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Keywords: Wildfires, Energy poverty, Australia

JEL Classification: I30, Q40, Q54

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Abstract

This study assesses the effects of the 2009 Black Saturday Bushfires (BSB), which was the deadliest bushfire in Australia's history, on household energy poverty. Using a linear panel event-study design, applied to matched longitudinal household and geographical data, our results suggest a significant increase in the likelihood of experiencing energy poverty among households residing within 15 kilometers of wildfire areas. Specifically, we find that for households directly affected by the fires, the likelihood of being in energy poverty increases by 10.45-12.23 percentage points in 2010, and by 12.30-13.62 percentage points in 2011, compared to 2005-2007, which is the reference period. We examine the causal effects of exposure to the BSB on personal wellbeing, labor market outcomes and community social capital and find that personal wellbeing and community social support were channels through which exposure to the BSB affected energy poverty. We also consider the role of personality, locus of control and financial foresight as moderators and find that greater openness to experience and adopting longer-term financial planning mitigated the effects of bushfire exposure on energy poverty.

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1. Introduction

Climate change increases instances of extreme weather events, contributing to the frequency and intensity of natural disasters (Peterson et al., 2012; Kunkel et al., 2013; Ghazali et al., 2018). Natural disasters adversely affect economic activities and livelihoods (Arouri et al., 2015; Ishizawa and Miranda, 2019; Kocornik-Mina et al., 2020; Carvalho et al., 2021) and exacerbate poverty and income inequality (Padli et al., 2019; Salvucci et al., 2020). Wildfires are one of the main consequences of global warming and extreme weather events (Scheffran & Battaglini, 2011; Doerr & Santín, 2016). Increasingly frequent wildfires have become a significant environmental and social challenge in many parts of the world. On average, approximately four percent of the global land surface is affected by wildfires annually (Doerr & Santín, 2016).

Over the past two decades, extreme wildfire events worldwide have shown a strong upward trend, with the frequency and intensity of fires more than doubling (Cunningham et al., 2024; Cartwright, 2024). Notable examples of extreme wildfires include the 2009 Black Saturday Bushfires (BSB) in Australia, the 2021 wildfires in Russia, the 2023 Canadian wildfires, and the 2025 Southern California wildfires. These fires, fuelled by extreme weather (excessive temperatures, minimal precipitation, and strong winds), have had catastrophic effects on local infrastructure and adversely impacted the lives of local residents (Black Saturday Royal Commission, 2010; Voronova et al., 2022; Hu et al., 2024; Sheldon & Sankaran, 2017; Tedim et al., 2018). A large literature documents the adverse effects of wildfire on myriad outcomes, including individuals' physical and mental health (Martin et al., 2013; Reid et al., 2016; Johnston et al., 2021), air quality (Haque et al., 2021), property values (Paudel, 2022b) and energy security (Dumka et al., 2022; Nazemi et al., 2022). Ulubaşoğlu et al. (2019), Filkov et al. (2020), and Ulubasoglu and Onder (2020) have detailed the economic consequences of wildfires in Australia, including lost productivity, lower household income and reduced wellbeing. One potential consequence of wildfires that has not received very much attention is how wildfires contribute to household energy stress and the underlying mechanisms.

Energy poverty is defined as lacking access to sustainable, modern, clean energy services and products and inability to afford energy for domestic needs, which serves as a good proxy for the energy stress of households (Bradshaw & Hutton, 1983; Delugas & Brau, 2021; Faiella et al., 2022). It is a widespread problem worldwide (Okushima, 2016). Tarekegne (2020) suggested that over one billion people across the globe suffer from energy poverty. Increased frequency and intensity of wildfires caused by extreme weather is likely to contribute to higher energy poverty. Assessing how exposure to wildfires affects the probability of households experiencing energy poverty contributes to the understanding of the micro-level impact of wildfires (Paudel, 2021). Zhang and Sheldon (2025) found that following wildfires, people in affected areas delayed increasing their household consumption of essential goods for adaptation. By extension, household energy consumption behavior and energy stress may also be affected by wildfires, as energy is a common household necessity (Meier et al., 2013). Additionally, Zhang and Sheldon (2025) argued that households may be more likely to remain indoors following extreme events, such as wildfires, reflecting safety concerns. Spending more time at home can also be expected to contribute to higher household energy stress.

In this study, we extend the literature by evaluating the causal effect of the BSB, which was the deadliest bushfire event in Australia's history, on the likelihood of households being in energy poverty using an event-study approach. To do so, we combine longitudinal household-level data from the Household Income Labour Dynamics in Australia (HILDA) survey with data on proximity to bushfire pockets at the Statistical Area Level 1 (SA1), representing BSB exposure. We examine the causal effects of exposure to the BSB on personal wellbeing, labor market outcomes, and community social capital as potential channels through which BSB exposure contributed to energy poverty. We also investigate the moderating role of non-cognitive skills - personality traits, locus of control (LoC) and financial planning - in attenuating the impact of BSB exposure on energy poverty. Assuming time invariance and randomness in wildfire occurrence are important for establishing the exogeneity of wildfire events. In the pre-BSB analysis, we find no significant differences in energy poverty or the potential mechanism variables between the groups during the period leading up to the BSB, supporting the assumption that any post-BSB differences in these variables can be attributed to the BSB itself.

We find that the likelihood of being in energy poverty was significantly higher for households residing within 15 kilometers (km) of the fires in the slightly delayed aftermath of the BSB, compared to the pre-disaster period. While the effects of exposure to the BSB on energy poverty in 2009 (the BSB year) were insignificant, the point estimates suggest that for households residing within 15 km of the fires, the probability of being in energy poverty increased by 10.45-12.23 percentage points in 2010, and by 12.30-13.62 percentage points in 2011, compared to the 2005-2007 reference period. The effects of BSB exposure on energy poverty dissipate over time and there is no evidence of long run persistence.

We find that the main channels through which BSB exposure affects energy poverty is via its impacts on personal wellbeing and community social support. We find that in 2010, exposure to the BSB lowered life satisfaction, vitality, mental health, and social functioning. Additionally, in both 2010 and 2011, exposure to the BSB adversely affected perceived safety. We also find that exposure to the BSB causes an increase in community social support in the post-BSB period, offsetting at least part of the adverse effects of the BSB transmitted through personal wellbeing. With respect to the moderators, we find that greater openness to experience and adopting longer-term financial planning attenuated the adverse effect of the BSB on energy poverty. Our main results remain robust to a series of sensitivity checks.

There is a large body of literature focusing on various factors influencing energy poverty, including high energy prices (Renner et al., 2019; Cheikh et al., 2023), low household incomes (Bezerra et al., 2022; Igawa & Managi, 2022), and lack of knowledge about energy efficiency (Thomson et al., 2017). Other studies have found that housing costs (Belaïd & Flambard, 2023), Protestantism (Awaworyi Churchill & Smyth, 2022c), LoC (Awaworyi Churchill & Smyth, 2021), and childhood adversity (Cheng et al., 2022) are significant factors influencing energy poverty. Previous studies have documented the extent to which natural disasters affect energy consumption (Lee et al., 2021; Dou et al., 2023; Fujimi et al., 2014; Yin et al., 2022; Paudel, 2022a). There are relatively few studies, however, that have examined the effect of natural disasters on energy poverty. Lei et al. (2024) found that more frequent and intense earthquakes have had a long-term adverse effect on energy poverty in China. Okyere et al. (2023) found that flooding has had an adverse effect on energy poverty in Tanzania.

Lee et al. (2021) and Paudel (2021) are the only studies that specifically consider the effects of wildfires on energy outcomes. Lee et al. (2021) examined the effect of natural disasters, including wildfires, on energy consumption. We differ from Lee et al. (2021) in that our exclusive focus is on wildfires, and we examine their effect on energy poverty as opposed to energy consumption, as energy poverty better reflects household energy stress. The study that is perhaps closest to ours is Paudel (2021), who examined the impact of forest fires on energy poverty in Nepal, finding that an increase in the intensity of forest fires is associated with a decline in both energy expenditure and energy poverty. While Paudel (2021) considered the general effect of forest fires on energy poverty over time, in focusing on the BSB, we examine how an extreme wildfire event influences the incidence of energy poverty. Notably, whereas

Paudel (2021) found that general forest fires reduce the incidence of energy poverty in Nepal, we find that exposure to an extreme wildfire has the opposite effect in Australia.

We contribute to the literature on wildfires and energy poverty in two ways. First, Dwyer and Hardy (2016) called for more research on the micro-level effects of extreme wildfire events. We provide the first study to specifically examine the effect of an extreme wildfire event on the incidence of energy poverty. This is important because extreme wildfire events are larger in scale and may have different impacts on energy poverty compared with smaller seasonal wildfires, which occur routinely. Second, we extend Paudel (2021) on the underlying mechanisms by examining personal wellbeing, labor market outcomes and community social capital as channels, as well as the role of non-cognitive skills in moderating this relationship. Because extreme wildfires are more severe, we expect them to have stronger effects on the pathways through which they ultimately affect energy outcomes than smaller routine wildfires.

2. Overview of Australian bushfires and the Black Saturday Bushfires

Australia is the most fire-prone country in the world. Figure A1 illustrates the change in the number of days per year that the Forest Fire Danger Index (FFDI), which is an indicator of dangerous fire weather conditions, exceeded the 90th percentile based on conditions observed between 1950 and 2024. The risk of extreme wildfires in Australia is increasing with a clear upward trend in the number of days experiencing dangerous weather conditions (Australian Institute of Health and Welfare, 2023; Dowdy, 2020; Pitman et al., 2007). Since 2000, Australia has recorded over one million wildfire incidents, with the average annual fire radiative power (FRP) exceeding 100,000 megawatts (NASA, 2021). Figure A2 presents a composite satellite map showing bushfires that occurred in Australia between 1997 and 2008. The red markers indicate the geographical regions that were affected by wildfires during this period.

The BSB, which began on February 7, 2009, ranks as the second most deadly natural disaster in Australian history and is among the top 10 deadliest wildfires worldwide in terms of fatalities (Cameron, 2009; Clear Insurance, 2021). The BSB claimed 173 lives, destroyed 2,029 homes, and damaged more than 2,000 other structures. In total, 78 communities were affected, with major fires burning over 350,000 hectares (Black Saturday Royal Commission, 2010). These devastating fires were part of a series of forest fires that spread across the state of Victoria, fueled by an intense heatwave and extreme winds that had enveloped the region.

In the decade leading up to the fires, Victoria experienced its warmest period in 154 years of recorded history, culminating in extreme conditions on the eve of the fires (Black Saturday Royal Commission, 2010). The last week of January saw one of the most severe and prolonged heatwaves on record in southeastern Australia. In the days leading up to the fires, temperatures soared to 43°C. On February 7, 2009, the day that the BSB started, Victoria experienced its hottest and driest day on record. As shown in Figure A3, temperatures across much of the region exceeded 45°C, and rainfall on that day was almost zero. Bushfires intensified as a wind change swept through in the afternoon, propelled by winds gusting at up to 100 km/h.

3. Direct and indirect effects of exposure to extreme wildfire on energy poverty

3.1. Direct effect of exposure to extreme wildfire on energy poverty

Exposure to extreme wildfires could directly affect the probability of households being in energy poverty. First, extreme wildfires may damage household assets, such as electrical appliances (Horwich, 2000; Dercon et al., 2005), which could restrict household energy use and contribute to higher energy poverty. Second, extreme wildfires can damage energy infrastructure and limit energy supply, which restricts energy availability and contributes to higher energy poverty (Bach et al., 2013; Hughes, 2015; Lyster et al., 2022; Asadi et al., 2024). If energy infrastructure is damaged by extreme wildfire events, households may also be forced to substitute less efficient and dirtier energy services, contributing to energy poverty (Thulstrup et al., 2020; Okyere et al., 2023). Third, in the post-disaster recovery phase, the immediate needs of reconstruction contribute to additional energy demands on households (Agarwal et al., 2020; Kim & Kwon, 2023), which could exacerbate household energy stress.

3.2. Mechanisms

3.2.1. Personal wellbeing

We examine the causal effects of exposure to extreme wildfire on three commonly used measures of personal wellbeing: life satisfaction, perceived safety and quality of life (Cooke et al., 2016; Camacho et al., 2019; González-Carrasco et al., 2019). To measure quality of life, we employ four widely used indicators: general health, mental health, social functional status and psychological status (vitality) (O'dea et al., 1999). We expect exposure to extreme wildfire to have an adverse effect on each of these indicators of personal wellbeing.

Existing literature shows that the stress, trauma and exposure to extreme heat associated with extreme wildfires have adverse effects on life satisfaction (Ambrey et al, 2017a; Johnston et al, 2021). The uncertainty and potential ongoing risks associated with wildfires make people feel less safe (Ambrey et al., 2017a; Hudson et al., 2019; Shi & Jin, 2022). In terms of quality of life, exposure to wildfire has adverse effects on general health (Balasooriya et al., 2022; Hahn et al., 2022; Xu et al., 2022) and mental health (Bryant et al., 2014; Saeed & Gargano, 2022; Zhang et al., 2022). Detrimental health effects impair an individual's social functioning, restricting their normal social activities, such as interactions with their family, friends, neighbors (Heo et al., 2008; Pfitzer et al., 2016; Zahnow et al., 2019). Additionally, smoke and high temperatures in the aftermath of wildfire events, along with the deterioration of health status, can lead to a decline in personal vitality and a reluctance to go outdoors (Wasiak et al., 2013; Agarwal et al., 2020). Lower personal wellbeing lower productivity and alter households' energy consumption preferences, which, in turn, can increase the incidence of energy poverty (see, e.g., Armaroli & Balzani, 2007; Ortiz et al., 2017; Warr & Nielsen, 2018; Isham et al., 2020; Bernard et al., 2021; Piao & Managi, 2023; Yang & Zikos, 2024).

3.2.2. Labor market outcomes

Extreme wildfire events have negative macroeconomic effects, which can cause downturns in the labor market in fire-affected communities. Disruptions to regional economies can decrease labor demand (Xiao, 2011; Park et al., 2017; Khan et al., 2020) and increase job search time (Ohtake et al., 2012), resulting in fewer job opportunities (Burrus Jr et al., 2002; Xiao, 2011; Bui et al., 2014; Ambrey et al., 2017b). Additionally, following natural disasters, employers seeking to restore production may opt to offer temporary, informal, or short-term casual contracts (Jiménez Martínez et al., 2020). The negative effects of exposure to extreme wildfires on personal wellbeing may make it difficult for an individual to work at all or force them into casual employment (Baez et al., 2010; Paudel & Ryu, 2018; Ezoji et al., 2019). Exposure to extreme wildfires may also lead to a loss of human capital, which reduces affected individuals' competitiveness in the labor market. The deterioration in labor market outcomes could increase the probability of households experiencing energy poverty by reducing income and/or increasing demand for energy due to more time spent at home.

3.2.3. Community social capital

Another potential explanation for the relationship between extreme wildfire exposure and energy poverty may involve the role of community social capital. In contrast to the predicted adverse effects of disasters on personal wellbeing and labor market outcomes, exposure to disasters could increase community social capital (Bernardini & Hart, 2011). Bakic and

Ajdukovic (2021) found that in disaster-affected communities, community social capital is a strong predictor of post-disaster recovery. Community social capital consists of community trust and social bonds (potential community social capital), as well as community social support and community collaboration (mobilized community social capital) (Kwon et al, 2013).

3.2.3.1. Potential community social capital

Potential community social capital consists of community trust and social bonds. First, community trust represents expectations for opportunities promoting personal and collective planning in each community, stemming from an individual's confidence in the abilities and integrity of others (Mayer et al., 1995; Di Napoli et al., 2019). Interactions during the post-disaster reconstruction phase foster familiarity among community members, thereby enhancing trust (Coleman, 1988; Lee, 2020; Schilpzand, 2023). Second, social bonds represent the breadth of organizational memberships among residents (Knack & Keefer, 1997). Voluntary membership in community organizations, which reflects an individual's identification with their community, is often used as a proxy for social bonds, as community social capital can be formed through such membership (Kwon et al., 2013; Awaworyi Churchill et al., 2023). After experiencing natural disasters, assistance that individuals receive from other community members can enhance their sense of community identity, which, in turn, makes them more likely to become voluntary members of community organizations (Vezzali et al., 2015; Lee & Fraser, 2019). Increases in community trust and social bonds aid the post-disaster recovery of households by contributing to higher income, improving the efficiency of information dissemination, and facilitating support from external sources, each of which could reduce the incidence of household energy poverty (Knack & Keefer, 1997; Adger et al., 2005; Middlemiss et al., 2019; Awaworyi Churchill & Smyth, 2020; Grossmann et al., 2021).

3.2.3.2. Mobilized community social capital

Community social support reflects the willingness of individuals to help each other within the community (Kaniasty, 2020). Exposure to natural disasters can coalesce community cohesion and the likelihood of mutual help and collaboration within communities (Sweet, 1998; Fischer, 2008; Ludin et al., 2019). The shared experience of a disaster inspires solidarity and collaboration among community members, especially in the recovery phases (Chang, 2010; Sweet, 1998). For example, Whitt and Wilson (2007) found that group cooperation among individuals within the community increased after Hurricane Katrina in the United States. Increases in mutual assistance and collaboration among community members could promote the community's collective efficacy, which increases individuals' efficiency in facing challenges.[1] Therefore, greater mobilized community social capital is important for reducing the incidence of energy poverty (Ren et al., 2023; Zhu et al., 2024).

3.3. Moderating effects of non-cognitive traits

3.3.1. Locus of Control

LoC is a psychological concept that describes an individual's perception of their ability to control events in their lives (Rotter & Mulry, 1965). Individuals with a more external LoC tend to believe that their life events are determined by external forces such as fate and luck. In contrast, those with a more internal LoC believe that their actions and outcomes are primarily determined by their own efforts, abilities, and decisions, enabling them to influence their own lives. Individuals with a more internal LoC are better able to cope with the negative shocks of natural disasters and are more resilient (Berlemann, 2016; Güzel et al., 2024). Scott et al. (2010) argued that individuals with an internal LoC exhibit more active and effective coping behavior. They are likely to recover more effectively from the consequences of disasters because they tend to take proactive measures in disaster scenarios, such as actively seeking energy-support information and resources or adjusting household expenditures to reduce economic pressure.

3.3.2. Big 5 personality traits

The Big 5 is a widely used five-item construct for measuring personality traits. The five items are extroversion, agreeableness, conscientiousness, emotional stability, and openness to experience (John, 1990; John et al., 1991; John & Srivastava, 1999). Higher levels of extroversion, agreeableness, conscientiousness, emotional stability and openness to experience are considered protective factors that can dampen the adverse impacts of exposure to disasters (Borja & Callahan, 2008; Bagherian & Mojambari, 2016; Burro et al., 2023). Individuals with these personality traits are more likely to make rational economic decisions post-disaster, better manage their energy expenditures and actively seek information about assistance and support (Donnelly et al., 2012; Lisciandra, 2018; Burro et al., 2023). We expect these traits to mitigate the adverse impacts of exposure to extreme wildfires on energy poverty.

[1] Collective efficacy refers to a group's shared belief in its collective ability to meet environmental challenges and improve living conditions through joint efforts (Elms et al., 2023).

3.3.3. Financial foresight

Financial foresight, measured by how far households typically plan ahead when making their financial decisions, reflects household financial resilience. Individuals with long-term financial planning habits are better able to withstand financial stress and cope with sudden negative shocks, thereby enhancing ability to manage risks (Ameriks et al., 2003; Lusardi & Mitchell, 2011; Strömbäck et al., 2017). Therefore, we expect that households with more extended financial plans are better able to cope with rising energy prices after exposure to wildfires and to mitigate the negative impacts of exposure to extreme wildfires on energy poverty.

4. Data and variables

We use annual data from the HILDA survey from 2005 to 2019, with the BSB occurring in 2009. While the first wave of HILDA was administered in 2001, data on energy expenditure was only collected from Wave five (2005). We only consider data up to Wave 19 (2019) due to the onset of the COVID-19 pandemic in 2020, which significantly altered household energy consumption and income patterns due to lockdowns. We employ data for the four years following the BSB, up to 2013, in the main analysis (2005-2013), in which our focus is on examining the short-term effects on energy poverty. We employ the HILDA data up to 2019 in order to examine whether the effects are persistent in the long run.

4.1. Energy poverty

We employ the HILDA data to construct our energy poverty indicator (EPI). Energy poverty is assessed at the household level, as outlined by Awaworyi Churchill and Smyth (2020). The HILDA survey can sometimes contain multiple entries for a single household in a particular year, leading to more than one observation per household in those instances. Since there is no designated reference person or head for each household in the HILDA survey, studies on energy poverty that use the HILDA survey define the designated household reference person as the individual with the highest current personal income in the household (Awaworyi Churchill & Smyth, 2022b). In contrast to the existing literature, we consider the highest baseline individual income - defined as the individual's income in the initial year in which they joined the sample - rather than the highest current individual income each year in the household to identify the reference person for each household, as individual income may vary each year. This approach helps minimize the impact of fluctuations in income each year. The results, however, are also robust to using current income to define the household reference person.

Our EPI is low income-high cost (LIHC), which is widely recognized as the most accurate and comprehensive EPI for high-income countries (Hills, 2012; Awaworyi Churchill & Smyth, 2022a).[2] Based on the LIHC measure, a household is defined as experiencing energy poverty if its energy costs exceed the national median level and its disposable income - after deducting energy expenses - falls below the official poverty line. Thus, compared to alternative EPIs, such as the ratio of energy expenditure to income or threshold indicators, it has the advantage that it better reflects the essence of being in energy poverty. To be categorised as being in energy poverty under the LIHC measure, households need to not only have high expenditure on energy, but low disposable incomes. The problem with the alternative EPIs is that high income households might have very high energy bills, but they are not in energy poverty because they can readily afford to spend a lot on energy. Following Vera-Toscano and Brown (2022), we define the official poverty line as 60 percent of the national median disposable income. The modified OECD scale is used to equivalize household income and energy costs to account for differences in household size and composition (Brown & Vera-Toscano, 2021). We also employ household weights when constructing the LIHC to reflect the different representations of households. The household weight refers to the cross-sectional population weight for all households responding to the relevant wave of the HILDA survey.

4.2. The BSB areas

The Black Saturday Royal Commission (2010) provides detailed maps for 12 different pockets of fires in a raster data format, which constituted the BSB. Figure 1 shows all 12 pockets of fires, while Figure 2 depicts two of these pockets that were situated very close together, where BSB fatalities were highest and the fire-burnt areas were largest. Utilizing the ESRI Shapefile format for the digital boundary of SA1 from the Australian Bureau of Statistics (ABS), we conduct a location-based analysis following the approach described by Johnston et al. (2021). This approach involves adopting a household location identifier at the SA1 level.

[Figure 1]

[Figure 2]

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[2] In high income countries, EPIs typically focus on ability to pay for energy needs. This differs from developing countries, in which energy poverty is often defined in terms of access to clean energy. This is not really an issue in a country such as Australia in which 100 per cent of the population has access to electricity.

In Australia, the SA1 level generally denotes local geographical areas with a population between 200 and 800 people, with an average population of about 400 people. We employ the restricted version of the HILDA survey, which provides information on the SA1 in which the respondent lives. We approximate the distance from where the respondent lived to the location of the fires by calculating the distance from the SA1, in which each household is located, to the nearest BSB pockets. These distances represent level of exposure to the BSB, and we establish the treatment and control groups based on these distances.

We focus on five fatal bushfires that occurred on BSB: the Kilmore East fire, the Churchill fire, the Murrindindi fire, the Bendigo fire, and the Beechworth-Mudgegonga fire, in which fatalities occurred. Figure 3 shows the locations of the five fires and rings for different radii from the outer edge of each fire. The main sample includes all households residing within a 50 km radius of the outer borders of these five bushfire areas, as well as households living within these five burnt areas. In our main specification, the treatment group is defined as locations within 15 km of the fires (including households within the burnt areas), while the remaining households residing between 15 and 50 km away are classified as the control group. To examine the robustness of our results, we consider different treatment and control groups. Initially, two treatment groups are defined as locations 0-15 km and 15-30 km from the fires, with the control group defined as 30-50 km from the fires. Additionally, we expand the distance range of our sample to examine whether our findings hold in a broader geographical context. In this robustness analysis, we include all households residing within a 100 km radius of the outer borders of the bushfire areas. Similarly, we alternate the treatment groups, first considering only the 0-15 km rings and then both the 0-15 km and 15-30 km rings.

[Figure 3]

4.3. Mechanisms

4.3.1. Personal wellbeing

We consider three dimensions of personal wellbeing: perceived safety, life satisfaction, and quality of life, where quality of life is measured by vitality, mental health, general health, and social functioning. In the HILDA survey, perceived safety is measured based on a single-item survey question that asks respondents to rate the degree of safety that they feel in their living environment (Ambrey et al., 2017a; Awaworyi Churchill & Smyth, 2022a). Responses are on an 11-point scale, where zero represents 'totally dissatisfied' and 10 represents 'totally satisfied'. To measure life satisfaction, we utilize the single-item HILDA question: 'How satisfied are you with your life' (Ambrey et al., 2014; Kubiszewski et al., 2018). The responses are also on an 11-point scale. Each measure of quality of life is contained in the 36-Item Short Form Health Survey (SF-36), which is administered as part of the HILDA survey. Responses are scored on a 0-100 scale (Stewart & Ware, 1992), with higher scores representing better general and mental health, improved social functioning and enhanced vitality.

4.3.2. Labor market outcomes

The three measures of labor market outcomes are employment indicators for the household reference person: employment status (employed =1), duration of any unemployed spell (the percentage of time that the individual was unemployed in the current financial year), and employment type (employed as casual worker = 1).

4.3.3. Community social capital

Community social capital encompasses potential community social capital and mobilized community social capital. Potential community social capital consists of community trust and social bonds. The question on community trust in the HILDA survey is asked only in waves 6 and 10 over the period of the short-run analysis (2005-2013). Respondents are asked: 'To what extent do you agree or disagree with people in your neighborhood can be trusted?' Responses are coded on a seven-point scale, where one represents 'strongly disagree' and seven represents 'strongly agree'. We employ data from wave 6 to represent the community trust in the pre-BSB period (2005-2008), and data from wave 10 to denote community trust in the period following the BSB (2009-2013). We measure social bonds by using a question about voluntary membership in community organizations. In all waves of the HILDA survey, respondents were asked, "Are you currently an active member of a sporting, hobby, or community-based club or association?" An affirmative response indicates stronger social bonds.

Mobilized community social capital consists of community social support and community collaboration. Community social support is measured using the HILDA survey question: 'How commonly do neighbors help each other out in your local neighborhood?' Responses are coded on a five-point scale, where one represents 'never happens' and five represents 'very common'. Community collaboration is measured using the HILDA survey question: 'How common are the neighbors doing things together in your local neighborhood?' Responses are coded on a five-point scale, where one represents 'never happens' and five represents 'very common'.

Since information on community social support and community collaboration is only available in waves 6, 8, 10, and 12 during our main study period, we calculate the average of waves 6 and 8 for each measure to represent mobilized community social capital in the pre-BSB period (2005-2008). Similarly, the average of waves 10 and 12 is used to represent mobilized community social capital in the post-BSB period (2009-2013).

Following Awaworyi Churchill et al. (2024), we aggregate the levels of these indicators at the SA1 level. We use sample-balancing weights provided in the HILDA survey to adjust the community samples to match their respective populations. To illustrate that these indicators of community social capital are independent and measure different dimensions, we compare the correlation between the two indicators relative to a commonly used threshold. Table A1 shows that the combination of pairs among the four dimensions of community social capital yields correlation coefficients below 0.8 in all cases, suggesting that they are independent measures (Rönkkö & Cho, 2022; Awaworyi Churchill et al., 2024).

4.4. Potential moderators

4.4.1. Locus of control

LoC is measured using the seven-item Pearlin and Schooler (1978) Mastery Scale. We employ a composite indicator comprising seven items to measure LoC, ranging from one (external LoC) to seven (internal LoC). In the HILDA survey, participants provided information on this scale in waves 7 and 11 during our main study period. We calculate the average LoC across the two waves. Panel A of Figure A4 demonstrates that, following the BSB, there were no large fluctuations in LoC during our main study period, reflecting the relative stability of LoC.

4.4.2. Big 5 personality traits

The Big 5 personality traits - extraversion, agreeableness, conscientiousness, openness to experience, and emotional stability - are measured on a seven-item scale, with higher scores representing higher values on these traits. The Big 5 are available in HILDA waves 5, 9, and 13 during the main study period. We take the average of these traits over the three waves (Prakash & Munyanyi, 2021). Panel B to F of Figure A4 show that, following the BSB, there were no large fluctuations in Big 5 personality traits during our main study period, suggesting that the Big 5 personality traits are relatively stable.

4.4.3. Financial foresight

To measure household financial foresight, we consider the most important period that the household reference person uses when planning savings and spending, which reflects the household's ability to cope with unexpected negative shocks. The HILDA survey asks respondents: 'In planning your saving and spending, which of the following periods is most important to you?' The answer is coded on a six-point scale. Larger values indicate that individuals consider the long term to be more important in financial planning. Considering that bushfire exposure may alter an individual's financial foresight, we use data from the household reference person in 2008, the year before the BSB, to measure the moderating effect of financial foresight on the relationship between BSB exposure and energy poverty.

Table A2 provides descriptive statistics for all variables used in the main analysis.

5. Empirical specification

We employ a linear panel event-study design to assess the impact of exposure to the BSB on energy poverty:

$$EP_{i,j,t} = \sum_{y=2008}^{2013} \beta^{y} Exposure_{i,t}^{y} + \mu_j + \tau_t + \varepsilon_{i,j,t} \tag{1}$$

$EP_{i,j,t}$ indicates the energy poverty status of household i residing in SA1 j in year t. $Exposure_{i,t}^{y}$ is an interaction term that combines the treatment group indicators with indicators representing the waves/years y. It equals one if household i is in the treatment group, which is defined as being located within a specific radium ring, in year y, and zero otherwise. This is designed to capture year-specific changes in the probability of a household being in energy poverty due to exposure to the BSB during 2008-2013, compared to their average likelihood of being in energy poverty during the reference period of 2005-2007. The interaction terms between the treatment group indicators and the year 2008 (the pre-BSB year) are also included to assess the presence of any pre-BSB trends. We designate one distance category, K, as the control group and omit the corresponding interaction term in order to simplify the interpretation of the model. Therefore, the coefficients β^{y}, which measure the BSB effects in the treatment group for year y with respect to the omitted control group, are of particular interest to us.

We include SA1 fixed effects (μ_j) and year fixed effects (τ_t) to control for factors that may have an impact on the study results over time and to control for invariant regional characteristics that may exist within each SA1, such as geographic location, climate conditions, and infrastructure level. In Equation (1), we do not add additional controls to avoid the over-controlling problem (Dell et al., 2014). In the robustness checks, we assess the robustness of the results to incorporating household and individual characteristics as additional controls. We measure the distance from fires using residential location in 2008, the year before the BSB event, ensuring that the distance of each household's SA1 from the fires is a fixed household characteristic. Given that people may migrate due to the BSB and including movers would bias the estimates, we restrict the sample to households that did not relocate during the study period. In a robustness check, we include households that relocated during the main study period and the results remain qualitatively the same. Standard errors are clustered at the SA1 level.

The exogeneity of treatment is the key causal identification assumption. The fires are treated as an exogenous event, implying that their occurrence is random. Forecasting wildfire is difficult (Radočaj et al., 2022). Although the locations of wildfires are not random, as they typically occur in flammable areas such as forests and grasslands, the timing of these fires within these susceptible areas is considered to be as close to random as possible (Johnston et al., 2021). This is because the exact timing of a fire is influenced by unpredictable factors, such as extreme weather events (especially temperature and wind direction). This temporal randomness implies that the occurrence of fires is exogenous and independent of other time-varying factors that could affect the incidence of energy poverty, such as individual characteristics and behavior of residents in the region. Overall, the BSB affected 12 non-contiguous areas, but it comprised sporadic fires spread across various parts of Victoria. A significant factor in the spread of the BSB fires was unusual weather patterns on that specific day, including the direction and strength of the winds. These characteristics of the BSB support the argument that the BSB was an exogenous event. Another consideration is that the fires also affected households indiscriminately, reducing the possibility of biased results.

Another key assumption underpinning the identification strategy is that major differences between households within different groups are constant, thereby ensuring that observed differences in energy poverty can be attributed to wildfire exposure, rather than to pre-existing disparities. We conduct a formal version of the falsification test to assess whether there are pre-existing differences (Beatty & Shimshack, 2010; Perez-Truglia, 2018; Miller, 2023). Specifically, we estimate the effects of exposure to the BSB on energy poverty in 2005 to 2007 to examine whether there were significant pre-BSB differences in energy poverty between those residing close (within a 15 km radius) and further away (15-50 km and 15-100 km) from the BSB, relative to 2008. The results, which are presented in Table 1, are that differences in energy poverty for each pre-BSB year are statistically insignificant, indicating that before the BSB, trends in energy poverty were similar between treatment and control groups. This parallel trend finding supports our identification approach. The results from this analysis are also presented in Figure 4. There appears to be a trend in the estimated differences prior to the BSB, suggesting that households residing close to the fires may have experienced different levels of energy poverty compared those living further away. However, since all pre-BSB effects are statistically insignificant, the empirical evidence supporting the presence of a pre-trend remains weak. Additionally, in Figure 4, we observe a dramatic positive trend in the estimated differences in energy poverty for 2010 and 2011 (after the BSB), relative to 2008.

[Table 1]

[Figure 4]

In Panel A and Panel B of Table A3, we present the estimated effects in 2010 and 2011 for differently defined treatment groups. A notable finding is that the estimates indicate that the BSB effects increased and then decreased as the geographical area within the treatment group increases. Our main specification uses the 0-15 km range since it balances the need for a treatment group that is spatially close to the fires while ensuring that the sample size of treated households is not too small. This area shows the peak of the BSB effects.

To overcome the limitations of intermediary effects arising from the potential endogeneity of the channels and to strengthen causal inference, we follow the approach used in Dian et al. (2024), Hao et al. (2024), and Li et al. (2025) to test each of the potential mechanisms. Specifically, we use a variation of Equation (1), in which the outcome variable, $Channelk_{i,j,t}$, denotes each of the potential channels, k, as described in Section 4.3.

$$Channelk_{i,j,t} = \sum_{y=2008}^{2013} \alpha_1^y Exposure_{i,t}^y + \mu_j + \tau_t + \varepsilon_{i,j,t} \quad (2)$$

To ensure that any observed differences are attributed to BSB exposure rather than pre-existing disparities, we examine whether there were systematic differences in personal wellbeing and labor market outcomes between treatment and control groups prior to the BSB.[3] Specifically, we estimate the effects of exposure to the BSB on perceived safety, life satisfaction, vitality, mental health, social functioning, general health, employment status, annual unemployment period, and employment type for the years 2005, 2006, and 2007, using 2008 as the reference year. This allows us to assess whether households residing close to the BSB (0-15 km) differed significantly from those further away (15-50 km) before the event.

Panel A of Table A4 reports the results of the pre-BSB parallel trends analysis for personal wellbeing, and Panel B of Table A4 presents the corresponding results for labor market outcomes. We find no significant differences in any of the potential mechanism variables between the treatment and control groups during the period leading up to the BSB. These results suggest that major differences between households in the two groups remained constant, thereby supporting the credibility of our mechanism approach. The results from this analysis are also presented in Figure A5. There appears to be a trend in the estimated differences for each of the potential mechanism variables prior to the BSB, suggesting that households residing closer to the fires may have experienced different wellbeing and labor market outcomes compared to those living further away. However, as all pre-BSB effects are statistically insignificant, the empirical evidence supporting the existence of a pre-trend remains weak.

To examine the potential attenuating effects of non-cognitive traits, we employ a two-step approach (Awaworyi Churchill & Smyth, 2022a; Xu et al., 2022). In the first step, we add the potential moderator as an additional covariate in Equation (1), where the coefficient of the potential moderator represents the direct effect of the potential variable on energy poverty. In the second step, we add both the potential moderator and its interaction with exposure to the BSB to capture the moderating effect of the potential moderator. Building on Equation (1), the following models are employed to examine the moderation effects, where $Modm_{i,j,t}$ denotes the potential moderator m, as described in Section 4.4.

$$EP_{i,j,t} = \sum_{y=2008}^{2013} \beta^y Exposure_{i,t}^y + \eta_1 Modm_{i,j,t} + \mu_j + \tau_t + \varepsilon_{i,j,t} \quad (3)$$

[3] We cannot conduct pre-trend tests for community social capital, given it was only collected in one wave between 2005 and 2008. For community social support, we examine the average post-BSB effect relative to the pre-BSB period.

$$EP_{i,j,t} = \sum_{y=2008}^{2013} \beta^y Exposure_{i,t}^y + \sum_{y=2008}^{2013} \eta_3^y (Exposure_{i,t}^y \times Modm_{i,j,t}) + \eta_2 Modm_{i,j,t} + \mu_j + \tau_t + \varepsilon_{i,j,t} \qquad (4)$$

6. Results

6.1. Main Results

Table 2 presents the results based on different samples, as well as alternative treatment and control groups. The treatment effects reported across all columns are relatively similar. Columns (1) and (2) contain the results where the sample is households residing within a 50 km radius of the BSB. The main results in Column (1) indicate that the probability of being in energy poverty increased if the household was within 0-15 km of the BSB by 11.88 percentage points in 2010 and by 12.97 percentage points in 2011, relative to the 2005-2007 period.

The effect of BSB exposure on household energy poverty was slightly delayed, as the effect on energy poverty in the year in which the BSB occurred (2009) was insignificant. Zhang and Sheldon (2025) also found that the positive effects of the California wildfires on household consumption of essential goods were slightly delayed. One plausible explanation for the delayed effect in our case is that a series of immediate emergency responses from a variety of authorities helped households in high-exposure areas to cope with initial energy stress. In the immediate aftermath of the fires, the Victorian Bushfire Reconstruction and Recovery Authority (VBRRA) was established to support the short-term recovery of affected households (Black Saturday Royal Commission, 2010). The State and Federal Governments implemented extensive emergency relief measures throughout 2009 to support fire-affected areas.[4] Most emergency assistance in the aftermath of the BSB was for immediate implementation and was fully delivered in 2009, with only a small portion of aid continuing to be offered into 2010. Long-term assistance beyond 2010 was limited to the provision of business-as-usual services (Black Saturday Royal Commission, 2010). This could also explain why our results show that 2011 was a more challenging year for household energy poverty than 2010.

[4] State and Federal Governments provided Temporary Living Expenses Grants and an Emergency Personal Hardship Payment to assist households with their living expenses and immediate needs (VBRRA, 2009). Additionally, the Federal Government provided targeted assistance for specific groups and purposes (Department of Home Affairs, 2024). For example, via the Australian Government Disaster Recovery Payment (AGDRP), a one-off, immediate financial assistance payment was provided to those who suffered serious adverse effects from the BSB and submitted a claim before August 2009. Between February and November 2009, the Federal Government offered Income Recovery Subsidies for individuals who lost income due to the fires. The Federal Government also allocated $7.5 million for emotional and psychosocial support in 2009.

Although our main analysis focuses on households located within 0-15 km of the BSB as the primary treatment group, the effect of the BSB demonstrates a non-monotonic relationship with distance. To analyse this trend more thoroughly, we establish multiple treatment groups for comparison. Column (2) includes both the 0-15 km and 15-30 km rings as the treatment groups. The estimates for the 0-15 km group are similar to that in Column (1). In contrast, the estimates for the 15-30 km ring are smaller and statistically insignificant, suggesting that households further from the fires were less affected. In Columns (3) and (4) of Table 2, we expand the sample to include households residing within a 100 km radius of the BSB. The results are consistent with those from the narrower geographical sample in Columns (1) and (2). Notably, the estimated coefficients for 2008 are statistically insignificant across all four columns, indicating no significant differences in energy poverty relative to the control groups in the year before the BSB. This further supports the parallel trends assumption.

[Table 2]

The magnitude of the effect sizes on household energy poverty in 2010 and 2011 might, at first blush, appear to be unusually large. A possible explanation is not only the catastrophic nature of the BSB itself, but also a shift in the pattern of energy consumption resulting from temporary government emergency support following the BSB. Specifically, the BSB was a large-scale and long-lasting extreme wildfire event, significantly more severe than general wildfires. Such extreme events are more likely to have pronounced effects on both household income and energy consumption. These characteristics may help explain the substantial impact observed on household energy poverty. Furthermore, when government emergency support was withdrawn, households may have continued the elevated energy consumption patterns that evolved during the assistance period, at least in the short run, which could have exacerbated household energy poverty after the cessation of emergency aid.[5]

Although no existing studies have examined the causal effects of extreme wildfires on energy poverty, several studies have assessed the impacts of other types of extreme natural disasters

[5] In addition to the main analysis, we conduct several robustness checks. While results vary slightly depending on the methodology used, the estimated effects on energy poverty remain consistently positive and statistically significant for both 2010 and 2011. The magnitudes are substantial, ranging from 9.69 to 13.91 percentage points in 2010 and from 7.06 to 13.62 percentage points in 2011, relative to the 2005-2007 reference period.

and report size effects of similar magnitudes. For example, Okushima (2016) found that two years after the 2011 Great East Japan Earthquake, the household energy poverty rate increased from 6.8 percent in 2010 to 8.4 percent in 2013, with rising energy costs identified as a significant mediating factor. Additionally, a growing body of literature documents the negative effects of extreme natural disasters on other household outcomes. Yin et al. (2022) found that exposure to the 2008 Wenchuan earthquake in China caused a 2.7 percent reduction in household total consumption, and that this effect persisted into 2009. This extreme magnitude 8.0 earthquake event also significantly reduced household energy consumption by 7.34 percent. In addition, Luo and Kinugasa (2020) reported that exposure to the 2008 Wenchuan earthquake resulted in sharp declines in household saving rates – from 24 percent to 7 percent in rural areas, and from 23 percent to 21 percent in urban areas. Salvucci and Santos (2020) found that the 2015 Flood in Mozambique reduced household consumption in the short term by 11 to 17 percent, and that it increased the household poverty rate by 6.2 percentage points.

In contrast, studies have assessed the impact of more routine wildfires and flooding that occur in most years and are not as extreme in severity. Paudel (2021) found that a one-unit increase in FRP from the previous year’s forest fires is associated with a 0.43 percent decline in energy expenditure and a 0.36 percent decrease in energy poverty among Nepalese households. Yamamura (2015), using cross-country panel data from 1970 to 2004, argued that floods lead to a delayed increase in the Gini coefficient by 0.65 percentage points. Overall, our results align with existing studies and highlight that the impacts of extreme wildfires, such as the BSB, are significantly more catastrophic compared to more routine general forest fires.

Table 2 shows that there were no significant differences in the probability of being in energy poverty in 2012 and 2013 relative to 2005-2007, suggesting that households may have largely returned to their pre-disaster trajectories after 2011. To explore the long-run effect of the BSB, we extend the analysis to 2019. The results in Table 3 show that there is no significant difference in the likelihood of being in energy poverty after 2011 relative to 2005-2007 This indicates that households reverted to their pre-disaster energy poverty trajectories after 2011, confirming the absence of long-term BSB effects on household energy poverty.

[Table 3]

6.2. Mechanism analysis

6.2.1. Personal wellbeing

Table 4 reports the causal effects of BSB exposure on each indicator of personal wellbeing in 2010 and 2011, which are the years in which exposure to the BSB is found to have significant impacts on energy poverty. Column (1) indicates that the effect of being exposed to the BSB on perceived safety was statistically significant and negative in both 2010 and 2011, suggesting a reduction in perceived safety due to exposure to the BSB for individuals living within 15 km of the fires in these years relative to 2005-2007. Column (2) presents the results for the effects of exposure to the BSB on life satisfaction. The BSB had a statistically significant and negative effect on life satisfaction in 2010, but not 2011. The results for the effects of exposure to the BSB on each of the indicators of quality of life from the SF-36 - vitality, general health mental health, and social functioning - in Columns (3) to (6) - are the same as those for life satisfaction. The last column indicates that general health was not significantly affected by BSB exposure.

[Table 4]

6.2.2. Labor market outcomes

Table 5 reports the results of the causal analysis for each labor market indicator. The three columns show that employment status, duration of any unemployed spell, and employment type were not significantly affected by BSB exposure in either 2010 or 2011, suggesting that they are unlikely to be pathways through which BSB exposure affects energy poverty. While some studies have found that natural disasters negatively affect employment outcomes, our findings regarding the relationship between extreme wildfires and employment align with Johar et al. (2022), who found no significant impact of natural disasters on employment. In our case, a likely explanation for this result is that, in the aftermath of the BSB, the Federal and Victorian Governments provided targeted labor market relief in fire-affected regions, with a view to softening the adverse effects of the BSB on labor market outcomes.[6]

[Table 5]

[6] The Federal and Victorian Governments provided support through a $51 million joint package for small businesses and primary producers directly affected by the BSB, including financial assistance, concessional loans and business support (Department of Home Affairs, 2024). Additionally, the Commonwealth and State Governments collaborated under the Government's Jobs Fund program, allocating over $24 million to affected areas to create new jobs and employment opportunities (Parliament of Australia, 2010).

6.2.3. Community social capital

The results for the causal impacts of exposure to the BSB on each dimension of community social capital are presented in Table 6. Since data on social bonds are available for all waves, Column (2) reports the results for social bonds in 2010 and 2011, which are years for which exposure to the BSB had significant effects on energy poverty. Additionally, as the average of available waves before and after the BSB are used to represent pre- and post-BSB level of community trust and mobilized community social capital, Columns (1), (3) and (4) report the estimated average post-BSB effects on community trust, community social support, and community collaboration, respectively, relative to the pre-BSB period.

[Table 6]

The third column of Table 6 indicates a significant and positive causal relationship between BSB exposure and community social support in the post-BSB period, relative to the pre-BSB period, with the effect weakly statistically significant at the 10 percent level. This result provides evidence for the proposed mechanism. This positive result indicates that community social support offsets part of the adverse effects of BSB exposure on energy poverty transmitted through personal wellbeing and household income. The remaining columns show no statistically significant relationships between exposure to the BSB and community trust, social bonds, or community collaboration, which implies that these three types of community social capital are not channels through which BSB exposure affects energy poverty.

6.3. Moderating effects of non-cognitive traits

We examine whether non-cognitive skills attenuate the impact of exposure to the BSB on the incidence of energy poverty. The results are reported in Table 7. The results in Panel A suggest that LoC is not a moderator. The results in Panels B to F suggest that the only of the Big 5 personality traits that attenuates the effect of exposure to the BSB on the incidence of energy poverty in 2010 is openness to experience. Households whose reference person scored higher on openness to experience had a lower likelihood of being in energy poverty following exposure to the extreme wildfires. Thus, a high level of openness to experience can be considered a protective factor. The results in Panel G indicate that, in 2010, having longer-term financial planning habits dampened the effect of exposure to the BSB on the incidence of energy poverty. In summary, greater openness to experience and long-term financial foresight attenuated the effect of exposure to the BSB on the incidence of energy poverty in 2010.

[Table 7]

7. Robustness checks and other extensions

7.1. LIHC using an alternative poverty line

In the main analysis, following the approach in Vera-Toscano and Brown (2022), we define the official poverty line as 60 percent of the national median disposable income. In Table A5, we use half of the national median disposable income as the official poverty line (Parliament of Australia, 2024). As in Table 2, our sample consists of households residing within 50 km of the BSB, with those residing within 15 km of the BSB as the treatment group. The estimates remain robust to the different threshold used to construct the LIHC.

7.2. Different samples and controls

Our main estimates exclude households where the reference person moved during the study period to remain consistency. We examine the robustness of our estimates to including households that moved during the main study period from 2008 to 2013. The results in the first column of Table A6 affirm that our estimates remain robust when movers are included. In the main results, shown in Table 2, we only control only for year and SA1 fixed effects to avoid over-controlling (Dell et al, 2014). To examine the potential for bias due to omitted variables, we incorporate household characteristics and details of the reference person, including age, employment status, education level, annual disposable income, household size, and the number of dependent children as additional controls. The second column of Table A6 shows that including these additional controls does not significantly alter the BSB effect estimates, reinforcing the reliability of our findings. The last column confirms that using household fixed effects instead of SA1 fixed effects does not change the main conclusions.

7.3. Alternative methods for selecting the household reference person

We assess the sensitivity of our results to alternative approaches for addressing the issue of multiple observations per household in the HILDA survey. The first column of Table A7 shows results using current individual incomes to identify the household reference person. In the second column, we address the presence of multiple observations per household by weighting these households differently. We divide the HILDA household weight variable by the household size and apply this adjusted household weight. This approach enables us to retain all observations in households. Overall, the results in Table A7 confirm that our conclusions remain consistent, regardless of the method used to address multiple records for a household.

7.4. Falsification test

We conduct a falsification test in which we randomly assign households to either the treatment or control group using random numbers, instead of grouping them based on actual geographical distance. The proportion of households assigned to each group matches the actual sample proportions, ensuring that any differences can be attributed to the random assignment rather than differences in statistical power due to changes in sample size. In Table A8, the randomly assigned falsification treatment fails to replicate the significance of the results reported in Table 2. That the random grouping results are statistically insignificant suggests that the significant effects observed in the main analysis are not random, but closely related to actual exposure, further supporting the credibility of our conclusions.

7.5. Fixed effects panel models with time invariant variables

We treat the distance to the BSB in 2008 as a time invariant variable and employ the Fixed Effects Filtered (FEF) model (Pesaran & Zhou, 2018) and the Linear Dynamic Panel Data model (Kripfganz & Schwarz, 2019) to estimate the causal effects of exposure to the BSB on energy poverty.[7] The FEF model proposed by Pesaran and Zhou (2018) provides an approach to estimate time-invariant effects using panel data, which includes two steps. In the first step, we compute the coefficients of the time-varying variables and the associated residuals. In the second step, we compute the time averages of the residuals obtained in the first step and use them as a dependent variable in a cross-section Ordinary Least Squares (OLS) regression that includes the time-invariant regressor and an intercept. Kripfganz and Schwarz (2019) exploit an approach to identify the coefficients of time-invariant variables in a dynamic Hausman and Taylor (1981) model, where the FEF models can be treated as a special case. The two-stage estimation procedure proposed by Kripfganz and Schwarz (2019) is more robust, and their approach allows for a more flexible choice of the first-stage estimators.

[7] As the Stata command 'xtfef,' developed by Pesaran and Zhou (2018), cannot be implemented when including respondents who moved between waves, we excluded movers when estimating the FEF model. This limitation is overcome by using the Stata command 'xtseqreg' for the Linear Dynamic Panel Data model developed by Kripfganz and Schwarz (2019).

Table A9 presents the results for the Pesaran and Zhou (2018) FEF model and the Kripfganz and Schwarz (2019) Linear Dynamic Panel model, which leverage the panel structure of the data. The first two columns present the results using the main specification sample, which consists of panel data from 2005 to 2013 and households living within 50 km of the fires. The last two columns show the results for the entire sample from 2005 to 2019 and households living within 100 km of the fires. The sample size for the FEF model is smaller because it is a static panel model that cannot handle movers. The results are consistent with our main findings and suggest that the probability of households experiencing energy poverty increases as the distance to the BSB decreases, although the effect is insignificant in Column (3).

7.6. Robustness of the moderating effects of non-cognitive traits

Some studies suggest that while LoC remains relatively stable for working-age adults, it is not exogenous for adolescents or older people (Cobb-Clark & Schurer, 2013; Buddelmeyer & Powdthavee, 2016; Awaworyi Churchill & Smyth, 2022b). In our main sample, the age range is between 16 and 96. Following the approach in Awaworyi Churchill and Smyth (2022a), we restrict our sample to adult respondents aged between 21 and 59 to examine the robustness of our results for LoC as a moderating variable. This restriction results in the loss of 2,107 observations. Panel A of Table A10 shows that the results based on the restricted sample are consistent with our main findings in Section 6.3; namely, that LoC is not a moderator.

Personality traits also potentially change in adolescence and early adulthood (Borghuis et al., 2017); however, McCrae (2003) argued that personality change is the exception rather than the rule after age 30. Therefore, following McCrae (2003), we restrict our sample to respondents aged over 30 to examine the robustness of the Big 5 personality traits as moderators, resulting in the loss of 286 observations for extroversion and 334 observations for the remaining four Big 5 personality traits. The results in Panels B to F of Table A10 confirm that our conclusions about the moderating effect of the Big 5 personality traits on the effect of the BSB on energy poverty remain consistent, regardless of whether the sample is restricted to a specific age range.

7.7. Unpacking the energy poverty effects

The main results indicate that exposure to the BSB contributed to an increase in energy poverty, denoted by LIHC, in both 2010 and 2011. The increase in LIHC could reflect an increase in household energy expenditure, a reduction in household income or both. To disentangle these effects, we examine the impact of exposure to the BSB on household energy expenditure and household income by regressing each separately as a continuous dependent variable.

Table A11 presents the regression results quantifying the impact of exposure to the BSB on household energy consumption and household income. Column (1) shows that in 2011, exposure to the BSB increased household energy expenditure, with the effect weakly statistically significant at the 10 percent level. Column (2) indicates that exposure to the BSB reduced household total disposable income in 2010. Overall, the results in Table A11 suggest that the impact of BSB exposure on energy poverty in 2010 was primarily driven by a reduction in household income, whereas in 2011, the increase in the probability of experiencing energy poverty appears to be driven by higher household energy expenditure.

A potential explanation for our findings is that, initially in 2010, the labor market downturn following the BSB led to reduced earnings among affected households, which in turn increased the likelihood of experiencing energy poverty. By 2011, as labor market conditions began to improve and housing and physical infrastructure were gradually rebuilt, household energy expenditure increased. The descriptive analysis in Panel A of Figure A6 suggests a distinct shift in the trend of average household energy expenditure for the treatment group after the BSB, with a significant increase observed in 2011. Figure A6, Panel B, illustrates a marked decline in household income for the treatment group in 2010. These findings are consistent with the quantitative results presented in Table A11.

7.8. Is energy poverty proxying income poverty and broader welfare indicators?

One might wonder whether the results for energy poverty are simply proxying income poverty and broader measures of welfare. To explore this issue, we estimate the effects of exposure to the BSB on income poverty and other welfare indicators, shifting the focus from energy poverty to explore whether broader welfare outcomes exhibit a similar pattern. The first two columns of Table A12 present the results for income poverty based on two different definitions. In Column (1), households are classified as being in income poverty if their income falls below the official poverty line, defined as 60 percent of the national median household disposable income (Vera-Toscano & Brown, 2022). In Column (2), following Lozano Alcántara and Vogel (2023), we calculate the poverty line using the equivalised disposable household income of individuals aged 17 years or older to determine the restricted median national disposable household income, and then apply the 60 percent of this value as the income poverty threshold.

The results in Columns (1) and (2) of Table A12 indicate that exposure to the BSB significantly increased the probability of households falling into income poverty in 2010 and 2011, if they were located within 0-15 km of the fires, relative to the 2005-2007 period. However, the effect sizes are smaller than those observed for energy poverty. This finding highlights the importance of considering the separate effects of exposure to extreme wildfires on the incidence of energy poverty, rather than focusing solely on general income poverty. One potential explanation for the larger size effects for the incidence of energy poverty is that the LIHC measure captures not only the income-related deprivation caused by BSB exposure but also the rebound in energy expenditure that followed.

We also examine other welfare indicators to further assess whether exposure to extreme wildfires have catastrophic effects on broader aspects of welfare. Column (3) of Table A12 reports the results for overall job satisfaction. In the HILDA survey, overall job satisfaction is measured using a single-item question in which respondents rate their satisfaction with various aspects of their job on an 11-point scale, ranging from zero ('totally dissatisfied') to 10 ('totally satisfied') (Ambrey et al., 2017a; Awaworyi Churchill & Smyth, 2022a). Column (4) of Table A12 presents the results for the SF-36 reported health transitions, which measure individual's perceived changes in their general health over a specified period. Higher score indicates that respondents believe their health has improved or remained stable relative to the past. The results in the last two columns suggest that exposure to the BSB had no statistically significant effect on the overall job satisfaction or SF-36 reported health transitions of the household reference person.

Also relevant here is the estimates in Tables 4 to 6 of exposure to the BSB on various welfare indicators, including personal wellbeing, labor market outcomes, and community social capital. To enable comparison across variables measured on different scales, we calculate standardized coefficients for those factors significantly affected by BSB exposure, as identified in Tables 4 to 6. Panels A and B of Table A13 report that the magnitudes of the standardized effects are smaller than the standardized effect of BSB exposure on energy poverty.

In summary, these differences between the results for energy poverty and other welfare indicators, including income poverty, suggest that the effects on energy poverty are not merely a proxy for broader welfare impacts. Therefore, it is important to consider energy poverty as a distinct outcome, rather than viewing it solely as a proxy for general welfare effects.

7.9. Excluding instances of energy expenditure with extreme values

In Table A2, we observe some cases with extremely high energy expenditure, which may be attributable to the inclusion of both household and business-related expenses in the reporting. For example, households operating family farms may report combined expenditures on household and farm energy bills. To address the influence of potential outliers, we conduct an additional robustness check that excludes extreme values. Specifically, we remove households in the top 10 percent of the energy expenditure distribution. Tables A14 and A15 present the results for the short- and long-term effects of BSB exposure on household energy poverty, respectively. The findings remain consistent with the main results reported in Tables 2 and 3.

8. Conclusion

In this paper, we employ an event-study approach to assess the short- and long-term causal impact of exposure to the 2009 BSB, which is Australia's deadliest wildfire, on the incidence of energy poverty. Our main finding is that there was a slightly delayed positive effect of exposure to the BSB on household energy poverty. Specifically, the probability of households within the 15 km radius being in energy poverty increased significantly in 2010 and 2011, relative to the 2005-2007 reference period. However, the impact of BSB exposure on energy poverty did not persist in the long term; rather, households returned to their previous trajectory after experiencing short-term impacts. These results are robust to a number of sensitivity checks. Examining the effect of BSB exposure on income poverty and other welfare indicators suggests that the result for energy poverty is not merely a proxy for broader welfare impacts.

We find that personal wellbeing and community social support are important channels through which BSB exposure affected energy poverty. Specifically, in 2010, exposure to the BSB significantly increased the incidence of energy poverty through the deteriorations in most facets of personal wellbeing - ie. life satisfaction, perceived safety and the quality of life, with the only measure of personal wellbeing unaffected being general health. In 2011, perceived safety was the only factor responsible for the increase in the incidence of energy poverty. Additionally, the positive effects of BSB exposure on community social support in the post-BSB period offset part of the adverse effects transmitted through personal wellbeing. The results of the moderation analysis show that in 2010, being more open to experience and having long-term financial planning habits mitigated the adverse impact of BSB exposure on energy poverty.

The results for the factors that attenuate the adverse effect of the BSB on energy poverty have some policy implications. Being more open to experience can help individuals adapt more quickly to negative shocks and more readily accept new solutions in response (Burro et al., 2023). Investing in targeted programmes can nudge households toward higher levels of openness to experience, thus enhancing their resilience after disasters (Wuepper et al., 2020). Government can organize personal development sessions in communities or schools to effectively motivate individuals to improve their levels of openness to experience (Robinson et al., 2015). Interventions aimed at enhancing openness, such as the *Do Something Different* program (Fletcher & Pine, 2012), may be useful in facilitating such desired changes.

Our results also point to the value of investing in financial literacy training programs, which have been shown to positively impact individuals' financial planning behaviors (Braunstein & Welch, 2002; Hilgert et al., 2003; Howlett et al., 2008). Enhanced financial literacy can lead individuals to develop long-term financial planning habits, thereby increasing their financial resilience. Considering longer-term periods when making spending and saving plans can help households better manage their energy stress when facing negative shocks. A potential challenge is the cost at scale. Our results suggest that targeting such programs geographically to regions prone to wildfires and other natural disasters can increase their cost-effectiveness.

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Figures and tables

Figure 1 The 2009 BSB
Source: Black Saturday Royal Commission (2010)

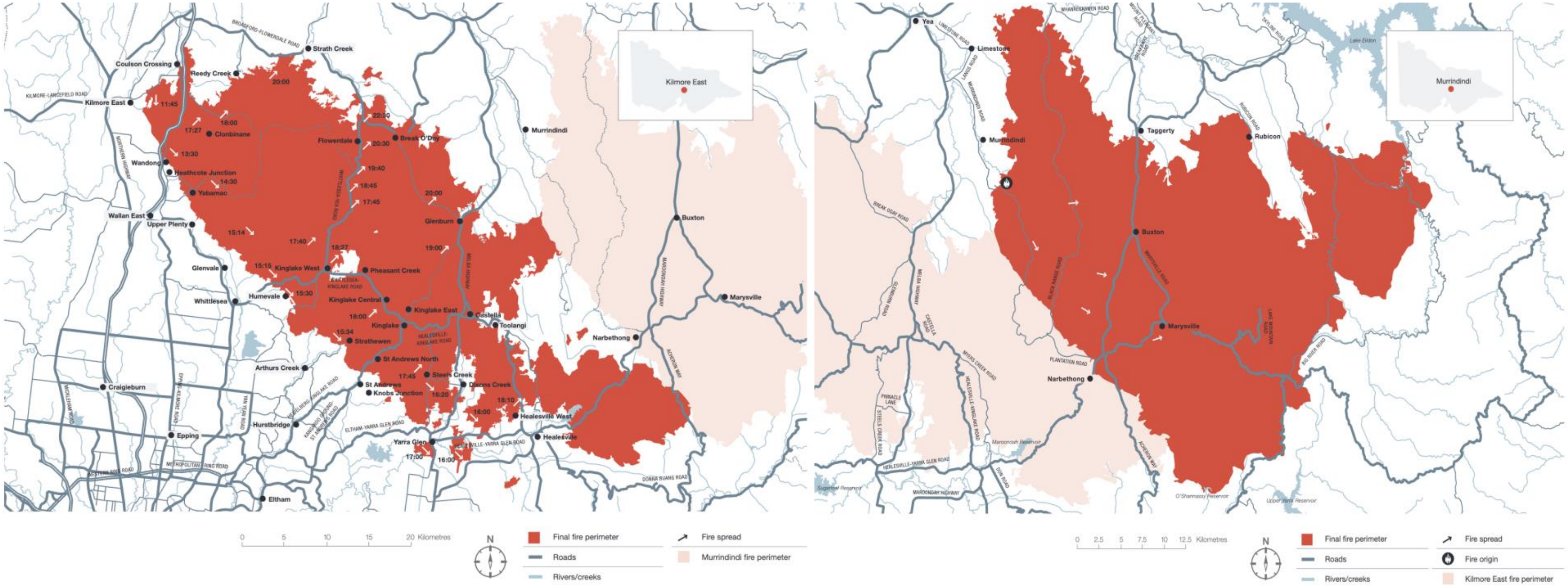

Figure 2 The Kilmore East fire (lift) and the Murrindindi fire (right)
Source: Black Saturday Royal Commission (2010)

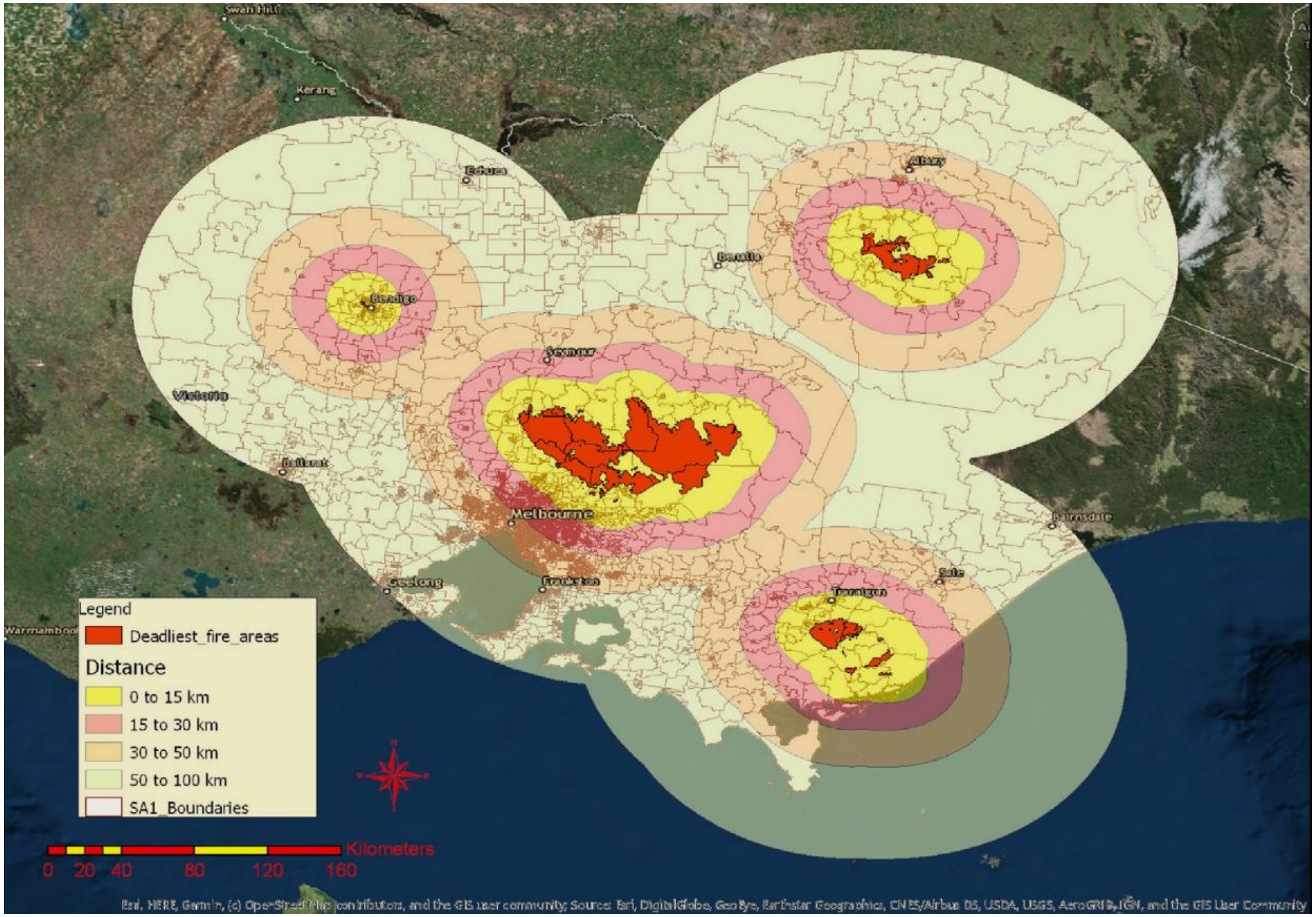

Figure 3 Location of deadliest fire zones and different radius rings
Source: Johnston et al. (2021)

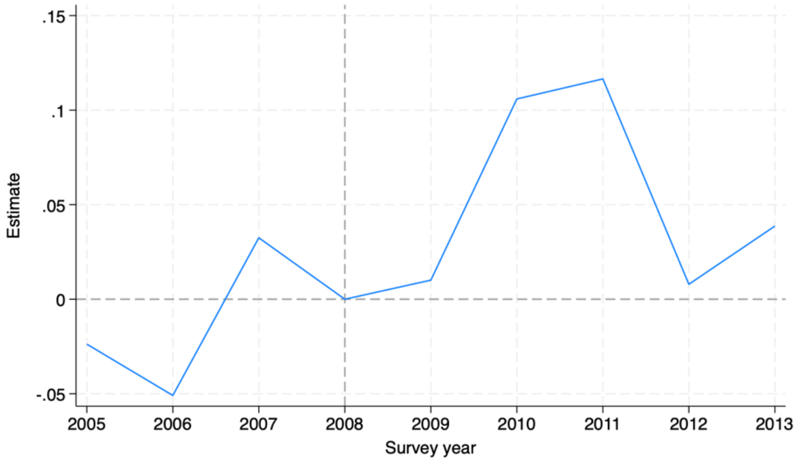

Figure 4 Panel A: Event study analysis (0-50 km)

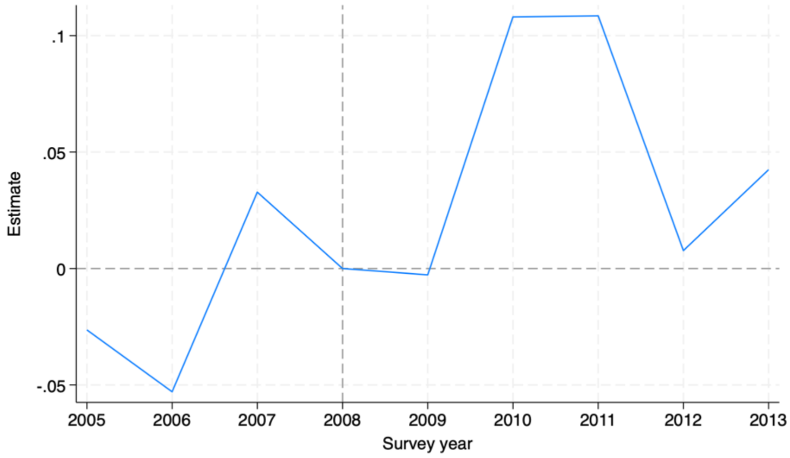

Figure 4 Panel B: Event study analysis (0-100 km)

Table 1: Event study analysis - parallel trend

	(1) LIHC	(2) LIHC
0-15km * 2005	-0.0238	-0.0264
	(0.0388)	(0.0381)
0-15km * 2006	-0.0509	-0.0529*
	(0.0320)	(0.0313)
0-15km * 2007	0.0325	0.0328
	(0.0361)	(0.0355)
Observations	6,883	8,918
R-squared	0.244	0.261
SA1 Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Within 50 km	Yes	No
Within 100 km	No	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The regression specification corresponds to Panel A and B of Figure 4, allowing for BSB effects in 2005, 2006, 2007, 2009, 2010, 2011, 2012 and 2013, with 2008 being the reference year. Standard errors are clustered at the SA1 level.

Table 2: The short-term effects of the BSB on energy poverty: A ring approach

	(1) LIHC	(2) LIHC	(3) LIHC	(4) LIHC
0-15 km * 2008	0.0127	0.0120	0.0140	0.0142
	(0.0293)	(0.0308)	(0.0287)	(0.0295)
0-15 km * 2009	0.0230	0.0220	0.0116	0.0055
	(0.0367)	(0.0384)	(0.0365)	(0.0375)
0-15 km * 2010	0.1188***	0.1045**	0.1223***	0.1149***
	(0.0395)	(0.0411)	(0.0393)	(0.0404)
0-15 km * 2011	0.1297***	0.1362***	0.1230**	0.1238**
	(0.0483)	(0.0492)	(0.0481)	(0.0489)
0-15 km * 2012	0.0210	0.0310	0.0222	0.0292
	(0.0374)	(0.0387)	(0.0370)	(0.0377)
0-15 km * 2013	0.0519	0.0501	0.0570	0.0585
	(0.0475)	(0.0490)	(0.0472)	(0.0480)
15-30 km * 2008		-0.0016		0.0007
		(0.0248)		(0.0233)
15-30 km * 2009		-0.0023		-0.0188
		(0.0240)		(0.0226)
15-30 km * 2010		-0.0334		-0.0229
		(0.0233)		(0.0221)
15-30 km * 2011		0.0149		0.0026
		(0.0250)		(0.0244)
15-30 km * 2012		0.0227		0.0209
		(0.0255)		(0.0241)
15-30 km * 2013		-0.0038		0.0046
		(0.0252)		(0.0233)
Observations	6,883	6,883	8,918	8,918
R-squared	0.243	0.244	0.261	0.261
SA1 Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	No	No
Within 100 km	No	No	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2013 are the post-BSB years. Standard errors are clustered at the SA1 level. We include only non-movers during the study period from 2008 to 2013.

Table 3: The long-term effects of the BSB on energy poverty: A ring approach

	(1)	(2)	(3)	(4)
	LIHC	**LIHC**	**LIHC**	**LIHC**
0-15km * 2008	0.0006	-0.0053	0.0035	0.0013
	(0.0332)	(0.0351)	(0.0326)	(0.0337)
0-15km * 2009	-0.0030	-0.0146	-0.0138	-0.0265
	(0.0366)	(0.0393)	(0.0361)	(0.0376)
0-15km * 2010	0.1136**	0.1013*	0.1159**	0.1094**
	(0.0519)	(0.0536)	(0.0517)	(0.0529)
0-15km * 2011	0.1270**	0.1286**	0.1204**	0.1178**
	(0.0565)	(0.0579)	(0.0563)	(0.0574)
0-15km * 2012	-0.0118	0.0013	-0.0111	-0.0026
	(0.0463)	(0.0484)	(0.0458)	(0.0470)
0-15km * 2013	0.0404	0.0337	0.0537	0.0569
	(0.0540)	(0.0567)	(0.0536)	(0.0549)
0-15km * 2014	-0.0266	-0.0224	-0.0233	-0.0188
	(0.0408)	(0.0425)	(0.0404)	(0.0417)
0-15km * 2015	-0.0047	-0.0088	-0.0142	-0.0218
	(0.0503)	(0.0530)	(0.0496)	(0.0509)
0-15km * 2016	0.0019	-0.0244	0.0137	0.0040
	(0.0474)	(0.0500)	(0.0467)	(0.0480)
0-15km * 2017	0.0004	-0.0207	-0.0039	-0.0191
	(0.0500)	(0.0523)	(0.0489)	(0.0500)
0-15km * 2018	-0.0460	-0.0578	-0.0421	-0.0473
	(0.0578)	(0.0602)	(0.0571)	(0.0584)
0-15km * 2019	-0.0441	-0.0624	-0.0513	-0.0665
	(0.0559)	(0.0585)	(0.0552)	(0.0566)

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	(1) LIHC	(2) LIHC	(3) LIHC	(4) LIHC
15-30 km * 2008		-0.0131		-0.0065
		(0.0275)		(0.0256)
15-30 km * 2009		-0.0260		-0.0378
		(0.0280)		(0.0257)
15-30 km * 2010		-0.0275		-0.0193
		(0.0262)		(0.0247)
15-30 km * 2011		0.0027		-0.0081
		(0.0295)		(0.0284)
15-30 km * 2012		0.0274		0.0236
		(0.0304)		(0.0281)
15-30 km * 2013		-0.0149		0.0083
		(0.0299)		(0.0263)
15-30 km * 2014		0.0080		0.0116
		(0.0296)		(0.0284)
15-30 km * 2015		-0.0095		-0.0225
		(0.0346)		(0.0313)
15-30 km * 2016		-0.0567*		-0.0281
		(0.0325)		(0.0294)
15-30 km * 2017		-0.0459		-0.0443
		(0.0376)		(0.0344)
15-30 km * 2018		-0.0259		-0.0153
		(0.0344)		(0.0312)
15-30 km * 2019		-0.0398		-0.0438
		(0.0348)		(0.0316)
Observations	8,250	8,250	10,693	10,693
R-squared	0.233	0.234	0.247	0.248
SA1 Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	No	No
Within 100 km	No	No	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2019 are the post-BSB years. Standard errors are clustered at the SA1 level. We include only non-movers during the study period 2008-2019.

Table 4: Mechanism analysis – Personal wellbeing

	(1) Perceived safety	(2) Life satisfaction	(3) Vitality	(4) Mental health	(5) Social functioning	(6) General health
0-15km * 2010	-0.3613***	-0.3454**	-4.6020**	-4.5939**	-4.8054**	-2.8130
	(0.1270)	(0.1561)	(1.8140)	(2.0197)	(2.3680)	(1.7131)
0-15km * 2011	-0.3291***	-0.2423	-2.2358	-1.8194	-0.9750	-1.6760
	(0.1177)	(0.1501)	(1.7430)	(1.9645)	(1.8368)	(1.9708)
Observations	6,877	6,875	6,143	6,138	6,192	6,095
R-squared	0.343	0.322	0.373	0.391	0.354	0.423
SA1 Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The outcome variable in Column (1) is perceived safety of household reference person in their life. The outcome variable in Column (2) is the life satisfaction of household reference person. The outcome variable in Column (3) is the vitality scale (SF-36: 0-100) of household reference person. The outcome variable in Column (4) is the mental health score (SF-36: 0-100) of household reference person. The outcome variable in Column (5) is the social functioning scale (SF-36: 0-100) of household reference person. The outcome variable in Column (6) is the general health scale (SF-36: 0-100) of household reference person. All regressions include SA1 and year fixed effects. Standard errors are clustered at the SA1 level. We include only non-movers during the study period from 2008 to 2013.

Table 5: Mechanism analysis – Labor market outcomes

	(1) Employment status	(2) Annual unemployment period	(3) Employment type
0-15km * 2010	-0.0295	-1.6735	0.0390
	(0.0369)	(1.6992)	(0.0394)
0-15km * 2011	-0.0073	-1.7301	0.0694
	(0.0408)	(1.7113)	(0.0497)
Observations	8,918	6,274	3,598
R-squared	0.465	0.201	0.447
SA1 Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Within 50 km	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The outcome variable in Column (1) is the employment status of the household reference person, indicating whether they were employed. The outcome variable in Column (2) is the percentage of time that the household reference person was unemployed during the year. The outcome variable in Column (3) is whether household reference person is employed as a casual or permanent worker. All regressions include SA1 and year fixed effects. Standard errors are clustered at the SA1 level. We include only non-movers during the study period from 2008 to 2013.

Table 6: Mechanism analysis – Community social capital

	Potential social capital		Mobilized social capital	
	(1)	**(2)**	**(3)**	**(4)**
	Community trust	**Social bonds**	**Community social support**	**Community collaboration**
0-15km * post-BSB (2009-2013)	0.2174		0.1533*	-0.0361
	(0.1422)		(0.0869)	(0.1328)
0-15km * 2010		0.0008		
		(0.0539)		
0-15km * 2011		-0.0030		
		(0.0579)		
Observations	6378	6592	6560	6540
R-squared	0.798	0.572	0.791	0.797
SA1 Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Community trust is measured by the extent to which the respondents agree or disagree that people in their neighborhood can be trusted. Social bonds are measured by whether the respondents are currently active members of a sporting, hobby, or community-based club or association. Community social support is measured by how common it is for neighbors to help each other out in the respondents' local neighborhood. Community collaboration is measured by how common it is for neighbors to do things together in the respondents' local neighborhood. We include only non-movers during the study period from 2008 to 2013.

Table 7: Moderation analysis - Moderation effect

	(1) LIHC	(2) LIHC	(3) LIHC
Panel A: Locus of control			
0-15km * 2010	0.1188***	0.1123***	0.1186***
	(0.0395)	(0.0387)	(0.0370)
0-15km * 2011	0.1297***	0.1286***	0.1393***
	(0.0483)	(0.0444)	(0.0453)
LoC (Z)		-0.0600***	-0.0551***
		(0.0150)	(0.0144)
0-15km * 2010* Z			-0.0597
			(0.0524)
0-15km * 2011* Z			-0.0823
			(0.0557)
Observations	6,883	6,098	6,098
R-squared	0.243	0.280	0.282
Panel B: Big 5 Extroversion			
0-15km * 2010	0.1188***	0.1190***	0.1201***
	(0.0395)	(0.0398)	(0.0389)
0-15km * 2011	0.1297***	0.1368***	0.1380***
	(0.0483)	(0.0481)	(0.0484)
Big-5 Extroversion (Z)		-0.0048	-0.0060
		(0.0116)	(0.0117)
0-15km * 2010* Z			0.0013
			(0.0362)
0-15km * 2011* Z			0.0057
			(0.0507)
Observations	6,883	6,428	6,428
R-squared	0.243	0.251	0.251
Panel C: Big 5 Agreeableness			
0-15km * 2010	0.1188***	0.1178***	0.1060**
	(0.0395)	(0.0400)	(0.0413)
0-15km * 2011	0.1297***	0.1357***	0.1181**
	(0.0483)	(0.0479)	(0.0457)
Big-5 Agreeableness (Z)		-0.0073	-0.0027
		(0.0105)	(0.0107)
0-15km * 2010* Z			-0.0518
			(0.0382)
0-15km * 2011* Z			-0.0829
			(0.0592)
Observations	6,883	6,429	6,429
R-squared	0.243	0.251	0.253

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	(1) LIHC	(2) LIHC	(3) LIHC
Panel D: Big 5 Conscientiousness			
0-15km * 2010	0.1188***	0.1195***	0.1258***
	(0.0395)	(0.0398)	(0.0412)
0-15km * 2011	0.1297***	0.1371***	0.1452***
	(0.0483)	(0.0483)	(0.0554)
Big-5 Conscientiousness (Z)		-0.0067	-0.0044
		(0.0109)	(0.0108)
0-15km * 2010* Z			-0.0558
			(0.0446)
0-15km * 2011* Z			-0.0676
			(0.0639)
Observations	6,883	6,426	6,426
R-squared	0.243	0.251	0.252
Panel E: Big 5 Emotional stability			
0-15km * 2010	0.1188***	0.1184***	0.0935***
	(0.0395)	(0.0398)	(0.0322)
0-15km * 2011	0.1297***	0.1362***	0.1342***
	(0.0483)	(0.0479)	(0.0502)
Big-5 Emotional stability (Z)		0.0069	0.0058
		(0.0130)	(0.0132)
0-15km * 2010* Z			0.0686
			(0.0606)
0-15km * 2011* Z			0.0033
			(0.0564)
Observations	6,883	6,427	6,427
R-squared	0.243	0.251	0.252
Panel F: Big 5 Openness to experience			
0-15km * 2010	0.1188***	0.1151***	0.0787**
	(0.0395)	(0.0394)	(0.0369)
0-15km * 2011	0.1297***	0.1336***	0.1352***
	(0.0483)	(0.0475)	(0.0446)
Big-5 Openness to experience (Z)		-0.0375***	-0.0349***
		(0.0107)	(0.0115)
0-15km * 2010* Z			-0.0876***
			(0.0325)
0-15km * 2011* Z			0.0067
			(0.0485)
Observations	6,883	6,423	6,423
R-squared	0.243	0.257	0.258

Table continues to the next page

	(1) LIHC	(2) LIHC	(3) LIHC
Panel G: Financial foresight in 2008 (pre-BSB)			
0-15km * 2010	0.1188***	0.0926***	0.2570***
	(0.0395)	(0.0353)	(0.0751)
0-15km * 2011	0.1297***	0.1151**	0.1614**
	(0.0483)	(0.0506)	(0.0802)
Financial foresight (Z)		-0.0473***	-0.0448***
		(0.0084)	(0.0083)
0-15km * 2010* Z			-0.0887***
			(0.0324)
0-15km * 2011* Z			-0.0227
			(0.0357)
Observations	6,883	5,444	5,444
R-squared	0.243	0.312	0.315

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. All regressions include SA1 and year fixed effects. Standard errors are clustered at the SA1 level. We include only non-movers during the study period from 2008 to 2013.

Appendix.

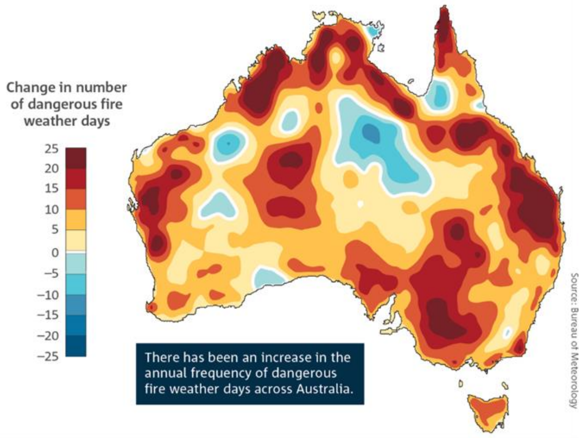

Figure A1 The frequency of dangerous fire weather days in Australia from 1950 to 2024.
Source: Bureau of Meteorology (2022)

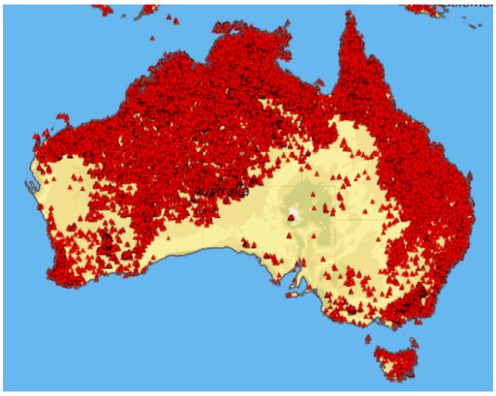

Figure A2 Australian bushfire history 1997 to 2008.
Source: National Aeronautics and Space Administration (2009)

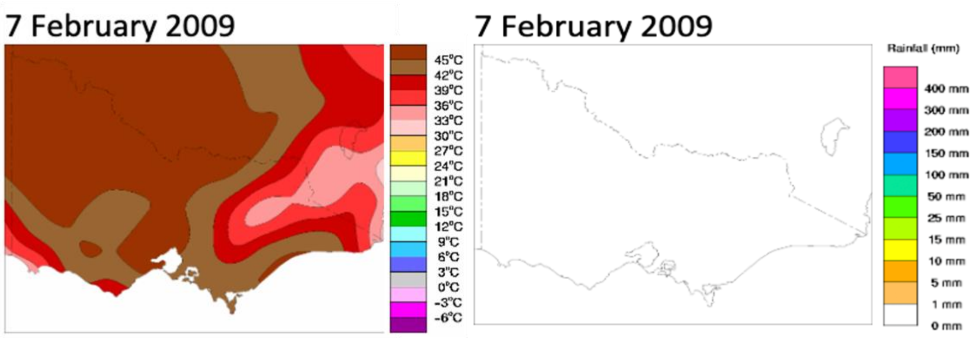

Figure A3 Daily maximum temperature and rainfall on 7 February 2009.
Source: Bureau of Meteorology (February 2009)

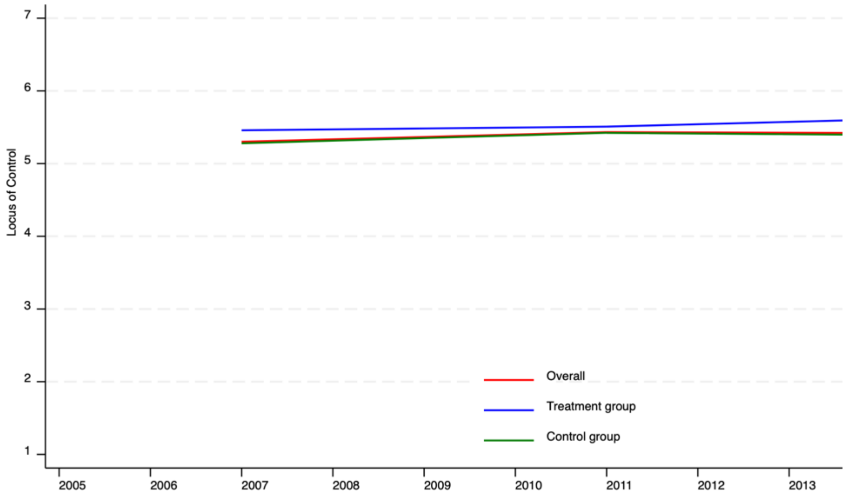

Figure A4 Panel A: LoC of Control trends over time (0-50 km, non-movers)

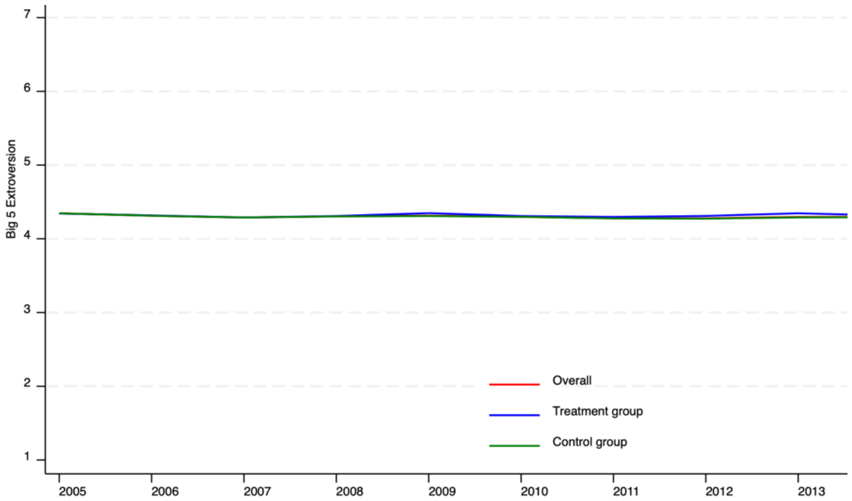

Figure A4 Panel B: Big 5 Extroversion trends over time (0-50 km, non-movers)

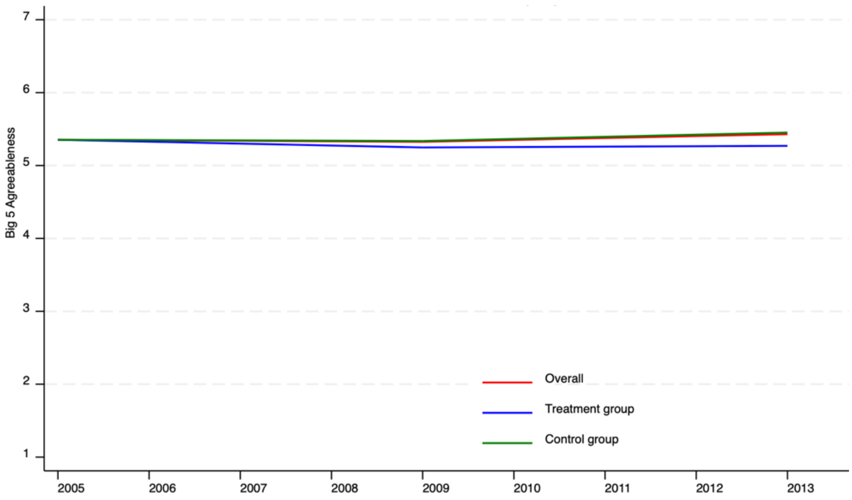

Figure A4 Panel C: Big 5 Agreeableness trends over time (0-50 km, non-movers)

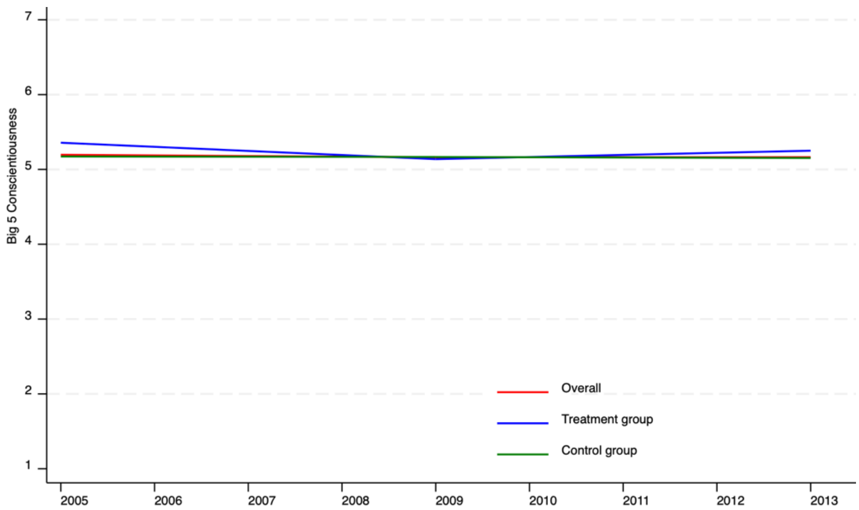

Figure A4 Panel D: Big 5 Conscientiousness trends over time (0-50 km, non-movers)

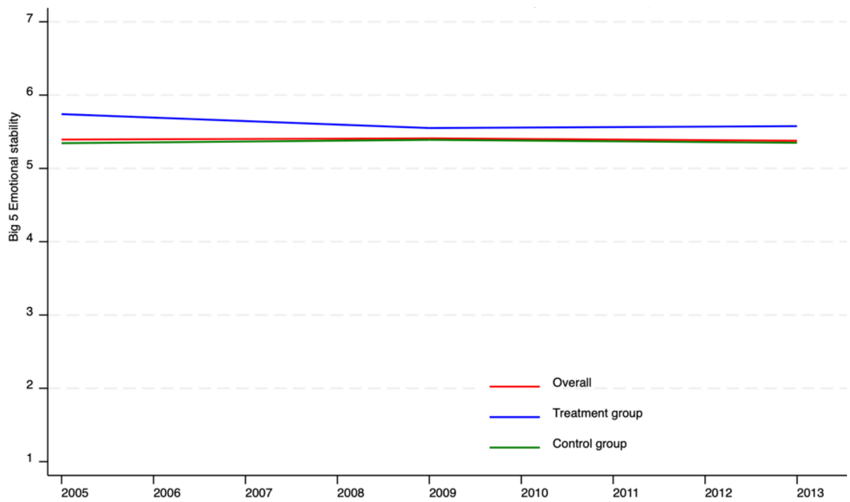

Figure A4 Panel E: Big 5 Emotional stability trends over time (0-50 km, non-movers)

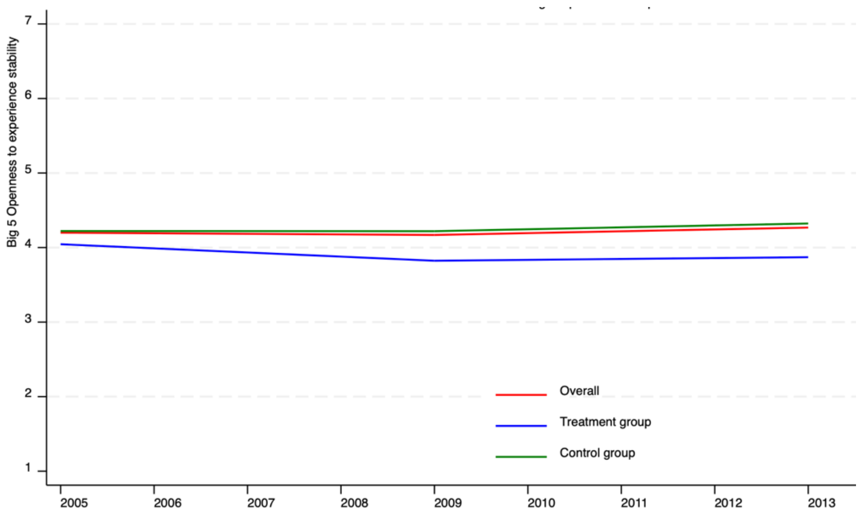

Figure A4 Panel F: Big 5 Openness to experience trends over time (0-50 km, non-movers)

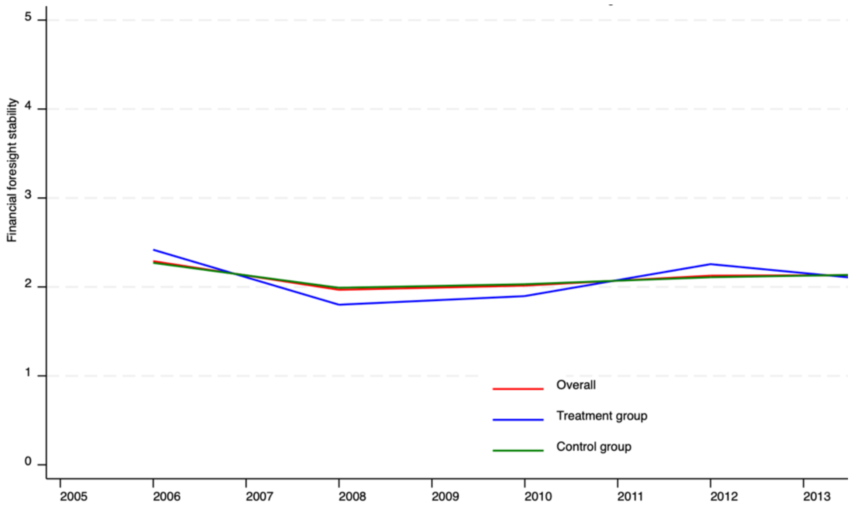

Figure A4 Panel G: Financial foresight trends over time (0-50 km, non-movers)

Figure A5 Panel A: Event study analysis (0-50 km) - Perceived safety

Figure A5 Panel B: Event study analysis (0-50 km) - Life satisfaction

Figure A5 Panel C: Event study analysis (0-50 km) - Vitality

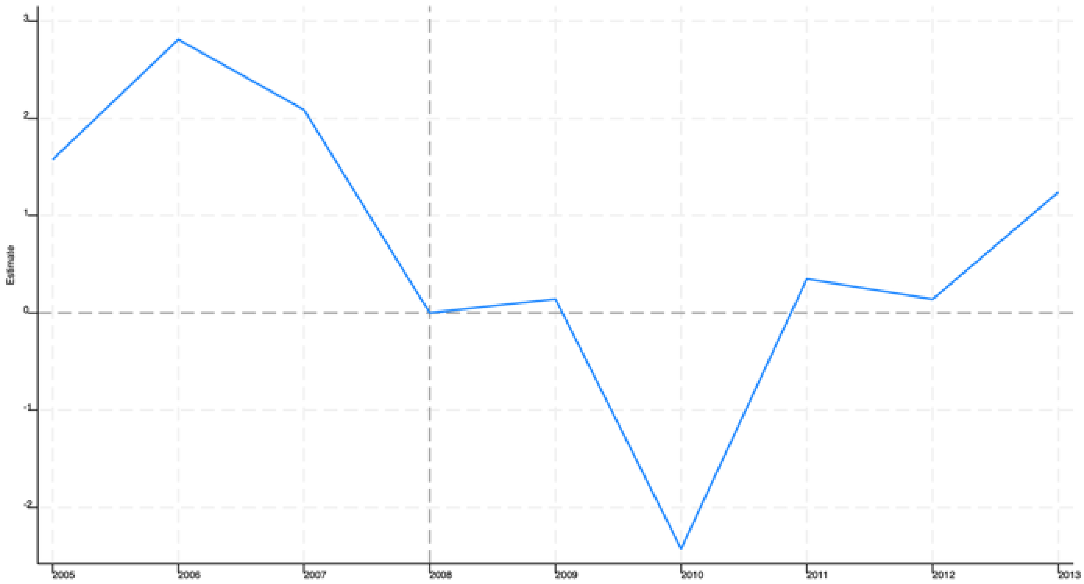

Figure A5 Panel D: Event study analysis (0-50 km) - Mental health

Figure A5 Panel E: Event study analysis (0-50 km) - Social functioning

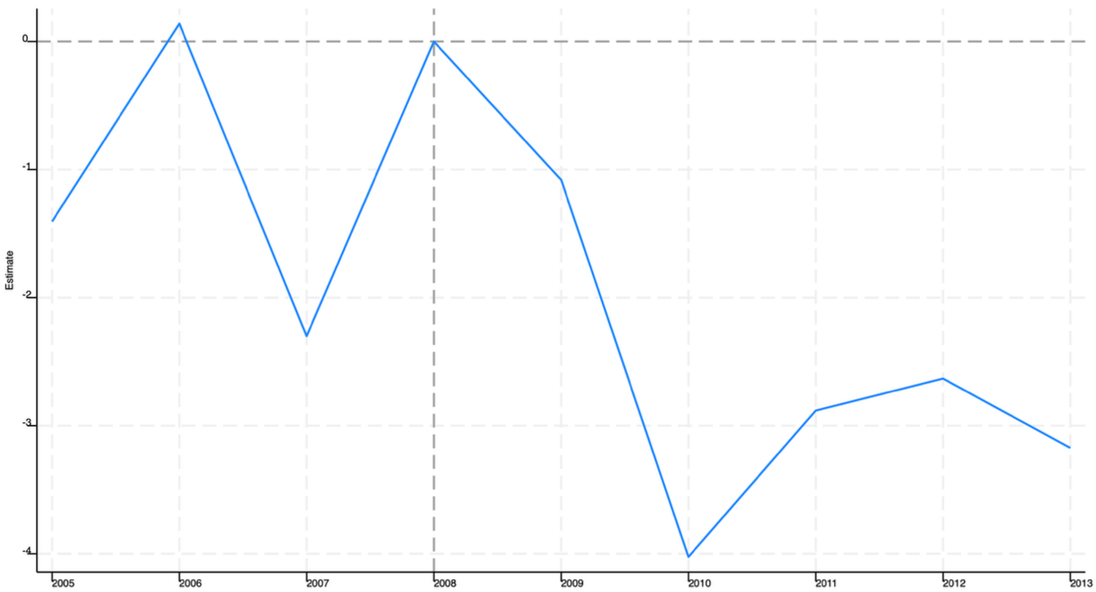

Figure A5 Panel F: Event study analysis (0-50 km) – General health

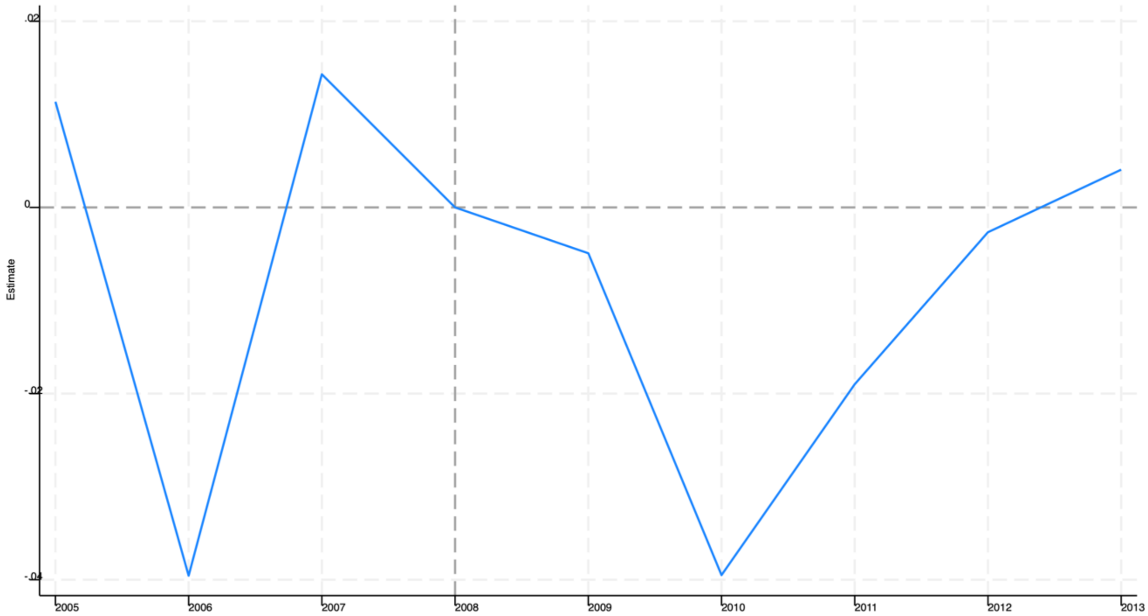

Figure A5 Panel G: Event study analysis (0-50 km) – Employment status

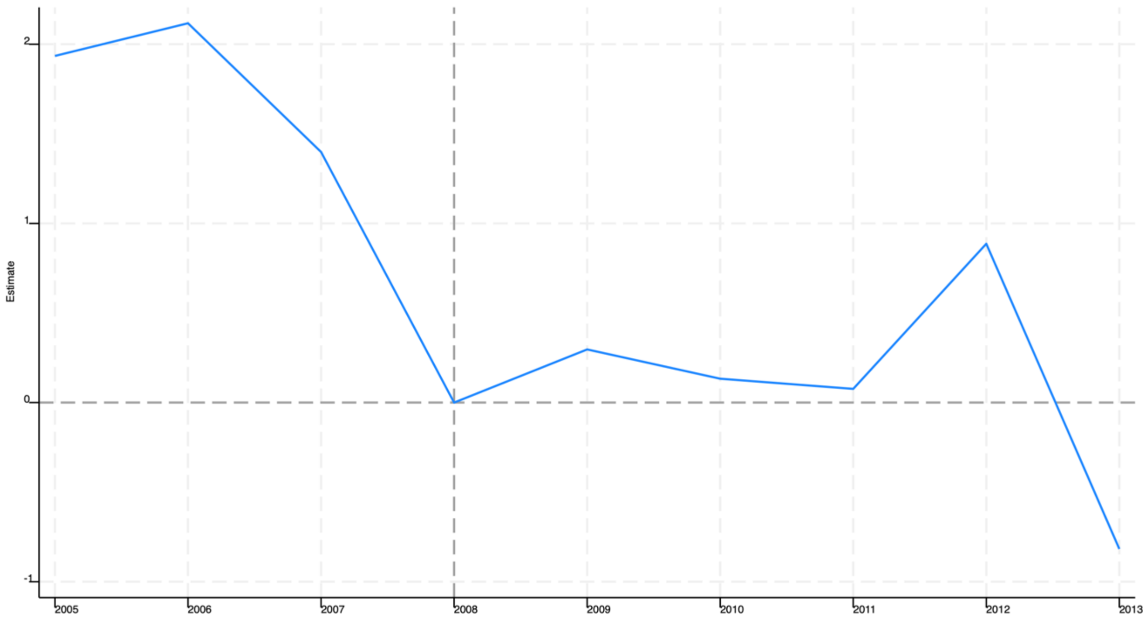

Figure A5 Panel H: Event study analysis (0-50 km) – Annual unemployment period

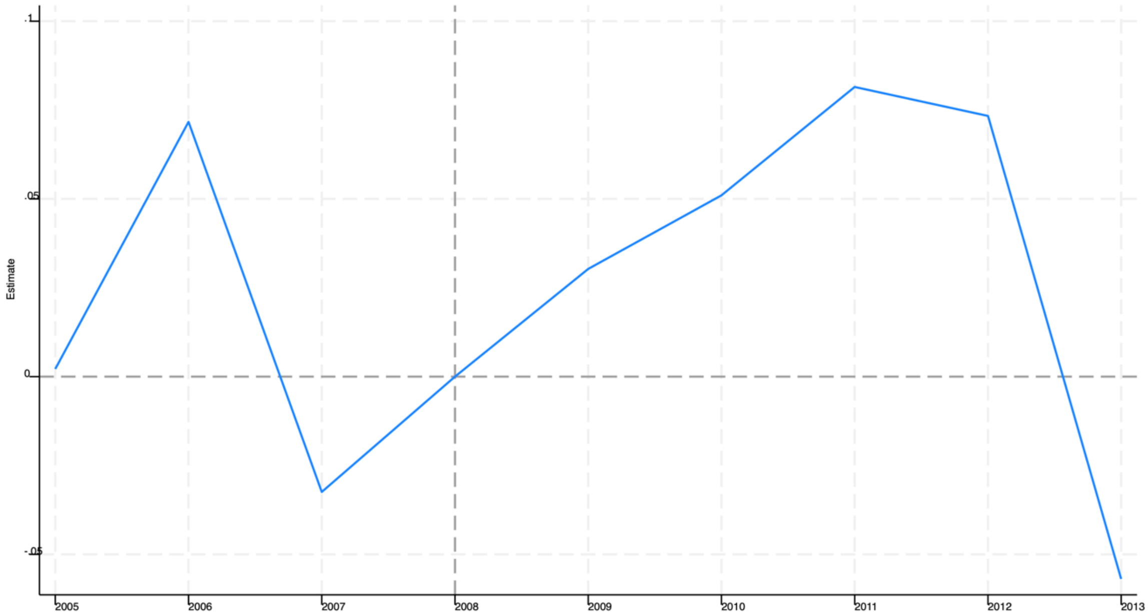

Figure A5 Panel I: Event study analysis (0-50 km) – Employment type

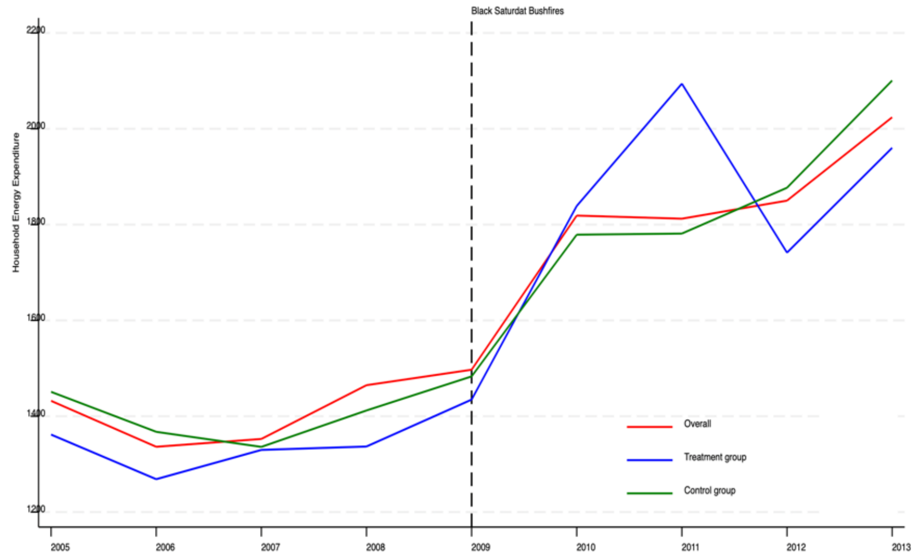

Figure A6 Panel A: Household energy expenditure trends over time (0-50 km, non-movers)

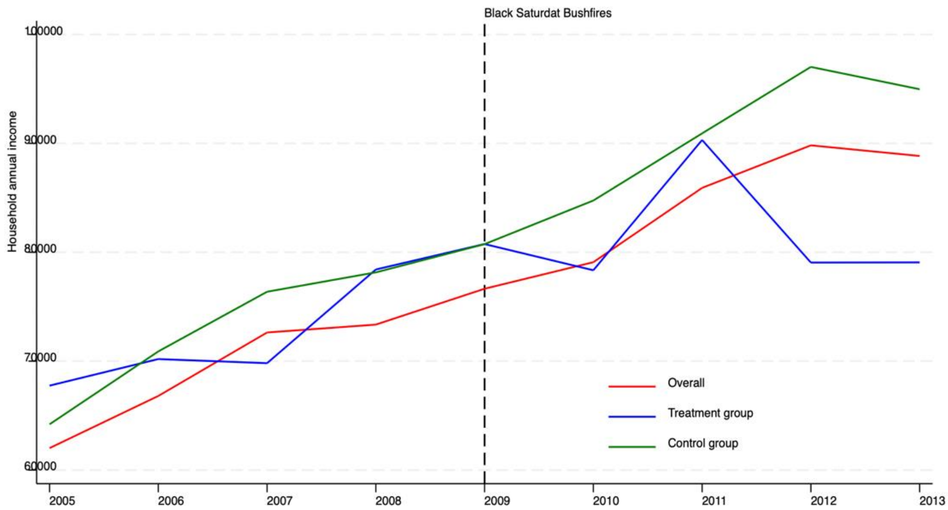

Figure A6 Panel B: Household annual disposable income trends over time (0-50 km, non-movers)

Table A1: Correlation matrix

	Potential social capital		Mobilized social capital	
	(1)	(2)	(3)	(4)
	Trust	Social bonds	Social support	Collaboration
Trust	1			
Social bonds	0.187	1		
Social support	0.462	0.151	1	
Collaboration	0.406	0.132	0.727	1

Notes: The sample consists of households residing within a 0-50 km radius ring of the BSB. The first variable serves as an indicator of community trust. The second variable is an indicator of community social bonds. The third variable serves as indicator of community social support. The third variable serves as an indicator of community social support. The last variable serves as an indicator of community collaboration.

Table A2: Descriptive statistics

Variable	Mean	S.D.	Min.	Max.
Energy expenditure	1,652	1,319.8	0	30,000
Household income	81,824.1	83,349.9	0	1,565,431
LIHC	0.132	0.338	0	1
Households within 0-15 km ring in 2008	0.122	0.328	0	1
Households within 15-50 km ring in 2008	0.878	0.328	0	1
Non-movers during main study period	0.840	0.366	0	1
Perceived safety	8.093	1.532	0	10
Life satisfaction	7.819	1.449	0	10
Vitality	60.788	19.729	0	100
Mental health	75.231	16.610	0	100
General health	67.566	21.280	0	100
Social functioning	83.172	23.478	0	100
Employment status	0.663	0.473	0	1
Unemployment period	1.551	10.033	0	100
Employment type	0.129	0.335	0	1
Community trust (Potential social capital)	4.859	0.861	1	7
Social bonds (Potential social capital)	0.412	0.358	0	1
Social support (Mobilized social capital)	3.559	0.637	1	5
Collaboration (Mobilized social capital)	2.924	0.681	1	5
Locus of Control	5.338	1.035	1	7
Big 5 Extroversion	4.302	0.953	1	7

Table continues to the next page.

Variable	Mean	S.D.	Min.	Max.
Big 5 Agreeableness	5.362	0.847	1	7
Big 5 Conscientiousness	5.169	0.932	1	7
Big 5 Emotional stability	5.440	0.924	1	7
Big 5 Openness to experience	4.173	1.015	1	7
Financial foresight	2.025	1.566	0	5

Notes: The table presents the descriptive statistics for the main specification, which utilizes data from 2005 to 2013. This analysis focuses on households within a 50 km radius who did not relocate during the study period from 2008 to 2013, detailing the mean, standard deviation, minimum, and maximum values.

Table A3: The short term estimated effects of the BSB on energy poverty in using alternative treatment groups

Treatment group	No. of household in treatment group	Estimate	Std. Error
Panel A: In 2010			
0-5 km	35	-0.0007	0.0547
0-10 km	66	0.0087	0.0456
0-14 km	84	0.0279	0.0407
0-15km	108	0.1059	0.0456
0-16 km	123	0.1043	0.0427
0-20 km	185	0.0370	0.0355
0-25 km	301	0.0083	0.0313
0-30 km	454	-0.0497	0.0271
Panel B: In 2011			
0-5 km	33	0.0518	0.1025
0-10 km	61	0.0598	0.0678
0-14 km	76	0.0743	0.0565
0-15km	98	0.1165	0.0519
0-16 km	112	0.1156	0.0480
0-20 km	185	0.0620	0.0387
0-25 km	296	0.0361	0.0339
0-30 km	429	-0.0073	0.0304

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. This table shows results for our main 0-50 km sample. We include only non-movers during the study period 2008-2013. Panel A displays the BSB effects for various treatment groups in 2010, and Panel B displays the BSB effects for various treatment groups in 2011, with 2008 being the reference year. Standard errors are clustered at the SA1 level.

Table A4 Panel A: Event study analysis - parallel trend (personal wellbeing)

	(1) Perceived safety	(2) Life satisfaction	(3) Vitality	(4) Mental health	(5) Social functioning	(6) General health
0-15km * 2005	-0.1566	0.0073	1.0240	1.5762	0.7412	-1.4059
	(0.1315)	(0.1849)	(1.7551)	(1.7807)	(2.6114)	(1.8686)
0-15km * 2006	0.0484	0.1931	3.1106	2.8109	0.8202	0.1394
	(0.1587)	(0.2089)	(2.1682)	(1.7630)	(2.7432)	(2.5086)
0-15km * 2007	0.0179	0.1653	1.5439	2.0886	-0.5558	-2.3010
	(0.1361)	(0.1785)	(1.9053)	(1.9687)	(2.8098)	(1.4371)
Observations	6877	6875	6143	6138	6192	6095
R-squared	0.343	0.322	0.373	0.391	0.354	0.423
SA1 Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The regression specification corresponds to Panel A to F of Figure A5, allowing for BSB effects in 2005, 2006, 2007, 2009, 2010, 2011, 2012 and 2013, with 2008 being the reference year. Standard errors are clustered at the SA1 level.

Table A4 Panel B: Event study analysis - parallel trend (labor market outcomes)

	(1) Employment status	(2) Annual unemployment period	(3) Employment type
0-15km * 2005	0.0114	1.9348	0.0022
	(0.0445)	(1.5608)	(0.0477)
0-15km * 2006	-0.0396	2.1172	0.0717
	(0.0365)	(1.8782)	(0.0680)
0-15km * 2007	0.0143	1.3987	-0.0324
	(0.0339)	(1.2355)	(0.0370)
Observations	6883	6274	3598
R-squared	0.438	0.201	0.448
SA1 Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Within 50 km	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The regression specification corresponds to Panel G to I of Figure A5, allowing for BSB effects in 2005, 2006, 2007, 2009, 2010, 2011, 2012 and 2013, with 2008 being the reference year. Standard errors are clustered at the SA1 level.

Table A5: Results for LIHC using an alternative poverty line

	LIHC
0-15km * 2008	0.0236
	(0.0276)
0-15km * 2009	0.0242
	(0.0285)
0-15km * 2010	0.1233***
	(0.0401)
0-15km * 2011	0.0706**
	(0.0278)
0-15km * 2012	0.0397
	(0.0292)
0-15km * 2013	0.0368
	(0.0449)
Observations	6,883
R-squared	0.222
SA1 Fixed Effects	Yes
Year Fixed Effects	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2013 are the post-BSB years. Standard errors are clustered at the SA1 level. We use households which residing within 50 km radius rings as the sample. We include only non-movers during the study period 2008-2013. In this table, LIHC is constructed using half of the national median disposable income as the official poverty line.

Table A6: Robustness - Different samples or controls

	(1) LIHC	(2) LIHC	(3) LIHC
0-15km * 2008	0.0006	0.0150	0.0031
	(0.0279)	(0.0275)	(0.0309)
0-15km * 2009	0.0129	0.0267	0.0109
	(0.0346)	(0.0369)	(0.0254)
0-15km * 2010	0.1084***	0.1082***	0.0969**
	(0.0371)	(0.0372)	(0.0424)
0-15km * 2011	0.1139**	0.1222***	0.1296***
	(0.0479)	(0.0407)	(0.0472)
0-15km * 2012	0.0134	0.0087	0.0244
	(0.0379)	(0.0305)	(0.0401)
0-15km * 2013	0.0494	0.0424	0.0498
	(0.0448)	(0.0447)	(0.0421)
Observations	8,568	6,883	6,731
R-squared	0.227	0.339	0.510
Additional controls	No	Yes	No
Year Fixed Effects	Yes	Yes	Yes
SA1 Fixed Effects	Yes	Yes	No
Household Fixed Effects	No	No	Yes
Within 50 km	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2013 are the post-BSB years. Standard errors are clustered at the SA1 level. Column (1) presents the estimated results including both movers and non-movers during the study period from 2008 to 2013. Column (2) reports result with additional controls: age, employment status, and educational status of the household reference person, household income, the number of in-scope persons in the household, and the number of dependent children in the household. Column (3) reports the regression results that include year and household fixed effects instead of the controls used in the main analysis. We include only non-movers during the study period from 2008 to 2013 for Columns (2) and (3).

Table A7: Robustness - Alternative approaches for the household reference person

	(1) LIHC	(2) LIHC
0-15km * 2008	0.0180	0.0088
	(0.0294)	(0.0301)
0-15km * 2009	0.0204	0.0271
	(0.0351)	(0.0380)
0-15km * 2010	0.1195***	0.1068***
	(0.0400)	(0.0408)
0-15km * 2011	0.1312***	0.1072**
	(0.0498)	(0.0428)
0-15km * 2012	0.0256	0.0251
	(0.0381)	(0.0306)
0-15km * 2013	0.0530	0.0776
	(0.0481)	(0.0487)
Observations	6,879	17,125
R-squared	0.241	0.242
SA1 Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Within 50 km	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2013 are the post-BSB years. Standard errors are clustered at the SA1 level. We include only non-movers during the study period 2008-2013. Column (1) reports the estimated results that select the household reference person based on current year individual income. Column (2) reports the results using the reweighting method. We utilize the HILDA household weight divided by the household size as the new household weight.

Table A8: Falsification tests

	(1) LIHC	(2) LIHC	(1) LIHC	(2) LIHC
0-15 km * 2008	0.0113	0.0180	-0.0236	-0.0159
	(0.0417)	(0.0425)	(0.0325)	(0.0334)
0-15 km * 2009	-0.0071	-0.0061	0.0002	0.0005
	(0.0461)	(0.0472)	(0.0403)	(0.0414)
0-15 km * 2010	0.0294	0.0362	0.0116	0.0177
	(0.0440)	(0.0443)	(0.0383)	(0.0386)
0-15 km * 2011	-0.0279	-0.0200	-0.0300	-0.0283
	(0.0416)	(0.0426)	(0.0370)	(0.0382)
0-15 km * 2012	-0.0300	-0.0284	-0.0343	-0.0314
	(0.0301)	(0.0324)	(0.0286)	(0.0304)
0-15 km * 2013	0.0258	0.0183	0.0131	0.0076
	(0.0518)	(0.0535)	(0.0420)	(0.0433)
15-30 km * 2008		0.0192		0.0226
		(0.0230)		(0.0216)
15-30 km * 2009		0.0039		0.0006
		(0.0238)		(0.0225)
15-30 km * 2010		0.0207		0.0187
		(0.0279)		(0.0248)
15-30 km * 2011		0.0239		0.0051
		(0.0258)		(0.0232)
15-30 km * 2012		0.0039		0.0088
		(0.0283)		(0.0243)
15-30 km * 2013		-0.0222		-0.0168
		(0.0298)		(0.0254)
Observations	6,883	6,883	8,918	8,918
R-squared	0.241	0.242	0.260	0.260
SA1 Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	No	No
Within 100 km	No	No	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2013 are the post-BSB years. Standard errors are clustered at the SA1 level. We include only non-movers during the study period from 2008 to 2013. We conduct the falsification tests by randomly assign exposure measure according to the actual proportions of samples in each group.

Table A9: Historical distance and energy poverty – Panel analysis

Dependent variable:	LIHC			
	Fixed Effects Filtered model	**Linear dynamic panel data model**	**Fixed Effects Filtered model**	**Linear dynamic panel data model**
	(1)	**(2)**	**(3)**	**(4)**
Distance to the fires in 2008	-0.509***	-0.003***	-0.041	-0.002***
	(0.038)	(0.001)	(0.026)	(0.001)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SA1 FE	Yes	Yes	Yes	Yes
Movers	No	Yes	No	Yes
Observations	5,801	8,621	9,110	16,630

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the individual level. In Columns (1) and (2), we adopt the panel data from 2005 to 2013 for households living within 50 km of the fires, consistent with our main specification. In Columns (3) and (4), we use the entire sample from 2005 to 2019 for households living within 100 km of the fires. The results in Column (1) and (3) are obtained using the Stata package "xtfef" developed by Pesaran and Zhou (2018), while the results in Columns (2) and (4) use the Stata package "xtseqreg" developed by Kripfganz and Schwarz (2019). The numbers of observations in Columns (1) and (3) are lower because individuals who moved across SA1s during 2005-2013 and 2005-2019, respectively, are excluded. Individual controls include the age, employment status, and educational status of the household reference person. Household controls include household income, the number of in-scope persons in the household, and the number of dependent children in the household.

Table A10: Sample restriction for moderation analysis on Locus of Control and Big 5 personality traits

	(1) LIHC	(2) LIHC
Panel A: LoC		
0-15km * 2010	0.074	0.079
	(0.045)	(0.055)
0-15km * 2011	0.063	0.035
	(0.051)	(0.059)
LoC (Z)	-0.030***	-0.031***
	(0.011)	(0.010)
0-15km * 2010* Z		-0.027
		(0.084)
0-15km * 2011* Z		0.107
		(0.093)
Observations	4,155	4,155
R-squared	0.309	0.315
Panel B: Big 5 Extroversion		
0-15km * 2010	0.113***	0.113***
	(0.041)	(0.040)
0-15km * 2011	0.132**	0.132**
	(0.051)	(0.051)
Extroversion (Z)	-0.012	-0.012
	(0.012)	(0.012)
0-15km * 2010* Z		-0.005
		(0.038)
0-15km * 2011* Z		0.000
		(0.054)
Observations	6,198	6,198
R-squared	0.253	0.253
Panel C: Big 5 Agreeableness		
0-15km * 2010	0.111***	0.104**
	(0.041)	(0.041)
0-15km * 2011	0.130**	0.120**
	(0.051)	(0.048)
Big-5 Agreeableness (Z)	-0.012	-0.009
	(0.012)	(0.012)
0-15km * 2010* Z		-0.023
		(0.037)
0-15km * 2011* Z		-0.042
		(0.054)
Observations	6,199	6,199
R-squared	0.254	0.254

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	(1) LIHC	(2) LIHC
Panel D: Big 5 Conscientiousness		
0-15km * 2010	0.114***	0.119***
	(0.041)	(0.044)
0-15km * 2011	0.133***	0.142**
	(0.051)	(0.061)
Big-5 Conscientiousness (Z)	-0.017	-0.015
	(0.013)	(0.013)
0-15km * 2010* Z		-0.038
		(0.047)
0-15km * 2011* Z		-0.054
		(0.066)
Observations	6,196	6,196
R-squared	0.254	0.255
Panel E: Big 5 Emotional stability		
0-15km * 2010	0.112***	0.073**
	(0.041)	(0.031)
0-15km * 2011	0.132***	0.113**
	(0.051)	(0.057)
Big-5 Emotional stability (Z)	0.003	0.000
	(0.013)	(0.013)
0-15km * 2010* Z		0.094*
		(0.056)
0-15km * 2011* Z		0.042
		(0.054)
Observations	6,197	6,197
R-squared	0.253	0.254
Panel F: Big 5 Openness to experience		
0-15km * 2010	0.109***	0.069*
	(0.041)	(0.037)
0-15km * 2011	0.128**	0.130***
	(0.051)	(0.048)
Big-5 Openness to experience (Z)	-0.038***	-0.035***
	(0.011)	(0.012)
0-15km * 2010* Z		-0.087***
		(0.029)
0-15km * 2011* Z		0.006
		(0.042)
Observations	6,193	6,193
R-squared	0.259	0.261

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. All regressions include SA1 and year fixed effects. Standard errors are clustered at the SA1 level. In Panel A, following Awaworyi Churchill and Smyth (2022a), we restrict our sample to adult respondents between the ages of 21 and 59. In Panel B to F, following McCrae (2003), we restrict our sample to respondents aged over 30.

Table A11: What is driving the effect on energy poverty?

	(1) Household energy consumption (0.01*)	(2) Household income (0.0001*)
0-15km * 2010	-0.4936	-0.9390**
	(1.4040)	(0.4754)
0-15km * 2011	2.9471*	-0.7121
	(1.7269)	(0.7580)
Observations	6,883	6,883
R-squared	0.259	0.361
Within 50 km	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The outcome variable in Column (1) is household annual energy expenditure. The outcome variable in Column (2) is household annual disposable income. All regressions include SA1 and year fixed effects. Standard errors are clustered at the SA1 level.

Table A12: BSB exposure and other welfare indicators

	(1) Income poverty - all sample	(2) Income poverty - age restricted	(3) Overall job satisfaction	(4) SF-36 Reported health transitions
0-15km * 2008	0.0125	-0.0091	0.2698	0.0157
	(0.0452)	(0.0444)	(0.1964)	(0.0725)
0-15km * 2009	-0.0103	-0.0213	0.0311	0.0057
	(0.0392)	(0.0386)	(0.2027)	(0.0628)
0-15km * 2010	0.1138**	0.1094**	-0.3709	0.0793
	(0.0462)	(0.0428)	(0.2499)	(0.0684)
0-15km * 2011	0.0800*	0.1100**	-0.3965	-0.0462
	(0.0480)	(0.0506)	(0.2556)	(0.0833)
0-15km * 2012	0.0253	0.0074	-0.1462	0.0311
	(0.0429)	(0.0506)	(0.1820)	(0.0750)
0-15km * 2013	0.0614	0.0301	0.0531	-0.0234
	(0.0483)	(0.0485)	(0.1740)	(0.0804)
Observations	6,883	6,883	4,540	6,111
R-squared	0.342	0.353	0.296	0.170
SA1 Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Column (1) shows the effects of BSB exposure on income poverty, with the poverty line defined as 60% of the national median household disposable income. In Column (2), the median national disposable household income is calculated using the equivalised disposable household income of individuals aged 17 years or older, applying the 60% thresholds. The outcome variable in Column (3) is the overall job satisfaction of household reference person. The outcome variable in Column (4) is the reported health transitions (SF-36: 0-100) of household reference person. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2013 are the post-BSB years. Standard errors are clustered at the SA1 level. We include only non-movers during the study period from 2008 to 2013.

Table A13 Panel A: Standardized coefficients of energy poverty and other welfare indicators

	(1) Std_Energy poverty	(2) Std_Perceived safety	(3) Std_Life satisfaction	(4) Std_Vitality
0-15km * 2010	0.0268***	-0.0183***	-0.0185**	-0.0179**
	(0.0089)	(0.0064)	(0.0084)	(0.0071)
0-15km * 2011	0.0278***	-0.0159***	-0.0124	-0.0083
	(0.0104)	(0.0057)	(0.0077)	(0.0065)
Observations	6,883	6,877	6,875	6,143
R-squared	0.243	0.343	0.322	0.373
Within 50 km	Yes	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The outcome variable in Column (1) is standardized energy poverty indicator. The outcome variable in Column (2) is standardized perceived safety of household reference person. The outcome variable in Column (3) is standardized life satisfaction of household reference person. The outcome variable in Column (4) is standardized vitality of household reference person. All regressions include SA1 and year fixed effects. Standard errors are clustered at the SA1 level.

Table A13 Panel B: Standardized coefficients of energy poverty and other welfare indicators

	(1) Std_Mental health	(2) Std_Social functioning	(3) Std_Communite social support
0-15km * post-BSB (2009-2013)			0.0545**
			(0.0254)
0-15km * 2010	-0.0208**	-0.0154**	
	(0.0091)	(0.0076)	
0-15km * 2011	-0.0079	-0.0030	
	(0.0085)	(0.0056)	
Observations	6,138	6,192	7,267
R-squared	0.391	0.354	0.783
Within 50 km	Yes	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The outcome variable in Column (1) is standardized mental health of household reference person. The outcome variable in Column (2) is standardized social functioning of household reference person. The outcome variable in Column (3) is standardized community social support. All regressions include SA1 and year fixed effects. Standard errors are clustered at the SA1 level.

Table A14: The short-term effects of the BSB on energy poverty: Exclude outliers

	(1) LIHC	(2) LIHC	(3) LIHC	(4) LIHC
0-15 km * 2008	-0.0007	-0.0005	0.0002	0.0007
	(0.0345)	(0.0357)	(0.0340)	(0.0347)
0-15 km * 2009	0.0253	0.0246	0.0139	0.0079
	(0.0366)	(0.0382)	(0.0363)	(0.0373)
0-15 km * 2010	0.1317***	0.1158***	0.1391***	0.1325***
	(0.0424)	(0.0439)	(0.0421)	(0.0431)
0-15 km * 2011	0.1208**	0.1254**	0.1102**	0.1078**
	(0.0495)	(0.0505)	(0.0494)	(0.0504)
0-15 km * 2012	0.0154	0.0259	0.0146	0.0210
	(0.0394)	(0.0407)	(0.0390)	(0.0398)
0-15 km * 2013	0.0633	0.0573	0.0674	0.0658
	(0.0490)	(0.0508)	(0.0486)	(0.0495)
15-30 km * 2008		0.0005		0.0018
		(0.0255)		(0.0241)
15-30 km * 2009		-0.0016		-0.0182
		(0.0241)		(0.0227)
15-30 km * 2010		-0.0380		-0.0213
		(0.0261)		(0.0248)
15-30 km * 2011		0.0104		-0.0071
		(0.0254)		(0.0251)
15-30 km * 2012		0.0242		0.0193
		(0.0274)		(0.0261)
15-30 km * 2013		-0.0137		-0.0052
		(0.0275)		(0.0252)
Observations	6,452	6,452	8,384	8,384
R-squared	0.247	0.247	0.261	0.261
SA1 Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	No	No
Within 100 km	No	No	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2013 are the post-BSB years. Standard errors are clustered at the SA1 level. We include only non-movers during the study period from 2008 to 2013. we exclude observations with the top 10% of energy expenditure.

Table A15: The long-term effects of the BSB on energy poverty: Exclude outliers

	(1)	**(2)**	**(3)**	**(4)**
	LIHC	**LIHC**	**LIHC**	**LIHC**
0-15km * 2008	-0.0067	-0.0075	-0.0065	-0.0068
	(0.0349)	(0.0360)	(0.0344)	(0.0350)
0-15km * 2009	0.0222	0.0198	0.0101	0.0029
	(0.0355)	(0.0371)	(0.0352)	(0.0362)
0-15km * 2010	0.1227***	0.1060**	0.1299***	0.1227***
	(0.0432)	(0.0446)	(0.0429)	(0.0439)
0-15km * 2011	0.1091**	0.1116**	0.0985*	0.0949*
	(0.0509)	(0.0519)	(0.0508)	(0.0517)
0-15km * 2012	0.0085	0.0171	0.0075	0.0126
	(0.0399)	(0.0410)	(0.0394)	(0.0402)
0-15km * 2013	0.0570	0.0501	0.0601	0.0573
	(0.0496)	(0.0513)	(0.0492)	(0.0501)
0-15km * 2014	0.0529	0.0590	0.0578	0.0638
	(0.0440)	(0.0457)	(0.0433)	(0.0443)
0-15km * 2015	-0.0183	-0.0226	-0.0249	-0.0306
	(0.0405)	(0.0431)	(0.0397)	(0.0410)
0-15km * 2016	0.0028	-0.0127	0.0184	0.0168
	(0.0402)	(0.0424)	(0.0392)	(0.0403)
0-15km * 2017	-0.0449	-0.0567	-0.0408	-0.0459
	(0.0480)	(0.0501)	(0.0467)	(0.0476)
0-15km * 2018	-0.0722	-0.0741	-0.0691	-0.0685
	(0.0493)	(0.0519)	(0.0484)	(0.0496)
0-15km * 2019	-0.0026	-0.0131	-0.0116	-0.0223
	(0.0626)	(0.0644)	(0.0620)	(0.0629)

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	(1) LIHC	(2) LIHC	(3) LIHC	(4) LIHC
15-30 km * 2008		-0.0018		-0.0011
		(0.0257)		(0.0243)
15-30 km * 2009		-0.0056		-0.0225
		(0.0243)		(0.0229)
15-30 km * 2010		-0.0398		-0.0231
		(0.0266)		(0.0253)
15-30 km * 2011		0.0056		-0.0110
		(0.0256)		(0.0254)
15-30 km * 2012		0.0197		0.0152
		(0.0272)		(0.0260)
15-30 km * 2013		-0.0158		-0.0086
		(0.0270)		(0.0247)
15-30 km * 2014		0.0132		0.0180
		(0.0315)		(0.0294)
15-30 km * 2015		-0.0095		-0.0175
		(0.0329)		(0.0300)
15-30 km * 2016		-0.0343		-0.0046
		(0.0336)		(0.0309)
15-30 km * 2017		-0.0266		-0.0158
		(0.0399)		(0.0368)
15-30 km * 2018		-0.0042		0.0013
		(0.0368)		(0.0335)
15-30 km * 2019		-0.0238		-0.0331
		(0.0386)		(0.0362)
Observations	9,502	9,502	12,355	12,355
R-squared	0.222	0.222	0.234	0.234
SA1 Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Within 50 km	Yes	Yes	No	No
Within 100 km	No	No	Yes	Yes

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. The reference period is 2005-2007. 2008 is the year prior to the BSB, 2009 is the BSB year, and 2010-2019 are the post-BSB years. Standard errors are clustered at the SA1 level. We include only non-movers during the study period 2008-2019. we exclude observations with the top 10% of energy expenditure distribution.