survey
	Involvement in the community		
Engagement and voice	Voter turnout in general elections	% of enrolled electors who voted in the general election	Electoral Commission
	Voter turnout in local elections	% of enrolled voters who voted in the contested mayoral elections	Local Authority Election Statistics, Department of Internal Affairs
	Having a say in government	% of people aged 16-65 who agree they have a say in what the Government does	Programme for the International Assessment of Adult Competencies survey, OECD
	Perception of public influence	% of people who say the public has some or large influence on the decisions their council makes	Quality of Life Survey
Income, consumption and wealth	Disposable income	Median real equivalised household incomes after taxes and transfers, and before housing costs	Household Economic Survey
	Financial wellbeing	Proportion of the population who report they do not have enough money to meet everyday needs	General Social Survey
	Consumption	Average real weekly household expenditure	Household Economic Survey
	Child poverty - material hardship	% of children living in households experiencing material hardship	Household Economic Survey
	Household net worth	Average household net worth	National accounts - annual balance sheet, Stats NZ
	Food insecurity	% of children aged under 15 living in households where food sometimes or often runs out	New Zealand Health Survey, Ministry of Health
Housing	Household crowding	% of people living in a crowded house	Census, Stats NZ
		International statistic: Average number of rooms per person	How's Life? OECD
	Housing quality	% of people reporting major repairs needed	General Social Survey
	Housing cost - share of income	Proportion of households with housing cost greater than 30% of income	Household Economic Survey
	Housing cost - deposit affordability		
	Housing cost - mortgage affordability		
	Housing cost - rent affordability		
Environmental amenity	Health impacts of air quality	Restricted annual activity days due to illness resulting from exposure to human-made PM10 pollution	Environmental Reporting series, Ministry for the Environment & Stats NZ
	Access to the natural environment	% of adults who said it was very easy to get to their nearest park or green space	General Social Survey
	Drinking water management	% of people served with drinking water that met all treatment management standards	Annual Report on Drinking Water Quality, Ministry of Health
	Droughts	Prevalence of agricultural drought	Environmental Reporting series, Ministry for the Environment & Stats NZ

	Perceived environmental quality	% of people who rated the overall state of the natural environment in New Zealand as good or very good	Public Perception of New Zealand's Environment survey, Lincoln University
	Swimmability (rivers)	% of state of the environment monitored river sites in each of the E.coli attribute bands	Land, Air, Water Aotearoa
Leisure and play	Leisure and personal care	Average hours per day devoted to free time and personal care (e.g. Sleeping, eating, personal hygiene and grooming) by people aged 12 or over	Time Use Survey, Stats NZ
	Satisfaction with work-life balance	% of adults who are very satisfied or satisfied with their work-life balance	Survey of Working Life, Stats NZ
	Participation in sport and recreation	% of adults participating in play, active recreation and sport each week	Active NZ Survey, Sport New Zealand
Family and friends	Face-to-face contact	% of adults who had face-to-face contact with friends who did not live with them at least once a week	General Social Survey
	Loneliness	% of adults who felt lonely at least some of the time in the past four weeks	General Social Survey
	A place to stay	% of adults who reported that, if they urgently needed a place to stay, it would be easy or very easy to ask someone they know	General Social Survey
	Social network support	*% of adults who report they have friends or relatives they can count on in times of trouble*	
	Someone to turn to		
	Feeling loved		
Safety	Intentional homicide rate	Deaths caused by assault, age-standardised rate per 100,000 people	Mortality Collection, Ministry of Health
	Family violence	% of adults who were victims of family violence in the past year	Crime and Safety Survey, Ministry of Justice
	Workplace accident rate	Number of work-related injury claims per 1,000 full-time equivalent employees (FTEs)	Accident Compensation Corporation, Stats NZ
	Feeling safe	% of adults who feel safe when walking alone in their neighbourhood after dark	General Social Survey
	Childhood injuries	All fatal, non-fatal and serious injuries, age-standardised rates for children aged 0-14	Serious injury outcome indicators, Stats NZ
	Road toll	Number of road accident deaths	Safety - Annual Statistics, Ministry of Transport
Subjective wellbeing	General life satisfaction	% of people with a score of 7/10 or higher for life satisfaction	General Social Survey
	Sense of purpose in one's life	% of people with a score of 7/10 or higher for feeling that life is worthwhile	General Social Survey

Source: NZ Treasury (2022). Note: indicators in italics have not yet been integrated into the dashboard.

Appendix 2 Wellbeing Outcomes Framework

Table 37 Wellbeing Outcomes Framework (tabular)

Indicator	Measurement	Source	Datasets	Data
Education				
Secondary educational attainment of the adult population	% of individuals aged between 16-19 who were either born in New Zealand and/or were enrolled in at least two years in secondary institutions in New Zealand (equivalent to NCEA Level 2)	Ministry of Education	Student Qualification	Have achieved at least National Qualifications Framework (NQF) Level 2
		Ministry of Education	Tertiary Qualification Completion	Have achieved at least qualification level 2
		Ministry of Education	Industry Training	Have been awarded at least qualification level 2
		Ministry of Education	Targeted Training	Have achieved at least course level 2
Tertiary educational attainment of the adult population	% of adults aged 25-64 with a Bachelor's degree or higher qualification	Ministry of Education	Student Qualification	Have achieved at least National Qualifications Framework (NQF) Level 7
		Ministry of Education	Tertiary Qualification Completion	Have achieved at least qualification level 7
		Ministry of Education	Industry Training	Have been awarded at least qualification level 7
Labour market				
Youth NEET rate	% of young people aged 15-24 not in education, employment or training (NEET)	Ministry of Education	Course, Student Enrolment, Industry Training, Targeted Training	Does not appear in any of the education or training datasets
		Inland Revenue	Employee Monthly Schedule	Receive no wages and salary per income source code = 'W&S'
Employment rate	% of adults aged 25-64 who receive wages and salary	Inland Revenue	Employee Monthly Schedule	Receive wages and salary per income source code = 'W&S'
Median and average monthly earnings	Median and average wages and salaries	Inland Revenue	Tax revenue data	All wages and salary per income source code = 'W&S' greater than 100, adjusted for $NZD 2021.
Benefit recipiency (any benefit)	% of adults (aged 15+) who receive any benefits	Inland Revenue	Employee Monthly Schedule	Recipient of any benefit as per income source code = 'BEN'

Benefit recipiency (unemployment or sickness-related)	% of adults (aged 15+) who receive unemployment or sickness-related benefits	Inland Revenue	Benefit Dynamics	Recipient of any unemployment or sickness-related benefits
Physical health				
Emergency department (ED) admissions	Adults (aged 15+) who were admitted into the emergency department, age-standardised rate per 1,000	Ministry of Health	National Non-Admitted Patient Collection (NNPAC)	Attendance to an emergency department
Cardiovascular disease (CVD) related hospitalisations	Adults (aged 30+) who have been hospitalised for cardiovascular diseases, strokes, heart failure and rheumatic heart disease and other CVD-related, age-standardised rate per 1,000	Ministry of Health	National Minimum Dataset (NMDS)	Publicly funded hospital admission and discharge information related to cardiovascular diseases
Respiratory-related hospitalisations	Total number of hospital admissions related to any respiratory diseases, age-standardised rate per 1,000	Ministry of Health	National Minimum Dataset (NMDS)	Publicly funded hospital admission and discharge information related to respiratory diseases
Mental health				
Mental healthcare utilisation	Number of adults (15+) who have been referred to mental health services, prescribed medication such as anti-anxiety, antidepressants or antipsychotic, receive benefits for mental health reasons, or admitted in hospital for mental health reasons, age-standardised rate per 1,000	Ministry of Health	Pharmaceutical data (Pharms)	Claim and payment information from government-subsidised medication related to psychotropic medication
		Ministry of Health	National Minimum Dataset (NMDS)	Publicly funded hospital admission and discharge information related to mental health diagnoses
		Ministry of Health	Programme for the integration of mental health data (PRIMHD)	Mental health services provided in public secondary care (referred to by primary care provider). Does not include mental health care provided in primary care setting or private sector.
		Ministry of Health	SOCRATES	Individuals receiving Disability Support services for mental health-related reasons
		Ministry of Social Development	Incapacity Benefit	Individuals who receive the incapacity benefit and unable to work where the reason for their incapacity is related to mental health

Self-harm (including self-harm that results in death)	Events and/or deaths caused by intentional self-harm, age-standardised rate per 1,000	Accident Compensation Corporation	Claims	Claim that involves self-inflicted harm and/or the outcome of the claim was death
		Ministry of Health	National Minimum Dataset (NMDS)	Publicly funded hospital admission and discharge information related to intentional self-harm
		Ministry of Health	Mortality collection	Deaths for which underlying cause is identified as death by suicide. Note there is a two-year lag in availability due to coronial processes
		Oranga Tamariki	Abuse Events	Abuse events where self-harm and/or suicide has occurred
Crime				
Victimisation rates for:				
- Family violence	Total number of victims of family violence offences, rate per 1,000	New Zealand Police	Pre-count Victimisations	Victimisation occurrences for corresponding Traffic Precedent and Offence Classification (TPOC) and Australian and New Zealand Standard Offence Classification (ANZSOC) codes
- Assault	Total number of victims of assault-related offences, rate per 1,000			
- Sexual Assault	Total number of victims of sexual assault offences, rate per 1,000			
- Theft and related offences	Total number of victims of theft and related offences, rate per 1,000			
- Abduction and kidnapping	Total number of victims of abduction, harassment and other related offences, rate per 1,000			
- Robbery, extortion and related offences	Total number of victims of robbery, extortion and related offences, rate per 1,000			
Safety				
Work-related accidents and injuries	Number of work-related injury claims for individuals between 25 and 64, rate per 1,000 employed people	Accident Compensation Corporation	Claims	Claim where accident or injury took place at work
Home-related injuries and accidents	Number of home-related injury claims, rate per 1,000	Accident Compensation Corporation	Claims	Claim where accident or injury took place at home
Road injuries and accident	Number of road-related injury claims, rate per 1,000	Accident Compensation Corporation	Claims	Claim where accident or injury took place on the road

Source: IDI 2024.

Appendix 3 Address Notification Dataset

The Address Notification (AN) Full table is used in this research to form a derived AN dataset. There are four columns of interest in the AN Full dataset: [ant_notification_date] and [ant_replacement_date] which is the recorded start and end date for each new address an individual lives in, [snz_idi_address_register_uid] which is an encrypted address identifier and used to represent one dwelling, and [ant_meshblock_code] which is the corresponding meshblock for that address.[30]

The AN Full dataset lists all address sources and spells for each individual. Stats NZ applies a set of prioritisation rules to the AN Full dataset to derive the AN dataset where individuals can only be in one geographic location at any point in time (Stats NZ, 2017a). For example, an individual has provided different addresses for the Ministry of Social Development (MSD) and to Waka Kotahi for their motor vehicle registration that cover the same time period. The AN dataset will prioritise and use the address provided to MSD over the address given to Waka Kotahi in the AN dataset; the AN Full dataset will have both records. The prioritisation rules are determined by:

- *Address quality tiers and address rank* - there are two tiers of address quality: tier one addresses are used to create or amend address spells, and tier two addresses that 'support' existing addresses. The address rank is the relative ranking of an address source within each tier. Within tier one addresses, the address ranking is (in order of preference):
    1. Census (2018 and 2013)
    2. Ministry of Social Development Residential (MSDR)
    3. Ministry of Health National Enrolment System (MOH NES)
    4. Ministry of Health Primary Health Organisation (MOH PHO)
    5. Ministry of Heath National Health Index (MOH NHI)
    6. Waka Kotahi Motor Vehicle Registration (NZTA)

[30] If an address is current, [ant_replacement_date] is coded to '9999-12-31' to indicate if that is the last known address recorded.

Tier two addresses that share the same address identifier as a tier one address is used to "support" the tier one address source.

- *Property type rank* – equal to 1 or 2 if an address is considered a home/house, 3 otherwise
- *Outlier rank* – an indicator if there is an unusually high amount of address notifications received for an individual (from 0, …, n where 0 is the lowest outlier ranking). StatsNZ will provide an outlier ranking to each address with prioritisation preference given to the lowest outlier ranking.
- *Effective rank (ER)* – the ranking of an address based on the above indicators multiplied by weights:

$$Effective\ Rank\ (ER) = Address\ Tier\ * 10{,}000$$

$$+ Address\ Ranking * 1{,}000$$

$$+ Propery\ Type * 100$$

$$+ Outlier\ Rank * 1$$

The lower the ER, the higher the rank of the address and likelihood to be prioritised.

- The sequence of prioritisation is as follows:
  1. If the next address is the same as the current address, then 'support' the current address.
  2. If the next address is different to the current address, it has been 30 days or less since the current address has been used or last 'supported', and:
     - The ER of the next address is lower than the ER of the current address, then replace the current address with the next address.
     - The ER of the next address is higher than the ER of the current address, then 'discard' the next address.
  3. If the next address is different to the current address, it has been more than 30 days since the current address has been used and:
     - The address tier of the next address is lower or equal to the address tier of the current address, then replace the current address with the next address.
     - The address tier of the next address is higher than the address tier of the current address, then discard the next address.

All rows from AN Full dataset where addresses have been replaced or have taken over other addresses are used to form the StatsNZ AN dataset.

The same set of prioritisation rules was used except for Census addresses. That is, other Tier 1 address sources were used to populate individual address spells, except if an individual's only address source in the AN Full table was a Census entry. However, individuals who had only a Census address entry In the AN Full Table were those in New Zealand at the time of the Census and were not a usual resident as per the Estimated Resident Population data.

Appendix 4 Age-standardisation - 2013 Estimated Resident Population

This research used the 2013 Estimated Resident Population (ERP) in the Integrated Data Infrastructure as the reference population.[31] This gives the following table:

Table 38 Age group and proportions using the 2013 Estimated Resident Population

Age Group	Proportion (to 5 decimal places)
0 – 4	0.06216
5 – 9	0.06802
10 – 14	0.06563
15 – 19	0.06905
20 – 24	0.07332
25 – 29	0.06532
30 - 34	0.06231
35 – 39	0.06181
40 – 44	0.07063
45 – 49	0.07001
50 – 54	0.07047
55 – 59	0.06072
60 – 64	0.05329
65 +	0.14729

Source: StatsNZ Resident Population table in the IDI.

Calculations for age-standardised rates per 1,000 is given by the following equation:

$$ASR(X)_{st} = \sum_{i=1}^{n} \left(\frac{X_{ist}}{P_{ist}}\right) Wi * 1{,}000$$

Where the age-standardised rates (ASR) for some outcome variable X for SA2 s at time t is the sum, for each age group i:

- the incidence for some outcome variable X for age group i for SA2 s at time t
- divided by the population P for age group i for SA2 s at time t
- multiplied by the weight for age group i for the reference population
- multiplied by 1,000.

[31] IDI table: [IDI_Clean_XXX].[data].[snz_res_pop] where [srp_ref_date] = '2013-06-30'

For example, we are interested in calculating the ASR for emergency department (ED) admissions (X) per 1,000 for Bayswater (s) in July 2017 (t). Table 39 provides hypothetical crude ED rates and population numbers for Bayswater in July 2017:

- For each age group i in column I, divide the crude rate (X) (column II) by the population (P) (column III) to give column IV.
- Multiply column IV by the proportion for each age group in the reference population (column V) to give column VII.
- Sum across all rows in column VI to get the age-standardised rate for ED admissions per 1,000 population.

This gives the age-standardised rate for ED admissions for Bayswater in July 2017 as 12.4 per 1,000 population.

Table 39 Hypothetical emergency department admissions by age group

Age Group	Crude incidence rate	Population	Crude rate / population	Proportion from reference population	Multiplied by 1,000
I	II	III	IV	V	VI
0 – 4	2	134	0.014925	0.06216	0.927761194
5 – 9	1	185	0.005405	0.06802	0.367675676
10 – 14	3	142	0.021127	0.06563	1.386549296
15 – 19	1	197	0.005076	0.06905	0.350507614
20 – 24	0	268	0.000000	0.07332	0
25 – 29	2	198	0.010101	0.06532	0.65979798
30 - 34	1	201	0.004975	0.06231	0.31
35 – 39	3	244	0.012295	0.06181	0.759959016
40 – 44	2	350	0.005714	0.07063	0.4036
45 – 49	4	277	0.014440	0.07001	1.010974729
50 – 54	1	301	0.003322	0.07047	0.234119601
55 – 59	3	298	0.010067	0.06072	0.611275168
60 – 64	7	192	0.036458	0.05329	1.942864583
65 +	9	388	0.023196	0.14729	3.416520619

Appendix 5 Codes for Health Outcomes

Table 40 ICD-9 and ICD-10 codes for cardiovascular diseases

Cardiovascular diseases	ICD-10 Clinical Codes	ICD-9 Clinical Codes
Clinical system code	10, 11, 12, 13, 14, 15	06
Acute rheumatic fever	I00%, I01%, I02%	390%, 391%, 392%
Chronic rheumatic heart disease	I05%, I06%, I07%, I08%, I09%	393%, 394%, 395%, 396%, 397%, 398%
Hypertensive disease	I10%, I11%, I12%, I13%, I15%	401%, 402%, 403%, 404%, 405%
Ischaemic heart disease, including myocardial infarction	I20%, I21%, I22%, I23%, I24%, I25%	410%, 411%, 412%, 413%, 414%
Pulmonary heart disease	I26%, I27%, I28%	415%, 416%, 417%
Cerebrovascular diseases, including strokes and transient cerebral ischaemic attacks	I60%, I61%, I62%, I63%, I64%, I65%, I66%, I67%, I68%, I69% G450%, G451%, G452%, G453%, G454%, G458%, G459%, G460%, G461%, G462%, G463%, G464%, G465%, G466%, G467%	430%, 431%, 432%, 433%, 434%, 435%, 436%, 437%, 438%
Atherosclerosis, aortic aneurysm and dissection, other aneurysm and dissection	I70%, I71%, I72% I790%	440%, 441%, 442%
Coronary bypass graft, coronary angioplasty implant and graft	Z951%, Z955%	V4581%, V4582%
Other heart disease	I30%, I31%, I32%, I33%, I34%, I35%, I36%, I37%, I39%, I40%, I41%, I42%, I43%, I44%, I45%, I46%, I47%, I48%, I49%, I50%, I51%, I52% I980%, I981%	420%, 421%, 422%, 423%, 424%, 425%, 426%, 427%, 428%, 429%
Other peripheral vascular disease	I738%, I739%	4439%, 44381%, 44389%
Procedures/operations related to cardiovascular disease	3530400, 3530401, 3530500, 3531000, 3531001, 3531002, 3531003, 3531004, 3531005, 3849700, 3849701, 3849702, 3849703, 3849704, 3849705, 3849706, 3849707, 3850000, 3850001, 3850002, 3850003, 3850004, 3850005, 3850300, 3850301, 3850302, 3850303, 3850304, 3863700, 3845619, 3864308, 380500, 9020100, 9020101, 9020102, 9020103	3601%, 3602%, 3603%, 3604%, 3605%, 3606%, 3607%, 3610%, 3611%, 36125, 3613%, 3614%, 3615%, 3616%, 3620%, 3621%, 3623%, 3624%, 3625%, 3626%, 3627%, 3628%

Source: Ministry of Health (2018). Note that the wildcard operator % indicates that the clinical code can be followed by any character.

Table 41 ICD-9 and ICD-10 codes for respiratory-related diseases

Respiratory-related diseases	ICD-10 Clinical Codes	ICD-9 Clinical Codes
Clinical system code	10, 11, 12, 13, 14, 15	06
Acute upper respiratory infections	J00%, J01%, J02%, J03%, J04%, J05%, J06%	460%, 461%, 462%, 463%, 466%
Influenza and pneumonia	J09%, J10%, J11%, J12%, J13%, J14%, J15%, J16%, J17%, J18%	480%, 481%, 482%, 483%, 484%, 485%, 486%, 487%, 488%
Chronic obstructive pulmonary disease (COPD)/emphysema and other allied conditions, including asthma and bronchiectasis	J20%, J21%, J22%, J40%, J41%, J42%, J43%, J44%, J45%, J46%, J47%, Q334%	490%, 491%, 492%, 495%, 496%, 493%, 494%, 74861%
Other diseases of respiratory tract	J30%, J31%, J32%, J33%, J34%, J35%, J36%, J37%, J38%, J39%	470%, 471%, 472%, 473%, 474%, 475%, 476%, 477%, 478%
Lung diseases due to external agents	J60%, J61%, J62%, J63%, J64%, J65%, J66%, J67%, J68%, J69%, J70%	500%, 501%, 502%, 503%, 504%, 505%, 506%, 507%, 508%
Other respiratory diseases	J80%, J81%, J82%, J83%, J84%, J85%, J86%, J90%, J91%, J92%, J93%, J94%, J95%, J96%, J98%, J99%	510%, 511%, 512%, 513%, 514%, 515%, 516%, 517%, 518%, 519%

Source: Barnard and Zhang (2021) and Dixon (2015). Note that the wildcard operator % indicates that the clinical code can be followed by any character.

Table 42 Chemical ID and ICD-9/ICD-10 codes for mental health pharmaceutical dispensing

Mental health category	Pharms chemical ID[a]	NMDS ICD-10 Clinical Codes	NDMS ICD-9 Clinical Codes
Clinical system code	-	10, 11, 12, 13, 14, 15	06
Anxiety/mood	1080, 1166, 1316, 1730, 1760, 1780, 1911, 2301, 2632, 2636, 2638, 3901, 6006	F064%, F39%, F400%, F401%, F402%, F408%, F409%, F410%, F411%, F412%, F413%, F418%, F419%, F420%, F421%, F422%, F428%, F429%, F430%, F431%, F432%, F438%, F439%, F450%, F451%, F452%, F453%, F454%, F458%, F459%, F480%, F680%, F681%, F930%	2960%, 2961%, 2962%, 2963%, 2964%, 2965%, 2966%, 2967%, 2968%, 2969%, 30000%, 30001%, 30002%, 30003%, 30006%, 30009%, 30010%, 30011%, 30012%, 30013%, 30014%, 30015%, 3002%, 3003%, 3004%, 3005%, 3006%, 3007%, 3008%, 3009%, 3060%, 3061%, 3062%, 3063%, 3064%, 30650%, 30652%, 30653%, 30659%, 3066%, 3067%, 3068%, 3069%, 30780%, 30789%, 3080%, 3081%, 3082%, 3083%, 3084%, 3089%, 3090%, 3091%, 30922%, 30923%, 30924%, 30928%, 30929%, 30981%, 30982%, 30989%, 3099%, 30113%
Dementia	3750, 3923	F00%, F01%, F02%, F03%	2900%, 2092%, 2903%, 2904%, 2908%, 2909%, 2941%

Depression	1059, 1180, 1379, 1437, 1438, 1642, 1760, 1824, 2285, 2301, 2638, 3753, 3785, 3901	F251%, F320%, F321%, F322%, F323%, F328%, F329%, F330%, F332%, F333%, F334%, F338%, F339%, F341%, F348%, F349%, F380%, F381%, F388%, F412%	
Disruptive behaviours including ADHD and/or intellectual disability	1389, 1809, 3880, 3887	F70%, F71%, F72%, F73%, F78%, F79%, F84%, F900%, F901%, F908%, F909%, F910%, F911%, F912%, F913%, F918%, F920%, F928%, F929%	29900%, 29901%, 29910%, 31400%, 31401%, 3171%, 3172%, 3173%, 3174%, 3175%, 3179%, 3180%, 3181%, 3182%, 3191%, 3192%, 3193%, 3194%, 3195%, 3198%, 3199%
Eating disorder		F500%, F501%, F502%, F503%, F508%, F509%, F982%, F983%	3071%, 30750%, 30751%, 30754%, 30759%
Emotional and personality disorders including schizophrenia and bipolar	1030, 1069, 1125, 1190, 1193, 1955, 2636, 3926, 3927, 6009	F252%, F258%, F310%, F311%, F312%, F313%, F314%, F315%, F316%, F317%, F318%, F319%, F300%, F301%, F302%, F308%, F309%, F340%, F600%, F601%, F602%, F603%, F604%, F605%, F606%, F607%, F608%, F609%, F61%, F620%, F621%, F628%, F629%, F63%, F68%, F69%, F920%, F938%, F939%, F928%, F929%	3010%, 30110%, 30111%, 30112%, 30120%, 30121%, 30122%, 30150%, 30159%, 3016%, 3017%, 3018%, 3019%
Psychosis	1007, 1078, 1226, 1283, 1532, 1533, 1535, 1583, 1732, 1799, 1950, 1990, 1994, 2255, 2260, 2298, 2530, 2820, 3803, 3873, 3884, 3898, 3940, 4025, 8792	F175%, F200%, F201%, F202%, F203%, F204%, F206%, F208%, F209%, F21%, F220%, F228%, F229%, F230%, F231%, F232%, F233%, F238%, F239%, F24%, F250%, F251%, F252%, F258%, F259%, F28%, F29%	2950%, 2951%, 2952%, 2953%, 2954%, 2955%, 2956%, 2957%, 2958%, 2959%, 2970%, 2971%, 2972%, 2973%, 2978%, 2979%, 2980%, 2981%, 2982%, 2983%, 2984%, 2988%, 2989%
Substance problems	1252, 1273, 1432, 1795, 1841, 2367, 3793, 3950	F100%, F101%, F102%, F103%, F104%, F105%, F106%, F107%, F108%, F109%, F110%, F111%, F112%, F113%, F114%, F115%, F116%, F117%, F118%, F119%, F120%, F121%, F122%, F123%, F124%, F125%, F126%, F127%, F128%, F129%, F130%, F131%, F132%, F133%, F134%, F135%, F136%, F137%, F138%, F139%, F140%, F141%, F102%, F143%, F144%, F145%, F146%, F147%,	2910%, 2911%, 2912%, 2913%, 2914%, 2915%, 2918%, 2919%, 2920%, 2921%, 2922%, 2928%, 2929%, 3030%, 3031%, 3032%, 3033%, 3034%, 3035%, 3036%, 3037%, 3038%, 3039%, 3040%, 3041%, 3042%, 3043%, 3044%, 3045%, 3046%, 3047%, 3048%, 3049%, 3050%, 3052%, 3053%, 3054%, 3055%, 3056%, 3057%, 3058%, 3059%

		F148%, F149%, F150%, F151%, F152%, F153%, F154%, F155%, F156%, F157%, F158%, F159%, F160%, F161%, F162%, F163%, F164%, F165%, F166%, F167%, F168%, F169%, F170%, F171%, F172%, F173%, F174%, F175%, F176%, F177%, F178%, F179%, F180%, F181%, F182%, F183%, F184%, F185%, F186%, F187%, F188%, F189%, F190%, F191%, F192%, F193%, F194%, F195%, F196%, F197%, F198%, F199%, F550%, F551%, F552%, F553%, F554%, F555%, F556%, F558%, F559%	
Sleep problems	2484, 3735	F510%, F511%, F512%, F513%, F514%, F518%, F519%	
Mental health not defined	1002, 1011, 1013, 1111, 1140, 1183, 1217, 1315, 1397, 1578, 1729, 1865, 1876, 1956, 2166, 2224, 2295, 2436, 2466, 2539, 3248, 3722, 3878, 3892, 3920, 3935, 4037, 6007	F04%, F05%, F06%, F07%, F09%, F488%, F489%, F52%, F53%, F59%, F930%, F931%, F932%, F950%, F951%, F952%, F958%, F959%, F980%, F981%, F984%, F988%, F989%, F99%	2931%, 2932%, 2933%, 2938%, 2939%, 2940%, 2948%, 2949%, 29911%, 29980%, 29981%, 29990%, 29991%, 30016%, 30019%, 30151%, 3027%, 30651%, 3074%, 30921%, 3100%, 3101%, 3102%, 3108%, 3109%, 3123%, 3130%, 3131%

Source: Bowden et al. (2019), Bowden et al. (2020) & Social Investment Agency (2019). Note that the wildcard operator % indicates that the clinical code can be followed by any character.

[a] Chemical IDs may appear for several mental health categories if they are used to treat multiple mental health issues.

Table 43 Mental health access and self-harm datasets

Dataset	Code
Mental health access	
PRIMHD	All activity types except for: T08, T32, T33, T35, T37
SOCRATES	Disability codes: 1201, 1301, 1302, 1303, 1304, 1305, 1306, 1399, 1815
MSD Benefit	Incapacity reasons: 006, 007, 008, 009, 160, 161, 162, 163, 164, 165, 170, 171, 172
Self-harm (Including self-harm that results in death)	
ACC Claims	[acc_cla_wil_self_infl_stat_text] = 'CONFIRMED'
NMDS	Diagnosis type code = E ('External') and ICD-10 clinical code: X60%, X61%, X62%, X63%, X64%, X65%, X66%, X67%, X68%, X69%, X70%, X71%, X72%, X73%, X74%, X75%, X76%, X77%, X78%, X79%, X80%, X81%, X82%, X83%, X84% If the event end type code is recorded as 'Died' (DD) or 'Died while still in emergency department acute facility' (ED) then self-harm resulted in death.
ACC Claims	[acc_cla_wil_self_infl_stat_text] = 'CONFIRMED'
Mortality Collection	ICD-10 clinical code: X60%, X61%, X62%, X63%, X64%, X65%, X66%, X67%, X68%, X69%, X70%, X71%, X72%, X73%, X74%, X75%, X76%, X77%, X78%, X79%, X80%, X81%, X82%, X83%, X84% Note that the Mortality Collection has a 2-year lag.
CYF Abuse Events	Abuse codes: SHM, SHS, SUC Note that CYF is now Oranga Tamariki but still uses its legacy name in the IDI.

Source: IDI 2024. Note that the wildcard operator % indicates that the clinical code can be followed by any character.

Appendix 6 Family Violence Codes

Table 44 Family violence Traffic Precedent and Offence Classification (TPOC) codes

TPOC code	TPOC code description
1541	Male Assaults Female (Firearm)
1542	Male Assaults Female (Other Weapon)
1543	Male Assaults Female (Manually)
1544[32]	Male Assaults Female (Stabbing/Cutting Weapon)
1545	Assault on person in family relationship
1581	Common Assault (Domestic)Crimes Act (Firearm)
1582	Common Assault (Domestic)Crimes Act (Other Weapon)
1583	Common Assault (Domestic)Crimes Act (Manually)
1587	Common Assault (Domestic) (Stabbing/Cutting Weapon)
1641	Common Assault (Domestic) (Firearm)
1642	Common Assault (Domestic) (Other Weapon)
1643	Common Assault (Domestic) (Manually)
1647	Common Assault (Domestic) (Stabbing/Cutting Weapon)
2153	Husband Rapes Wife (With Weapon)
2154	Husband Rapes Wife (No Weapon)
2157	Unlawful Sexual Connection With Spouse (Weapon)
2158	Unlawful Sexual Connection With Spouse (No Weapon)
2163	Attempts Sexual Violation Spouse (Weapon)
2164	Attempts Sexual Violation Spouse (No Weapon)
2167	Assaults W Intent To Commit Sexual Violation Spouse (Weapon)
2168	Assaults Intent Commit Sexual Violation Spouse (No Weapon)
2311	Father Incest Daughter
2312	Brother Incest Sister
2313	Other Incest Other Relative
2319	Other Incest
2654	Husband Rapes Wife
2658	Unlawful Sexual Connection With Spouse
2664	Attempt To Rape Spouse
2668	Attempted Unlawful Sexual Connection Spouse
2674	Assault With Intent To Commit Rape Spouse
2678	Assault Intent Commit Sex Connect-Spouse
2711	Parent Incest Child Under 12
2712	Parent Incest Child 12-16
2713	Parent Incest Child Over 16
2714	Brother Incest Sister Under 12
2715	Brother Incest Sister 12-16
2716	Brother Incest Sister Over 16
2719	Other Incest
2731	Sexual Connection Dependent Family Member
2732	Attempt Sex Connection Dependent Family Member
2733	Indecent Act On Dependent Family Member
3851	Contravenes Protection Order (Firearm)
3852	Contravenes Protection Order (No Firearm)

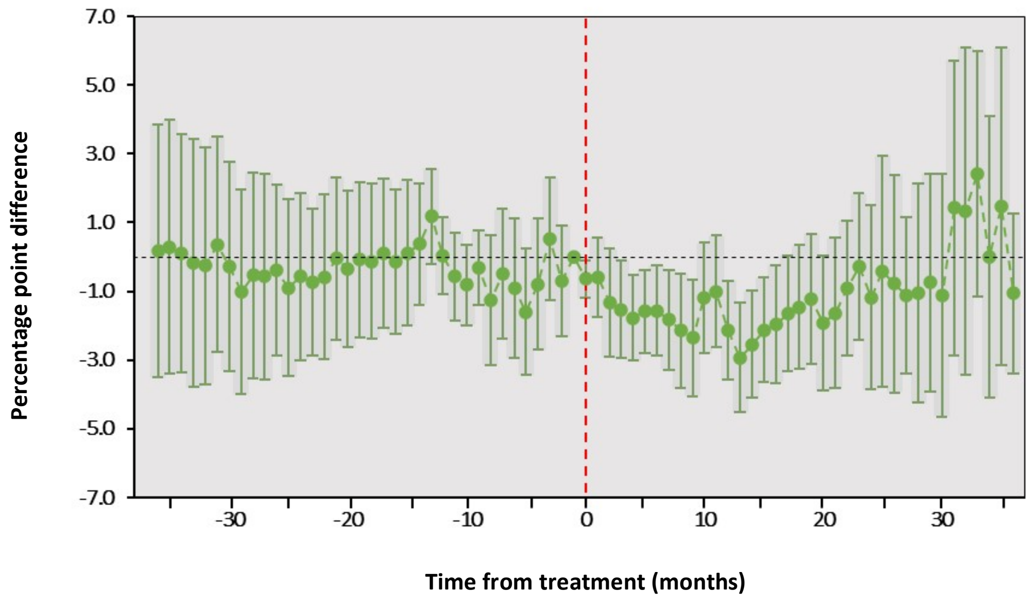
[32] The Social Wellbeing Agency note that while TPOC codes 1541 – 1544 are not strictly family violence, the majority of incidents with these codes are family violence related.

3853	Fails To Comply With Conditions Of Order (Firearm)
3854	Fails To Comply With Conditions Of Order (No Firearm)
3855	Fails To Attend Program
3856	Breach Publications Restrictions
3858	Detention by Constable - Failure or Refusal to Remain
3859	Other Breaches Of Domestic Violence Act
3871	Contravenes Protection Order - Family Violence
3872	Contravenes Protection Order - Unauthorised Contact
3873	Contravenes Protection Order - Encourages a Person to Engage in Behaviour
3874	Contravenes Protection Order - Dowry-Related Violence
3875	Contravenes Protection Order - Breach of Special Condition
3876	Fail to Comply w/Cond Protection Order - Fail/Refuse to Surrender Weapon
3877	Fail to Comply w/Cond Protection Order - Fail/Ref Surrender Firearms License
3878	Fail to comply with conditions of protection order - Possess Weapon
3879	Fail to comply w/conditions of protection order - Held Firearms Licence
3881	Contravenes Protection Order - Occupation Order
3882	Contravenes Protection Order - Tenancy Order
3883	Contravenes Protection Order - Ancillary Furniture Order
3884	Contravenes Protection Order - Furniture Order
3885	Fails to Attend Programme - Family Violence Act 2018
3886	Breach Publication Restrictions - Family Violence Act 2018
7224	Coerced person into marriage/civil union
2173	Induce Sexual Intercourse Pretence Of Marriage
2620	Abduction For Marriage Or Sex
2621	Abduction For Marriage Girl Under 12
2622	Abduction For Marriage Girl 12-16
2623	Abduction For Marriage Female Over 16
2627	Abduction For Marriage - Male
2629	Other Abduction For Marriage Or Sex
2641	Inducing Sexual Intercourse Pretence Of Marriage
3723	Breach Of Nonmolestation Order
3741	Offences Against Domestic Protection Act
3749	Other Miscellaneous Family Offences
3857	Failure To Comply With Police Safety Order (Not a criminal prosecution)
6122	Trespass Family Proceed Act

Source: Social Wellbeing Agency Github SQL coding. Retrieved from https://github.com/nz-social-wellbeing-agency.

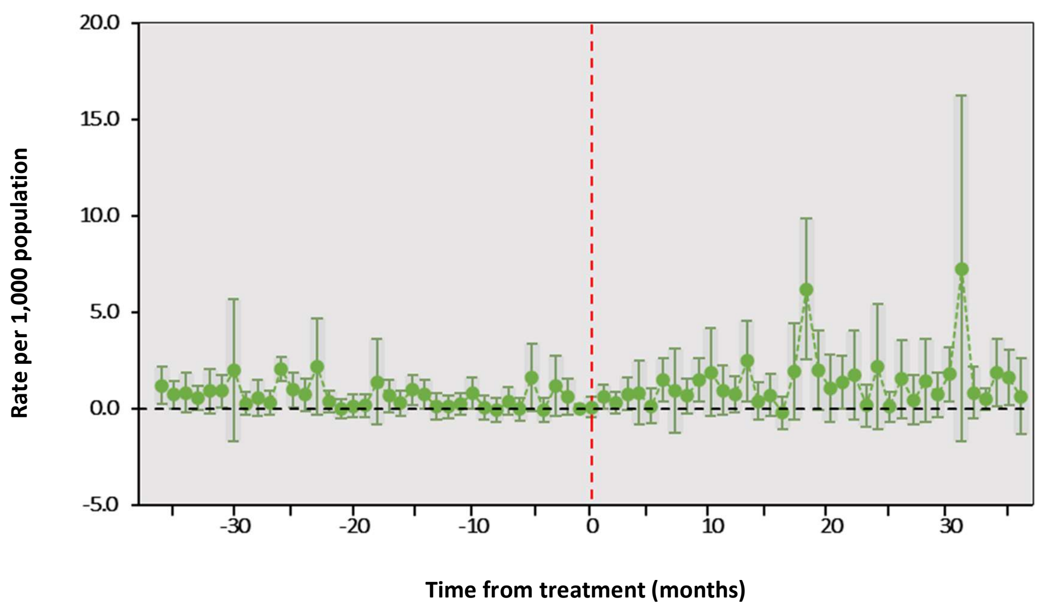
Appendix 7 Supplementary Results

Figure 136 DiD - urban regeneration on female employment rate (High UR SA1, Social Housing)



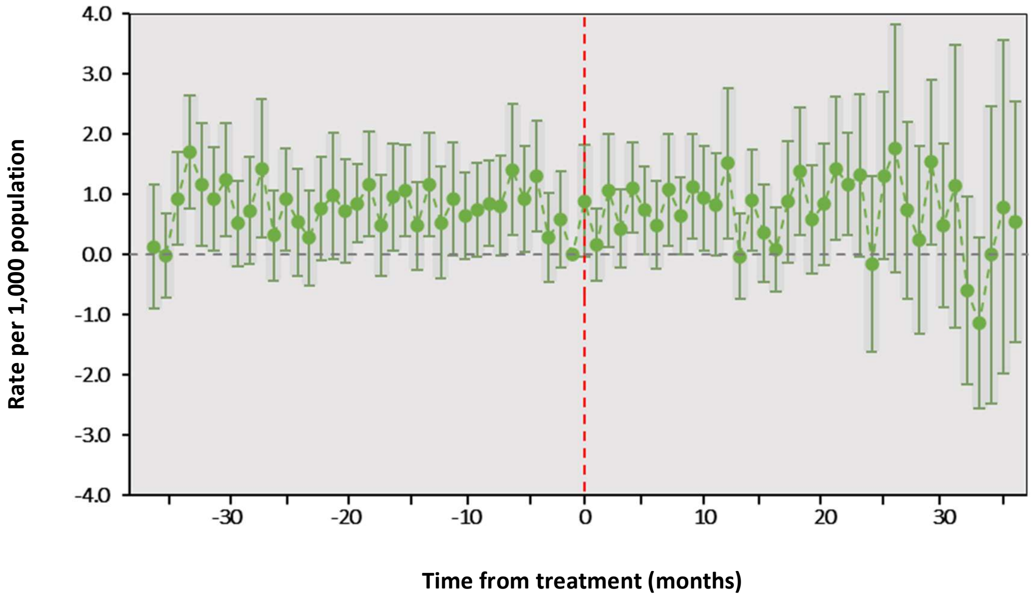
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 137 DiD - urban regeneration on family violence victimisations (Low UR SA2, Social Housing)



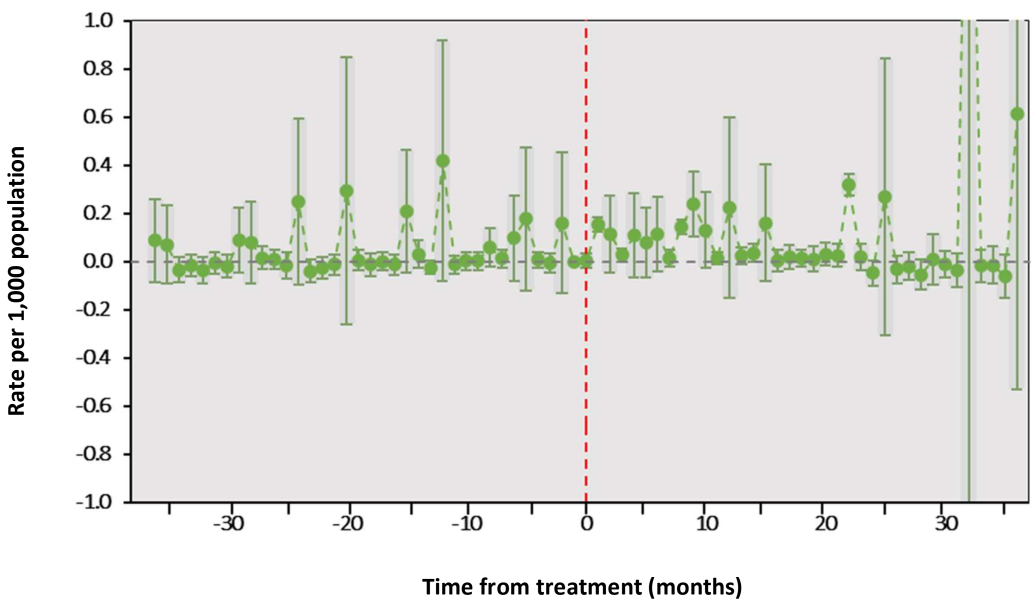
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.

Figure 138 DiD - urban regeneration on theft victimisations (High UR SA1, All Population)



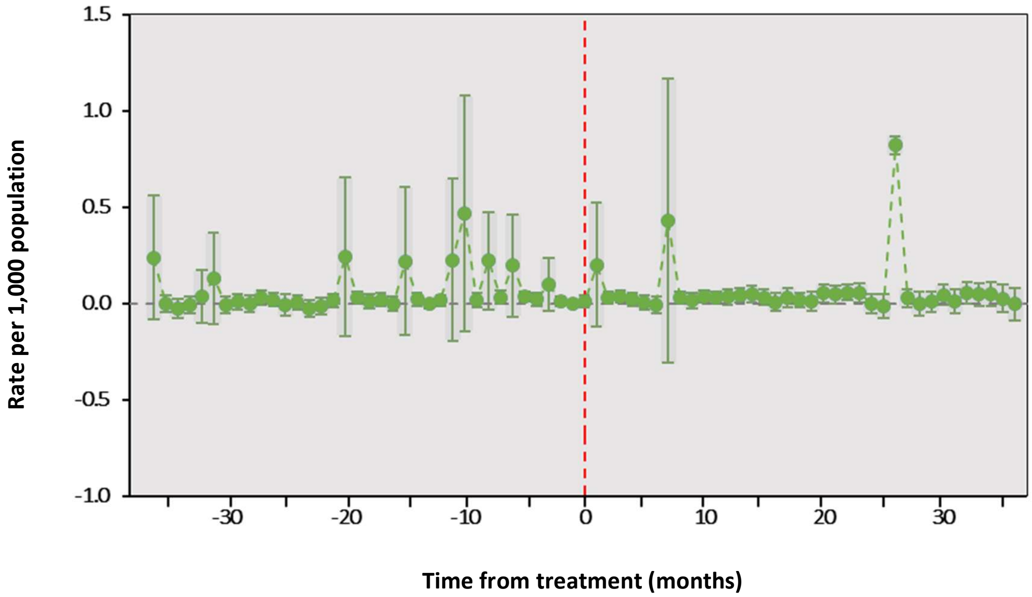
Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\widehat{\boldsymbol{\delta}}_{e\ell}$, from Equation (1.1) in Section 5.5.

Figure 139 DiD - urban regeneration on robbery victimisations (High UR SA1, Non-Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\widehat{\boldsymbol{\delta}}_{e\ell}$, from Equation (1.1) in Section 5.5. Note: y-axis truncated to show small values between 0 to 6 months from treatment.

Figure 140 DiD - urban regeneration on robbery victimisations (High UR SA1, Social Housing)



Source: IDI 2024. Coefficients refer to the average treatment effect for each relative time period by averaging the estimated CATT2, $\hat{\boldsymbol{\delta}}_{\boldsymbol{e\ell}}$, from Equation (1.1) in Section 5.5.