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The impact of the Canterbury earthquakes on household income and expenditure in the Canterbury region in New Zealand

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Abstract. Using New Zealand's Integrated Data Infrastructure (IDI), we evaluate the impact of the 2010-2011 Canterbury earthquakes on household economic behaviour, focusing on changes in income and expenditure. Using nationally representative data from the Household Economic Survey (HES) linked to measures of earthquake intensity, we implement a difference-in-differences design comparing pre- and post-earthquake outcomes for earthquake-affected households with a matched comparison group. We find that, relative to matched comparison households, total household income in high-intensity areas increases by about NZD 7,600 in the post-earthquake period. Total expenditure shows no clear average DiD effect, but expenditure composition shifts markedly: receipts and refunds, which capture insurance reimbursements and related inflows, more than double, and diary-recorded day-to-day spending rises by about 14%. Spending also increases in transportation, travel, fees and subscriptions, and social insurance contributions. Additional analysis shows that households that relocated out of Canterbury faced substantially higher housing costs (around NZD 25,000) and lower mortgage and loan repayments (around NZD 9,500) than households that remained, while average incomes are similar across the two groups. These findings provide evidence on household economic adjustment to disasters and offer policy-relevant insights into post-disaster financial support, social security design, and the management of population movements.

1. Introduction

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Disasters such as earthquakes, floods, and cyclones impose large and persistent economic costs. Beyond damage to housing and infrastructure, major shocks disrupt employment, reallocate income sources, and force difficult choices about consumption, saving, and relocation. Understanding these household-level adjustments is essential for evaluating disaster relief, social protection, insurance, and the incidence of disaster-related losses.

The 2010-2011 Canterbury earthquakes in New Zealand provide a stark illustration. A sequence of major earthquakes caused extensive residential damage, prompted large-scale red-zoning and demolition, and triggered an unprecedented reconstruction programme in and around Christchurch. The institutional environment was also distinctive: insurance coverage was near-universal, public and private compensation flows were sizable, and the rebuild generated strong local labour demand over several years. Together, these features make the Canterbury earthquakes an informative case for studying how households adjust income and expenditure after a large but geographically concentrated shock.

A substantial macroeconomic and regional literature has documented how disasters affect aggregate output and local growth. Cross-country and regional studies find persistent level losses alongside reconstruction-driven booms, with heterogeneous effects across events and locations (e.g. Cavallo et al., 2013; Noy and duPont, 2018). More recent work using quasi-experimental designs and high-resolution data has refined estimates of local impacts and recovery dynamics (Dube et al., 2023). Using municipality-level panels and a synthetic control design, duPont et al. (2015) document long-lived regional economic costs after the Kobe earthquake, consistent with persistent scarring. These perspectives, however, are largely silent on how aggregate patterns map onto household behaviour and welfare.

Household- and individual-level evidence remains comparatively limited. U.S. studies following Hurricane Katrina and other events document sharp changes in migration, labour supply, and income trajectories, with outcomes varying across demographic groups and locations (Groen and Polivka, 2010; Deryugina et al., 2018). Work on household balance sheets and credit markets shows that disasters can trigger substantial portfolio re-optimisation, with interactions between insurance, debt, and government transfers that are largely invisible in macro aggregates (Gallagher and Hartley, 2017). Yet there is still relatively little evidence on

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how disasters reshape the composition of household spending across detailed categories, including essentials, housing costs, and insurance-related flows.

For New Zealand, micro evidence on the Canterbury earthquakes has begun to emerge. Existing research documents macro and sectoral consequences of the rebuild, including construction-led productivity gains and the reallocation of activity within Christchurch (Parker and Steenkamp, 2012; Wood et al., 2016). More recent work uses administrative microdata to track individual incomes and labour-market trajectories in the affected region, highlighting heterogeneous impacts across sectors and along the income distribution (Abdeljawad and Noy, 2025a, 2025b). However, this literature does not directly analyse household-level income and expenditure responses using nationally representative survey data, nor does it examine in detail how the composition of spending changes across categories and household types.

This paper addresses three questions. First, did the Canterbury earthquakes change household income and the composition of spending for households located in exposed areas relative to matched households in comparable unexposed areas? Second, how did these responses vary across the income distribution and with earthquake intensity within Canterbury? Third, how did income and expenditure responses differ between households that remained in Canterbury and those that relocated elsewhere after the earthquakes?

To answer these questions, we link the Household Economic Survey (HES) to administrative data within the Integrated Data Infrastructure (IDI). Using Inland Revenue address histories and meshblock-level Modified Mercalli Intensity (MMI) measures, we define exposed households whose reference person lived in Canterbury at the time of the earthquakes and construct a matched comparison group outside Canterbury. Propensity score matching balances pre-earthquake characteristics, and a difference-in-differences design — supplemented by an event-study specification — compares pre- and post-earthquake outcomes while exploiting variation over time and across intensity levels.

The main results are as follows. Household incomes in the most severely affected parts of Canterbury increased relative to the matched comparison group in the post-earthquake years, consistent with heightened labour demand during the reconstruction period, alongside

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disaster-related support and compensation mechanisms that improved households' overall financial positions. Total household expenditure shows no clear average DiD effect, but expenditure composition shifts markedly. High-income households in high-intensity areas increase spending on transportation, travel, fees and subscriptions, and social insurance contributions, while low-income households primarily adjust spending on diary items (i.e., items recorded via the HES two-week expenditure diary, largely small day-to-day purchases). As expected, insurance payouts and reimbursements increase for both income groups, with a markedly larger rise among high-income households. Finally, among exposed households, those that relocate out of Canterbury face higher housing costs and lower mortgage and loan repayments than those that remain; conditional on observable characteristics such as age and household size, average incomes are similar across the two groups.

This paper contributes to the disaster and household-finance literatures in three ways. First, it provides new causal evidence on the Canterbury earthquakes' impacts on household incomes and spending using nationally representative microdata, complementing existing macro and administrative studies. Second, by disaggregating expenditure into detailed categories and examining heterogeneity by income and migration status, it sheds light on post-disaster adjustment channels and distributional consequences across household types. Third, it illustrates how survey data linked to administrative records within the IDI can be combined with propensity score matching and modern DiD methods to study localized shocks.

The remainder of the paper is structured as follows. Section 2 presents the empirical strategy, including the difference-in-differences framework, the event-study specification, the propensity score matching procedure, and the identification assumptions. Section 3 describes the data sources and linkage, outlines the construction of the treatment and control groups using address histories and earthquake-intensity measures, and defines the key income and expenditure outcomes. Section 4 reports descriptive evidence on pre- and post-earthquake patterns in household characteristics, income, and spending, and documents exposure gradients by intensity. Section 5 presents the main causal estimates and heterogeneity analyses by income group, earthquake intensity, and post-earthquake migration status, alongside robustness

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checks. Section 6 discusses interpretation and limitations, draws policy implications, and concludes.

2. Methodology

2.1 Difference-in-differences

Difference-in-differences (DiD) is a widely used econometric design for estimating the causal effects of policy changes or exogenous shocks on outcomes of interest when randomised controlled trials are infeasible. The basic idea is to compare changes in outcomes over time for an exposed (treated) group relative to a suitable comparison (control) group, thereby netting out time-invariant differences between groups and shocks common to all units in a given period (Wing et al., 2018).

In this study, we use DiD to estimate the causal impact of the 2010 – 2011 Canterbury earthquake sequence on household income and expenditure. We treat the earthquakes as an exogenous shock and exploit cross-regional variation in earthquake intensity to classify households into exposure groups. By interacting this intensity-based exposure measure with an indicator for the post-earthquake period, we estimate how household income and expenditure evolved with different levels of seismic exposure.

The conventional DiD approach relies on the parallel trends assumption: in the absence of the shock, exposed and comparison households would have followed similar trajectories over time. Under this assumption, the difference in changes between the two groups can be interpreted as the causal effect of the earthquakes (Angrist and Pischke, 2009). In our empirical specifications, we include region fixed effects and year fixed effects to account for time-invariant regional characteristics and year-specific shocks shared by all households.

Finally, because disaster impacts plausibly vary with exposure intensity, we follow recent contributions in the disaster economics literature and incorporate earthquake intensity into heterogeneous DiD specifications (e.g. Abdeljawad and Noy, 2025a). Specifically, we interact earthquake intensity with the post-earthquake indicator to estimate how the effects on household income and expenditure differ across intensity levels.

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In summary, the regression model adopted in this study takes the following form:

$$Y_{it} = \alpha + \beta_1(LowMMI_i \times Post_t) + \beta_2(HighMMI_i \times Post_t) + \gamma_1 Age_{it} + \gamma_2 HHSize_{it} + \mu_{ta} + \lambda_t + \epsilon_{it} \quad (1)$$

Here, Y_{it} denotes the outcome (dependent) variables, including *Total Household Expenditure*, *Total Household Income*, *Total Household Regular Income* and different expenditure categories, where i indexes HES households and t indexes survey years. $LowMMI_i$ and $HighMMI_i$ are are indicators for households located in meshblocks assigned to the low- and high-intensity groups, respectively.The omitted category comprises households in unexposed meshblocks (MMI = 0), so β_1 and β_2 are interpreted relative to the unexposed baseline. $Post_t$ is a post-earthquake dummy variable, taking the value of 1 for the years 2011/12 and onward, and 0 otherwise. Age_{it} denotes the age of the household reference person, and $HHSize_{it}$ denotes household size.

The regression model controls for year fixed effects λ_t and region fixed effects μ_{ta}, where the regions are defined at the Territorial Authority (TA) level, in order to account for spatial correlation and regional heterogeneity. To ensure robustness in statistical inference, standard errors are clustered at the TA level to adjust for potential intra-regional correlation in household income and expenditure outcomes (Bertrand et al., 2004).

2.2 Propensity score matching

To improve the control group's suitability as a counterfactual to the earthquake-affected households group, we construct a control group that closely resembles the earthquake-treated group in terms of observable pre-earthquake characteristics. This facilitates a more credible assessment of the causal effects of the earthquakes on household income and expenditure. Following standard practice in the disaster economics literature (Bondonio & Greenbaum, 2018; Yan, Zhou & Qi, 2025), we employ PSM to select an appropriate control sample.

To respect the Stable Unit Treatment Value Assumption (SUTVA), in particular its no-interference component, which requires that treatment effects on treated units do not spill over to control units, we restrict attention to households that were never exposed to the Canterbury earthquake sequence. We draw on existing research indicating that the impacts of

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the earthquakes were largely confined to the Canterbury region and its immediate surroundings (Parker & Steenkamp, 2012; Wood et al., 2016). Accordingly, when constructing the control group we exclude all households located in the South Island, as well as those that had migrated out of the Canterbury region. The control pool therefore consists only of households that consistently resided in the North Island over the sample period.

During the matching stage, we estimate each household's propensity to reside in Christchurch in 2010 using a logit model based on key pre-earthquake demographic characteristics. Specifically, the propensity score p_i for household i is obtained from the following logit specification:

$$Pr\,(D_i = 1|X_i) = p_i = \frac{e^{X_i\beta}}{1+e^{X_i\beta}} \quad (2)$$

where D_i=1 if household i was located in Canterbury in 2010, and D_i=0 if it was located in the North Island. The vector X_i contains pre-earthquake household-level covariates. On the basis of the estimated propensity scores, we implement 1:2 nearest-neighbour matching without replacement, matching each treated household with two North Island households that serve as control observations.

To enhance matching quality, we impose a strict caliper restriction (caliper = 0.2) on the propensity score distance to ensure a high degree of similarity in the covariate space for variables unlikely to be influenced by the earthquakes, including the age of the household reference person, household size, the reference person's gender, and their highest educational qualification. Moreover, all matches are required to fall within the same survey year in order to eliminate potential confounding arising from inter-year variation (Austin, 2011a).

To evaluate the quality of the matching, we assess covariate balance for each survey year from 2006/07 to 2017/18 using two standard diagnostics: the standardized mean difference (SMD) and the variance ratio (VR). Across all years, the matched samples satisfy commonly used balance criteria: all SMD values are below 0.1 and the variance ratios for continuous variables are below 2 (see Appendix B), indicating a high level of covariate balance and satisfactory matching performance (Stuart, 2010).

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On this basis, we obtain a high-quality control group pool that underpins the subsequent DiD estimates and strengthens the identification of the causal effects of the Canterbury earthquakes on household income and expenditure. Table 1 reports, for each survey year, the number of treated households, the size of the eligible control pool used for matching, and the final number of matched control households selected through PSM. These figures confirm that efficient matching was consistently achieved across all years (Austin, 2011a; Austin, 2011b; Stuart, 2010).

Table 1. Sample sizes of treated households, eligible control pool, and matched controls by survey year

SurveyYear	Treated Households	Eligible control pool	Matched control households
2006/07	417	1512	831
2007/08	462	1917	924
2008/09	459	1887	921
2009/10	432	1692	867
2010/11	432	1971	867
2011/12	486	1938	972
2012/13	411	1608	822
2013/14	438	1896	873
2014/15	705	3135	1407
2015/16	420	1995	840
2016/17	456	2118	909
2017/18	633	3165	1263

2.3 Examining the parallel trends assumption

A key assumption of the DiD design is that, in the absence of the earthquake shock, treated and control groups would have followed parallel trends. To assess this assumption, we estimate an event-study specification that traces the dynamic effects before and after the earthquakes.

In this specification, we interact the treatment-group indicator with a full set of year dummies, using 2006/07 as the omitted (base) year. This allows us to recover the trajectory of treatment effects over time. The regressions control for key household covariates, including the age of the reference person and household size, and include two-way fixed effects for year and region.

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Robust standard errors are clustered at the territorial authority level to account for within-area correlation in the error terms and to ensure valid inference.

It is important to note that each wave of the HES runs from July of one year to June of the next, and is therefore labelled as a "cross-year" survey. For example, "2006/07" refers to interviews conducted between July 2006 and June 2007. Although the magnitude 7.1 earthquake on 4 September 2010 was substantial, the most severe destruction resulted from the major aftershock on 22 February 2011, which caused extensive loss of life and property and had a shallower epicentre much closer to the Christchurch city centre.

The 22 February 2011 event severely disrupted data collection. For instance, the 2011 Census, originally scheduled for March 2011 (shortly after the most damaging earthquake), was postponed to 2013. Many of the most severely affected households were therefore not captured in the 2010/11 HES wave. In this study, we accordingly classify the 2006/07 – 2010/11 survey waves as the pre-earthquake period and the 2011/12 – 2017/18 waves as the post-earthquake period.

Furthermore, documentation from Stats NZ indicates substantial differences in how expenditure data were collected across HES waves. In the 2006/07, 2009/10, 2012/13 and 2015/16 waves, the total household expenditure variable aggregates spending across all categories. In the remaining waves, however, this variable covers only housing-related costs, such as rent, mortgage payments, local authority rates and building insurance. As a result, comparability in total expenditure across waves is limited and the series is affected by changes in data-collection methods and sampling design. Given these inconsistencies, we restrict our analysis of total household expenditure to the 2006/07, 2009/10, 2012/13 and 2015/16 waves.

Appendix C presents event-study plots for total household income, regular income and total expenditure. In the five pre-earthquake waves (2006/07 – 2010/11), the estimated coefficients for all three outcomes fluctuate around zero and their confidence intervals consistently include zero, indicating no systematic pre-trends and supporting the validity of the parallel trends assumption.

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Taken together, Figures C.1-C.3 present event-study estimates that not only confirm the validity of the parallel trends assumption in the pre-earthquake period, but also reveal a canonical DiD pattern (Autor, 2003; Clarke & Tapia-Schythe, 2021): the treated group experiences systematic and statistically significant changes in income and expenditure following the earthquakes, whereas the control group exhibits no comparable shifts.

3. Data

3.1 Data sources and treated group identification method

The Household Economic Survey is a nationwide survey conducted annually by Stats NZ to measure households' economic conditions, including income, housing costs and living expenditures. Information on total household income and regular income is collected every year. By contrast, the full expenditure module is fielded only once every three years: in the 2006/07, 2009/10, 2012/13 and 2015/16 waves. In the remaining years, the annual questionnaire covers income and housing costs only. Accordingly, our analysis of detailed expenditure relies exclusively on these four waves.

A key challenge in identifying the impact of the earthquakes lies in defining the treated group, households that were residing in the Canterbury region at the time of the earthquakes and were therefore directly exposed to the seismic shock. Because households may have relocated for various reasons before or after the earthquakes, the residential address recorded in the HES when the survey was conducted does not necessarily reflect their location at the time of the disaster. To address this, we combine multiple administrative data sources to reconstruct the residential history of each household reference person over time.

Specifically, each household reference person in the HES sample is linked, via their unique identifier (snz_uid), to address records from five administrative sources: Inland Revenue (IR), Accident Compensation Corporation (ACC), the Ministry of Social Development (MSD), the Household Labour Force Survey (HLFS) and the cross-agency address notification dataset

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(address_notify). The address reference period is defined as 1 January 2010 to 22 February 2011—the date of the main earthquake—hereafter referred to as the "treated period"[1].

By combining administrative address data with residential information from the HES survey year, we classify all sample households into four groups.

Group 1 consists of households whose HES survey address is in Canterbury and whose last registered administrative address prior to the earthquakes is also in Canterbury. These households were living in the affected area both before the earthquakes and at the time of the survey, and are therefore included in the treated group. For around 20% of household reference persons, the region code of their most recent pre-earthquake address is missing. In these cases, if the most recent non-missing pre-earthquake address and the first post-earthquake address are located in the same meshblock in Canterbury, we also classify the household as having resided in Canterbury at the time of the earthquakes and allocate it to Group 1.

Group 2 comprises households whose HES survey address is outside Canterbury but whose last administrative address prior to the earthquakes is in Canterbury. These households are treated as part of the treated group unless there is clear evidence that they had relocated before the earthquakes. Specifically, a small number of Group 2 households whose HES interview date falls after the date of their last administrative address record and whose HES survey address is outside Canterbury are excluded from the treated group, as they are likely to have moved out of Canterbury before the earthquakes.

Group 3 comprises households whose HES survey address is in Canterbury but whose last administrative address prior to the earthquakes is outside Canterbury. These households are likely to be post-quake in-migrants to the earthquake-affected region, and are therefore excluded from the treated and control groups.

[1]The IR dataset records only address changes and does not include observations when an address remains unchanged. As a result, households that stayed at the same address throughout the treated period would not have any corresponding record in the IR systemfor the treated period, which may lead to the erroneous exclusion of households that were in fact stably residing in the Canterbury region during this period. To mitigate this potential bias, we relax the address timestamp requirement for cases in which address information is available only from the IR source and is absent from all other sources. For these IR-only cases, we extend the acceptable timeframe for the most recent address record back to 1 January 2000, effectively retaining up to ten years of historical address data in order to recover pre-earthquake residential information as accurately as possible.

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Group 4 includes households whose HES survey address and pre-earthquake administrative address are both outside Canterbury. These households were not directly exposed to the disaster and are included in the control-group pool if they resided in the North Island (and excluded altogether if they resided in the South Island).

Under this classification, the treated group consists only of households for which there is reliable evidence that the reference person resided in Canterbury at the time of the earthquakes, while the control group comprises households that have never been recorded as living in Canterbury in any of the linked address sources.

Group sizes vary across waves. Group 1 includes 387-648 households per wave; Groups 2 and 3 are small (typically 12-66 and 12-63 households, respectively; suppressed in some waves); and Group 4 is the largest group (1,890-3,774 households per wave). The full year-by-year distribution is reported in Table A.1 Appendix A.

3.2 Analysis of missing address rates

Despite linking HES records to multiple administrative datasets, pre-earthquake addresses cannot be recovered for a non-trivial share of households. Across survey waves, the share of reference persons with no usable pre-earthquake address record ranges from about 15 to 19 percent, with no evidence of a systematic time trend. This suggests that the missing-address problem is persistent but relatively stable over time, rather than being driven by earthquake-related disruptions in a particular survey year. Table A.2 in Appendix A reports the year-by-year unmatched rates.

To assess whether these missing-address rates primarily reflect limitations of our linkage procedure or more general structural features of the underlying data, we perform a parallel exercise using the 2013 Census. Linking Census records to Inland Revenue address histories yields unmatched rates of roughly 11 to 23 percent across HES survey years, a pattern that is very similar in magnitude and timing to the rates observed for the HES sample itself (Table A.3 in Appendix A). This close correspondence suggests that the missing-address problem is largely driven by the nature of the administrative address data, rather than by the specific way in which HES records were linked.

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Further analysis and discussions with Stats NZ indicate that the unmatched cases can be broadly divided into two groups. The first consists of young adults whose address histories are genuinely short or incomplete: in the HES these reference persons are often under age 22, have recently left the parental home, and are still transitioning between study and work, so that few reliable historical addresses are available. The second group comprises hard-to-track individuals, including those with very frequent moves, intermittent labour-market attachment, or periods of living overseas. These individuals are systematically more likely to have missing or inconsistent address records in both administrative data and Census linkages.

The fact that similar unmatched rates are observed in both the HES-linked sample and the standalone Census linkage, and that the unmatched cases cluster in these two specific demographic groups, increases confidence that the missing-address issue does not introduce arbitrary selection into the treated and control groups. While non-random missingness at the extreme margins cannot be ruled out, the patterns are logically coherent and consistent across multiple data sources and survey waves. This suggests that the remaining missing-address cases do not pose a substantial threat to the validity of the study's conclusions.

3.3 Variable definition and construction

The level of earthquake intensity experienced by each household is measured using the MMI scale. To capture earthquake exposure, we utilise high-resolution seismic observation data for the February 2011 earthquake provided by New Zealand's national earthquake monitoring agency, GeoNet. These data are spatially overlaid with meshblock boundaries, small geographic units defined by Stats NZ, to construct a meshblock-level map of maximum ground-shaking intensity. Each household in the sample is then matched to its corresponding meshblock, yielding a household-level MMI value that serves as the key treatment-intensity indicator in our earthquake-exposure-heterogeneity analysis.

Earthquake exposure is categorised into three groups: households in meshblocks with MMI < 4 are assigned to the control group; those with MMI values in the range $[4, 7)$ form the low-intensity group; and those with MMI$\geqslant 7$ form the high-intensity group. This classification follows practical thresholds commonly used in the disaster management literature (e.g. Kaiser

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et al., 2012; Saunders et al., 2022) and effectively distinguishes between areas that experienced mild shaking and those with potentially severe damage.

Although all treated-group households are identified from administrative records as residing in the Canterbury region prior to the earthquakes, the number of households that can ultimately be matched to MMI intensity data is slightly smaller than the total treated group. This reflects two main factors, discussed below.

First, a small number of households that are classified as treated based on their Canterbury residence are located in meshblocks with MMI values below 4, reflecting greater distance from the earthquake's epicentre. Second, some households have confirmed pre-earthquake administrative addresses in Canterbury but lack corresponding meshblock-level geographic identifiers. For these units, no precise spatial match can be performed and no MMI value can be assigned. Together, these two subsets account for only a small fraction of the treated group and are excluded solely from the heterogeneity analysis conducted later in the study.

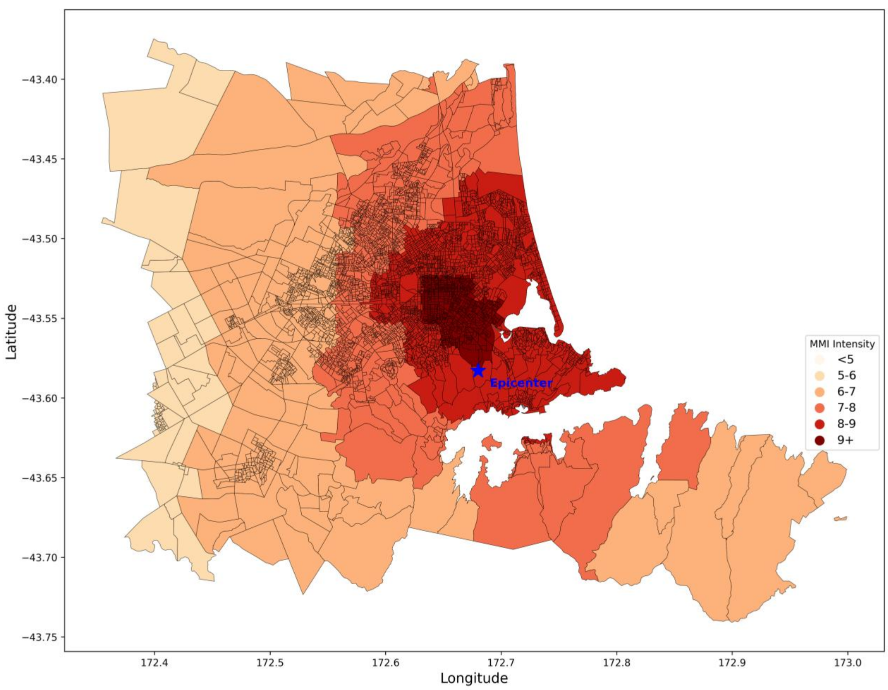

Figure 1. Meshblock-level earthquake intensity (MMI) in Christchurch City

Note: The figure displays a meshblock-level map of maximum Modified Mercalli Intensity (MMI) for the 22 February 2011 earthquake, constructed using shaking data from GeoNet and meshblock boundaries from Stats NZ. Darker shading indicates higher earthquake intensity and thus closer proximity to the epicentre. The location of the 22 February 2011 epicentre is marked with a blue asterisk.

In addition to earthquake intensity, we also consider households' homeownership status as a supplementary indicator of economic stability and post-disaster recovery capacity. We construct a binary variable with two categories: "owned/trust", which includes dwellings directly owned by household members or held through a family trust (a relatively common arrangement in Aotearoa New Zealand); and "rented", which includes market rentals, public or social housing, and other non-ownership occupancy arrangements.

This distinction is particularly important in the context of disaster resilience. Existing studies show that homeowners typically possess more assets and have better access to credit, which supports stronger recovery resilience and a greater capacity to mobilise resources following a disaster (Sawada & Shimizutani, 2008). By contrast, renting households are more likely to face liquidity constraints and housing insecurity, potentially limiting their ability to adjust economic behaviour in response to shocks. Including homeownership status as a control variable thus enhances the explanatory power of the model and allows us to identify potential heterogeneity in disaster impacts across different forms of property tenure.

For the expenditure analysis, we follow the HES classification and divide total household expenditure into 18 categories that together cover both routine and longer-term expenses. These categories are: domestic fuel and power; housing costs; receipts and refunds; general insurance; miscellaneous payments; mortgages and loans; other property; transportation; contribution schemes; medical and health; diary (expenditure-diary items); travel; telecommunications; fees and subscriptions; education, recreation, sport and culture; household operations; household maintenance; and credit and debit accounts. As discussed in Section 2.3, the definition of total household expenditure differs across HES waves; we therefore restrict total-expenditure analyses to 2006/07, 2009/10, 2012/13 and 2015/16.

It is important to note that the HES employs three different data-collection methods for different types of expenditure:

1. Expenditure diary: Respondents record each small and easily forgotten purchase over a consecutive 7-day period (to be completed within 14 days). There is no minimum or maximum amount for diary entries, and all entries are annualised using a fixed factor of 26.07.

2. Expenditure questionnaire - most recent payment: This module is used for infrequent, periodic or fixed large payments. Interviewers may verify bills on-site or ask respondents for immediate estimates. Reported amounts are annualised using frequency-specific factors—for example, weekly (×52), fortnightly (×26), monthly (×12), annually (×1) or every four weeks (×13).

3. Expenditure questionnaire - past 12 months: This module retrospectively captures expenditures that may have occurred sporadically over the previous year.

4. Descriptive Statistics

To clarify the relationship between earthquake exposure and household economic characteristics, the descriptive analysis is organised into two subsections: a cross-sectional comparison by earthquake intensity and control-group status (Section 4.1), and an analysis of heterogeneity within the treated group that compares households who remained in place with those who relocated (Section 4.2).

In constructing the summary statistics, we treat variables as follows. The age of the reference person and household size are reported as arithmetic means, as is standard in the descriptive-statistics literature and because these variables are bounded and not driven by extreme outliers. By contrast, total household income, regular income, total expenditure and housing expenditure are summarised using medians to reduce the influence of outliers, such as high-net-worth and net-income households.

For mortgages and loans, a large proportion of households report zero or missing values, so the median is equal to zero in most years and provides little discriminatory power. We therefore

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report the mean for this variable, which better reflects the average level of mortgage and loan payments among households with positive expenditure. This approach follows standard practice in New Zealand's official statistics when dealing with left-censored consumption items.

4.1 By earthquake intensity and control-group status

Table D.1 in Appendix D reports key characteristics of the sample across groups, including the average age of the reference person, household size, the share of female reference persons, and the homeownership rate. The high-intensity group (MMI $\geqslant$ 7) has a slightly lower average age of the reference person than both the low-intensity and control groups (mean age: High = 51.5; Low = 54.6; Control = 52.7). This pattern may reflect the greater presence of younger households in central urban areas, which were also exposed to higher seismic intensity, but the differences are modest and should be interpreted with caution.

There are more pronounced differences in homeownership status. Across all survey years, the share of households that own their dwelling or hold it in a family trust is approximately 10 percentage points lower in the high-intensity group than in the low-intensity group, whereas the difference between the treated and control groups is not statistically significant. This pattern is consistent with the concentration of rental housing in central urban areas, which were also among the locations most severely affected by the 2011 earthquake (Kaiser et al., 2012).

4.2 Heterogeneity within the treated group: stayers versus relocators

To further explore differences in household responses to the earthquakes, we divide the treated group into two categories. The "stay" group consists of households whose HES survey-year address and last pre-earthquake administrative address are both located in the Canterbury region. The "relocation" group comprises households whose post-earthquake HES survey address is outside Canterbury, but whose last pre-earthquake administrative address was within the region[2].

[2] The relocation group does not exclusively represent post-earthquake out-migrants. By construction, it includes households whose HES survey address lies outside Canterbury while their last administrative address prior to the earthquakes is in Canterbury, and who therefore are treated as having been resident in the affected area immediately before the disaster. There is a small subset of cases in which the HES interview date falls after the date of the last recorded administrative address and the HES survey address is outside Canterbury. For these households, there is

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When defining relocation, we classify households based on the combination of their location at the time of the earthquakes (using administrative address records for January 2010 – February 2011) and their location at the time of each HES interview. Households in the relocation group are those whose reference person lived in Canterbury immediately before the earthquakes but are later observed in HES interviews residing outside Canterbury. In contrast, the stayed group comprises households whose reference person remained in Canterbury both at the time of the earthquakes and at the time of interview. In the post-earthquake waves (2011/12 – 2017/18), the relocation group therefore primarily captures households that moved out after the earthquakes.

As shown in Table D.2 in Appendix D, the average age of reference persons in the stay group is generally higher than in the relocation group across most survey years. This pattern suggests that migration behaviour is more prevalent among relatively younger individuals, consistent with international evidence on post-disaster migration (Fussell, 2015).

There are also sizeable differences in homeownership. In the post-earthquake years, the homeownership rate in the stay group is generally around or above 70%, whereas in the relocation group it fluctuates around 50%. This suggests that households remaining in Canterbury tend to enjoy greater housing stability, while households that relocate are more likely to be in rental or temporary accommodation.

In terms of income, both total and regular household income medians are consistently higher for the stay group in most years, indicating that relocation households tend to face more fragile income conditions. The relocation group also exhibits larger standard deviations in income, reflecting greater income heterogeneity.

For expenditure, the two groups display broadly similar medians in total and housing-related spending across most years. However, there are pronounced differences in the mortgages-and-loans variable, with the stay group consistently reporting higher values. This pattern is consistent with these households being more commonly owner-occupiers in the mortgage repayment phase.

evidence that they may have moved out of Canterbury before the earthquakes; we therefore exclude them from the treated group to avoid misclassification.

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Taken together, relocation households display weaker economic profiles than stay households in most survey years. Regardless of whether they moved before or after the earthquakes, these households tend to experience greater income volatility and housing insecurity. While migration is self-selected and this pattern does not imply that relocation itself causes vulnerability, it does highlight a strong correlation between mobility and economic disadvantage.

5. Results

5.1 DiD Results for income

As shown in Table 2, both total household income and regular household income increase significantly in high-intensity areas. On average, households in these areas experience an increase of around NZD 7,626 in total income ($p < 0.05$) and NZD 7,426 in regular income ($p < 0.10$). By contrast, the estimated effects for low-intensity areas are also positive but not statistically significant.

These findings contrast with the conventional view that disasters primarily exert negative economic effects as the earthquakes were associated with higher household incomes in the most severely affected areas. The possible mechanisms underlying this pattern are explored in the following sections.

Table 2. DiD results for total and regular household income

Variable	Total Household Income	Total Regular Household Income
MMI group:Low × Post	4799.54 (3022.60)	5277.87 (2878.50)
MMI group:High × Post	7626.42** (3444.07)	7426.38* (3333.84)
Age of reference person	-147.18*** (39.27)	-168.10*** (39.13)
Household size	15328.42*** (683.80)	14905.46*** (669.27)

Observations: 17,202
*** p<0.01, ** p<0.05, * p<0.1

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Each column reports coefficients from a separate DiD regression. Robust standard errors clustered at the Territorial Authority (TA) level are in parentheses. Year and TA fixed effects are included.

This pattern can be understood in light of the distinction between aggregate output measures and household-level outcomes. Although disasters are often associated with output losses, regional GDP in Canterbury did not fall markedly after the earthquakes (Stats NZ, 2023b). In this setting, a large reconstruction programme and related labour-demand effects provide a plausible channel through which household incomes could rise in the post-earthquake period, particularly in the years following the shock (e.g. Wood et al., 2016).

Second, post-disaster migration may affect the observed income distribution through compositional change. In our linked-address classification, the treated group includes only households for which there is reliable evidence that the reference person resided in Canterbury at the time of the earthquakes (Groups 1 and 2), while likely post-earthquake in-migrants to Canterbury are excluded (Group 3). As a result, migration-related compositional effects in our estimates operate primarily through selective out-migration among pre-earthquake residents (Group 2) and differences between stayers and movers, rather than through in-migration into the affected region. For example, if lower-income households are more likely to leave Canterbury due to housing damage or heightened housing insecurity, the median income among those remaining can rise even without broad-based income gains. This mechanism is consistent with patterns in our descriptive statistics. In addition, inflows from insurance payouts, particularly important in New Zealand given near-universal earthquake insurance coverage, as well as government assistance programmes may have boosted households' disposable income following the disaster. Selective out-migration may also affect the observed income distribution through compositional change. Consistent with this possibility, Section 4.2 (and Appendix D2) documents that households observed outside Canterbury after the earthquakes tend to be younger, less likely to own their home, and to have weaker income profiles than those who remain. As a result, the median income among remaining households can rise even without broad-based income gains.

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Existing literature provides complementary evidence on these mechanisms. Dube, Tran and Wilson (2023) show that in the United States, per capita income in disaster-affected counties increased by an average of 0.5% over the eight years following a disaster, with some areas, such as those impacted by Hurricane Katrina, experiencing increases of more than 3%. The mechanisms they highlight include job growth in construction and related sectors, higher average wages, and inflows of insurance payouts and government reconstruction funds. These mechanisms align with the interpretation of our findings, suggesting that in settings with substantial reconstruction activity and compensation flows, household incomes may increase even as disasters impose large welfare losses through other channels.

It is important to emphasise that the spatial distribution and group-specific heterogeneity of post-earthquake income changes remain important avenues for future research. Given the repeated cross-sectional structure of the HES and sample-size constraints, especially the small number of households in Groups 2 and 3 in each wave, this study cannot fully characterise differential recovery trajectories by income group, ethnicity, housing tenure, or social capital. Future work leveraging longitudinal micro-level tracking in the IDI could provide more granular evidence on changes in the income distribution and the inequality implications of large natural hazards (Abdeljawad and Noy, 2025b).

5.2 DiD results for expenditure

In contrast to the income results, the DiD estimates for total household expenditure are positive but not statistically significant in either the low- or high-intensity group (Table 3). However, when total expenditure is disaggregated into categories, several components exhibit sizeable and statistically significant treatment effects.

Table 3. DiD results for total household expenditure

Variable	Estimate
MMI group:Low × Post	3414.14 (2322.80)
MMI group:High × Post	1831.58 (1399.87)
Age of reference person	-237.91*** (21.40)
Household size	3105.63*** (193.57)

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Observations: 5,025
*** p<0.01, ** p<0.05, * p<0.1

Certain expenditure categories, such as receipts and refunds, exhibit highly skewed distributions. For receipts and refunds, for example, roughly 90% of observations are zero, and the remaining values are concentrated in a heavy right tail. Estimating ordinary least squares (OLS) regressions directly on these raw levels forces the model to fit a small number of very large observations, allowing them to exert disproportionate influence on the estimated coefficients.

To address these distributional features and improve interpretability, we estimate the category-level regressions using a log transformation of the absolute value plus one of each expenditure variable, that is, log(1+|y|). This transformation substantially stabilises the regression estimates and yields coefficients that capture relative differences in the magnitude of expenditure rather than being driven by a few extreme observations. For example, after this transformation, the coefficient for receipts and refunds in the high-intensity treatment group is 0.718, implying that the magnitude of receipts and refunds (plus one) in the treatment group is approximately 2.05 times ($e^{0.718}$) that in the control group.

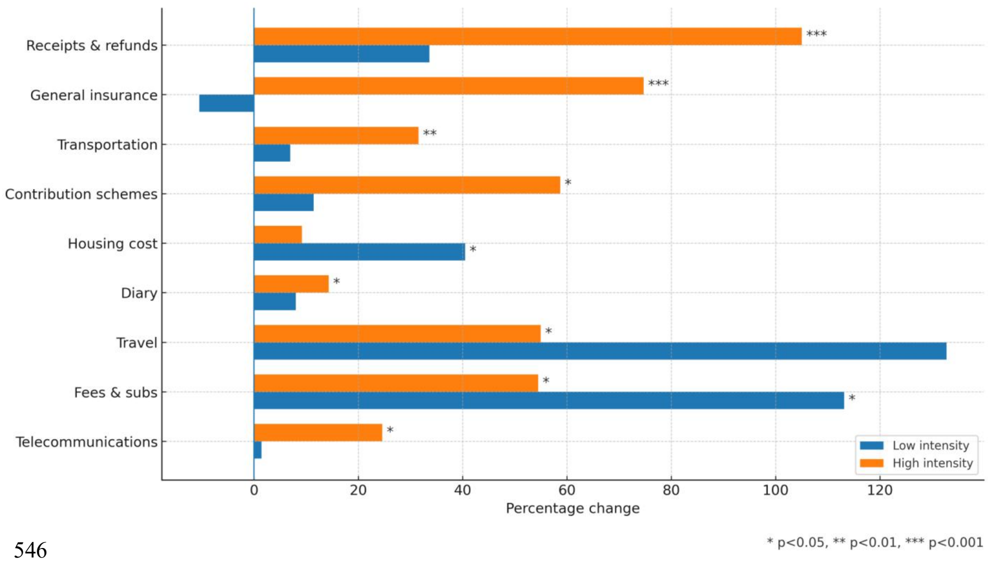

Figure 2. Post-earthquake changes in expenditure categories by EQ intensity

As shown in Figure 2 (with full regression estimates reported in Appendix E), several expenditure categories exhibit statistically significant responses to the earthquakes, particularly among households in high-intensity areas.

Households in high-intensity areas show a large and statistically significant increase in receipts- and refunds-related entries following the earthquakes. As noted above, this category also captures insurance reimbursements, which are recorded as negative expenditure items rather than income to avoid double-counting with other income sources such as wages or transfer payments (Stats NZ, 2020). The estimated log coefficient for the high-intensity group is 0.718, implying that the magnitude of receipts and refunds (plus one) is approximately 2.05 times ($e^{0.718}$) that in the control areas. This pattern likely reflects increased insurance claims after the disaster. Higher refund activity may also be consistent with more cautious consumption behaviour, as households may have been more inclined to return purchases or liquidate assets in response to heightened uncertainty.

Compared with the control group, the 'diary' expenditure category also increases by around 14.3% in high-intensity areas (coefficient = 0.134, $p < 0.05$). This effect is statistically significant and economically meaningful, especially given that the diary category primarily captures essential household expenditures, such as food, beverages and personal care, that typically exhibit low elasticity to income changes and limited responsiveness to external shocks.

Because the diary module records transactions in real time and is less susceptible to recall bias or privacy-related underreporting, the resulting data are generally of high quality. It is therefore notable that the estimated treatment effect for diary expenditure is both large and precisely estimated.

Transportation, telecommunications and travel all show statistically significant increases in high-intensity areas. Households may have incurred substantial additional costs related to vehicle repairs and replacements following the earthquakes. The observed rise in travel expenditure may be associated with additional trips taken to avoid disaster-affected areas, visit relatives or manage post-earthquake uncertainty.

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Both the low- and high-intensity groups exhibit increases in fees-and-subscriptions expenditure, with the high-intensity group showing a statistically significant rise. According to the HES classification, this category includes payments for club memberships, professional association fees, subscriptions to recreational or educational programmes and other recurring service fees. The observed increase suggests that, rather than cutting back on discretionary items, households may have maintained or even expanded their engagement with subscription-based services in the aftermath of the earthquakes. This may reflect a desire for continuity, social connection and access to structured recreational or educational activities during a period of post-disaster uncertainty and dislocation.

Expenditure on social security and retirement contribution schemes increases significantly after the earthquakes. According to the HES definition, this category primarily includes Accident Compensation Corporation (ACC) contributions, KiwiSaver retirement savings contributions, private superannuation scheme contributions, other pension and retirement fund contributions and other social insurance scheme contributions. This pattern is consistent with macroeconomic and microeconomic evidence that heightened uncertainty associated with exposure to large shocks fosters precautionary saving: households continue to invest in social protection and long-term retirement planning rather than reducing such payments (e.g., Aizenman & Noy, 2015). It also suggests sustained trust in, and reliance on, institutional mechanisms for long-term risk management among New Zealand households.

Unexpectedly, it is the low-intensity group, not the high-intensity group, that experiences a statistically significant increase in housing-related expenditure (around 40.5%; coefficient = 0.340, $p < 0.05$). This increase may reflect moderate disruption even in less severely affected areas, including repairs, temporary relocations or upward pressure on rents in neighbouring areas due to population displacement from harder-hit areas where many houses were no longer suitable for occupation. The absence of significant changes in the high-intensity group may be due to more severe housing damage, with reconstruction delayed or financed directly through insurance (through the public insurer's Managed Repair programme) and thus not immediately captured in household expenditure records.

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As shown in Appendix F, a comparison of census data across New Zealand's 16 regions between 2006 and 2013 indicates that Canterbury's compound annual growth rate in median household income reached 4.46%, ranking second only to the West Coast (5.5%) and third in absolute median-income growth behind Auckland and Wellington (Stats NZ, 2014). This growth rate is substantially higher than in most other regions, suggesting that Canterbury's post-2006 income growth was relatively strong in the post-earthquake period, potentially reflecting reconstruction and recovery alongside other regional factors.

5.3 Heterogeneous effects by income group

As shown in Figure 3 and Table G1, G2 in Appendix G, among households with income above the median, post-earthquake increases in expenditure remain broad but exhibit some notable shifts in statistical significance across categories. The regression results indicate that high-income households experienced statistically significant increases in spending on contribution schemes, telecommunications, general insurance, transportation and travel. In particular, the substantial rise in household maintenance and general insurance expenditure suggests that higher-income households were more actively engaged in mobility, risk management and longer-term repair or relocation activities following the disaster.

This pattern is consistent with international evidence that post-disaster reconstruction activities and insurance payouts tend to benefit middle- and high-income households more, as they are better positioned to finance reconstruction and to make effective use of incoming funds (Kousky, 2014). The significant increases in contribution schemes further indicate that these households continued to invest in institutional protection mechanisms, such as retirement savings and social insurance, in the face of increased salience of disaster-related uncertainty.

Receipts and refunds also increase markedly for high-income households. The estimates imply that, in the post-disaster period, these households receive larger amounts of refunds, proceeds from second-hand sales and insurance reimbursements than in earlier periods. This pattern likely reflects the lagged nature of certain compensatory inflows, such as insurance settlements or asset liquidations, which may continue to generate cash inflows beyond the immediate aftermath of the disaster as claims are processed and households adjust their asset portfolios.

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Among high-income households in the low-intensity group, fees and subscriptions also rise sharply: the coefficient is 1.17 ($p < 0.05$), corresponding to a very large proportional increase of about 222.8% in the magnitude of fees and subscriptions relative to the control group. This suggests that higher-income households maintained, or gradually resumed, discretionary spending on memberships and subscriptions during the post-disaster period.

For low-income households, post-earthquake expenditure adjustments are statistically significant in only a small number of categories, predominantly those covering essential goods and services. The notable increase in diary expenditure (about 15.5%; coefficient = 0.144, $p < 0.05$) underscores this pattern, as the diary category encompasses routine, inelastic expenses such as food, beverages and personal care. The concentration of significant changes in these fundamental consumption items suggests that lower-income households faced tighter financial constraints that limited their ability to adjust discretionary spending. Observed expenditure shifts primarily take the form of modest increases in basic necessities, likely driven by immediate post-disaster needs or inflationary pressure on essential goods, rather than deliberate reallocation across broader consumption categories.

Receipts and refunds also increase significantly for low-income households in high-intensity areas (about 34.6%; coefficient = 0.297, $p < 0.05$), largely reflecting post-disaster cash inflows —most likely as insurance reimbursements,. Given New Zealand's atypical and near-universal household insurance coverage, even low-income households in severely affected areas benefited from claims settlements, leading to observable increases in this category. However, the magnitude of this effect is considerably smaller than for high-income households, for whom the estimated increase is around 188.64% (coefficient = 1.06). This gap likely reflects differences in insurance depth and asset portfolios: higher-income households typically own more insurable assets and higher-value possessions, generating larger claim amounts and subsequent refunds, whereas lower-income households, despite similar insurance coverage rates on paper, insure fewer high-value items, limiting the scale of post-disaster compensatory inflows (Owen & Noy, 2019). Thus, while receipts and refunds provide important liquidity relief across income groups, the disparity in effect size underscores underlying wealth and asset inequalities in recovery capacity.

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The relatively narrow range of significant spending increases among low-income households more broadly reflects their constrained post-disaster financial capacity. Compared with higher-income households, low-income households tend to have less access to savings, credit, insurance, and informal financial support, which limits their ability to adjust expenditures beyond essential needs (Deryugina, 2017; Hickel & Hallegatte, 2022).

Taken together, these findings highlight the heterogeneous nature of household financial responses to disasters. High-income households exhibit broad-based post-disaster adjustments in several expenditure categories, whereas low-income households respond more narrowly, with targeted changes in more core spending categories. This divergence reinforces the central role of income in shaping differential post-disaster expenditure dynamics and is consistent with the emerging literature on disaster-related inequality (Dube, Tran & Wilson, 2023; Hickel & Hallegatte, 2022).

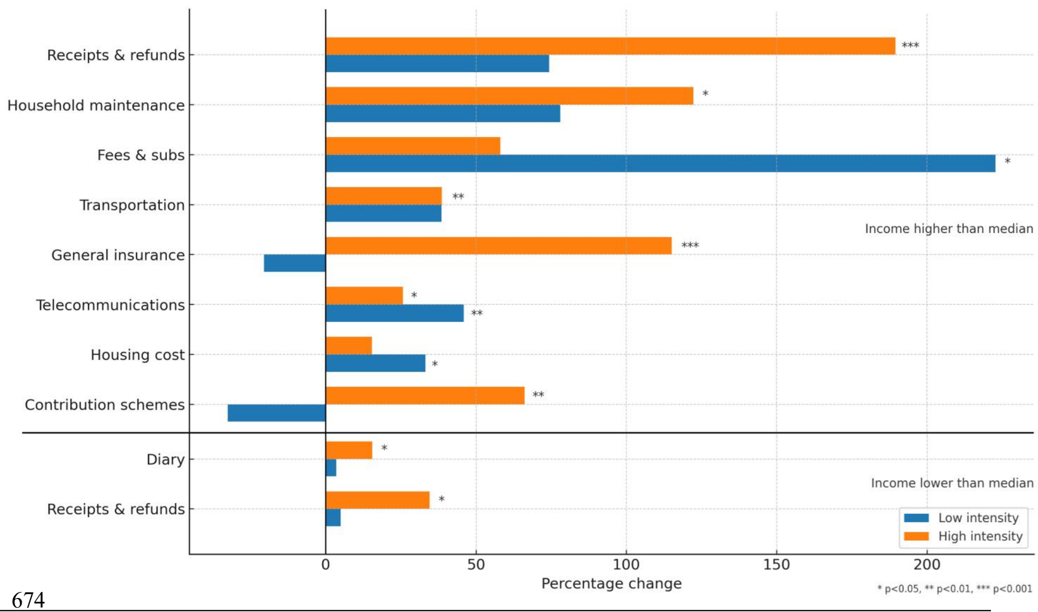

Figure 3. Post-earthquake changes in expenditure by income group

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5.4 Heterogeneous effects of migration

To assess the heterogeneous effects of post-earthquake migration, we compare households that remained in Canterbury ("stay" households) with those that relocated out of the region ("relocation" households) across five key economic indicators: total household income, total regular household income, total household expenditure, housing costs and mortgages and loans. These five variables are consistently available in each HES wave and thus allow for a balanced comparison over time. We estimate separate linear regressions for each outcome, including a dummy variable for relocation households, and control for the age of the reference person and household size. The regression results are reported in Table 4.

Table 4. Covariate-adjusted differences between stay and relocation households (descriptive)

	Total income	**Regular income**	**Total expenditure**	**Housing cost**	**Mortgages and Loans**
(Intercept)	56036.34***	53813.65***	25027.08***	39004.28***	17853.49**
	(6602.26)	(6055.57)	(1567.71)	(5752.67)	(5468.04)
relocator indicator	754.24	1331.31	672.64	24967.88***	-9466.120*
(1 = relocation group, 0 = stay group)	(5124.44)	(4700.12)	(1216.80)	(4465.02)	(4244.10)
age	-235.68**	-227.56**	-259.79***	-676.11***	-377.65***
	(87.07)	(79.86)	(20.68)	(75.87)	(72.12)
household size	17879.34***	17359.14***	2536.17***	14145.13***	13639.13***
	(1144.84)	(1050.04)	(271.84)	(997.52)	(948.16)
Observations	3546	3546	3546	3546	3546

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Estimates report covariate-adjusted mean differences between the relocation and stay groups within the treated sample. The relocation indicator reflects a post-earthquake migration outcome that may be endogenous; coefficients should therefore be interpreted as associations conditional on included covariates, not causal effects of relocation.

First, for total household income, the difference between the two groups is not statistically significant. This suggests that, on average, households that relocated did not experience systematically higher or lower income levels than those that remained in place after the earthquakes. Migration per se therefore does not appear to have been a decisive factor in

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driving income changes, which are more likely to have been shaped by other socioeconomic characteristics or by the severity of earthquake exposure.

Second, the difference in regular household income between the two groups is also statistically insignificant. Even for more stable and predictable income sources, such as wages and salaries, pensions and fixed transfer payments, there is no statistically detectable gap between relocated and stay households. This further supports the interpretation that migration decisions primarily reflect residential coping strategies in response to the disaster, rather than deliberate income-maximising strategies.

By contrast, more pronounced heterogeneity emerges when focusing on housing-related expenditure. For housing costs, relocation households exhibit significantly higher spending than stay households, with an estimated coefficient of 24,967 (standard error = 4,465, $p < 0.001$). This indicates that households who moved out of Canterbury faced substantially greater housing-related costs after the earthquakes, potentially due to higher rents in destination areas and upfront expenses associated with securing new accommodation, such as relocation costs, rental bonds and agency fees. These findings reflect the direct impact of the earthquakes on housing markets and on the cost structure of household accommodation for migrants.

For mortgages and loans, by contrast, the relocation group shows significantly lower expenditure than the stay group, with an estimated coefficient of -9,466 (standard error = 4,244, $p < 0.05$). This suggests that relocated households were more likely to rent rather than purchase new homes, thereby avoiding new long-term debt obligations and mortgage commitments. In contrast, households that remained in place were more inclined to retain ownership of their original properties or invest in the reconstruction of damaged homes, resulting in higher loan burdens.

It is noteworthy that across all five models, the age of the household reference person and household size are consistently highly significant (all $p < 0.01$). In our specification, age enters the regression linearly, so the estimates capture only the average slope across the observed age distribution. The negative coefficients on age suggest that, conditional on household size and migration status, households with older reference persons tend to have somewhat lower income

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and expenditure levels on average. This pattern is consistent with the downward-sloping portion of the life-cycle profile (Modigliani, 1986). However, we cannot recover the earlier increasing phase, typically peaking in middle age, because the model does not include non-linear terms such as age squared. A robustness check with quadratic age terms would be expected to reveal the familiar inverted-U shape, but in the current linear specification the dominant relationship is the declining trend at older ages.

By contrast, the positive and sizable coefficients on household size indicate that, holding age and migration status constant, larger households tend to have higher income and expenditure levels, which is consistent with the presence of multiple earners and greater consumption needs. The pattern is consistent with theoretical expectations regarding scale effects in household: as households grow in size, they typically include more potential earners and face greater aggregate consumption needs, leading to higher total income and expenditure (Browning et al., 2013).

In summary, although migration is self-selected and the estimated differences cannot be interpreted as causal effects of relocation, the data reveal clear and systematic contrasts in housing-related costs between relocated and non-relocated households. Relocation households exhibit substantially higher rental expenses and one-off housing payments, alongside significantly lower long-term mortgage and loan expenditures, compared with households that remained in place. These differences likely reflect pre-existing disparities in housing tenure, financial circumstances and other unobserved characteristics that jointly shape both migration decisions and housing-expenditure patterns.

This shift in expenditure structure underscores the considerable heterogeneity in housing consumption and asset-investment decisions following disaster-induced migration. It also reinforces the plausibility of the treated-group definition and the robustness of the heterogeneity analysis employed in this study, while providing important insight into post-disaster housing markets and household financial decision-making.

5.5 Robustness check

Table 5. Robustness checks for total household income

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	Origin	**Caliper = 0.1**	**Ratio = 1:1**	**Remove "sex"**
	4799.54	5098.34	4775.33	3920.06
MMI group: Low	(3022.60)	(3010.53)	(3504.71)	(3003.32)
	7626.42*	7942.88*	7642.97*	6839.82
MMI group: High	(3444.07)	(3375.99)	(3493.27)	(3885.10)
Observations	17202	16902	11280	16926

Table 6. Robustness check for total household regular income

	Origin	**Caliper = 0.1**	**Ratio = 1:1**	**Remove "sex"**
	5277.87	5577.69	5887.25	4198.68
MMI group: Low	(2878.50)	(2877.63)	(3402.98)	(2924.62)
	7426.38*	7747.90*	8068.11*	6420.08
MMI group: High	(3333.84)	(3246.88)	(3482.68)	(3757.12)
Observations	17202	16902	11280	16926

Table 7. Robustness check for total household expenditure

	Origin	**Caliper = 0.1**	**Ratio = 1:1**	**Remove "sex"**
	3414.14	2522.22	2375.70	2967.91
MMI group: Low	(2322.80)	(2282.56)	(2661.57)	(2256.22)
	1831.58	1098.99	847.77	1517.95
MMI group: High	(1399.87)	(1319.69)	(1837.96)	(1292.40)
Observations	5025	5016	3354	5025

To ensure the reliability of the estimated post-earthquake effects on household income and expenditure, we conduct a series of robustness checks using alternative PSM specifications. The original model employs nearest-neighbour matching with a caliper of 0.2, a 1:2 matching ratio, a logit-based propensity score and four matching covariates: age of the reference person, household size, sex and education. We then alter one dimension at a time and re-estimate the DiD models. The results are summarised in Tables 5 – 7.

Using a stricter caliper (from 0.2 to 0.1) yields slightly larger estimated effects for the low-intensity treatment group and marginally smaller p-values. This indicates that the main results remain robust even when matching is restricted to closer neighbours in the

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propensity-score space. When we reduce the matching ratio to 1:1 (instead of 1:2), the estimated treatment effects become somewhat larger in magnitude and standard errors increase slightly. The same effects nevertheless remain economically meaningful and statistically significant at conventional levels, suggesting that the results are not driven by the choice of matching ratio.

We next exclude the reference person's sex from the set of matching covariates. Removing sex has only a modest impact on the estimated coefficients: the direction and magnitude of the treatment effects remain stable, while statistical significance declines slightly, consistent with a small reduction in matching precision after omitting a potentially informative covariate. Lastly, we replace the logit model with a probit specification when estimating the propensity scores[3]. The resulting DiD estimates are nearly identical to the baseline, indicating that the matched-sample results are robust to the choice of link function in the propensity-score model.

We further conduct a series of additional checks in which each matching covariate is removed one at a time. The results are consistent with the patterns described above. Excluding any single covariate generally worsens covariate balance to some extent, as reflected in slightly higher standardised mean differences or variance ratios, but the estimated treatment coefficients remain directionally stable and their magnitudes are not materially altered.

Taken together, these robustness checks show that the magnitude, direction and statistical significance of the estimated treatment effects are broadly consistent across a wide range of matching specifications, reinforcing the credibility of our findings.

6. Conclusion and Discussion

[3] We also re-estimate the models using propensity scores derived from a linear probability model (LPM) instead of a logit specification. Diagnostic statistics, such as the maximum standardised mean difference and variance ratios, indicate that the LPM-based matching procedure achieves covariate balance that is comparable to that of the baseline logit-based matching. However, the estimated treatment effects obtained from the LPM-based propensity scores are smaller in magnitude and generally less statistically significant than those based on logit or probit models. This pattern is consistent with existing methodological evidence. Austin (2011b) shows that matching on the logit of the propensity score with a caliper of 0.2 standard deviations tends to yield substantial bias reduction and efficiency gains, whereas alternative specifications perform less well. Thus, while balance metrics look similar on average, the attenuated coefficients and reduced significance under the LPM specification likely reflect its weaker ability to distinguish units at the extremes of the treatment-probability distribution, leading to marginally poorer matches and larger standard errors near the boundaries.

This study systematically evaluates the medium- to long-term impact of the 2010-2011 Canterbury earthquakes on household income and expenditure in New Zealand's Canterbury region. By combining a Difference-in-Differences econometric strategy with Propensity Score Matching, the analysis aims to strengthen both the causal interpretation and the robustness of the estimated effects. We provide a comprehensive assessment across multiple dimensions— total and household income and a wide range of expenditure categories.

6.1 Key findings

First, in terms of income effects, households in high-intensity earthquake areas experience a significant post-disaster increase in income, with estimates consistently statistically significant at conventional levels. This finding diverges from the traditional view that disasters primarily lead to income losses and instead aligns with more recent microeconomic work emphasising post-disaster economic recovery and inflows of financial resources (e.g., Deryugina, 2017). In particular, increased labour demand associated with reconstruction, together with inflows from insurance payouts and government assistance programmes, appear to jointly contribute to the observed rise in household income.

Second, for expenditure, aggregate changes in total household spending are not statistically significant. However, when expenditure is disaggregated by category, substantial heterogeneity emerges. The categories with significant post-earthquake increases are concentrated in transportation, travel, domestic fuel and power, household maintenance and repair, social insurance and retirement contributions, and medical and health-related expenses. These changes reflect a marked shift in household demand structures following the disaster, driven in part by compulsory cost increases related to vehicle repairs, risk-avoidance travel, energy use and home repairs. In addition, the pronounced rise in social insurance and healthcare spending points to heightened attention to risk management and health needs in the aftermath of the earthquakes, highlighting an important dimension of household economic resilience.

Furthermore, the results show a sizeable and statistically significant increase in receipts and refunds, a category that in the HES primarily records insurance reimbursements and related inflows as negative expenditure items. Given New Zealand's near-universal residential

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earthquake insurance coverage, this pattern is most plausibly interpreted as reflecting the large volume of insurance settlements and associated claim payments following the earthquakes, rather than deliberate shifts in household consumption behaviour.

In addition, the heterogeneity analysis within the treated group reveals significant differences between relocated households and those who remained in place in terms of housing tenure and housing-related costs. In descriptive statistics, relocated households also display less favourable income distributions and greater income volatility, although average income levels are similar once observable characteristics are controlled for. These findings underscore the close relationship between post-disaster migration and household economic vulnerability and resilience (Fussell, 2015).

6.2 Limitations and directions for future research

This study has several limitations related to sample size and the measurement of income and expenditure in the HES. In particular, the use of short diary windows for detailed expenditures and self-reported aggregates may introduce annualisation and measurement error, and may increase sensitivity to atypical weeks or transient shocks.

Detailed expenditure in the HES is collected using an expenditure diary for selected households, supplemented by two expenditure questionnaire modules (Stats NZ, 2023a). Annualised expenditure measures are constructed from the diary records and reported payment frequencies. A key limitation is that a single week may not represent longer-run consumption patterns and can be affected by atypical events (including behavioural responses to diary-keeping) or seasonal spending. These features can introduce non-trivial measurement error in annualised category-level expenditure.

These measurement features may help explain why effects appear in some disaggregated expenditure categories while total expenditure shows no clear average effect. Category-level measures are inherently noisier and may respond differently across households, and shifts in spending composition can offset at the aggregate level. Together, these factors can generate statistically significant movements in selected categories even when overall expenditure changes are small.

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In addition, the data-generating process differs across outcomes. Total income, regular income and total expenditure are based on direct self-reports by survey respondents rather than being derived from diary records or linked administrative sources such as Inland Revenue or bank records (Stats NZ, 2023a). Although respondents are encouraged to consult supporting documents (e.g., bank statements or tax returns), the final figures still rely on self-reported information. This raises the possibility of measurement error arising from recall difficulties, misclassification of income sources, and social desirability concerns. Such errors may increase noise and reduce statistical power, and any resulting bias need not be purely attenuating: depending on the nature of misreporting and its correlation with exposure status, estimates could be biased in either direction.

Because of these data constraints, the analysis is not able to examine in greater depth the heterogeneous effects of the earthquakes across groups defined by income source, ethnic background, levels of social capital (as a proxy for resilience) or household structure. In addition, the precision of the estimated effects, particularly when expressed in absolute monetary terms, may be limited.

Future research could build on this study in several directions. First, by leveraging larger-scale and higher-quality administrative household data, such as the Experimental Administrative Population Census in the IDI, it would be possible to compare results from household-level and individual-level analyses and to trace recovery dynamics over longer horizons. Though these administrative data do not typically include information about expenditures. Second, future work could investigate how the interaction between income distribution, housing conditions and social capital shapes post-disaster recovery trajectories, thereby providing a richer picture of distributional and spatial inequality in disaster impacts. Third, a systematic comparison of different household structures and intra-household labour divisions could yield valuable insights into the heterogeneous effects of disasters on household income and expenditure, as well as into the policy response mechanisms that could support or hinder recovery.

Through such extensions, researchers can develop a more comprehensive understanding of household resilience mechanisms and identify more effective policy options to strengthen socioeconomic resilience in the face of future shocks.

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Preprint. Discussion started: 10 March 2026

References

Abdeljawad, Y. & Noy, I. (2025a) The impact of the Canterbury earthquakes (2010-2011) on labour productivity in the Canterbury region in New Zealand. *Environmental hazards.* 24 (2), 178-193.

Abdeljawad, Y., & Noy, I. (2025b). The impact of 2010–11 Christchurch earthquakes on the individuals' income by sector and income level. *The Annals of Regional Science*, 74(2), 60.

Aizenman, J. & Noy, I. (2015) Saving and the long shadow of macroeconomic shocks. *Journal of Macroeconomics*. 46, 147-159.

Angrist, J. D., & Pischke, J. S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton university press.

Austin, P. C. (2011a) An Introduction to propensity score methods for reducing the effects of confounding in observational Studies. *Multivariate Behavioural Research.* 46 (3), 399-424.

Austin, P. C. (2011b) Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical Statistics*. 10 (2), 150-161.

Autor, D. H. (2003) Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*. 21 (1), 1-42.

Bertrand, M. et al. (2004) How much should we trust Differences-In-Differences estimates? *The Quarterly Journal of Economics*. 119 (1), 249-275.

Bondonio, D. & Greenbaum, R. T. (2018) Natural disasters and relief assistance: Empirical evidence on the resilience of U.S. counties using dynamic propensity score matching. *Journal of Regional Science*. 58 (3), 659-680.

Browning, M., Chiappori, P. A., & Lewbel, A. (2013). Estimating consumption economies of scale, adult equivalence scales, and household bargaining power. *Review of Economic Studies*, 80(4), 1267-1303.

https://doi.org/10.5194/egusphere-2026-1005
Preprint. Discussion started: 10 March 2026

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5), 1549-1561.

Clarke, D., & Tapia-Schythe, K. (2021). Implementing the panel event study. *The Stata Journal*, 21(4), 853-884.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. *American Economic Journal: Economic Policy*, 9(3), 168-198.

Deryugina, T., Kawano, L., & Levitt, S. (2018). The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2), 202-233.

Dube, A., Tran, B. R., & Wilson, D. J. (2023). The local economic impact of natural disasters. Federal Reserve Bank of San Francisco working paper 2020-34.

duPont Iv, W., Noy, I., Okuyama, Y., & Sawada, Y. (2015). The long-run socio-economic consequences of a large disaster: The 1995 earthquake in Kobe. *PloS One*, 10(10), e0138714.

Fussell, E. (2015) The long-term recovery of New Orleans' population after Hurricane Katrina. *The American Behavioural Scientist*. 59 (10), 1231-1245.

Gallagher, J., & Hartley, D. (2017). Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy*, 9(3), 199-228.

GeoNet. (n.d.). Earthquake statistics. https://www.geonet.org.nz/earthquake/statistics

Groen, J. A. & Polivka, A. E. (2010) Going home after hurricane Katrina: Determinants of return migration and changes in affected areas. *Demography*. 47 (4), 821-844.

Hickel, J. & Hallegatte, S. (2022) Can we live within environmental limits and still reduce poverty? Degrowth or decoupling? *Development Policy Review*. 40 (1).

Kaiser, A., Holden, C., Beavan, J., Beetham, D., Benites, R., Celentano, A., ... & Zhao, J. (2012). The Mw 6.2 Christchurch earthquake of February 2011: preliminary report. *New Zealand Journal of Geology and Geophysics*, 55(1), 67-90.

https://doi.org/10.5194/egusphere-2026-1005
Preprint. Discussion started: 10 March 2026

Kousky, C. (2014). Informing climate adaptation: A review of the economic costs of natural disasters. *Energy Economics*, 46, 576-592.

Modigliani, F. (1986). Life cycle, individual thrift, and the wealth of nations. *Science*, 234(4777), 704-712.

Noy, I., & duPont IV, W. (2018). The long-term consequences of disasters: What do we know, and what we still don't. *International Review of Environmental and Resource Economics*, 12(4), 325-354.

Owen, S., & Noy, I. (2019). Regressivity in public natural hazard insurance: a quantitative analysis of the New Zealand case. *Economics of Disasters and Climate Change*, 3(3), 235-255.

Parker, M., & Steenkamp, D. (2012). The economic impact of the Canterbury earthquakes. *Reserve Bank of New Zealand Bulletin*, 75(3), 13-25.

Saunders, J. K., Minson, S. E., & Baltay, A. S. (2022). How low should we alert? Quantifying intensity threshold alerting strategies for earthquake early warning in the United States. *Earth's Future*, 10(3), e2021EF002515.

Sawada, Y., & Shimizutani, S. (2008). How do people cope with natural disasters? Evidence from the Great Hanshin‐Awaji (Kobe) earthquake in 1995. *Journal of Money, Credit and Banking*, 40(2-3), 463-488.

Stats NZ. (2014). 2013 Census quick stats about income. https://www.stats.govt.nz/assets/Uploads/Retirement-of-archive-website-project-files/Reports/2013-Census-QuickStats-about-income/quickstats-income.pdf

Stats NZ. (2020). Household Economic Survey (HES) expenditure classification and methodology. https://statsnz.contentdm.oclc.org/digital/api/collection/p20045coll27/id/57/download

Stats NZ. (2023a). Household income and housing-cost statistics: Year ended June 2022. https://www.stats.govt.nz/information-releases/household-income-and-housing-cost-statistics-year-ended-june-2022/

https://doi.org/10.5194/egusphere-2026-1005
Preprint. Discussion started: 10 March 2026

Stats NZ. (2023b). Regional gross domestic product: Year ended March 2022. https://www.stats.govt.nz/assets/Uploads/Regional-gross-domestic-product/Regional-gross-domestic-product-Yearended-March-2022/Download-data/regional-gross-domestic-product-year-ended-march-2022-corrected.xlsx

Stuart, E. A. (2010) Matching methods for causal inference: A review and a look forward. *Statistical Science*. 25 (1), 1-21.

Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing difference in difference studies: best practices for public health policy research. *Annual Review of Public Health*, 39, 453–469.

Wood, A., Noy, I., & Parker, M. (2016). The Canterbury rebuild five years on from the Christchurch earthquake. *Reserve Bank of New Zealand Bulletin*.

Yan, J., Zhou, C., & Qi, S. (2025). Extreme climate risk and rural household consumption. *Journal of the Asia Pacific Economy*, 1-21.

https://doi.org/10.5194/egusphere-2026-1005
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Appendices

Appendix A: Sample classification and missing address rates

Table A.1. Distribution of households across the four sample groups, by survey year[4]

Survey Year	Group 1	Group 2	Group 3	Group 4
2006/07	399	18	18	1890
2007/08	447	15	18	2349
2008/09	450	12	12	2304
2009/10	426	S	15	2088
2010/11	435	S	18	2454
2011/12	465	21	24	2385
2012/13	387	27	21	2040
2013/14	408	30	24	2253
2014/15	648	54	45	3744
2015/16	390	30	48	2367
2016/17	414	42	42	2526
2017/18	567	66	63	3774

[4]In all tables in this paper, the letter "S" indicates that the sample size for that cell in the given year is fewer than 6 and has been suppressed in accordance with Stats NZ confidentiality rules. All other numeric values have been subject to RR3 random rounding as required.

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Table A.2. Unmatched pre-earthquake address records by HES survey year

Survey Year	Valid HES Households	Unmatched Addresses	Unmatched rate (%)
2006/07	2799	477	17.00%
2007/08	3393	561	16.50%
2008/09	3285	501	15.30%
2009/10	3033	492	16.20%
2010/11	3435	516	15.00%
2011/12	3450	555	16.10%
2012/13	2934	453	15.40%
2013/14	3363	645	19.20%
2014/15	5505	1014	18.40%
2015/16	3465	627	18.10%
2016/17	3675	645	17.60%
2017/18	5451	969	17.80%

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Table A.3. Unmatched address rates from linkage to 2013 Census records

Survey Year	Matched	Unmatched	Unmatched Rate (%)
2006/07	2226	669	23.10%
2007/08	2691	804	23.00%
2008/09	2706	672	19.90%
2009/10	2580	543	17.40%
2010/11	2943	591	16.70%
2011/12	3006	555	15.60%
2012/13	2664	339	11.30%
2013/14	2922	462	13.70%
2014/15	4827	732	13.20%
2015/16	3069	426	12.20%
2016/17	3138	564	15.20%
2017/18	4629	846	15.50%

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Appendix B. PSM matching quality-Max SMD and Variance Ratio by Survey Year

Survey Year	Max SMD	Max VR
2006/07	0.05	1.10
2007/08	0.07	1.08
2008/09	0.02	1.09
2009/10	0.02	1.09
2010/11	0.03	1.06
2011/12	0.05	0.97
2012/13	0.03	1.13
2013/14	0.04	1.01
2014/15	0.03	0.94
2015/16	0.02	1.04
2016/17	0.04	1.07
2017/18	0.03	1.16

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Appendix C. Event Study Plots for Parallel Trend Assumption Test

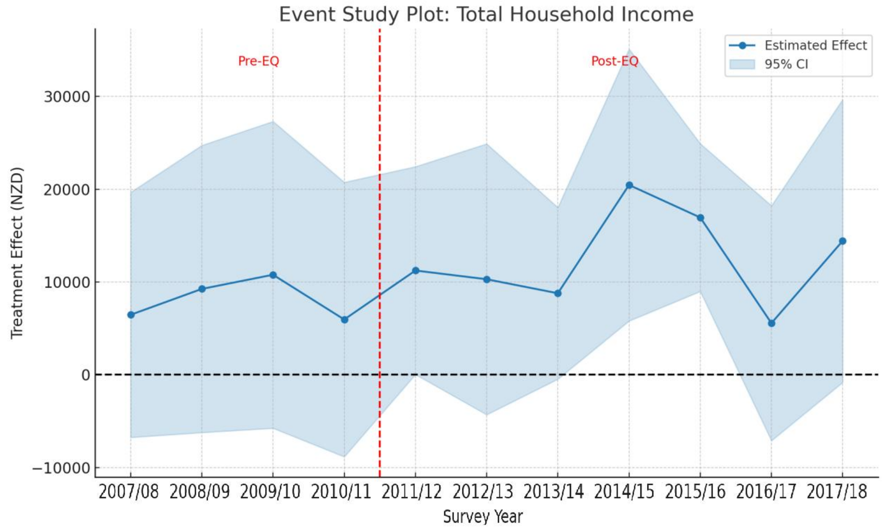

Figure C.1. Event-study estimates for Total Household Income

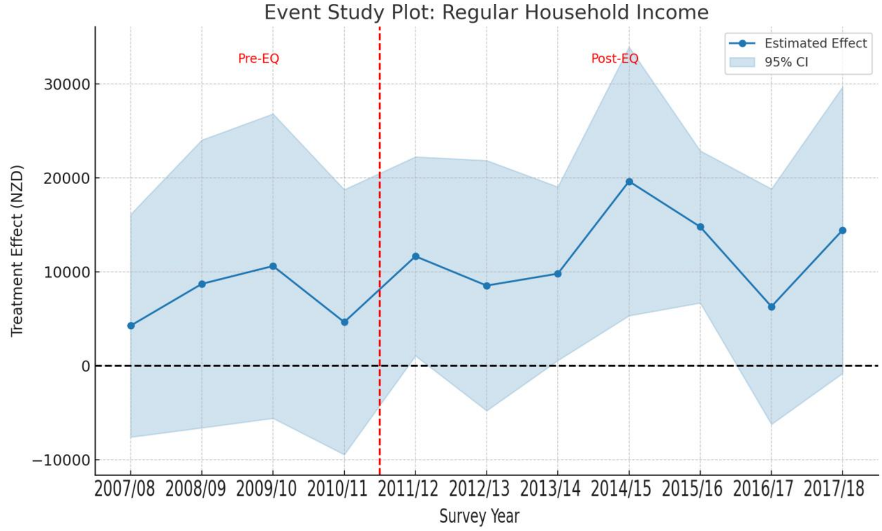

Figure C.2. Event-study estimates for Regular Household Income

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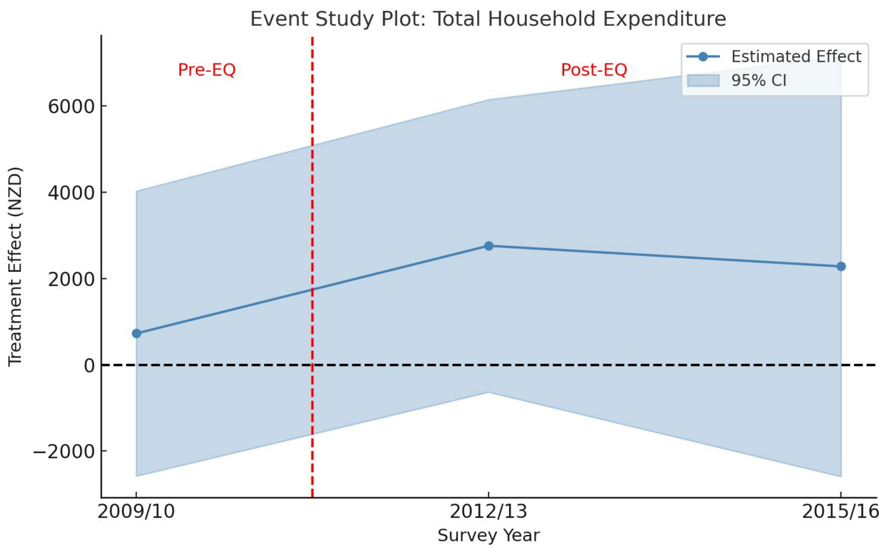

Figure C.3. Event-study estimates for Total Household Expenditure

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Appendix D. Descriptive Statistics

Table D.1. Descriptive Statistics by Earthquake Intensity and Control Group Classification

Survey Year	Group	Counts	Age	Household size	Ref_sex	Housing	Total household income		Total household regular income		Total household expenditure		Housing cost		Mortgages and loans cost	
			Mean	Mean	%Female	%Owned/Trust	Median	SD	Median	SD	Median	SD	Median	SD	Mean	SD
2006/07	Treated	417	49.6	2.5	54.0%	73.4%	64357	56067.5	63046.4	55089.4	45611.9	34314.9	9308	43656.5	25118	54783.2
	-Low	147	51.7	2.5	60.5%	85.7%	53790.5	37811.2	53289.7	37379.4	31652.1	27992.3	7529	21990.8	23040.7	47578.3
	-High	270	48.5	2.4	51.1%	65.6%	54938.3	53458.5	54259.6	52027.7	38767.6	37179.4	10529.2	51191.7	26346.5	58473.4
	Control	831	49.2	2.5	54.2%	67.5%	68761.8	54185.6	67350.9	53128.5	49739.4	41711.8	12480.3	36026.2	26093.9	54666.2
2007/08	Treated	462	51.6	2.4	54.5%	71.4%	70301.9	84767.9	65753.1	56468.7	10538.8	10208.4	9102	34326.1	25366.2	48469.3
	-Low	159	53.3	2.3	49.1%	73.6%	51768.6	46150.1	49807.9	41013.1	6830.7	8063.8	8571.8	19636.4	18654.5	37386.4
	-High	297	50.5	2.5	57.6%	70.7%	55191	99493	53738.8	63034.4	10528.6	11035.6	9563.2	39756.4	29212.2	53319.7
	Control	924	50.6	2.4	56.2%	66.9%	75385.2	75361.4	73243.6	69668.5	11512.2	12451.5	12457	34971	25877.7	63821.8
2008/09	Treated	459	50.8	2.3	59.5%	69.9%	70666.2	69565.6	68583.4	67340.8	10049.2	9801.4	9600.7	41916.9	23598.4	52551.3
	-Low	150	52.2	2.4	52.0%	78.0%	57320	84465.8	57180	81707.4	3910.7	8517.2	7236	31454	15289.3	35406.7
	-High	306	50.2	2.3	63.7%	64.7%	56935	61228	53627.6	59283.1	8645.9	10249.9	11262.9	45948.1	27469.2	58914.4
	Control	921	50.1	2.4	60.3%	65.8%	73543.9	72210.6	72179.9	70173.7	11657.7	12346.6	12884.3	52254.2	25221.3	64566.4
2009/10	Treated	432	51.7	2.4	57.6%	70.8%	72656.9	72316	70499	70158.2	48909.3	33203.6	11855.8	49444.8	21351.5	44541.5
	-Low	135	53.5	2.3	60.0%	75.6%	49969.2	101713.1	49969.2	100370	36842.3	27598.5	8817.5	24629.6	12933	30059.6
	-High	294	50.9	2.5	58.2%	68.4%	59306.4	53813.5	58229.3	50705.9	44945.7	35100.1	13713.6	55829.2	25320.2	49470.6
	Control	867	52.1	2.5	57.4%	67.8%	73793.7	66841.3	71960.4	64739	50816.5	36407.9	14165.9	53662.4	24036.5	59536.4
2010/11	Treated	432	51.7	2.4	54.9%	70.8%	75699.9	68565.1	72469.3	63612.4	10409.3	9248.4	11531.3	41544.3	23744.8	48414.3
	-Low	165	54.7	2.3	54.5%	80.0%	55872.4	49228.2	55872.4	40949.1	3076	7296.2	7538.3	23680.7	13885.6	31630
	-High	267	49.8	2.5	55.1%	65.2%	63023.4	77767.8	60691.2	73826.6	11471.4	9810.5	15214.4	48373	29963.4	55617.7
	Control	867	51.4	2.5	55.7%	66.4%	82139.7	78790.6	80312.9	74871.1	13325.5	14847.6	14235	48192.9	29323.3	66567.5
2011/12	Treated	486	51.7	2.4	59.9%	67.9%	74452.6	61820.2	73046.9	61000.5	10664.5	10269.8	12822	82047.8	24249.6	64118
	-Low	168	52.1	2.4	64.3%	73.2%	58914.3	76456.4	58914.3	76281.2	6470.3	7567.2	12304.7	20909.3	16072	37698
	-High	312	51.6	2.4	56.7%	64.4%	62134.1	52676.9	60360.9	51316.7	8503.7	11312.4	13992.1	99026.9	28377.3	74466.6
	Control	972	52.2	2.3	59.9%	64.2%	74060.4	64046.6	72457.7	62714.3	12736.6	11830.3	14020	42652.4	23521.3	53682.1
2012/13	Treated	411	52.8	2.4	62.8%	71.5%	81298.6	83189.7	77624.8	77034.9	51844.2	33178.1	13893.2	45717.5	22435.7	49959.2
	-Low	162	55.6	2.2	64.8%	81.5%	58639.3	48121	57527.3	44310.7	42478	26283.4	11112	20319.1	18423.9	34691.4
	-High	246	50.8	2.4	61.0%	64.6%	65801.7	99454.8	63171.9	92149.9	47026.3	36671.7	16382.5	55550.9	25276.4	57949.6
	Control	822	53.3	2.4	63.1%	67.5%	81347.4	83490	79490.7	81195.2	53823.7	41361.8	17002.7	53688.3	23630.5	56608.2
2013/14	Treated	438	52.5	2.4	59.6%	71.2%	84491.6	92265.4	80831.4	66605.9	12044	11290.2	13452.3	71752.7	21013.9	44766.4
	-Low	174	54.8	2.3	62.1%	77.6%	58407.3	58500.8	58059.7	56391.3	5560.7	10364	11658.7	28368.9	15100.8	31554.3
	-High	258	51.3	2.4	59.3%	68.6%	65306.3	108628.5	65306.3	71203.3	10428.6	11860.4	17822.1	89559.1	25367.7	51795.6
	Control	873	53	2.4	58.4%	68.4%	85110.4	83869.4	80480.6	72556	13849.7	16130.5	16263.2	48815.6	30211.5	77836
2014/15	Treated	705	53.5	2.4	57.4%	68.5%	90790.8	79499	87540.6	73970.3	12599.3	13184.5	17623.6	60999.3	29568.5	72044.8
	-Low	276	56	2.4	54.3%	79.3%	68774.3	68803.1	66349.4	64562.2	6302	14116.1	15705.1	25218.5	27010.9	71597.8
	-High	381	52.7	2.5	59.8%	65.4%	76181.3	85255.7	74581.4	78678.1	10349.9	12898.6	20087.6	73035.6	33831.7	75223.5
	Control	1407	53.6	2.4	57.8%	65.0%	81138.9	79995.4	78896.1	76931.4	13216.5	13355.3	16470.9	41896.1	25433.2	65626.7
2015/16	Treated	420	55.7	2.3	57.1%	73.6%	86660.2	73841.7	82928.3	66300.7	12563.5	11205	21828.6	52092.7	33720.7	83451.3

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Survey Year	Group	Counts	Age	Household size	Ref_sex	Housing	Total household income		Total household regular income		Total household expenditure		Housing cost		Mortgages and loans cost	
			Mean	Mean	%Female	%Owned/Trust	Median	SD	Median	SD	Median	SD	Median	SD	Mean	SD
	-Low	186	57.9	2.3	58.1%	75.8%	67450.1	63738.4	67033.8	62304.5	7038.2	9893.1	21104.8	29328.1	30785.1	63720.1
	-High	225	53.9	2.3	57.3%	72.0%	72157	81134	70191.3	69153.8	9508	12160	23508.9	64997.8	37427.5	97968.2
	Control	840	55.9	2.3	56.8%	71.1%	80748.5	76421.3	79128.7	71456.3	13931	16181.6	21897.8	53715.5	34915	149370.3
2016/17	Treated	456	55.1	2.4	54.6%	71.7%	87109.8	84423.4	84200.8	81756	13054.3	12826.2	21904.5	92275.3	34046.1	81449.2
	-Low	177	56	2.4	54.2%	83.1%	72783	91954.2	69050.9	88930.5	5974.3	13523.2	20341.9	48042.3	38837.3	94530.5
	-High	273	54.8	2.3	53.8%	64.8%	67284	79973.1	65545.2	77544.3	10417.9	12408.2	24158.3	112139.7	31458.5	72472.3
	Control	909	55.5	2.3	56.8%	68.3%	90476	95165.5	86835.6	81678.3	14253.5	13765.5	21505.7	61104.5	35654.3	102858.4
2017/18	Treated	633	53.7	2.3	55.0%	68.2%	92544.4	104170.4	90020.4	101953.1	14460	11991.1	27108.6	96966.1	37102.3	78344.9
	-Low	255	54.8	2.3	57.6%	74.1%	66596.6	62110.4	64480	61366.4	11469.4	11940	25070	92862.6	36894.6	72329
	-High	369	53.1	2.4	52.8%	63.4%	76510.6	125409.8	74052.7	122655.3	13035	12090.4	29198.4	99901.4	37432	82871.4
	Control	1263	54.2	2.3	57.0%	63.7%	86898.4	99394.7	84527.9	95787.6	14336	13506.8	23580.1	60452	33655.1	82833

Notes: (i)This table reports descriptive statistics by survey wave and exposure/control classification. Monetary variables are in NZD. For most monetary outcomes we report medians together with a dispersion measure (SD). (ii)Mortgages and loans cost is reported as a mean (with SD) because the distribution is strongly right-skewed; therefore, statistics across columns, especially those mixing means and medians, are not mechanically additive. (iii)The Stats NZ total household expenditure variable is not defined consistently across HES waves: in 2006/07, 2009/10, 2012/13 and 2015/16 it aggregates spending across all expenditure categories, whereas in the remaining waves it covers housing-related expenditure only (e.g., rent, mortgage payments, local authority rates and building insurance). Consequently, in housing-only waves, total household expenditure may appear close to housing cost plus mortgage repayments by construction. Where recorded separately in the HES classification, housing cost excludes mortgage repayments. Accordingly, the DiD analysis uses total household expenditure only in 2006/07, 2009/10, 2012/13 and 2015/16; other waves are shown here for descriptive purposes only. (iv)A small number of Canterbury meshblocks have very low seismic intensity (MMI < 4). These observations are included in the treated category in the descriptive tables because they are resident in Canterbury at the time of the earthquakes, but they are excluded from the DiD intensity-group specification and therefore do not enter the Low- or High-intensity groups, nor the control group.

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Table D.2. Descriptive Statistics by Migration

Survey Year	Group	Counts	Age	Household size	Ref_sex	Housing	Total household income		Total household regular income		Total household expenditure		Housing cost		Mortgages and loans cost	
			Mean	Mean	%Female	%Owned/Trust	Median	SD	Median	SD	Median	SD	Median	SD	Mean	SD
2006/07	Relocation	18	S	S	S	S	S	S	S	S	S	S	S	S	S	S
	Stay	399	50	2.5	54.9%	74.4%	62448.4	48236.2	61079.9	46985.8	44800	33704.6	9074.6	43268.5	23502.4	47973.3
2007/08	Relocation	15	S	S	S	S	S	S	S	S	S	S	S	S	S	S
	Stay	447	51.9	2.4	55.0%	72.5%	70238.9	85952.1	65526.9	56971.9	10470.3	10303.8	8985.9	34118.5	25846	49144.7
2008/09	Relocation	12	S	S	S	S	S	S	S	S	S	S	S	S	S	S
	Stay	450	51.3	2.3	59.3%	70.0%	71128.9	70289.1	69058.3	68036.7	10097.4	9900.7	9570.3	41752.1	23994.9	53086.1
2009/10	Relocation	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S
	Stay	426	51.9	2.4	57.7%	71.1%	72608.4	72365.9	70502.2	70316.2	48732	33152.6	11816.1	46818.3	21580.3	44750.2
2010/11	Relocation	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S
	Stay	435	51.7	2.4	54.5%	70.3%	75699.9	68565.1	72469.3	63612.4	10409.3	9248.4	11531.3	41544.3	23744.8	48414.3
2011/12	Relocation	21	42.2	3.2	S	S	57969.9	38186.8	57849.6	38183.4	16664	11513.2	61302.8	211406.7	14186.9	34283.4
	Stay	465	52.2	2.3	59.4%	69.0%	75197	62601.9	73733.2	61771.4	10393.6	10140.3	12539.5	68271.3	24704.1	65128.5
2012/13	Relocation	27	53.3	2.1	55.5%	44.4%	58116.9	43829.7	58116.9	43829.7	51231.3	26814.6	13988.1	63087.4	7268.6	21237
	Stay	387	52.8	2.4	62.8%	72.9%	82864.1	85001.1	78942.2	78635.9	51885.6	33592.9	13893.2	44258.7	23460	51175.4
2013/14	Relocation	30	41.4	2.4	60.0%	40.0%	77288.6	56194.2	77102.9	56320.7	18155.4	12085.6	28678.6	37718.9	20134.8	38166
	Stay	408	53.4	2.4	59.6%	72.8%	85038.8	94468.5	81114.7	67374.3	11579.6	11106.3	13064.2	73680.9	21080.7	45268.5
2014/15	Relocation	54	45.9	2.3	55.6%	44.4%	82883.6	101393.9	80950.5	99735.8	12894.6	9346.4	22942.8	82296.6	17962.8	51141.9
	Stay	648	54.1	2.5	57.9%	70.8%	91461.9	77417.9	88099.9	71431.8	12574.3	13465.1	17287.5	58639.1	30553.5	73491.2
2015/16	Relocation	30	48.9	2.6	50.0%	60.0%	82299.1	71753.2	77287.4	68710.8	14659	11511.1	22624	46080.7	26168.3	49464.9
	Stay	390	56.3	2.3	57.7%	74.6%	87019	74089.5	83392.3	66168.5	12391.1	11177.1	21792	52608.1	34341.9	85661.6
2016/17	Relocation	42	47.9	3	57.1%	64.3%	99701.6	100424.1	93235.5	94387.3	19767.7	16687.8	24045	241829.9	47791.5	88175.1
	Stay	414	55.8	2.3	53.6%	73.2%	85862.8	82709.2	83306	80472.6	12389.4	12204.6	21531.5	57814.8	32684.8	80739.8
2017/18	Relocation	66	44.7	2.4	50.0%	50.0%	125513	229835.2	123099.4	228960.8	18447	14496.8	34412.4	163711.7	29196.4	59267.8
	Stay	567	54.7	2.3	55.6%	60.3%	88758.2	77310	86221.6	74240.9	14002.1	11596.7	26292.6	85904.1	38010.3	80238

Notes: (i)This table reports descriptive statistics by survey wave and exposure/control classification. Monetary variables are in NZD. For most monetary outcomes we report medians together with a dispersion measure (SD). (ii)Mortgages and loans cost is reported as a mean (with SD) because the distribution is strongly right-skewed; therefore, statistics across columns, especially those mixing means and medians, are not mechanically additive. (iii)The Stats NZ total household expenditure variable is not defined consistently across HES waves: in 2006/07, 2009/10, 2012/13 and 2015/16 it aggregates spending across all expenditure categories, whereas in the remaining waves it covers housing-related expenditure only (e.g., rent, mortgage payments, local authority rates and building insurance). Consequently, in housing-only waves, total household expenditure may appear close to housing cost plus mortgage repayments by construction. Where recorded separately in the HES

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classification, housing cost excludes mortgage repayments. Accordingly, the DiD analysis uses total household expenditure only in 2006/07, 2009/10, 2012/13 and 2015/16; other waves are shown here for descriptive purposes only. (iv)Some cells are suppressed (S) where required by Stats NZ confidentiality rules.

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Appendix E. DiD Results for Expenditure Categories

	Receipts & refunds	General insurance	Transportation	Contribution schemes	Housing cost	Diary	Travel	Fees & subs	Telecommunications
MMI group: Low × post	0.29	-0.11	0.07	0.11	0.34*	0.08	0.85	0.76*	0.01
	(0.26)	(0.41)	(0.24)	(0.52)	(0.14)	(0.11)	(0.44)	(0.30)	(0.20)
MMI group: High× post	0.72***	0.55***	0.27**	0.46*	0.09	0.13*	0.44*	0.44*	0.22*
	(0.12)	(0.15)	(0.10)	(0.19)	(0.08)	(0.05)	(0.18)	(0.20)	(0.09)
ref = "Owned/trust"	-0.44**	-1.13***	-0.97***	-1.18***	1.01***	-0.54***	-1.53***	-0.59***	-1.06***
	(0.16)	(0.19)	(0.18)	(0.26)	(0.07)	(0.08)	(0.14)	(0.14)	(0.16)
sex	-0.01	-0.24**	-0.38***	-0.26*	0.04	-0.03	-0.23	-0.03	0.03
	(0.06)	(0.08)	(0.09)	(0.12)	(0.06)	(0.05)	(0.14)	(0.08)	(0.09)
log_income	0.18***	0.78***	0.79***	1.25***	0.22***	0.46***	1.13***	0.54***	0.55***
	(0.04)	(0.05)	(0.07)	(0.17)	(0.03)	(0.05)	(0.12)	(0.06)	(0.06)
age	-0.009*	0.019***	-0.003	-0.023***	-0.005**	0.004*	-0.007	-0.020***	0.024***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
household size	0.01	0.39***	0.45***	0.28***	0.24***	0.37***	0.1	0.88***	0.33***
	(0.03)	(0.06)	(0.04)	(0.07)	(0.02)	(0.01)	(0.07)	(0.09)	(0.04)
Num. Obs.	5016	5016	5016	5016	5016	5016	5016	5016	5016
R2	0.04	0.11	0.19	0.19	0.2	0.33	0.17	0.21	0.15
R2 Adj.	0.03	0.1	0.18	0.18	0.19	0.32	0.16	0.2	0.13
R2 Within	0.02	0.09	0.17	0.15	0.15	0.3	0.1	0.17	0.12
R2 Within Adj.	0.02	0.08	0.17	0.15	0.15	0.3	0.1	0.16	0.12
AIC	23936	27674.2	24699.9	28601.8	17982.7	16213.4	28987.6	27282.8	23190.8
BIC	24386	28124.1	25149.8	29051.7	18432.7	16663.4	29437.6	27732.7	23640.8
RMSE	2.59	3.76	2.8	4.13	1.43	1.2	4.29	3.62	2.41
Std. Errors	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code

* p < 0.05, ** p < 0.01, *** p < 0.001

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Appendix F. Median Household Income and Annual Growth of New Zealand regions in 2006 and 2013 (in NZD)

Region	Median Household Income (2006)	Median Household Income (2013)	Annual Growth Rate (%)
Auckland	63,400	76,500	2.72%
Canterbury	47,900	65,000	4.46%
Wellington	59,700	74,300	3.17%
Waikato	49,400	59,600	2.72%
Bay of Plenty	45,400	54,600	2.67%
Hawke's Bay	44,200	53,200	2.68%
Manawatu-Wanganui	41,200	50,000	2.80%
Northland	40,200	46,900	2.23%
Southland	44,200	57,400	3.80%
Otago	44,400	56,400	3.48%
West Coast	37,800	55,000	5.50%
Marlborough	45,500	55,200	2.80%
Nelson	43,900	54,300	3.08%
Tasman	43,000	53,500	3.17%
Gisborne	41,000	50,500	3.02%
Taranaki	44,700	58,400	3.89%

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Appendix G. Heterogeneous expenditure responses by income group

Table G.1. Expenditure classification of households with household income higher than the median

	Contribution schemes	**Housing cost**	**Telecommunications**	**General insurance**	**Transportation**	**Fees & subs**	**Household maintenance**	**Receipts & refunds**
MMI group: Low × post	-0.39	0.29*	0.38**	-0.23	0.33	1.17*	0.58	0.56
	(0.68)	(0.12)	(0.12)	(0.45)	(0.22)	(0.46)	(0.72)	(0.43)
MMI group: High × post	0.51**	0.14	0.23*	0.77***	0.33**	0.46	0.80*	1.06***
	(0.15)	(0.07)	(0.09)	(0.16)	(0.11)	(0.36)	(0.35)	(0.18)
ref = "Owned/trust"	-0.84**	1.30***	-0.46**	-0.77***	0.08	0.14	-3.44***	-0.58*
	(0.29)	(0.10)	(0.14)	(0.21)	(0.11)	(0.27)	(0.23)	(0.27)
sex	0.068	0.002	0.088	-0.048	-0.084	0.079	0.043	0.146
	(0.12)	(0.05)	(0.07)	(0.13)	(0.12)	(0.1)	(0.24)	(0.10)
log_income	2.07***	0.33**	0.50***	1.50***	1.00***	1.75***	1.68***	0.32
	(0.13)	(0.06)	(0.06)	(0.12)	(0.20)	(0.17)	(0.22)	(0.20)
age	0.000	-0.001**	0.017**	0.024***	0.004	-0.011*	0.030***	-0.011
	(0.006)	(0.002)	(0.005)	(0.006)	(0.003)	(0.005)	(0.006)	(0.006)
household size	0.13	0.18***	0.17**	0.20*	0.26***	0.83***	0.06	-0.06
	(0.07)	(0.02)	(0.06)	(0.08)	(0.03)	(0.06)	(0.08)	(0.05)
Num. Obs.	2508	2508	2508	2508	2508	2508	2508	2508
R2	0.12	0.18	0.07	0.07	0.1	0.17	0.13	0.05
R2 Adj.	0.1	0.16	0.05	0.05	0.08	0.14	0.11	0.03
R2 Within	0.05	0.12	0.04	0.05	0.06	0.12	0.1	0.01
R2 Within Adj.	0.05	0.12	0.04	0.04	0.05	0.11	0.1	0.01
AIC	14488.2	8677.3	10582.1	14001.5	11558	14156.5	14714.1	12726.3
BIC	14861.1	9050.2	10955.1	14374.4	11930.9	14529.4	15087	13099.3
RMSE	4.23	1.33	1.94	3.84	2.36	3.96	4.43	2.98
Std. Errors	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code	by: TA code

*p < 0.05, ** p < 0.01, *** p < 0.001

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Table G.2. Expenditure classification of households with household income lower than the median

	Diary	Receipts & refunds
MMI group: Low × post	0.04	0.05
	(0.18)	(0.29)
MMI group: High × post	0.14*	0.30*
	(0.06)	(0.12)
ref = "Owned/trust"	-0.66***	-0.25
	(0.10)	(0.13)
sex	-0.03	-0.12
	(0.08)	(0.06)
log_income	0.24***	0.06*
	(0.05)	(0.02)
age	0.01**	-0.01*
	(0.00)	(0.00)
household size	0.47***	0.03
	(0.04)	(0.04)
Num. Obs.	2508	2508
R2	0.19	0.03
R2 Adj.	0.17	0.00
R2 Within	0.16	0.00
R2 Within Adj.	0.16	0.00
AIC	8760.2	10914.7
BIC	9162.2	11316.8
RMSE	1.35	2.07
Std. Errors	by: TA code	by: TA code

* p < 0.05, ** p < 0.01, *** p < 0.001

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Code and data availability

The data used in this study are not publicly available due to access restrictions and confidentiality requirements. The primary microdata are from Stats NZ's Household Economic Survey (HES) and were accessed within the Stats NZ Integrated Data Infrastructure (IDI) under an approved project MAA2024-54 in accordance with the *Data and Statistics Act 2022* and Stats NZ microdata access protocols.

Researchers who meet the eligibility criteria may apply to access these data via Stats NZ's Data Lab and the IDI. Access procedures and conditions are available from Stats NZ.

To support reproducibility, the empirical code (data cleaning scripts, variable construction, and estimation routines) and documentation sufficient to replicate the reported tables and figures will be made available in a GitHub upon acceptance. If an embargo is required, the repository will provide time-stamped releases and version tags, and the materials can be shared with reviewers through the Copernicus "access limited to reviewers" mechanism during peer review.

Supplement link

Not applicable at this stage.

Team list

Not applicable.

Author contributions

Quanfu Zhang: Conceptualization; Data curation; Formal analysis; Methodology; Software; Visualization; Writing – original draft.

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Ilan Noy: Conceptualization; Methodology; Supervision; Writing – review & editing.

Yigit Saglam: Methodology; Validation; Writing – review & editing.

Competing interests

The authors declare that they have no competing interests.

Disclaimer

Disclaimer for output produced from Stats NZ surveys

Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the *Data and Statistics Act 2022*. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers.

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These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) which is carefully managed by Stats NZ. For more information about the IDI please visit https://www.stats.govt.nz/integrated-data/

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