Universiteit Utrecht

U.S.E. Master Thesis

Disasters Down Under: Assessing the Local Economic Impacts of Natural Disasters in Australia[1]

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Abstract

This thesis examines the economic impacts of natural disasters on local economies in Australia, focusing on the recovery dynamics of average income and new business creation in affected areas. To do so, I estimate the impact of various types of natural disasters (storms, tropical cyclones, wildfires and floods), taking into consideration short and run long effects as well as and the moderating effect of characteristics of the impacted localities. Utilising a novel, granular time series panel data set and a fixed effects linear regression framework, the study finds significant variation in growth and recovery trajectories based on the disaster type and the characteristics of the local economy. This divergence suggests that standard disaster-recovery models may need adjustment for better applicability to the Australian context. The findings offer insights into the economic resilience of different regions and provide a basis for policy recommendations aimed at improving disaster response and recovery strategies.

JEL Codes: Q54, R11, C23
Keywords: Natural Disasters, Local Economies, Economic Recovery, Time Series Panel Data, Fixed Effects Regression

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1. Introduction

This thesis examines the economic impacts of natural disasters on local economies in Australia, focusing on the recovery dynamics of average income and business creation in affected areas. Climate-induced natural disasters represent a key risk to the physical environment, material property and human life, generating sizable and asymmetrical impacts on the livelihood of affected economies. The frequency of weather-related catastrophes has risen substantially with accelerating climate change, producing more extreme temperatures, drought, floods and weather events and more acute risk to exposed communities. Hence, the urgency of climate change is felt predominantly in weather-induced natural disasters, with climate change increasing both the frequency and intensity of natural disasters[2] (Ebi et al., 2021; Hoeppe, 2016)[3]. Weather events classified by the Integrated Research on Disaster Risk (IRDR) as used by EM-DAT include meteorological (storms), hydrological (flooding, landslides, wave action) and climatological (droughts and wildfires) (EM-DAT, 2024a). Sizable loss-inducing natural disasters have increased threefold globally over the last 40 years, boosted by both increased occurrence and socio-economic factors including population growth, urbanisation and higher value at risk (Hoeppe, 2016).

Natural disasters represent exogenous shocks with direct and indirect impacts. The former includes physical damage to property, infrastructure, agriculture, human health (injuries and fatalities) and psychological impacts, whilst indirect impacts centre around the disaster-induced shifts in economic activity, including demand, supply, production levels, incomes, investment and property market developments. The indirect economic impacts of natural disasters are more difficult to accurately quantify. This implies that the policy solutions are conceived with bounded knowledge, complicating the predictability of applied policy solutions. Whilst direct impacts are assumed to be largely substantial negative costs (for which policymakers must quickly react with adequate recovery funds to address the calculated damage), the indirect impacts may materialise as both negative and positive spillovers, dependent on whether the shock dampens demand and economic activity or rather spurs economic growth through reconstruction efforts, shifting the local economy to a higher growth trajectory through Schumpeterian creative destruction dynamics (Botzen et al., 2019; Hsiang & Jina,

[2] The Intergovernmental Panel on Climate Change highlights that an increasing level of greenhouse gasses in the atmosphere is the key driver of more extreme weather events, through generating heatwaves and drought conditions, warmer ocean surfaces providing more energy for tropical storms and cyclones alongside an atmosphere holding more moisture which increases the severity of precipitation and floods. (IPCC, 2022).
[3] Geophysical disasters occurrence (earthquakes, tsunamis and volcanic events) has remained relatively stable (Hoeppe, 2016).

2014). The recovery trajectories may diverge in the short and long term, implying that net long term effects may be either positive or negative and differ from the initial impact (see (Deryugina et al., 2018; Roth Tran & Wilson, 2022)). The economic susceptibility to negative weather shocks and the recovery trajectory of a local economy is contingent on the characteristics of the local economy. Characteristics such as the economic composition, institutional framework, infrastructure, migration and adaptation capacities play a role in both the magnitude and direction of short and long-term economic impacts of disaster-stuck localities (Cevik & Jalles, 2023; Loayza et al., 2012; Ulubaşoğlu et al., 2019).

The primary research question that I investigate in this thesis is:

What are the short- and long-term impacts on local economies in Australia?

In addressing this question, I consider different types of economic impact, various types of natural shocks and I examine whether and how characteristics of localities influence the occurrence and size of the impacts and ensuing post-disaster growth trajectories. I place emphasis on differentiating my findings by disaster types (storms, tropical cyclones, wildfires, and floods) and the remoteness classification of the affected area.

Australia provides a remarkably interesting and important subject for analysis of natural disaster impacts due to the high frequency yet substantial variation in the type and severity of disaster experiences. Albeit an expansive land, Australia has relatively homogenous institutional quality across the country, allowing for investigation of local impact whilst assuming that parallel trends of the ability of the government to assist are largely accounted for. The Climate Council Australia (2024) found that 84% of the Australian population had been directly affected by a natural disaster over the last 5 years alone. The Australian data available from the Australian Bureau of Statistics allows for a granular examination of localised impacts affecting small areas averaging 10 000 inhabitants that largely engage as one local economy. The data spans around 20 years and is suitable for integration with NASA GDIS and EM-DAT data on natural disasters. The amalgamation of these two unique and rich data sources allows for direct impact assessment of affected local communities.

My research addresses a significant gap in the existing literature by undertaking the first comprehensive analysis of a wide range of disaster types across Australia at a granular, local-economy level. Previous studies have primarily focused on singular disaster types, highly aggregated economic indicators, or have concentrated on specific disaster events. This study's large-scale detailed approach employs econometric analysis to identify the strength of natural-disaster-induced impacts, taking into account the moderating or worsening effect of locality characteristics. My research provides novel insights into the diverse economic impacts of various natural disasters, offering a more complete understanding of their effects on local economies. The societal relevance of these findings is evident by offering more insights into the generation of economic impacts by various natural disasters, producing important policy implications.

This rest of this paper is structured as follows: in Section 2 I provide a detailed overview of the current theoretical framework underpinning my research, followed by a comprehensive overview of relevant empirical studies on natural disaster economic impacts. In Section 3 I explain my empirical strategy, detailing the process of data collection, matching and cleaning. I also provide a descriptive overview of the data, along with a detailed explanation of the econometric approach used to address my research question. In Section 4 I present my results and key findings on the impact of natural disasters on average income and total business creation dynamics. In Section 5 I explore the divergent recovery trajectories and the role of locality characteristics. I also discuss methodological limitations and discuss key policy implications and recommendations, emphasising the significance of my research. Section 6 concludes the paper with a summary of my key findings.

2. Literature Review

The field of natural disaster research has traditionally been dominated by the geosciences. However, its convergence with economics is a relatively recent phenomenon, gaining prominence over the past two decades. The existing research is thus relatively new and broad, oscillating between macro global-scale studies and the recent uptick in country-level and event-level studies. Cross-country studies facilitate conclusions on aggregate growth impacts based on varying levels of economic development and institutional quality between countries, whereas country and event-level studies provide more granular interpretations of disaster effects on localised economies. Understanding the extent of disaster impacts on both local and aggregate economies necessitates a comprehensive analysis of the literature across both categories.

The current state of the literature is sparse regarding within-country level disaster impacts covering a range of disaster types, which is the scope of my thesis[4]. Hence, this literature review provides a comprehensive analysis of differing levels of aggregation and differing disaster types, as the latter tends to provide more detail on local economy and disaster-specific impacts. I begin with an overview of theoretical literature on disaster impacts, followed by a global cross-country perspective, and then zoom into specific disaster types (cyclones, hurricanes, floods, and wildfires) focusing on country-level and event-level impacts. While most studies are US-focused due to the data availability at a national and sub-national level and advanced state of research in this area, I ensure the inclusion of more nuanced yet relevant Australian studies to paint a diverse landscape of Australian disaster impacts. I conclude this section by clarifying the gaps addressed by this thesis.[5]

Drawing on an adapted version of Dell et al.'s (2014) framework, the impact of natural disasters on an economy can be modelled through a causal relationship within a system of variables, formalised as follows:

$$Y = f(X|Z) \tag{1}$$

Whereby Y represents economic recovery indicators (economic production, in this research average income growth, and business growth), X represents the natural disaster occurrence and Z captures contextual factors (e.g., type of disaster, elapsed time since the disaster, remoteness of the locality).

[4] To the best of my knowledge, the only comparable studies as far as scope, disaster type distinction and similarities in dependent variables is Roth Tran & Wilson's (2022) study of natural disaster impacts on personal income and employment and Pleninger's (2022) study of impacts on income distribution, both in the US.
[5] I discuss the methodology implemented by the literature separately in the Data and Methods section of this study.

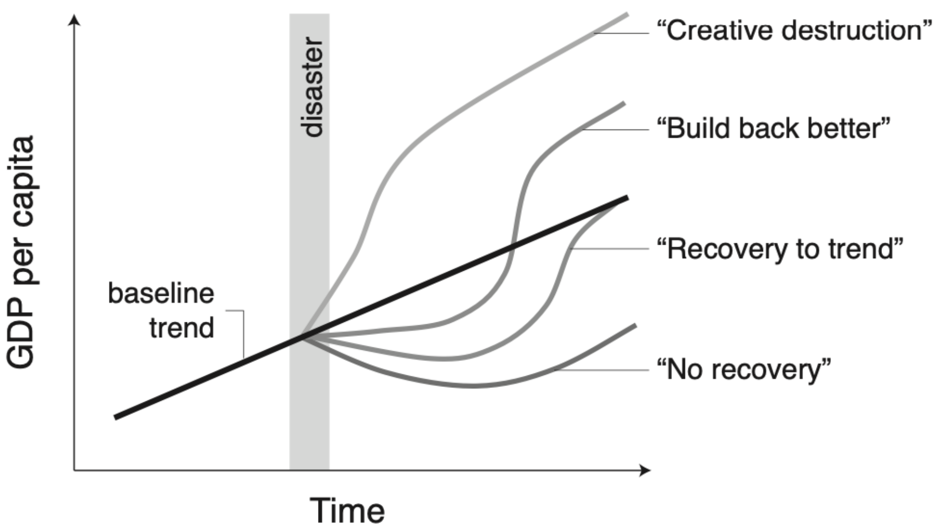
In this formulation, the occurrence of a disaster (X) has an effect on economic recovery indicators (Y) conditional on the contextual factors (Z). This implies that the impact of a disaster on economic growth and recovery is influenced by the disaster characteristics and the characteristics of the affected area.

This approach aligns with the neoclassical Solow Growth Model (Solow, 1956), which provides a foundation for understanding how shocks like natural disasters can temporarily reduce economic output by disrupting capital and human capital inputs. The destruction of capital shifts the capital-labour ratio in an economy leftward from k*, whilst loss to human life and thus human capital pushes the ratio rightward of k*. As the key finding of this model is that an economy returns to steady state capital-labour and output per capita levels in the long term, disaster impacts are considered temporary. Loayza et al., (2012) note that so long as the capital destruction impact outweighs the human life loss, this leads to increased average and marginal product of capital and output growth as economies rebuild, and potentially higher growth if replaced capital is more productive. In the context of natural disasters, lasting effects only materialise when shocks generate permanent changes in savings, depreciation and this capital-updating productivity growth (Botzen et al., 2019). This dynamic is expanded upon in endogenous growth theory (Romer, 1990) which incorporates the role of technological progress as an intrinsic component of economic growth. Investments in human capital, technology and innovation act as driving forces of economic growth, suggesting that policy measures can significantly influence growth rates and trajectories (Romer, 1990). In the context of natural disasters, destruction represents an accelerated capital depreciation, spurring the updating of capital stock. The degree to which this "technological leapfrogging" and embodied technical change occur as highlighted by Hallegatte & Dumas (2009) opens the discussion for divergent productivity growth trajectories post-disaster. In aggregate, Botzen et al. (2019) categorise the impacts of natural disasters into direct effects, such as asset damage (typically negative), and more ambiguous indirect growth effects which arise from changes in economic activity, including interruptions in activity, as well as the rebuilding and reconfiguration of economic operations.

As a baseline overview, Hsiang & Jina (2014) address the variation in outcomes with four possible scenarios: "Creative destruction", "Build-back-Better", "Recovery to trend" and "No recovery" (see *Figure 1*). Case 1 echoes Schumpeter's (1942) neoliberal "creative destruction" hypothesis, positing that he replacement of destroyed capital facilitates technological advancements, thereby accelerating economic growth. However, one could question the validity of this hypothesis due to the apparent oversight an initial short-term negative impact of direct capital destruction on economic activity. Case

2, the "build back better" hypothesis, asserts that although initial destruction results in negative growth, the subsequent replacement of assets propels the economy onto a new growth trajectory that surpasses the baseline trend. Case 3, referred to as the "recovery to trend" hypothesis, suggests that following an initial decline in growth due to income and asset loss from a natural disaster, the economy will eventually regain its momentum. This recovery is driven by an increase in the marginal product of capital, partly due to the heightened scarcity of human and capital resources, ultimately allowing the economy to re-align with the initial growth trajectory. The final scenario, Case 4, is the "no recovery" hypothesis. This scenario posits that the destruction of assets by disasters, coupled with the diversion of investment for rebuilding (rather than other growth-enhancing investment activity), fails to generate a recovery effect, resulting in a weakened growth trajectory that falls below the pre-disaster trend. Empirical evidence frequently assigns this scenario to least developed countries, where resources for reinvestment are scarce (Noy, 2009). Hence, theoretically the predicted growth impacts are ambiguous, as aggregate impacts of natural disasters on economic growth dynamics can be either positive or negative according to recovery dynamics and differ by context and time horizon.

Figure 1: Disaster-Growth Outcome Scenarios (Hsiang & Jina, 2014)



Empirical Evidence

In the context of cross-country analysis of natural disaster impacts, Botzen et al. (2019) generalise that the growth effects are predominantly negative but relatively minor for developed countries. Hallegatte & Dumas (2009) acknowledge indirect positive growth effects through capital updating and productivity enhancements; however, they maintain that the overall impact of disasters remains net-negative. Conversely, Sawada et al. (2019) observe that natural disasters can positively affect long-term per capita GDP growth in aggregate. This finding is echoed by Skidmore & Toya (2002), who report that higher frequencies of climatic disasters are correlated with increased human capital accumulation, total factor productivity, and long-term economic growth in developed countries. Acevedo et al. (2020) find that temperature shocks adversely affect output in hot climates by reducing investment, labour productivity and overall output; again, the level of economic development appears to be important, as high-income regions experience smaller negative growth effects. Noy (2009) also emphasises that developed countries suffer comparatively smaller output declines post-disaster, whereby institutional quality plays a crucial role in mitigating disaster impacts. Panwar and Sen (2019) and Loayza et al. (2012) corroborate these findings, adding to the mounting evidence that more developed countries such as Australia fare better due to better recovery capacities.

The analysis of disaster impacts has been delineated into sectoral impacts, indicating that divergent impacts are experienced according to both disaster type and sector. Panwar & Sen (2019) and Loayza et al. (2012) find in cross-country studies that floods improve agricultural growth, while droughts reduce agricultural output. Panwar & Sen (2019) observe that earthquakes boost GDP through non-agricultural rebuilding efforts and Loayza et al. (2012) find that storms similarly appear to boost industrial growth. Ulubaşoğlu et al. (2019) study the impact of floods and wildfires in Australia, finding that floods negatively affect agriculture, mining, construction, and financial services output while positively impacting utilities and public administration. Bushfires also exhibit mixed impacts: negative on construction, transportation, and financial services, but positive on utilities and retail, adding to the evidence that sectoral impacts are diverse and vary according to region.

Studies on the economic impacts of different disaster types indicate that GDP impacts vary significantly by disaster type on a cross-country level. Loayza et al. (2012) observe that GDP impacts are negative for droughts and earthquakes but positive for floods and storms. Shifting focus to personal incomes and differing disaster types in the US, Roth Tran & Wilson (2022) discover that in the US, disasters lead to an increase in both total and per capita income over the long term (8 years). The initial rise in income is driven by a boost in employment, while long-term income growth is attributed to higher wages. The most severe disasters, particularly hurricanes and tornadoes, result in significant long-term increases in per capita income[6]. Pleninger's (2022) study finds that hurricanes and storms decrease personal incomes in the US, whilst the impacts of fires, floods, and winter storms are

[6] The effects of other disaster types (floods, severe storms, extreme winter weather, and fires) are either minimal or statistically insignificant.

negligible, partly due to mandatory insurance (floods) and lower destruction (winter storms). In Australia, Johar et al. (2022) do not delineate by disaster type but find that direct natural disaster exposure generates an initial short-term negative impact on income but find no evidence for long term impacts.

Research on the economic impacts of cyclones and hurricanes examine both short- and long-term consequences. Hsiang & Jina (2014) find that globally, GDP declines relative to pre-disaster trends and does not recover over a 20-year horizon. Event studies in the US find increase worker earnings for hurricane-effected individuals in the short term (Belasen & Polachek, 2009; Groen et al., 2020; Guimaraes et al., 1993), albeit Deryugina et al. (2018) found income largely unimpacted in the short-term. In the long term, hurricanes induced significant relocation effects (Deryugina et al., 2018) and long-term boosts to earnings (Groen et al., 2020). When taking asymmetrical sectoral impacts into account, Guimaraes et al. (1993) observed neutral overall income effects of US hurricanes, whilst Lenzen et al. (2019) discovered significant job and income losses spillovers from cyclones in Australia to industries and regions not directly impacted, citing upstream supply issues. Evidently, the literature on the impacts of cyclones and hurricanes indicates a general trend of mixed short-term income impacts that transition into long-term income gains.

Studies on the impacts of wildfires indicate varied effects on income and employment. US studies find that wildfires positively impact short-term employment and wages and generate long-term income volatility (Nielsen-Pincus et al., 2013). This is echoed by An et al. (2024) who observe that wildfire smoke exposure is correlated destabilised financial security of affected individuals. A range of studies have focused on Australia's 2009 Black Saturday bushfires, the country's most severe wildfire event to date (Australian Disaster Resilience Knowledge Hub, n.d.b). Ulubaşoğlu et al. (2019) found evidence for disaster-induced overall declines in medium-term personal income, varying by the employment sector, whereby agriculture, retail, and tourism workers experienced significant losses, while healthcare workers saw gains. Johar et al. (2022) found that the bushfires caused delayed mental health issues, highlighting this as a possible cause for future negative income effects. Asbi et al. (2020) emphasise that the income bracket of affected individuals significantly influenced the ensuing post-disaster income recovery rate dynamics. Thus, the US studies lean towards short-term income gains, whilst the Australian studies underscore losses and nuanced behavioural impacts as possible catalysts for further losses.

Studies on the economic impacts of floods indicate short-term income disruptions with potential long-term recovery. In Germany, income losses from flood exposure are identified, with losses more acute for families and the elderly (Tovar Reaños, 2021). Evidence from US floods indicate a drag on personal income in the year of the disaster, which may rebound into a modest positive upswing in the medium run but ultimately neutralises in the long term (Roth Tran & Wilson, 2022; Xiao, 2011). In Australia, floods have been found to increase employment, yet no wage impacts were found to be significant (Hickson & Marshan, 2022). Overall, the literature points towards negative short-term income impacts of flooding which may fade or rebound in the longer run.

In aggregate, the current body of research on disaster impacts reveals a complex interplay of factors and variables. The general trends emerging from the data relevant to my study on a disaster-type basis indicate that the impacts of cyclones and hurricanes generally follow a pattern of short-term income losses transitioning into long-term income gains. The literature on wildfire impacts on income presents mixed results. Studies from the United States tend to demonstrate short-term income gains, whereas Australian studies underscore income losses, which are often dependent on the employment sector. Regarding flooding, the literature generally points to negative short-term income impacts, which may either diminish or rebound in the longer run.

Abstracting from the impacts of natural disasters on national income and personal income growth, the literature investigating the effects of disasters on local business creation dynamics is relatively sparse. On the business front, Boudreaux et al. (2023) determine that natural disasters encourage business creation in countries with high-quality governance, albeit merely in the short-term. Meltzer et al. (2021) find an increased probability of closure for retail businesses in flood-affected areas in the US, implying decreasing business numbers when exposed to natural disaster. Roy & Noy (2023) find cyclones and floods in New Zealand lead to a decline in profits for businesses in agriculture, trade, financial, and transport services, and business survival is endangered by cyclones, whereas floods have no significant impact. A couple of US studies point toward most businesses recovering from natural disasters in the short-term, in event studies of earthquakes and hurricanes (Dahlhamer & Tierney, 1998; Corey & Deitch, 2011). Evidently, the current literature and findings on the impact of disasters on businesses are difficult to syndicate into clear conclusions. Post-disaster, business creation does not appear to continue the growth trajectory or experience a rebound impact, rather businesses seem to experience only partial recovery.

Evidently, there are clear gaps in the literature which this thesis will address. Firstly, there is no systematic study investigating the impact of natural disasters on personal income delineating by disaster types in a similar vein to Roth Tran & Wilson (2022) and Pleninger's (2022) US studies. Furthermore, the literature on the impact of natural disasters on business creation as a secondary indicator of economic vitality is very limited, thus overseeing in large the indirect longer-run impacts of natural disasters on economies. Studies tend to focus either on cross-country analyses or on singular historical disaster events. Cross-country studies often lack depth in understanding localised impacts and may misjudge the magnitude of effects by focussing on aggregated measures of growth. Conversely, studies centred on singular events may fail to determine systematic relationships between disaster occurrences and produce results that are difficult to generalise or transfer to other contexts. Hence the current body of literature is fragmented and firstly lacks a comprehensive framework that integrates both personal income and business creation dynamics, and secondly is sparse in the analysis of disaster-type-specific analysis on a large and generalisable scale.

In light of the disjointed and fragmented nature of the current literature and theoretical framework, my central hypothesis posits that the short- and long-term growth dynamics vary depending on the type of disaster, resulting in unique disaster-growth outcome trajectories. This hypothesis aligns with the diverse findings in the existing literature on the economic impacts of natural disasters but introduces a nuanced aspect by adopting a disaster-type-based comparative approach.

I focus on Australia as it presents an under-researched and important case study, due to both the diversity of its climate and geography which make it prone to a range of natural disasters. Furthermore, the case of Australia allows me to leverage the country's diverse disaster experiences and high-quality, comparable data to draw more specific conclusions about disaster-specific economic impacts. This is particularly relevant given the broad range of mixed findings in the existing literature, which provide only unstable conclusions about general short-term losses and potential long-term recovery and gains, varying significantly from case to case.

Finally, this thesis will employ a dual approach, assessing the recovery dynamics of both average income and business creation in affected areas. This approach is explorative yet comprehensive, providing a holistic view of economic recovery post-disaster. By integrating these two indicators, the study will offer deeper insights into the overall economic vitality of local economies following natural disasters. Through addressing these gaps, this thesis aims to provide a clearer picture of understanding the nuances of localised impacts of natural disasters, thereby informing more effective policy making.

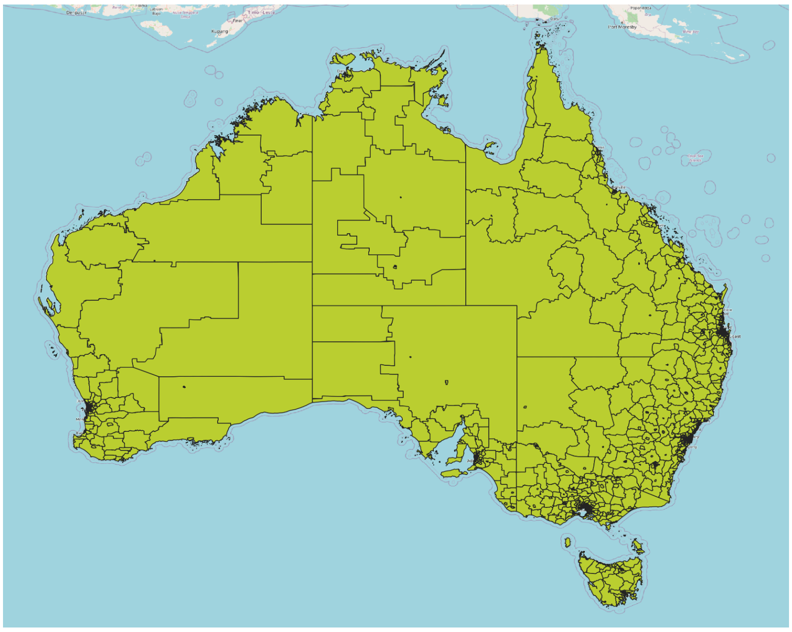
3. Data and Methods

To assess the local economic impacts of natural disasters in Australia, I focus on two key indicators: income and total number of businesses. The selection of these indicators addresses a gap in the literature by allowing for a comparative analysis of both short- and long-term impacts on individual incomes and the business environment. These variables are interrelated, yet each provides a distinct perspective on the economic impact. Analysing both average income and the number of businesses offers a comprehensive view of how disasters affect local economies. While average income reflects the financial well-being and stability of individuals, the number of businesses indicates the overall economic activity and entrepreneurial health of the area. The latter provides valuable insight into the possible positive or negative impacts of natural disasters on entrepreneurial activity.

ABS Data Collection & Description

To examine the local impacts of natural disasters in Australia on a granular level, this study utilises Australian Bureau of Statistics' (ABS) annual data at Statistical Level 2 (SA2) (*see Figure 2)*[7]. The SA2 regions divide Australia into approximately 2500 catchment regions averaging 10 000 inhabitants, representing communities that interact socially and economically (Australian Bureau of Statistics, 2021). This granular approach enables a novel assessment of small, localised communities.

Figure 2: Australian ABS SA2 Statistical Regions (Author's own, Data: ABS)



[7] See appendix for full documentation of ABS data sources.

The data I collated for the analysis from the ABS at SA2 level is summarised in *Table 1* and spans the period 2000-2019. I merged individual yearly datasets to generate a time series dataset, as the ABS typically provides data in separate files for each year. To incorporate labour market characteristics, I used census data in five-year intervals. Additionally, I assigned each statistical area its associated remoteness classification, to explore divergences in regional growth dynamics and to control for the estimated resident population as an indicator of the local area's size.

The process of creating my base dataset was extensive and involved merging ABS data on income, business, population, and census data. Since the ABS does not provide freely available time-series data, this required meticulously merging 20 years of spreadsheets for each of the income, business, and population variables, alongside individual census files. This effort resulted in a comprehensive overview of the Australian economy over the past 20 years.

In my analysis I use the percentage changes in average income and the number of businesses over one- and three-year periods as dependent variables. I refer to the latter dependent variable as business creation and business growth synonymously throughout the study[8]. (The percentage change in average income is chosen as a dependent variable because it serves as a crucial indicator of economic well-being and stability within a community. The percentage change in the number of businesses is selected to gauge the broader economic activity and entrepreneurial vitality of the affected areas.

Table 1: ABS Economic Indicators Data

Indicator	**Description**	**Unit**	**Level**	**Time Frame**	**Frequency**
Average Wages & Salaries Income	Summated total income earned by employees from employment, divided by the number of income earners. Measurement is for the 12 months up to June of a given year.	AUD	SA2	2001 - 2020	Annual
Total Number of Businesses	Count of actively trading businesses on June of a given year.	Number	SA2	2004-2019	Annual
Dependent Variables					
One-Year Change Income	One-year percentage change in income. Average Wages & Salaries Income (t=0) - Average Wages & Salaries Income (t=-1) /Average Wages & Salaries Income (t = -1)	% (own calculation)	SA2	2002-2019	Annual

[8] Whereby negative business creation implies a reduction in business numbers as a percentage change between two periods.

Three-Year Change Income	One-year percentage change in income. Average Wages & Salaries Income (t=0) - Average Wages & Salaries Income (t=-3) / Average Wages & Salaries Income (t = -3)	% (own calculation)	SA2	2002-2019	Annual
One-Year Change Businesses	One-year percentage change in number of businesses. Total Number of Businesses (t=0) - Total Number of Businesses (t=-1) / Total Number of Businesses (t = -1)	% (own calculation)	SA2	2002-2019	Annual
Three-Year Change Businesses	One-year percentage change in number of businesses. Total Number of Businesses (t=0) - Total Number of Businesses (t=-3) / Total Number of Businesses (t = -3)	% (own calculation)	SA2	2002-2019	Annual
Controls					
Estimated Residents Population (ERP)	Population measures adjusted annually for births, deaths and migration.	Persons	SA2	2001 - 2020	Annual
Remoteness Area	Classification based on an area's access to services and opportunities for social interaction.	Major city Inner regional Outer regional Remote Very remote	SA2	2001, 2006, 2011, 2016	5-yearly updates
Education1 Certificate I & II	Highest education equivalent to 3-12 month introductory vocational skills at TAFE[9].	% of surveyed population (own calculation)	SA2	2001, 2006, 2011, 2016	5-yearly Census
Education2 Certificate III & IV	Highest education equivalent to 1-2 year further training at TAFE.	% of surveyed population (own calculation)	SA2	2001, 2006, 2011, 2016	5-yearly Census
Education3 Advanced Diploma & Diploma	Highest education equivalent to 1-2 year advanced training at TAFE.	% of surveyed population (own calculation)	SA2	2001, 2006, 2011, 2016	5-yearly Census
Education4 Bachelor Degree	Highest education equivalent to 3-4 year degree at university.	% of surveyed population (own calculation)	SA2	2001, 2006, 2011, 2016	5-yearly Census
Education5 Graduate & Postgraduate Degree	Highest education equivalent to 1-4 years further university education	% of surveyed population (own calculation)	SA2	2001, 2006, 2011, 2016	5-yearly Census
Unemployment Rate	Unemployed, actively looking for work % of labour force	% of surveyed population (own calculation)	SA2	2001, 2006, 2011, 2016	5-yearly Census

[9] Australian TAFE (Technical and Further Education) institutions are similar to US community colleges, centred around vocational education and training and qualifications for specific trades and professions.

SA2 Code Matching Process

An important issue that I needed to resolve is that the borders of the SA2 regions have been adjusted over the analysis period, transitioning from the 2001, 2006 and 2011 codes to the 2016 format. To do so, I developed a matching methodology to retain as much data as possible. The analysis focuses on regions where SA2 2016 codes could be assigned, ensuring a minimum of 70% of the previous code fell into the SA2 2016 code catchment area. The ABS provided me with these catchment ratios between old and new codes in their correspondence documentation. This approach minimises the risk of generating duplicated data by preventing overlap where one previous code partially corresponds to multiple areas. By requiring a 70% overlap, this methodology ensures a largely 1:1 translation from one code to another, effectively ruling out the possibility of multiple matches. I tested the data and confirmed no duplicates were generated in this process.

Applying this process, 44 543 of the initial codes were assigned to 2016 SA2 codes, leaving 2307 unassigned (4.92% of the total dataset). Only the income data (Model A) was affected by this exclusion; the unassigned data did not include relevant business data for Model B regressions. To examine whether the matching may affect the regression results, I compared income data of the groups with and without 2016 SA2 codes able to be assigned. To do so, I employed the Welch Two Sample t-test and the Wilcoxon Rank-Sum test. The results, presented in the *Appendix Table 1*, indicate a statistically significant difference between the groups. *Appendix Table 2* presents the mean, standard deviation, and number of observations for key variables. The original dataset shows a slightly higher mean percentage change in average wage and salary income (3.74%) compared to the subset with blanks (3.64%), and a higher 3-year percentage change (11.54% vs. 11.14%). *Appendix Figure 1* plots Average Wage & Salary Income against years for both groups, showing higher income levels in the original dataset. The scatterplot in *Appendix Figure 2* indicates greater variability in the original dataset, partly due to the larger number of observations. The bulk of unassigned data is from 2001-2006 and 2016-2019. *Appendix Figures 3* and *4* present box plots comparing the percentage change in average wage and salary income (the key dependent outcome in Model A) between the two datasets, showing that the original dataset has a slightly higher median percentage change than the subset with blanks. Appendix Figure 6 compares the highest level of education attained, revealing largely similar datasets, except for a slightly higher share of the lowest-educated in the subset without SA2 ID codes. This educational disparity could explain much of the income gap observed between the two groups. Finally, the bar charts in *Appendix Figure 6* display the frequency of disaster exposure, indicating that the original dataset has a more balanced distribution of disaster types, whereas the subset with blanks has a higher proportion of wildfires and fewer storms (summarised in *Appendix Table 3*).

These analyses suggest some differences between the original dataset and the unassigned subset, implying that excluding observations with missing SA2 codes could impact the regression results. However, this impact is likely modest, given that the subset with missing SA2 codes constitutes only 4.92% of the total data. Additionally, controls for education and unemployment disparities should largely account for any further differences.

Outliers

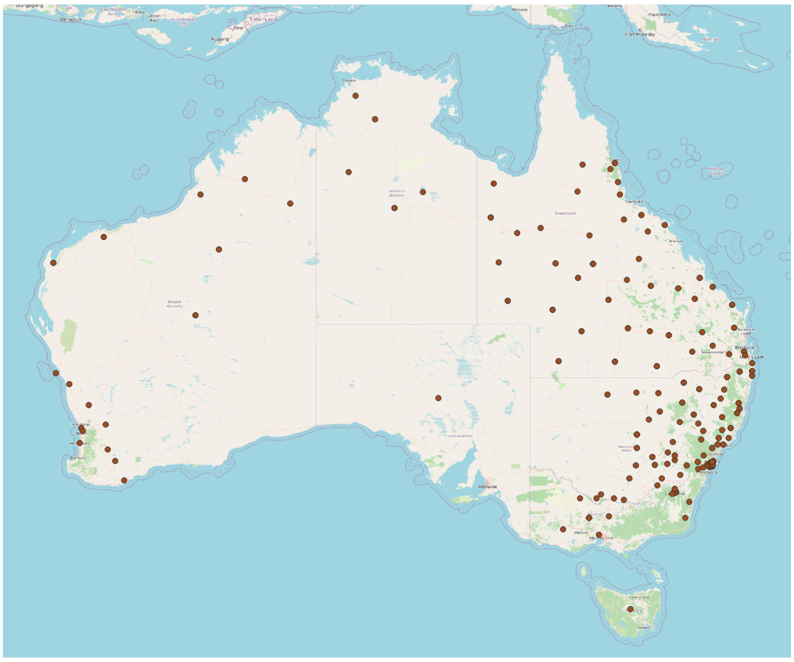
A number of outliers were identified within the dataset. To ensure robustness and mitigate potential distortions in the analysis, I employed a z-score method to filter out wage and business growth data exceeding five standard deviations from the mean. These outliers, which were significantly skewed to the upside, could have substantially influenced the outcomes. Specifically, 171 and 35 outliers for income growth and 11 and 3 outliers for business growth (one-year and three-year growth, respectively) were removed. The overall number of removed outliers was relatively modest. Scatter plots *Appendix Figures 11-18* illustrate the one-year and three-year income and business growth before and after cleaning, demonstrating a more harmonized distribution post-cleaning. Given the substantial variability in average wages and the total number of businesses across Australia, and considering that the fixed effects model accounts for these local economic disparities, addressing outliers in the raw data was deemed unnecessary.

Disaster Data

For the geospatial data concerning the natural disasters I implement the EM-DAT database which is open access and managed by the US Centre for Research on the Epidemiology of Disasters (EM-DAT, 2024b). My analysis focuses on four primary disaster types: storms, tropical cyclones, wildfires, and floods. These categories encompass meteorological (storms, tropical cyclones), hydrological (floods), and climatological (wildfires) disasters. The selection of these specific disaster types, totalling 94 relevant events, is driven by their increasing frequency and severity, closely linked to the growing risks of climate change. While other climatological disasters such as extreme temperatures and droughts are significant, they were excluded due to the EM-DAT database's lack of granularity for these types, often reporting entire states as affected, which hinders detailed localised analysis, a key strength of this study.

Initially, the extended NASA Socioeconomic Data and Applications Center (SEDAC) geocoded disasters dataset (GDIS)[10] was considered for extracting geospatial polygons to match with ABS SA2 local areas. However, the GDIS spatial boundaries were inconsistently granular, sometimes aligning with state boundaries rather than the more expected organic shapes of impact zones. Therefore, I use the recorded affected Local Government Areas (LGAs) as indicators of affected regions instead. Communication with the Australian Bureau of Meteorology revealed that granular data from Geoscience Australia and the Australian Institute for Disaster Resilience was not available free of charge for this research. Consequently, I focused on using the LGAs listed by EM-DAT as the affected areas for each disaster, matched with ABS LGAs. ABS data linking each SA2 area to the corresponding LGA facilitated the matching of individual disasters to specific SA2 areas. This matching process was undertaken with high precision, including manual cross-checking and noting any name changes over the 20-year period. The disasters are Australia-wide, albeit with more frequent occurrence on the East coast (*Figure 3*).

Figure 3: Centroids of GDIS Natural Disasters in Australia 2000 – 2018 (Author's own, Data: GDIS)



Next to information on the occurrence and location of natural disasters, the EM-DAT dataset also contains information on strength of impact (*Table 2*). However, all 94 relevant disasters are classified as level 2. Furthermore, the reported indicators such as duration, deaths, total affected and total damage are subject to considerable inconsistencies, preventing me from generating a reliable disaster intensity

[10] Disaster data is sourced from GDIS (Rosvold & Buhaug (2021)) and EM-DAT, CRED / UCLouvain (2024).

indicator. The only metric that I can use is total affected, as this contains data for 78 of the 94 disasters in the dataset. I am however confident that all disasters in the dataset are relevant, as their EM-DAT inclusion requires them to meet a selection criterion[11] indicating substantial impact (EM-DAT, 2024c).

Table 2: EM-DAT Natural Disaster Data

Indicator	Unit	Level	Time Frame	Source
Disaster Type	Storm Tropical Cyclone Wildfire Flood	LGA	2000-2019, each disaster is identified by date and unique disaster number	EM-DAT
Duration	Days	LGA	2000-2021	EM-DAT
Total Deaths	Persons	LGA	2000-2021	EM-DAT
Total Affected	Persons	LGA	2000-2021	EM-DAT
Total Damage Adjusted	‘000 USD, adjusted for local inflation (2015 base)	LGA	2000-2021	EM-DAT

Descriptive Overview of Cleaned and SA2-Code Assigned Data

Following the aforementioned data cleaning processes applied to both the ABS and EM-DAT datasets, the data for my analysis reveals several general trends. *Appendix Figures 19* and *20* illustrate a gradual increase and widening dispersion in average income and the total number of businesses. Upon closer examination of outliers in average income, these outliers align with expected results for the areas in question, primarily representing extremely wealthy mining enclaves and some high-income small areas in Sydney. The distribution of the total number of businesses is less even, with outliers predominantly representing business registrations in the central business districts of Sydney, Melbourne, Brisbane, and Perth.

Appendix Figures 21 and *22* display fluctuations in the one- and three-year percentage changes in average income over the analysed period, indicating varying rates of income growth with no clear trend. *Appendix Figures 23* and *24* similarly show fluctuations in the one- and three-year percentage changes in the total number of businesses, again with no evident trend, although growth rates become more dispersed, with higher tails in the one-year period. These scatterplots also highlight limitations in the ABS data, which is not available until 2003 and is sparse for the years 2005-2007.

Regarding the key dependent variables and regional impacts in Australia, *Appendix Figure 25* 's boxplots reveal a clear gradient in income levels from major cities to very remote areas, with major cities experiencing the highest median average income and a significant number of outliers skewed to the upside. Income variability is much lower in regional and remote areas. These disparities are likely partly due to differences in educational attainment levels, as highlighted in *Appendix Figure 26*, where vocational education is more prevalent in regional and remote Australia, while higher education is

[11] Ten or More People Reported Killed, 100 or More People Reported Affected (injured, homeless, or otherwise requiring immediate assistance, Declaration of a State of Emergency or a Call for International Assistance.

concentrated in major cities. There is a noticeable decline in university education with increasing remoteness. Finally, *Appendix Figure 27*shows a clear gradient in the number of businesses from major cities to very remote areas, with major cities having the highest median and a wider spread of business counts. Exceptional areas in major cities exhibit significantly higher numbers of businesses. Evidently, the economic impact of natural disasters is likely to vary substantially across different remoteness classifications of SA2 regions, underscoring the importance of investigating potential divergences in growth, recovery, and decline trajectories.

In terms of disaster occurrence, floods are the most frequent disaster type in the dataset, followed by storms, wildfires, and tropical cyclones (*Appendix Figure 28)*. *Appendix Figures 29* and *30* detail the frequency of disaster types per year, with specific years such as 2008 and 2010 particularly impacted by floods, affecting a substantial number of SA2 areas. This is evident from the high frequency of affected SA2s in *Appendix Figure 29*, compared to a less pronounced number of unique flood events in *Appendix Figure 30*. Partly due to the high concentration of SA2 codes in major cities, *Appendix Figure 31* highlights that major cities experience significantly more SA2 areas impacted by floods compared to regional and remote Australia.

It is pertinent to note that education and labour force data are available only at five-year intervals (2001, 2006, 2011, and 2016). Consequently, models incorporating these controls are constrained to a substantially smaller subset of observations.

Table 3 below gives an overview of the summary statistics by SA2 regions relevant for my analysis. The average number of businesses and personal income vary significantly, along with the changes in income and number of businesses over one- and three-year periods. This underscores the appropriateness of the fixed effects model specification discussed in the upcoming section. The education and unemployment data are comparatively more consistent across regions.

Table 3: Summary Statistics

Variable	**N**	**Mean**	**Standard Deviation**	**Median**	**Min**	**Max**
Total Number of Businesses	27470	1019.131	1354.636	761	0	43150.
Average Wage & Salary Income	36032	50532.397	14641.300	48560	2059	289910
ERP	43424	9629.424	6423.364	8298	0	51909
1y % Change Average Wage & Salary Income	33178	3.745	3.230	3.738	-18.865	26.662
1y % Change Total Number of Businesses	24412	1.315	7.827	0.841	-94.912	266.667
3y % Change Average Wage & Salary Income	28502	11.539	7.802	10.923	-72.156	96.565
3y % Change Total Number of Businesses	20500	6.285	40.979	1.981	-99.371	1266.667
Total Affected (Disaster)	2409	7484.149	13216.237	3000	20	52539
Education1 Certificate_I_and_II	4464	0.024	0.016	0.023	0.002	0.500
Education2 Certificate_III_and_IV	4546	0.296	0.109	0.317	0.033	1.000
Education3 Advanced_Diploma_and_Diploma	4519	0.143	0.037	0.143	0.022	1.000
Education4 Bachelor_Degree	4517	0.221	0.094	0.198	0.009	1.000
Education5 Grad_Postgraduate_Degree	4491	0.092	0.063	0.071	0.004	1.000

Unemployment Rate	4481	0.070	0.046	0.061	0.006	1.252
Disaster_Dummy_Storm =1	755				0	1
Disaster_Dummy_Tropical_Cyclone_Storm =1	360				0	1
Disaster_Dummy_Wildfire =1	582				0	1
Disaster_Dummy_Flood =1	1016				0	1
Unique SA2 Areas	2662					
Unique Disasters	94					
Disaster-Affected SA2 Areas	2085					
Years 2001-2019	19					

AV Plots and Interpretation

I generated Added Variable (AV) plots to visually assess the relationship between the dependent variable and each independent variable in my fixed effects regression models. The AV plots (*Appendix Tables 7-10*) illustrate the partial effect of each predictor after accounting for other variables. The comprehensive formula used includes all independent variables from the most controlled version of each base model[12]. Utilising AV plots in a fixed-effects setting is a robust methodology for visualizing these relationships while accounting for unobserved, time-invariant factors.

The AV plots reveal a positive association between ERP (Estimated Resident Population) and changes in average wage and salary income, suggesting that localities with a larger population experience higher wage growth. This relationship appears linear and consistent across different models. The plots for the disaster occurrence dummy and total affected show a nuanced relationship with the dependent variable. Some indicate a negative impact of past disasters on wage growth and business changes, while others show mixed results, necessitating further investigation, which is addressed in the results section and through interaction terms.

AV plots with regional dummies reveal significant differences in wage and business changes across regions, with major cities showing higher wage growth compared to remote areas. Higher education levels, such as bachelor's and postgraduate degrees, are positively associated with wage growth, aligning with expectations that higher education improves economic outcomes. The unemployment rate shows a negative relationship with wage growth and business changes, reinforcing the detrimental impact of higher unemployment on economic performance.

[12] Using the Disaster Occurred dummy rather than each individual disaster type. AV plots using each individual disaster types were also run as a robustness check and yielded similar results, with the data clouds being only marginally more sparse (available upon request).

The AV plots also serve as a diagnostic tool to assess data integrity. The minimal presence of extreme outliers and the consistency of observed relationships across variables indicate that the data is reliable and well-suited for regression analysis, ensuring the robustness of the conclusions drawn.

Regression Model Specification

Research on the effects of natural disasters employs various approaches to model the impact of natural disasters on income and GDP. Utilising time series panel data offers significant advantages, including the ability to control for unobserved heterogeneity, capture dynamics over time, and enhance the accuracy of estimates through incorporating both spatial and temporal variations.

I examine both short-term and long-term impacts through short-term (Type 1) and long-term (Type 2) models, respectively (A1, A2 and B1, B2, respectively, see overview in *Table 4*). The short-term models explore the impact of a disaster in the preceding year on the one-year percentage change in the dependent variable (average wage and salary income in the A models, total number of businesses in the B models). The one-year lag ensures the disaster occurred within six months before or the first six months of the base year. The long-term models provide a broader perspective by assessing the impact of a disaster three years prior on three-year average income and business growth. These lag lengths are selected to capture both initial impacts and longer-term recovery or rebound effects[13],[14].

Table 4: Overview of Model Specification

Dependent Variable / Key Independent Variable	1y Lag Disaster Occurred	1y Lag Storm	1y Lag Tropical Cyclone	1y Lag Wildfire	1y Lag Flood	3y Lag Disaster Occurred	3y Lag Storm	3y Lag Tropical Cyclone	3y Lag Wildfire	3y Lag Flood
1y % Change Average Wage & Salary Income	A1_1	A1_2	A1_3	A1_4	A1_5					
3y % Change Average Wage & Salary Income						A2_1	A2_2	A2_3	A2_4	A2_5
1y % Change Number of Businesses	B1_2	B1_2	B1_3	B1_4	B1_5					
3y % Change Number of Businesses						B2_1	B2_2	B2_3	B2_4	B2_5

Estimating the dependent variables in percentage growth rates effectively conducts the analysis in first differences, mitigating non-stationarity and making the data more suitable for regression analysis in time series panel data. While the dependent variable of average income in the A models has limitations,

[13] Lagging disaster variables in this manner appears to be standard practice in this setting (Nguyen & Mitrou, 2024).
[14] Each model includes population, average wages and total number of businesses measured in levels. This was chosen over the log transformation as initial estimations showed log transforming these variables resulted in a substantial increase in outliers, skewing results.

such as lacking detail in income distribution and susceptibility to outliers, these models still provide valuable insights. Outliers may distort the average and potentially mask true economic well-being, so results should be interpreted with caution. By focusing on changes in the dependent variable, this approach assesses dynamic growth impacts post-disaster, offering insights into long-term effects and informing future policymaking.

Each sub-model contains a different mix of control variables, detailed in *Table 5.* The selected controls primarily account for the health and productivity of the labour market by measuring the population shares according to their highest levels of educational attainment and the unemployment rate. These controls are particularly suitable for the A models, which focus on income dynamics. In the B models, which analyse business growth, the unemployment rate serves as a closely linked control, while the relevance of educational levels in supporting business growth is subject to debate. Although higher university education is known to support entrepreneurial activity, vocational training at Australian TAFE colleges is also heavily focused on fostering business creation.

Table 5: Overview of Sub-Model Specification (Control Inclusion) [15]

Each model calculated as:	
(1)	Disaster + Yt=0 + ERP
(2)	Disaster + Major_Cities_Dummy + Inner_Regional_Dummy + Outer_Regional_Dummy + Remote_Very_Remote_Dummy + ERP
(3)	Disaster*Major_Cities_Dummy + Disaster*Inner_Regional_Dummy + Disaster*Outer_Regional_Dummy + Disaster*Remote_Very_Remote_Dummy + ERP
(4)	Disaster + Total_Affected + ERP
(5)	Disaster + Education1_Certificate_I_and_II + Education2_Certificate_III_and_IV + Education3_Advanced_Diploma_and_Diploma + Education4_Bachelor_Degree + Education5_Postgraduate_Degree + Unemployment_Rate + ERP
(6)	Disaster + Total_Affected + Education1_Certificate_I_and_II + Education2_Certificate_III_and_IV + Education3_Advanced_Diploma_and_Diploma + Education4_Bachelor_Degree + Education5_Postgraduate_Degree Unemployment_Rate + ERP
(7)	Disaster*Major_Cities_+ Dummy Disaster*Inner_Regional_Dummy + Disaster*Outer_Regional_Dummy + Disaster*Remote_Very_Remote_Dummy + Education1_Certificate_I_and_II + Education2_Certificate_III_and_IV + Education3_Advanced_Diploma_and_Diploma + Education4_Bachelor_Degree + Education5_Postgraduate_Degree Unemployment_Rate + ERP

[15] Note: I have not included average income in total businesses model or vice versa in each other's models as I assume they are interlinked in showing the health of the local economy and both influence the trajectory of each other endogenously. Here, Disaster is the given disaster and appropriate lag depending on the model.
A further model specified as sub-model 7 with the addition of the Disaster dummy was run but was too heavily affected by multicollinearity issues to produce meaningful results.

Pooled OLS

I began by estimating a pooled OLS regression, acknowledging that this estimation likely suffers from omitted variable bias and endogeneity issues, particularly given the likelihood of geographic-specific fixed effects. The pooled OLS regressions with all variables and controls starts with the following equation:

$$\Delta\,\%Y_{i,t=0} = \alpha + \beta_1 Disaster_{i,t-1} + \beta_2 Y_{i,t=0} + \beta_3 EstimatedResidentPopulation_{i,t=0} + \beta_4 RemotenessAreaDummy_{i,t=0} + \beta_5 (RemotenessAreaDummy_{i,t=0} * Disaster_{i,t-1}) + \beta_6 TotalAffected_{i,t=0} + \beta_7 EducationControls_{i,t=0} + \beta_8 UnemploymentRate_{i,t=0} + \beta_9 Year_{t=0} + \varepsilon_{i,t} \quad (2)$$ [16]

$\Delta\,\%Y_{i,t=0}$ indicates the percentage change in the outcome variable (measured as the current value – previous value / previous value). Y is 1y percentage change in average wage and salary income (A1 models), 3y percentage change in average wage and salary income (A2 models), 1y percentage change in total number of businesses (B1 models), 3y percentage change in total number of businesses (B2 models). $Disaster$ is the binary dummy for occurrence of a natural disaster which varies by disaster type.

Fixed Effects

Next, I estimated a fixed effects model for each specification, indexing for SA2 codes and years. This approach controls for unobserved region-specific heterogeneity of the SA2 regions, correctly capturing time-invariant regional characteristics and dealing with the aforementioned omitted variable bias issues. Here μ_i represents SA2-specific fixed effects and θ_t represents time-specific fixed effects.

$$\Delta\,\%Y_{i,t=0} = \alpha + \beta_1 Disaster_{i,t-1} + Controls + \mu_i + \theta_t + \varepsilon_{i,t} \quad (3)$$

Random Effects

Considering the possibility that some explanatory variables are largely time-invariant (e.g., remoteness categorisation) and that unobserved individual-specific effects might not be correlated with the explanatory variables. Here μ_i represents the region-specific random effect, assumed to be randomly distributed and uncorrelated with the other explanatory variables.

$$\Delta\,\%Y_{i,t=0} = \alpha + \beta_1 Disaster_{i,t-1} + Controls + \mu_i + \theta_t + \varepsilon_{i,t} \quad (4)$$

[16] $RemotenessAreaDummy$: Major city, inner regional, outer regional, remote and very remote.
$EducationControls$: percentage of population which is level 1 – 5 educated (see *Table 1* for overview).

The fixed effects model was chosen as particularly well-suited for controlling unobserved time-invariant heterogeneity, crucial for my analysis, which involves panel data with location-specific variations. The fixed effects approach effectively captures time-invariant characteristics within each SA2 region, ensuring that these unobserved factors do not bias the estimated impact of natural disasters on the dependent variables. This methodology is the most used in the literature, especially in national and cross-country large-scale studies[17]. Whilst the difference-in-differences approach is robust for assessing causal impacts by comparing treated and control groups, it relies heavily on the parallel trends assumption, where in the absence of treatment, the treated and control groups would have followed the same economic trend over time. In the context of natural disasters, ensuring this on a large scale is challenging due to the diverse nature of regional economies and the unique ways they might respond to disasters, making it difficult to identify a comparable control group that strictly follows the same pre-treatment trend as the treatment group. Although a difference-in-difference framework provides an interesting extension, it appears more suitable for event studies in this framework[18]. In line with econometric theory, the Lagrange Multiplier test was applied to a pooled OLS baseline, followed by a Hausman test to ensure that Fixed effects rather than Pooled OLS of Random Effects was indeed the correct model specification.

In my models, I employed a one-year lagged disaster variable to examine the one-year changes in income and the number of businesses. The ABS measures income and business data by financial year, indicating that the data commence midway through the associated year. The dependent variables, representing one-year and three-year percentage changes, are calculated by comparing the current year to the preceding year or three years prior. Preliminary investigations of four- and five-year lags yielded largely insignificant results. For instance, in an A1 model for t = 2005, the t = -1 storm would have occurred in 2004, and the dependent variable is the growth rate in income from mid-2004 to mid-2005 (t = -1) compared to mid-2005 to mid-2006 (t = 1). This temporal alignment ensures that the disaster occurred either in the six months prior to t = -1 or within the first six months of the t = -1 base year. Although the disaster timing is not perfectly aligned with the financial year, this methodology reliably captures the disaster's impact within the base year or the preceding six months. Nevertheless, the results should be interpreted with some caution due to this potential timing imperfection.

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[17] Boudreaux, Jha & Escaleras (2023), Dell, Jones & Olken (2014), Deryugina, Kawano & Levitt (2018), Groen, Kutzbach & Polivka (2020), Hickson & Marshan (2022), Johar et al. (2022), Johar et al. (2022), Nguyen & Mitrou (2024b), Noy (2009), Panwar & Sen (2019), Roy & Noy (2023), Sawada, Bhattacharyay & Kotera (2019), Ulubaşoğlu et al. (2019).
[18] An, Gabriel & Tzur-Ilan (2023), Belasen & Polachek (2009), Hsiang & Jina (2014), Ulubaşoğlu (2020), Ulubasoglu & Beaini (2019).

4. Empirical Findings

The model results are significant yet mixed, illustrating the complex impact of natural disasters on income and businesses in Australia. The following explanation of the results focusses on statistically significant model estimates. Each model was estimated separately by disaster type (disaster occurred, storm, tropical cyclone, wildfire, flood), with seven different model sub-models which contain different mixes of control variables (specified at the bottom of the table). [19]

Key Findings: Change in Average Wage & Salary Income (Models A1 & A2)

The findings indicate that the impact of natural disasters on income growth is multifaceted and exhibits significant variability depending on the type of disaster and the region affected. Some areas demonstrate recovery or even positive growth over time, whereas others experience more pronounced and persistent downturns.

A1. One-Year Changes - income

*Table 6: A1 Models: One-Year Changes in Income by Differing Disaster Types**

Dependent Variable: 1y Percentage Change in Average Wage & Salary Income	(1)	(2)	(3)	(4)	(5)	(6)	(7)
General Disaster Occurred							
Lagged1y_Disaster_Occurred_Dummy	**0.369*****	**0.365*****	**1.230****	**0.393*****	0.239	0.202	
	(-0.069)	(-0.069)	(-0.515)	(-0.07)	(-0.278)	(-0.279)	
I(Lagged1y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			**-0.874***				**0.687***
			(-0.522)				(-0.388)
I(Lagged1y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)			-0.837				-0.292
			(-0.534)				(-0.409)
I(Lagged1y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)			**-1.003***				-0.697
			(-0.536)				(-0.512)
I(Lagged1y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)							-1.711
							(-1.534)
Storm							
Lagged1y_Disaster_Dummy_Storm	0.012	0.003	**-1.622*****	-0.004	**4.594*****	**4.554*****	
	(-0.12)	(-0.12)	(-0.428)	(-0.12)	(-0.923)	(-0.926)	
I(Lagged1y_Disaster_Dummy_Storm * Major_Cities_Dummy)			**1.691*****				**4.701*****
			(-0.449)				(-0.953)
I(Lagged1y_Disaster_Dummy_Storm * Inner_Regional_Dummy)			**1.564*****				**1.801*****
			(-0.502)				(-0.231)

[19] Please note that all coefficient regression findings represent raw / direct effects and are ceteris paribus.

Tropical Cyclone							
Lagged1y_Disaster_Dummy_Tropical_Cyclone	**-0.268***	**-0.271***	**1.697***	-0.191	-0.107	-0.197	
	(-0.151)	(-0.151)	(-0.961)	(-0.169)	(-0.978)	(-0.985)	
I(Lagged1y_ Disaster_Dummy_Tropical_Cyclone * Major_Cities_Dummy)			**-2.393****				
			(-0.98)				
I(Lagged1y_ Disaster_Dummy_Tropical_Cyclone * Inner_Regional_Dummy)			**-2.119***				-1.163
			(-1.085)				(-1.285)
I(Lagged1y_ Disaster_Dummy_Tropical_Cyclone * Outer_Regional_Dummy)			-1.46				2.081
			(-0.983)				(-1.432)
I(Lagged1y_ Disaster_Dummy_Tropical_Cyclone * Remote_Very_Remote_Dummy)							-2.152
							(-2.559)
Wildfire							
Lagged1y_Disaster_Dummy_Wildfire	**1.056*****	**1.048*****	0.217	**1.061*****	**2.087***	**2.125***	
	(-0.128)	(-0.129)	(-0.639)	(-0.128)	(-1.117)	(-1.12)	
I(Lagged1y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			1.061				1.972
			(-0.656)				(-1.755)
I(Lagged1y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)			0.348				2.225
			(-0.732)				(-1.488)
I(Lagged1y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)			-0.135				**2.169*****
			(-0.775)				(-0.258)
Flood							
Lagged1y_Disaster_Dummy_Flood	**0.498*****	**0.495*****	1.049	**0.489*****	-0.433	-0.471	
	(-0.117)	(-0.117)	(-0.672)	(-0.117)	(-0.298)	(-0.299)	
I(Lagged1y_Disaster_Dummy_Flood * Major_Cities_Dummy)			-0.607				-0.142
			(-0.691)				(-0.415)
I(Lagged1y_Disaster_Dummy_Flood * Inner_Regional_Dummy)			-0.413				-0.585
			(-0.692)				(-0.427)
I(Lagged1y_Disaster_Dummy_Flood * Outer_Regional_Dummy)			-0.66				**-1.541*****
			(-0.703)				(-0.483)
I(Lagged1y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)							-1.432
							(-1.661)
Controls							
Average_Wage_and_Salary_Income	x	x	x	x	x	x	x
ERP	x	x	x	x	x	x	x
Total_Affected		x		x		x	
Regional structure un-interacted dummies		x					
Education Dummies & Unemployment Rate					x	x	x

*All regressions include year and SA2 area fixed effects, Newey-West standard errors. Full results in Appendix (*Appendix Tables 4-8:* A1.1, A1.2, A1.3, A1.4 and A1.5).

General disaster occurrence impact on one-year income growth: The occurrence of any disaster shows a consistently positive impact on annual income growth, with the lagged disaster dummy registering significant boosts to average income of +0.369pp*** to 1.230pp** across sub-model specifications 1, 2, 3 and 4. Yet the regional area interaction terms show that in major cities and outer regions, the effect of disaster deviates from other types of regions. The general-disaster boost to income is weakened substantially, by -0.874pp* in major cities and -1.003pp* in outer regional areas in model 3. Sub-model 7 controls for labour force characteristics and only assesses interaction terms (no un-interacted disaster dummy). In this model the major city impact of disaster occurrence on average income is positive at +0.687pp*. Note the regional interaction effects are only significant at 10%.

Storm occurrence impact on one-year income growth: Storm occurrence exhibits a mixed impact on one-year income growth, with significant coefficients ranging from -1.6222*** in sub-model 3 to +4.595*** and +4.554*** in sub-models 5 and 6. The negative baseline dummy effect of -1.6222pp*** in sub-model 3 is produced when adding regional interaction terms, which show storms to increase income by 1.691pp*** in major cities and by1.564pp*** in inner regional areas (model 3). When controlling for labour market variables in sub-model 7, the interaction effect is substantial and positive for major cities, which experience a +4.701pp*** boost to average income growth and inner regional areas +1.801pp***.

Tropical Cyclones occurrence impact on one-year income growth: Cyclones in the year prior tend to have a small negative impact on year-on-year income growth overall, with effects slightly less significant compared to other disaster types. Adding regional interactions shows substantially stronger negative impacts in major cities, reducing one-year average income growth by -2.393pp* in sub-model 3, and similarly producing a -2.119pp* drag for inner regional areas. These regional impacts appear no longer significant when including labour market controls.

Wildfires occurrence impact on one-year income growth: Wildfires occurrence in the previous year indicate largely significantly positive impacts on average annual income growth, by +1.048pp*** (sub-model 2) to + 2.125pp* (sub-model 6). The majority of wildfire and regional area interaction terms are insignificant, barring a very significant +2.169pp*** (sub-model 7) increase in average growth for the outer-regional interaction term, implying that these areas specifically experience positive short-term growth impacts, even when controlling for education and unemployment.

Floods occurrence impact on one-year income growth: Floods in the year prior have mixed impacts, with small annual income growth acceleration effects on the disaster dummy in sub-models 1, 2 and 4 ranging from +0.489pp*** to +0.498pp***, whilst the interaction with the outer-regional dummy highlights a negative impact of -1.541pp*** (sub-model 7) implying that more regional areas display less disaster resilience, robust to education and labour force controls.

A.2 Three-Year Changes – Income

*Table 7: A2 Models: Three-Year Changes in Income by Differing Disaster Types**

Dependent Variable: 3y Percentage Change in Average Wage & Salary Income	(1)	(2)	(3)	(4)	(5)	(6)	(7)
General Disaster Occurred							
Lagged3y_Disaster_Occurred_Dummy	0.162	0.152	0.427	0.111	**3.512*****	**3.682*****	
	(-0.138)	(-0.139)	(-0.901)	(-0.138)	(-0.57)	(-0.585)	
I(Lagged3y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			-0.288				**2.859*****
			(-0.915)				(-0.702)
I(Lagged3y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)			0.282				**6.443*****
			(-0.948)				(-1.111)
I(Lagged3y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)			-0.835				**2.800****
			(-0.958)				(-1.208)
I(Lagged3y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)							0.678
							(-2.473)
Storm							
Lagged3y_Disaster_Dummy_Storm	-0.274	-0.293	**-6.270*****	-0.415	**3.072*****	**3.085*****	
	(-0.279)	(-0.28)	(-1.622)	(-0.28)	(-0.687)	(-0.687)	
I(Lagged3y_Disaster_Dummy_Storm * Major_Cities_Dummy)			**6.226*****				
			(-1.652)				
I(Lagged3y_Disaster_Dummy_Storm * Inner_Regional_Dummy)			**5.419*****				
			(-1.716)				
Tropical Cyclone							
Lagged3y_Disaster_Dummy_Tropical_Cyclone	**-1.834*****	**-1.840*****	0.352	**-1.959*****	**-3.611*****	**-3.629*****	
	(-0.3)	(-0.3)	(-1.461)	(-0.302)	(-0.74)	(-0.741)	
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Major_Cities_Dummy)			**-3.230****				**-3.619*****
			(-1.524)				(-0.788)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Inner_Regional_Dummy)			-1.671				-2.75
			(-1.766)				(-2.174)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Outer_Regional_Dummy)			-1.128				**-10.133*****
			(-1.511)				(-1.365)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Remote_Very_Remote_Dummy)							**-8.560*****
							(-1.387)
Wildfire							
Lagged3y_Disaster_Dummy_Wildfire	**2.134*****	**2.123*****	-0.849	**2.145*****	1.789	1.779	
	(-0.29)	(-0.291)	(-1.554)	(-0.29)	(-1.28)	(-1.28)	
I(Lagged3y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			**3.170****				**2.924*****
			(-1.591)				(-0.784)
I(Lagged3y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)			2.504				**3.298*****
			(-1.665)				(-1.186)
I(Lagged3y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)			2.658				-1.117
			(-1.937)				(-3.61)

Flood							
Lagged3y_Disaster_Dummy_Flood	**0.378***	**0.376***	0.685	**0.403***	**4.016*****	**4.175*****	
	(-0.217)	(-0.217)	(-1.34)	(-0.217)	(-0.602)	(-0.619)	
I(Lagged3y_Disaster_Dummy_Flood* Major_Cities_Dummy)			-0.564				**3.825*****
			(-1.364)				(-0.768)
I(Lagged3y_Disaster_Dummy_Flood * Inner_Regional_Dummy)			0.495				**5.550*****
			(-1.409)				(-1.318)
I(Lagged3y_Disaster_Dummy_Flood * Outer_Regional_Dummy)			-0.556				**3.464*****
			(-1.431)				(-1.226)
I(Lagged3y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)							1.726
							(-2.351)
Controls							
Average_Wage_and_Salary_Income	x	x	x	x	x	x	x
ERP	x	x	x	x	x	x	x
Total_Affected		x		x		x	
Regional structure un-interacted dummies		x					
Education Dummies & Unemployment Rate					x	x	x

*All regressions include year and SA2 area fixed effects, Newey-West standard errors. Full results in Appendix (*Appendix Tables 9-13:* A2.1, A2.2, A2.3, A2.4 and A2.5).

General disaster occurrence impact on three-year income growth: After three years, the occurrence of a disaster appears to have largely positively impacted three-year income growth by +3.512pp*** (sub-model 5) and + 3.682pp*** (sub-model 6). Significant positive impacts of disasters interacted with major city, inner regional and outer regional also show substantial positive impacts to three-year income growth rates of +2.859pp***, +6.449pp*** and +2.800pp** when controlling for education and unemployment in sub-model 7. This follows much softer general impacts in the short-term version of the model, and represents a considerable rebound effect when taking regionality into account.

Storm occurrence impact on three-year income growth: Storms exhibit varied impacts over three years, with substantial positive effects of +3.072*** (sub-model 5) and +3.085*** (sub-model 6), robust to education levels and unemployment controls. When interacted with regional areas, major cities and inner regional areas continue to show substantial positive growth impacts on three-year income growth (+6.226pp*** and +5.419pp*** in sub-model 3), yet the un-interacted term is strongly negative at -6.270pp*** implying the impact of storms is heavily dependent on the remoteness structure. This largely signals a continued growth upswing from the one-year impact findings.

Tropical Cyclones occurrence impact on three-year income growth: The occurrence of cyclones three years prior show significant negative impacts on three-year average income growth rates across models, ranging from -1.834pp*** in sub-model 1 to -3.629pp*** in sub-model 6, with results in sub-models 5 and 6 robust to labour market controls. Regional interaction effects further emphasise negative impacts, with major cities experiencing an additional -3.230pp** and -3.619pp*** drag on three-year growth in sub-models 2 and 7, with impacts substantially more severe in outer regional areas (-10.133pp***) and remote areas (-8.560pp***) in sub-model 7. The sub-model 7 results are robust to labour market controls. The shift from small negative impacts in the one-year lagged models to substantially more acute negative growth effects after three years imply tropical cyclones are a long-term detriment to growth.

Wildfires occurrence impact on three-year income growth: Wildfire occurrence continues to show significant positive impacts on three-year income growth rates, of +2.123pp*** to +2.145pp*** in sub-models 1, 2 and 4. Interactions with regional areas mirror this, with major cities registering boosts to average income growth of +2.924pp*** to 3.170pp** (sub-model 7, 3) and +3.298pp*** for inner-regional areas, robust to education and unemployment controls. These are of similar magnitude of one-year impacts, implying a general continuation of one-year lagged boosts to average income growth.

Floods occurrence impact on three-year income growth: Floods display largely positive impacts on income growth over three years, with large significant effects in sub-models 5 and 6 of +4.016pp*** and +4.175***, both robust to labour market controls. Interaction regional impacts on three-year income growth are also all positive, with inner-regional areas experiencing +5.550pp***, major cities and outer-regional +3.825pp*** and +3.464pp*** respectively in sub-model 7, robust to education and unemployment. These represent substantially stronger upticks in income growth in general, and a substantial rebound effect for the outer-regional areas which initially experienced a negative impact.

Overall Income Growth:

The general occurrence of natural disasters exhibits modest positive impacts on income growth in the short term, which tend to gather momentum and strengthen over the long term. Specifically, storms generally have a positive short-term impact that significantly intensifies over time, albeit findings are mixed when regional interactions are included. Tropical cyclones display a negative impact on income growth, which exacerbates into substantial long-term drags on income growth. Wildfires appear to be conducive to income growth, showing small but persistent increases in momentum over the long term. Floods have modest positive short-term impacts on income growth, which accelerate over the long term, particularly showing a rebound effect in outer-regional areas that initially experienced a downturn. In aggregate, most disaster types appear to be conducive to income growth, with the notable exception of tropical cyclones. This divergence in effects will be further explored in the discussion section. These effects are summarised in *Table 11* and visually presented in the box plots in *Appendix Figure 32*.

Key Findings: Change in Business Creation (Models B1 & B2)

The findings from the B models indicate that the impact of natural disasters on the number of businesses varies significantly depending on the type of disaster and the region affected. The results highlight both short-term and long-term impacts on business growth. Please see the B1 – B2 models in the appendix for full results.

B.1 One-Year Changes - Businesses

*Table 8: B1 Models: One-Year Changes in Business Creation by Differing Disaster Types**

Dependent Variable **1y Percentage Change in Total Business Numbers**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
General Disaster Occurred							
Lagged1y_Disaster_Occurred_Dummy	-0.017	-0.016	0.604	-0.036	**-0.780****	**-0.751****	
	(-0.16)	(-0.16)	(-0.68)	(-0.163)	(-0.348)	(-0.356)	
I(Lagged1y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			(-0.773)				**-1.889*****
			(-0.71)				(-0.414)
I(Lagged1y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)			(-0.389)				**1.667*****
			(-0.735)				(-0.516)
I(Lagged1y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)			(-0.407)				0.531
			(-0.747)				(-0.664)
I(Lagged1y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)							0.003
							(-2.541)
Storm							
Lagged1y_Disaster_Dummy_Storm	0.210	0.211	0.039	0.234	-1.184	-1.152	
	(-0.385)	(-0.385)	(-1.122)	(-0.386)	(-0.893)	(-0.9)	
I(Lagged1y_Disaster_Dummy_Storm * Major_Cities_Dummy)			0.182				-1.366
			(-1.182)				(-0.902)
I(Lagged1y_Disaster_Dummy_Storm * Inner_Regional_Dummy)							**4.461*****
							(-0.551)
Tropical Cyclone							
Lagged1y_Disaster_Dummy_Tropical_Cyclone	**0.901*****	**0.901*****	-0.872	**1.003*****	1.345	1.406	
	(-0.29)	(-0.29)	(-1.306)	(-0.35)	(-1.626)	(-1.644)	
(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Major_Cities_Dummy)			1.256				

			(-1.359)				
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Inner_Regional_Dummy)			**2.931***				2.122
			(-1.504)				(-2.24)
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Outer_Regional_Dummy)			**2.643***				**2.739***
			(-1.433)				(-1.664)
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Remote_Very_Remote_Dummy)							**-5.050***
							(-2.853)
Wildfire							
Lagged1y_Disaster_Dummy_Wildfire	**-1.078****	**-1.076****	-1.426	**-1.082****	-0.866	-0.899	
	(-0.443)	(-0.443)	(-1.646)	(-0.443)	(-0.996)	(-0.993)	
I(Lagged1y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			0.394				-0.914
			(-1.737)				(-1.128)
I(Lagged1y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)			0.355				0.147
			(-1.837)				-1.492
I(Lagged1y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)							**-7.555*****
							(-0.936)
Flood							
Lagged1y_Disaster_Dummy_Flood	-0.232	-0.231	**1.465****	-0.214	**-0.908*****	**-0.878****	
	(-0.177)	(-0.177)	(-0.681)	(-0.178)	(-0.347)	(-0.349)	
I(Lagged1y_Disaster_Dummy_Flood * Major_Cities_Dummy)			**-1.833****				**-2.042*****
			(-0.722)				(-0.465)
I(Lagged1y_Disaster_Dummy_Flood * Inner_Regional_Dummy)			**-1.407****				**1.752*****
			(-0.717)				(-0.479)
I(Lagged1y_Disaster_Dummy_Flood * Outer_Regional_Dummy)			**-1.950*****				0.256
			(-0.73)				(-0.624)
I(Lagged1y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)							**5.165****
							(-2.134)
Controls							
Average_Wage_and_Salary_Income	x	x	x	x	x	x	x
ERP	x	x	x	x	x	x	x
Total_Affected		x		x		x	
Regional structure un-interacted dummies		x					
Education Dummies & Unemployment Rate					x	x	x

*All regressions include year and SA2 area fixed effects, Newey-West standard errors. Full results in Appendix (*Appendix Tables 14-18:* B1.1, B1.2, B1.3, B1.4 and B1.5).

General disaster occurrence impact on one-year business creation: The occurrence of any disaster in the year prior leads to typically negative impacts on the annual growth rate of business numbers, implying overall business reduction. Notably, in sub-models 5 and 6, this constitutes a decline in business growth of -0.780pp** and -0.751pp** respectively, robust to labour market controls. The picture is somewhat mixed when interactions with regional areas are applied in sub-model 7, whereby major cities also experience a reduction in business growth (-1.889pp***) whilst inner regional areas experience a boost to business growth (+1.667pp***).

Storm occurrence impact on one-year business creation: The impact of storms the year before on one-year business growth is less clear, with the lagged disaster dummy only significant when interacted with the inner-regional dummy, leading to a +4.461pp*** increase in business creation.

Tropical Cyclone occurrence impact on one-year business creation: Tropical cyclones occurrence in the year prior has a generally positive impact on business creation, boosting the annual growth rate by +0.901pp*** in sub-models 1, 2 and by +1.003pp*** in sub-model 3. Additionally, the additional impacts of cyclones in inner regional and outer regional areas are also positive (+2.931pp* and +2.643* respectively) in sub-model 2. When controlling for labour market characteristics, the outer-region impact of cyclone occurrence is similarly +2.739pp* (sub-model 7). In contrast, cyclones appear to generate substantial reduction in business growth in remote areas (-5.050pp*). Note that these regional impacts are only significant at the 10% level.

Wildfires occurrence impact on one-year business creation: Wildfires in the year prior tend to have a negative impact on year-on-year business growth, evident in sub-models 1, 2 and 4 (-1.077pp** to -1.0832**). Specifically, the direct impact in outer regional areas signals a substantial decline (-7.555pp***), highlighting the vulnerability of business growth in these regions to wildfires. Only the latter impact is robust to labour market controls.

Floods occurrence impact on one-year business creation: Flood occurrence in the year prior exhibits varied impacts on business growth. While the overall lagged disaster dummy shows a positive growth effect in some models (+1.465pp** in sub-model 3), negative impacts on business growth are observed in 5 and 6 (-0.908pp*** and -0.878pp**), robust to labour market controls). Interaction terms imply a reduction in businesses in major cities of -1.833pp** in sub-model 3, -2.042pp*** in sub-model 7, the latter robust to labour market controls, suggesting floods generate a short-term drag, also echoed in inner and outewr regional areas (-1.407pp** and -1.950pp** in sub-model 3). Controlling for labour market conditions in sub-model 7, the impact of floods on business growth in inner regional areas becomes positive (+1.752pp***) and considerably large and positive for remote areas (+5.165pp**).

B.2 Three-Year Changes – Businesses

*Table 9: B2 Models: Three-Year Changes in Business Creation by Differing Disaster Types**

Dependent Variable 3y Percentage Change in Total Business Numbers	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
General Disaster Occurred							
Lagged3y_Disaster_Occurred_Dummy	0.549	0.568	11.766	0.492	**-2.515*****	**-2.902*****	
	(-0.764)	(-0.764)	(-13.053)	(-0.778)	(-0.584)	(-0.583)	
I(Lagged3y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			(-13.002)				**-5.987*****
			(-13.052)				(-0.749)
I(Lagged3y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)			(-8.573)				(-0.123)
			(-13.087)				(-1.274)
I(Lagged3y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)			(-10.783)				0.759
			(-13.333)				(-1.007)
I(Lagged3y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)							**6.289****
							(-2.809)
Storm							
Lagged3y_Disaster_Dummy_Storm	-0.693	-0.699	45.999	-0.793	**-6.400*****	**-6.369*****	
	(-1.317)	(-1.317)	(-94.694)	(-1.327)	(-0.738)	(-0.734)	
I(Lagged3y_Disaster_Dummy_Storm * Major_Cities_Dummy)			-47.839				**-6.212*****
			-94.694				(-0.795)
I(Lagged3y_Disaster_Dummy_Storm * Inner_Regional_Dummy)			-36.361				**-7.907*****
			(-95.061)				(-1.439)
Tropical Cyclone							
Lagged3y_Disaster_Dummy_Tropical_Cyclone	0.298	0.237	-2.019	0.203	**3.599*****	**3.566*****	
	(-1.399)	(-1.398)	(-6.521)	(-1.412)	(-0.827)	(-0.833)	
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Major_Cities_Dummy)			3.971				**4.081*****
			(-6.567)				(-0.916)
(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Inner_Regional_Dummy)			4.157				1.103
			(-6.737)				(-1.356)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Outer_Regional_Dummy)			-1.728				**-5.936****
			(-8.046)				(-2.891)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Remote_Very_Remote_Dummy)							**10.109*****
							(-2.077)
Wildfire							
Lagged3y_Disaster_Dummy_Wildfire	**3.176****	**3.085****	8.456	**3.160****	**3.210*****	**2.805****	
	(-1.283)	(-1.281)	(-12.339)	(-1.283)	(-1.221)	(-1.217)	
I(Lagged3y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			-6.637				0.945
			(-12.419)				(-1.238)
I(Lagged3y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)			-1.004				3.123
			(-12.662)				(-3.031)
I(Lagged3y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)			-14.224				**7.052*****
			(-14.325)				(-1.505)

Flood							
Lagged3y_Disaster_Dummy_Flood	0.548	0.633	20.095	0.521	**-1.614****	**-1.893*****	
	(-1.049)	(-1.049)	(-21.786)	(-1.051)	(-0.736)	(-0.723)	
I(Lagged3y_Disaster_Dummy_Flood * Major_Cities_Dummy)			-22.201				**-4.225*****
			(-21.75)				(-0.911)
I(Lagged3y_Disaster_Dummy_Flood * Inner_Regional_Dummy)			-18.862				1.369
			(-21.774)				(-1.25)
I(Lagged3y_Disaster_Dummy_Flood * Outer_Regional_Dummy)			-17.38				0.794
			(-21.917)				(-1.041)
I(Lagged3y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)							4.619
							(-2.912)
Controls							
Average_Wage_and_Salary_Income	x	x	x	x	x	x	x
ERP	x	x	x	x	x	x	x
Total_Affected		x		x		x	
Regional structure un-interacted dummies		x					
Education Dummies & Unemployment Rate					x	x	x

*All regressions include year and SA2 area fixed effects, Newey-West standard errors. Full results in Appendix (*Appendix Tables 19-23:* B2.1, B2.2, B2.3, B2.4 and B2.5).

General disaster occurrence impact on three-year business creation: Over a three-year period, the occurrence of disasters is associated with a decline in three-year business growth of -2.515pp*** and -2.902pp*** in sub-models 5 and 6 (robust to labour market controls). When specifying by regionality in sub-model 7, the interaction of a disaster three years ago with major cities generated an even larger drag (-5.987pp***), whilst showing the opposite for remote areas (+6.289pp**) implying substantial divergences in longer-term business growth trajectories contingent on regional classification. These results are also robust to labour market controls and largely demonstrate a deepening of the decline in overall business numbers compared to short-term outcomes.

Storm occurrence impact on three-year business creation: The long-term impact of storms on three-year business growth is largely negative, with significant negative coefficients observed in sub-models 5 and 6 (-6.400pp*** and -6.369pp***), robust to labour market controls. These impacts are echoed in the interaction effects with major cities and inner regional areas in sub-model 7 (-6.212pp*** and -7.907pp*** respectively), implying that more metropolitan areas experience a stronger decline. This sharp decline in long term business growth, contrasts with the initial (albeit murky) positive growth impact of storms on the one-year lagged model.

Tropical Cyclone occurrence impact on three-year business creation: The three-year impact of tropical cyclones on three-year business creation appears largely positive (+3.599pp*** and

+3.566pp*** in sub-models 5 and 6). These significant positive impacts are echoed in major cities and remote areas (+4.081pp*** and +10.109pp*** respectively) in interaction effects, yet the long-term business growth trajectory in outer-regional areas is negative (-5.936pp**). These results indicate that while some regions may experience substantial post-cyclone recovery, others continue to face challenges. In aggregate, there appears to be an acceleration in long term business growth three years post-cyclone compared to the short term.

Wildfires occurrence impact on three-year business creation: Wildfires continue accelerate business creation over three years, particularly in the sub-models 1, 2, 4, 5 and 6 (2.805pp** to 3.210pp***). The latter two models are robust to labour market controls. The interaction term with the outer regional dummy also highlights a significant and substantial boost to long-term business growth (+7.052pp***) following wildfires in this region. This constitutes a substantial rebound effect compared to short-term impacts.

Floods occurrence impact on three-year business creation: The long-term impact of floods three-years earlier on three-year business creation appears negative (-1.614pp** and -1.893pp***) in sub-models 5 and 6, robust to labour market controls). Specifically, the flood interaction with the major cities dummy shows a substantial decline in long term business growth (-4.225pp***) post-flooding. Compared to the one-year impacts, these results imply a steeper decline in business growth.

Overall Business Growth

The B model results suggest that the impact of natural disasters on the number of businesses is complex and varies significantly across different regions and types of disasters. Short-term impacts appear largely negative for overall disaster occurrence, wildfire and floods, whilst tropical cyclones appear conductive to short-term business growth. The regional context is significant, with inner-regional areas occasionally displaying unexpected growth effects compared to other regions or the overall disaster impact. Over the longer term, the impacts of disasters are either sustained or intensified for overall disaster occurrences, tropical cyclones, and floods. Conversely, storms experience a new downturn, while wildfires show a substantial rebound in business numbers.

Evidently, the results of my analysis confirms my hypothesis that the short- and long-term growth dynamics vary depending on the type of disaster resulting in unique disaster-growth outcome trajectories. In turn, these findings answer my primary research question of how these economic indicators recover post-disaster, considering various types of natural disasters (storms, tropical cyclones, wildfires and floods), the elapsed time since the event, and the remoteness of the impacted locality. In the upcoming discussion I contextualise the discovered trajectories in the current literature. *Table 10* below gives a condensed overview of the statistically significant disaster coefficient and visually presented in the box plots in *Appendix Figure 32*.

Table 10: Overview of Statistically Significant Disaster Coefficients

	Disaster Occurred				**Storm**				**Tropical Cyclone**			
	1y Changes Income	3y Changes Income	1y Changes Businesses	3y Changes Businesses	1y Changes Income	3y Changes Income	1y Changes Businesses	3y Changes Businesses	1y Changes Income	3y Changes Income	1y Changes Businesses	3y Changes Businesses
Average	0.589	3.597	-0.766	-2.709	2.509	-0.038		-4.251	0.386	-2.575	0.935	2.394
Maximum	1.23	3.682	-0.751	-2.515	4.594	3.085		0.016	1.697	-1.834	1.003	3.599
Minimum	0.365	3.512	-0.78	-2.902	-1.622	-6.27		-6.4	-0.271	-3.629	0.901	0.016

	Wildfire				Flood			
	1y Changes Income	3y Changes Income	1y Changes Businesses	3y Changes Businesses	1y Changes Income	3y Changes Income	1y Changes Businesses	3y Changes Businesses
Average	1.475	2.134	-1.079	2.575	0.494	1.870	-0.107	-1.754
Maximum	2.125	2.145	-1.076	3.21	0.498	4.175	1.465	-1.614
Minimum	1.048	2.123	-1.082	0.016	0.489	0.376	-0.908	-1.893

5. Discussion and Consolidation of Results

This analysis elucidates the complex and varied impacts of natural disasters on local economies, as measured by short- and long-term growth in average income and total business numbers.

Divergent Growth Dynamics

In general, most disasters (excluding tropical cyclones) tend to have positive impacts on both short- and long-term income growth, often accelerating over the longer term. I refer to this as the “continued boost” dynamic. The generally positive income effects observed over both short- and long-term horizons align with the creative destruction hypothesis, wherein initial negative shocks are mitigated by direct assistance and rebuilding efforts, effectively neutralising losses due to destroyed capital and human life within the first recorded growth period. However, the immediate positive growth impulse observed within the one-year dependent variable change suggests an absence of initial aggregate destruction, leading me to rename this dynamic as “continued boost” to reflect the dynamics displayed in the data and not presume initial aggregate destruction. Notably, a key caveat of my measurement of the dependent variable in changes alongside the measurement horizon of yearly averages in income and business number data is that very short-term negative impacts are possibly being overseen. Nevertheless, these disaster-induced increases in income are in line with the bulk of previous findings (Belasen & Polachek, 2009; Deryugina et al., 2018; Nielsen-Pincus et al., 2013; Roth Tran & Wilson, 2022; Pleninger, 2022), yet at odds with Johar et al. (2022) who find no long-term impact on income of generalised natural disaster occurrence.

Tropical cyclones are a notable exception, exhibiting substantial long-term detriments to income growth following initial positive growth boosts. This pattern aligns with a new theoretical framework I term "impulse-dip response," characterised by an initial positive shock due to immediate financial support, followed by a longer-term decline and is in line with findings by Guimaraes et al. (1993) and Groen et al. (2020)[20]. Again, the absence of data evidencing an initial aggregate destruction of income growth means the “creative destruction” dynamic cannot be confidently applied.

The impact of disaster exposure on total local business creation is more heterogeneous. Tropical cyclones display positive impacts on business growth rates, consistent with the “continued boost”

[20] Groen et al.’s (2020) study on Hurricane Katrina and Rita shows long-term income gains due to higher wages despite short-term earnings losses caused by a shift to unemployment.

dynamic. In contrast, other disasters, such as wildfires and floods, generally exhibit negative short-term impacts, with potential long-term rebounds ("build back better" for wildfires) or sustained negative effects ("no recovery" for floods, echoing findings by Meltzer et al. (2021)). Storms and floods show negative impacts on long-term business creation, contrasting with the positive long-term growth observed for wildfires and tropical cyclones. The positive growth trajectories experienced by the latter two reflect generalised findings of disaster-induced business creation by (Boudreaux et al., 2023). Notably, meaningful long-term impacts of storms on business growth were predominantly negative, however the short-term impact and thus a detailed growth trajectory was largely unobservable.

Figure 4 below displays my re-interpretation of disaster-growth outcome scenarios, extending on those stipulated by Hsiang & Jina (2014). *Table 11* summarises the classification of specific disasters according to the growth dynamic categories identified in this study.

Figure 4: Updated Disaster-Growth Outcome Scenarios (Author's Reinterpretation)

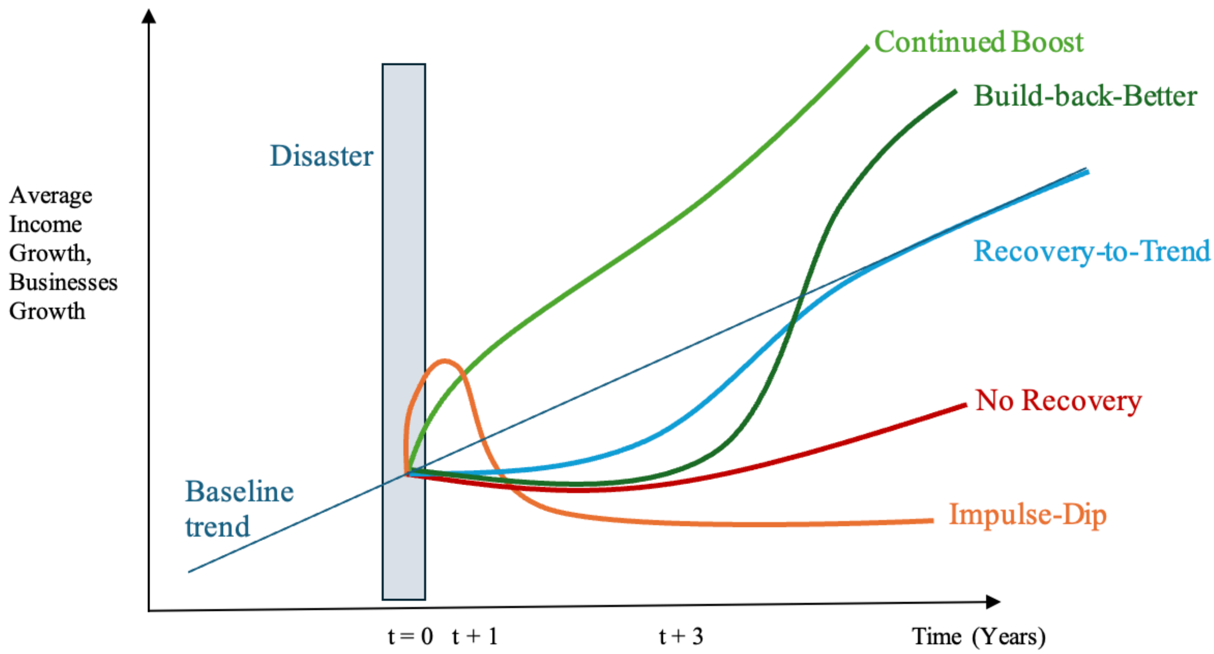


Table 11: Synthesis of Growth Dynamic Findings by Disaster Type

Disaster Type	Income Growth Dynamics	Business Creation Growth Dynamics
General Disaster Occurrence	Continued boost	No recovery
Storm	Impulse-dip	Unclear
Tropical Cyclone	Impulse-dip	Continued boost
Wildfire	Continued boost	Build-back-better
Flood	Continued boost	No recovery

Evidently, these is a consistent mismatch in average income and business creation growth dynamics across disaster types.

Continued Boost (experienced by Income and Business): In this scenario, reconstruction efforts, government support, stimulus and insurance payouts contribute to a swift influx of income support sustained economic growth post-disaster. In the case of businesses, the initial destruction may contribute to a demand for new businesses to assist with reconstruction or aforementioned government stimulus and payouts may create funds available for entrepreneurial activity.

Impulse-Dip (Income only): In this case, there is a swift economic boost from disaster relief and reconstruction efforts followed by long-term challenges which ultimately drag on growth, such as infrastructure damage, local inflationary pressures, dampened consumer sentiment and spending and environmental degradation. This category is notably only experienced in income dynamics, likely due to business creation being a more longer-term reaction due to business planning time spans compared to more reactive income growth.

Build-back-better (Business only): After an initial decline in business growth due to damage, weakened sentiment and spending and a worsening of local business conditions, investments in resilient infrastructure, longer-term government business-related stimulus and demand for recovery of lost businesses enhance economic revival and growth.

No Recovery (Business only): Persistent challenges like weak sentiment and demand, economic uncertainties, and dampened business viability thwart recovery to pre-disaster trajectories.

Consolidating the Mismatch Between Income & Business Growth Dynamics

Income and business growth dynamics exhibit different temporal recovery patterns post-disaster. In the short-term, immediate income support in the form of government aid, insurance payouts and charity donations provide swift financial relief, constituting an almost instantaneous bolstering of income levels for affected individuals. Conversely, the recovery or establishment of businesses and business operations is more protracted. Business owners likely require more time to assess damage, secure financial assistance, rebuild physical capital and required infrastructure. This divergence is evident in the short-term accelerations of average income growth post-disaster, while short-term business numbers generally decline[21].

The mismatches in long-term income and business creation dynamics are more complex. Where average income growth continues to rise whilst business numbers decline, a few explanations are possible. Post-disaster re-building efforts likely induce productivity increases, through technological and infrastructural upgrades (as found by Loayza et al. (2012). Increased productivity can boost average income regardless of business numbers. Additionally, disasters may lead to the consolidation of businesses, which could result in a reduced number of businesses whilst creating a more productive business landscape, which may be rewarded with higher local wages. Furthermore, post-disaster economies may become dominated by sectors such as reconstruction and healthcare, which may offer higher wages than the previous composition despite a reduction in overall business numbers. Furthermore, the influx of investment and capital post-disaster can stimulate economic growth and boost income growth without directly increasing business numbers. Lastly, despite controlling for population size to capture raw migration impacts, disasters may lead to population shifts. Affected areas may experience an influx of migrants seeking new economic opportunities and taking advantage of more affordable housing (as in Deryugina et al. (2018)). Should this constitute an influx of skilled workers, local income levels would rise.

Regionality

The regional impacts of natural disasters on income growth and business creation vary significantly. Major cities recover income faster but suffer in business growth, especially with storms and floods reducing business numbers long-term[22]. This likely reflects immediate recovery services and swift

[21] With the exception of tropical cyclones.
[22] Again with the exception of tropical cyclones.

government responses for larger populations, while the impact of disasters on these business-concentrated localities may impact more businesses and generate substantial negative spillover effects. Inner regional areas demonstrate resilience in income and business growth, benefiting long-term from wildfires and floods. Conversely, outer regional and remote areas have mixed outcomes, with limited significant results restricting the ability to draw broad conclusions. Their sluggish recovery may be due to resource access issues, more sector-dependent economic structures, and a less robust business ecosystem capable of absorbing economic shocks due to fewer diversified businesses. Local governments in these areas face financial constraints from a smaller tax base and unpredictable and delayed grants.

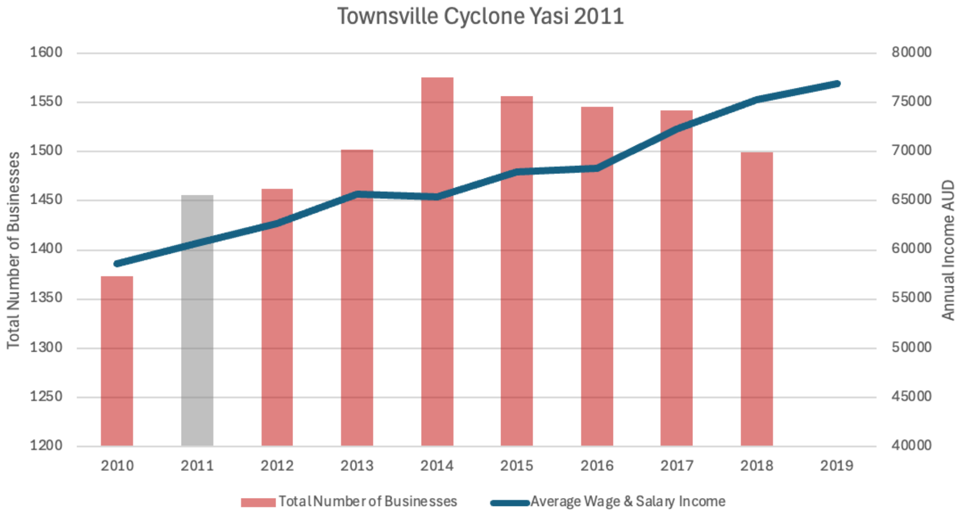
Outcome Divergence by Disaster Type

My analysis reveals that varied impacts of natural disasters on income growth and business creation, depending on disaster type (*Table 11*). Wildfires and floods tend to create "continued-boost" dynamics in income growth, while storms and tropical cyclones cause "impulse-dip" effects, the latter downturn likely due to more severe physical damage and lower preparation capacities. This is at odds with (Roth Tran & Wilson, 2022)'s comparable study of the US, which specifically finds hurricanes and tornados generating long-term income growth. A possible reason for this dynamic is that preventative measures, such as firebreaks and floodwalls, may mitigate impacts for wildfires and floods, whereas tropical cyclones' destruction is largely unavoidable. Additionally, the unique economic structure of affected areas, such as dependence on agriculture or tourism, would play a role, as illuminated by Panwar & Sen (2019), Loayza et al. (2012) and Ulubaşoğlu, Mehmet & Beaini (2019). Furthermore, aid and recovery responses vary by individual disaster and community resilience differs across Australia, with some areas better prepared for recurrent disasters.

Next, I examine two case studies that align with the growth dynamics identified in my analysis, providing additional context to the results discussed. Tropical Cyclone Yasi, a category 5 cyclone in 2011, caused significant damage, including the destruction of 1,000 homes, power loss to 200,000 properties, and an estimated AUD 300 million loss in agricultural output (Australian Disaster Resilience Knowledge Hub, n.d.a). The government responded with AUD 250 million in income recovery grants and concessional loans for affected farmers. *Figure 5* illustrates the "continued-boost" dynamic in business creation following this disaster[23].

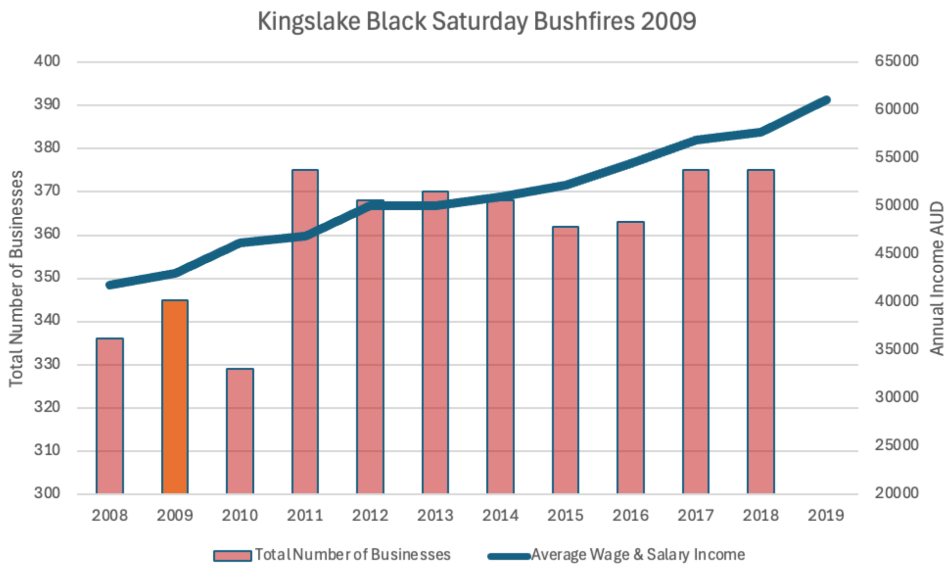
[23] Specific evidence for the income "impulse-dip" dynamic was not evident in this particular case.

Figure 5: Tropical Cyclone Yasi, Townsville, Queensland (Author's Representation, Data: ABS)



The 2009 Victoria Black Saturday bushfires claimed 173 lives, destroyed 2000 properties, 430 000 hectares of land and AUD 4 billion in estimated damages (Trounson, 2016). This met with substantial government income support and charity donations, facilitating direct financial aid and support for affected individuals (Trounson, 2016). Kingslake, Victoria was the most devastated locality. The graph below highlights how local incomes were bolstered post- event, maintaining an upwards trajectory (see *Figure 6*). Despite an initial short-term decline in businesses in 2010, business numbers had surpassed 2009 levels by 2012. This aligns with the "continued boost" dynamics for income growth and "build-back-better" experiences in the business environment identified in my wildfire findings.[24]

Figure 6: Black Saturday Bushfires, Kingslake, Victoria (Author's Representation, Data: ABS)



[24] Please note, that it is important to acknowledge the devastating human and environmental losses these disasters induce that my analysis does not consider.

Methodological Limitations and Extensions

This Master thesis was constrained by necessary time limitations. The data collection process was extensive, spanning four months' work to create a comprehensive time series data set covering the panel of 2662 statistical areas over 19 years, yet generated a novel and rich basis for future research.

Several methodological extensions could provide further insights into the underlying drivers of the differing growth dynamics experienced by disaster-exposed local economies. Introducing repetitive exposure parameters could reveal whether frequently hit areas develop greater resilience or undergo structural economic shifts The fixed effects regression specification was suitable for controlling for areas that are more frequently exposed to disasters, which tend to present economic disadvantages (Botzen et al., 2019; Currie & Rossin-Slater, 2013; Dell et al., 2009; Nguyen & Mitrou, 2024).

Additionally, the estimated regression model does not account for the potential compounding impacts of successive weather events. The correlation of specific weather events may generate unique impacts on outcome variables, suggesting that certain combinations of natural disaster events could produce specific outcomes not captured in this analysis.

Another key limitation is that this model does not control for varying levels of disaster recovery response efforts. The differing amounts of private insurance and government recovery and stimulus likely have significant impacts on the recovery trajectories of local economies. This variance may also differ according to the regionality of disaster locations, potentially making impacts more acute. An extension of this research could involve collecting data on the exact amounts of recovery funds allocated to each local area affected by disasters and incorporating this as a control variable in the fixed effects regression analysis.

Furthermore, the census data, available only at five-year intervals (2001, 2006, 2011, and 2016), limits the granularity of labour market controls. This could impact the robustness of findings related to income and business creation dynamics. Expanding the dataset would improve the number of observations available for assessment, generating more robust results. As touched upon in the Analysis Methodology section, both the lagging of disaster variables and the available controls for business dynamics were limited. Each lagged disaster variable would have impacted either the last six months of the previous financial year or the first six months of the base year. Although the analysis shows the time span from disaster impact can heavily influence outcome variables, a more precise approach to capturing exact timing dynamics would be beneficial. Additionally, while labour market controls are important for worker availability, they may not be as suitable for determining business growth dynamics, which are likely more influenced by the availability of start-up funding and other support schemes.

The fixed effects model accounts for unobserved, time-invariant factors but may overlook dynamic changes within regions. The model is limited by potentially low signal-to-noise ratios if within-group variation is limited, which was a concern given the annual data compared to more temporally spaced data. If changes within SA2 regions are small compared to differences between SA2 regions, the model may be limited in detecting the true effect of natural disasters. However, significant results suggest sufficient within-group variation, partly due to the large number of observations and model specification choices. A more detailed analysis of the economic impact radius of natural disasters could provide further clarity. Mobility data could reveal the extent to which SA2 economies are closed systems or interconnected networks, thus illuminating the full economic repercussions.

The models specified likely suffer from a degree of omitted variable bias, which distorts the actual relationships between variables. The fixed effects approach does not control for unobserved time-varying factors affecting the dependent variables, such as changes in local government policies and other macroeconomic shocks. While the panel data provides a robust framework, the findings' transferability could be enhanced with a larger sample size and more detailed data. The current analysis offers significant insights into the case of Australia but highlights the need for further research to fully understand the nuanced impacts of natural disasters on local economies and the transferability of these findings.

6. Policy Implications

Based on my analysis of the impacts of natural disasters on income and business growth dynamics, the following policy implications can be drawn.

Enhance and maintain immediate disaster response and recovery efforts. It appears aid directed at individuals' incomes is likely supporting the bolstered short-term income found in my analysis. Ensuring rapid distribution of aid and insurance payouts can help maintain this positive income growth trajectory post-disaster.

Infrastructure rebuilding needs to be prioritised in both urban and rural areas. Faster income recovery in major cities reflects immediate access to recovery services and swift government response in rebuilding essential infrastructure. Extending this level of response to outer regional and remote areas can help accelerate their recovery. More rural resource allocation can help bridge the recovery gap between urban and rural areas, resource allocation needs to consider the unique needs of affected areas tailored to the region and local economy impacted. Furthermore, investment in resilient infrastructure that can withstand disasters in essential to sustain productivity gains from rebuilding efforts to support long-term growth.

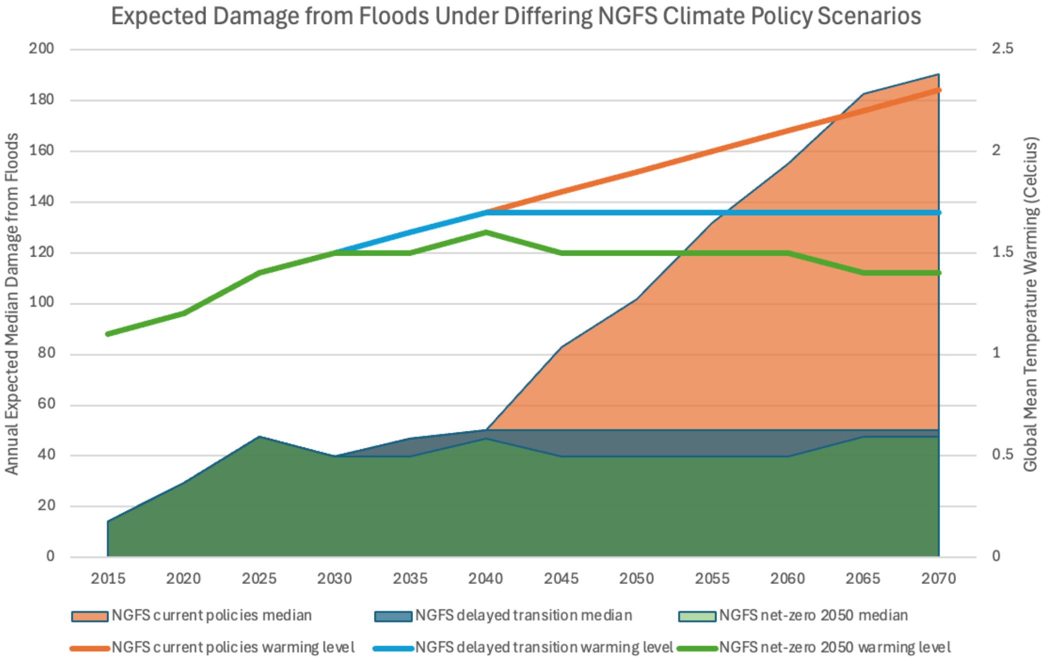
Promote economic diversification in outer regional and remote areas. Local business diversity is important to limit dependency of local economies on a limited number of businesses and sectors, reducing vulnerability of business numbers and local incomes. The scope to do so is however hampered in small and remote economies.

Provide targeted support for disaster-impacted businesses. My analysis indicates that local businesses likely require more immediate, liquid support to avoid the short-term declines in business numbers which can extend into long-term declines in some disaster settings. Policies should aim to minimise the number of businesses that go out of business following a natural disaster and facilitate the creation of new businesses after a negative shock. Grants, low-interest loans and resources for business support and planning when faced with natural disasters are key policy tools that should be implemented.

Ensure that recovery and resistance policies specifically address the needs of the most vulnerable. Albeit beyond the scope of my research, it is important to underline the importance of divergent socio-economic impacts natural disasters, as with many forms of economic shocks, can generate. This includes low-income, elderly, single-parent households and indigenous communities. Tailored support is paramount to ensuring equitable recovery.

Prioritise policy addressing climate change is paramount. Lastly, climate change adaption and mitigation policy are vital in reducing both the impact of natural disasters and the frequency of natural disasters linked to shifting climate dynamics. Climate resilience must be at the forefront of planning and development policy. Proactive climate policies are essential to minimise the adverse impacts of climate change and severe weather events, including investing in green infrastructure, promoting sustainability, and introducing effective policies to decarbonise emissions. For example, *figure 7* below implements the Central Bank Network for Greening the Financial System (NGFS) annual anticipated flood damage in Australia given climate policy scenarios and the related global mean temperature increase, highlighting that a continuation of current climate policy would lead to a stark increase in damages over the next four decades. Australian climate policy remains lagged on the international stage, especially concerning both the quantity of fossil fuels exported and lack of comprehensive domestic climate action. International criticism of Australia's insufficient climate targets and low adoption of clean energy signal that a shift to prioritisation of pro-climate policy is pivotal in mitigating the adverse impacts of natural disasters exemplified in my findings.

Figure 7: Expected Damage Annual from Floods in Australia under Differing Climate Policy (Author's representation, Data: Climate Analytics & NGFS (2024))[25]



[25] Policy scenarios: Current policies: current climate policies are preserved. Delayed transition: annual emissions continue to rise until 2030, strong policies required to limit warming to 2 degrees. Net-zero 2050: hard climate policies and innovation limit warming to 1.5 degrees. (NGFS, 2024)

7. Conclusions

This thesis confirms the hypothesis that diverse growth trajectories can emerge following the impacts of natural disasters. By focusing on average income and business creation, this research provides empirical evidence for multiple distinct post-disaster economic growth dynamics, contingent on disaster type and remoteness structures within the Australian context.

Through my analysis of fixed effects models spanning 2662 unique statistical areas over 19 years and 94 unique disasters, I have, to the best of my knowledge, performed the inaugural systematic examination of the impacts of different disaster types on local income and business number dynamics in Australia. This approach contrasts with current research, which often concentrates on individual case studies or state- and nation-wide impacts, lacking the granularity of individual local economic responses. It expands on previous research that primarily focused on broader geographic scales, less differentiated types of disasters, or very specific event studies with less transferable findings. By examining specific disaster types and their distinct economic impacts, this thesis offers a more nuanced understanding of how different natural disasters uniquely affect local economies.

Understanding the variety of economic impacts of natural disasters and the drivers of these divergent outcomes is crucial for informing policymakers to create more targeted and effective disaster response and longer-term recovery strategies. Emphasis should also be placed on addressing rural-urban dynamics and divides, tailoring disaster responses accordingly. Additionally, the effectiveness of early detection and warning likely significantly influences the level of destruction caused by natural disasters and their economic outcomes. Research in this field could also be fruitful in establishing best practices for damage minimisation.

Extensions of my thesis could investigate the impacts on housing markets and migration, as well as the varying socioeconomic effects on different demographic groups to better understand the relationship between disaster exposure and inequality. Recent research on mental health impacts represents a further step towards a socio-economic holistic approach to studying disaster shocks. Repeating this study design across different countries could provide insights into whether the disaster-specific outcomes are unique to the Australian context or reflect a more global phenomenon. Identifying universal patterns or unique regional characteristics is important in the planning of foreign disaster aid. However, data limitations may constrain the applicability of such studies, especially in developing nations where statistical surveying is less advanced. By addressing these areas, future research can build on the findings of this thesis, generating critical insights into the evolving dynamics of natural disasters.

Understanding the economic impacts of these increasingly frequent and severe disaster events is crucial for forging resilient and adaptive communities and underscoring the pressing need for academic research to continue to pave the way for promoting pro-climate preventative policymaking.

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Appendix

Appendix Table 1: Tests for Comparing Unassigned SA2 Codes to Assigned Data

Test	Statistic	p-value	Mean (Original)	Mean (Subset with Blanks)
Welch Two Sample t-test	4.0276	5.819e-05	50 532.40	48 844.59
Wilcoxon Rank-Sum Test	42,932,728	< 2.2e-16		

Appendix Table 2: Overview Comparing Unassigned SA2 Codes to Assigned Data

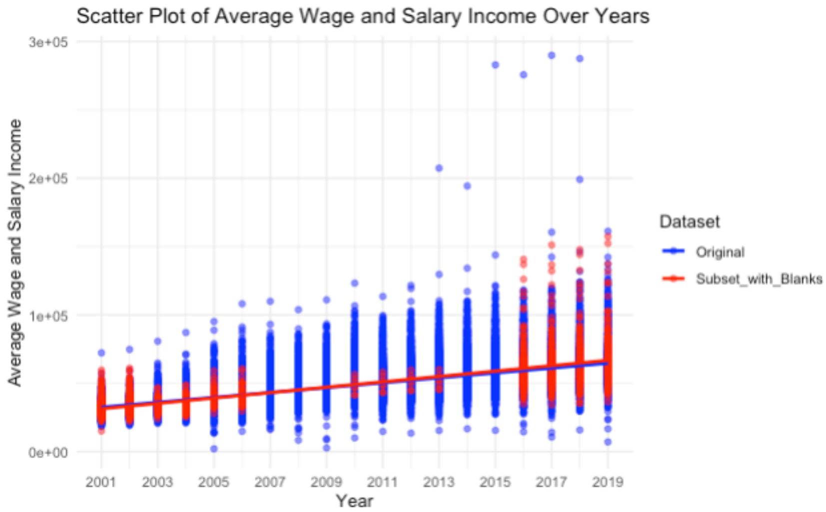
Changes in Income	Cleaned Data Set	Subset with Blanks	Difference
One-year Percentage Change			
Mean	3.744985	3.641915	-0.1030698
Standard Deviation	3.230222	2.434282	-0.7959405
Number of Observations	33178	1466	-31712
Three-year Percentage Change			
Mean	11.53914	11.13765	-0.4014975
Standard Deviation	7.802193	4.843099	-2.959094
Number of Observations	28502	351	-28151

Appendix Table 3: Overview Disasters Data Comparing Unassigned SA2 Codes to Assigned Data

	SA2 Assigned Data				No SA2 Code Data			
	Wildfire	**Flood**	**Storm**	**Tropical Cyclone**	**Wildfire**	**Flood**	**Storm**	**Tropical Cyclone**
Disasters	362	841	540	342	32	22	24	1
Total	2085, 4.68% disaster hit rate on SA2 codes				79, 3.42% disaster hit rate on SA2 codes			

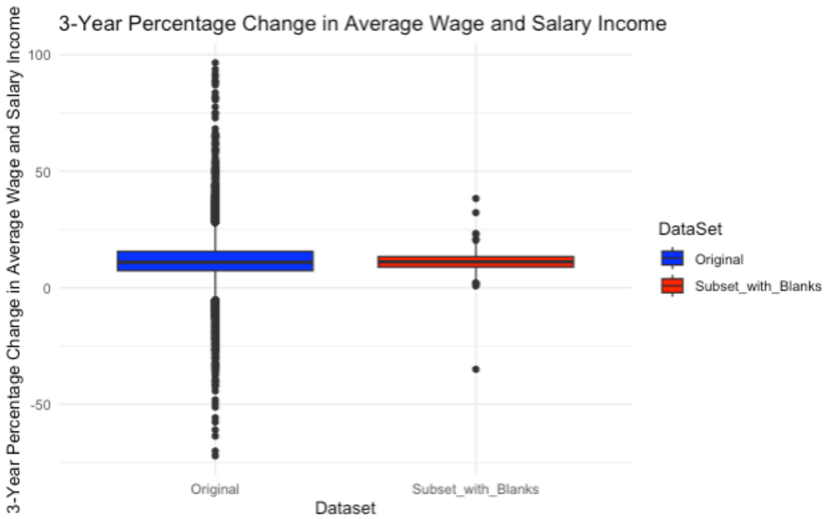
Appendix Figure 1: Income - Comparing Unassigned SA2 Codes to Assigned Data

Appendix Figure 2: Income - Comparing Unassigned SA2 Codes to Assigned Data

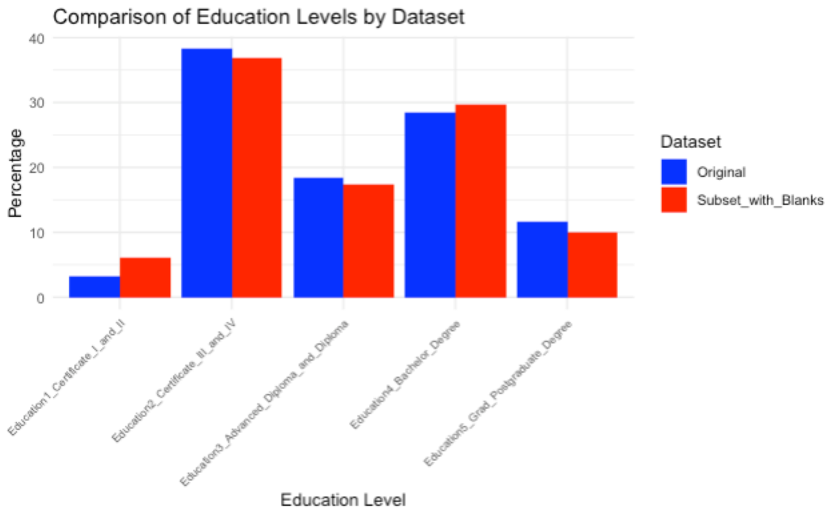


Appendix Figure 3: Income - Comparing Unassigned SA2 Codes to Assigned Data

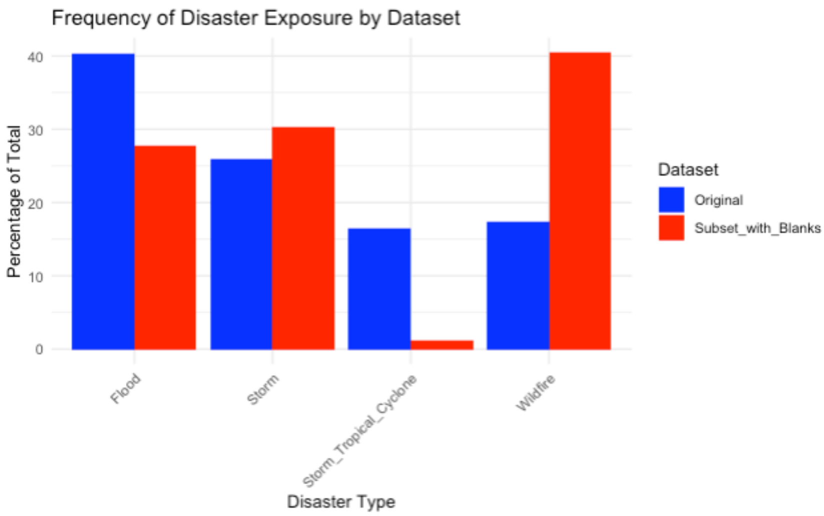
Appendix Figure 4: 3-Year Income - Comparing Unassigned SA2 Codes to Assigned Data



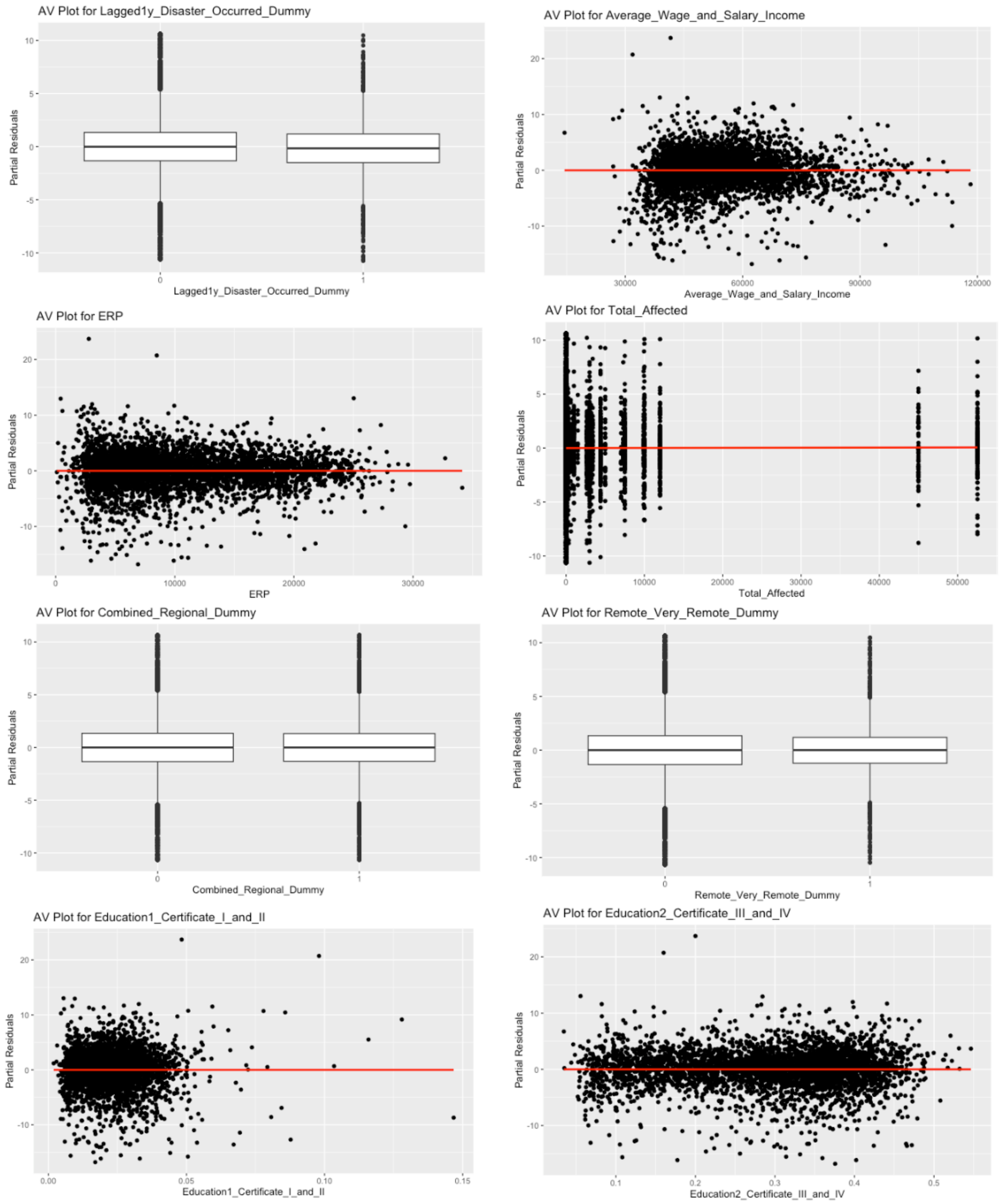
Appendix Figure 5: Education - Comparing Unassigned SA2 Codes to Assigned Data



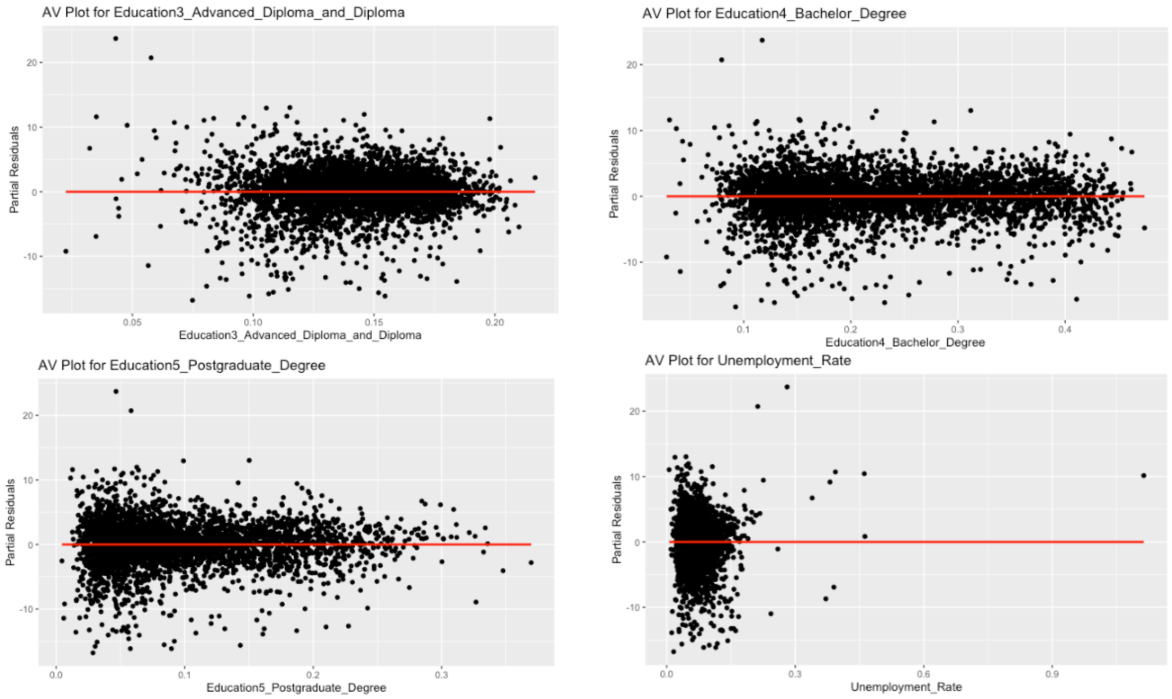
Appendix Figure 6: Disaster Exposure - Comparing Unassigned SA2 Codes to Assigned Data



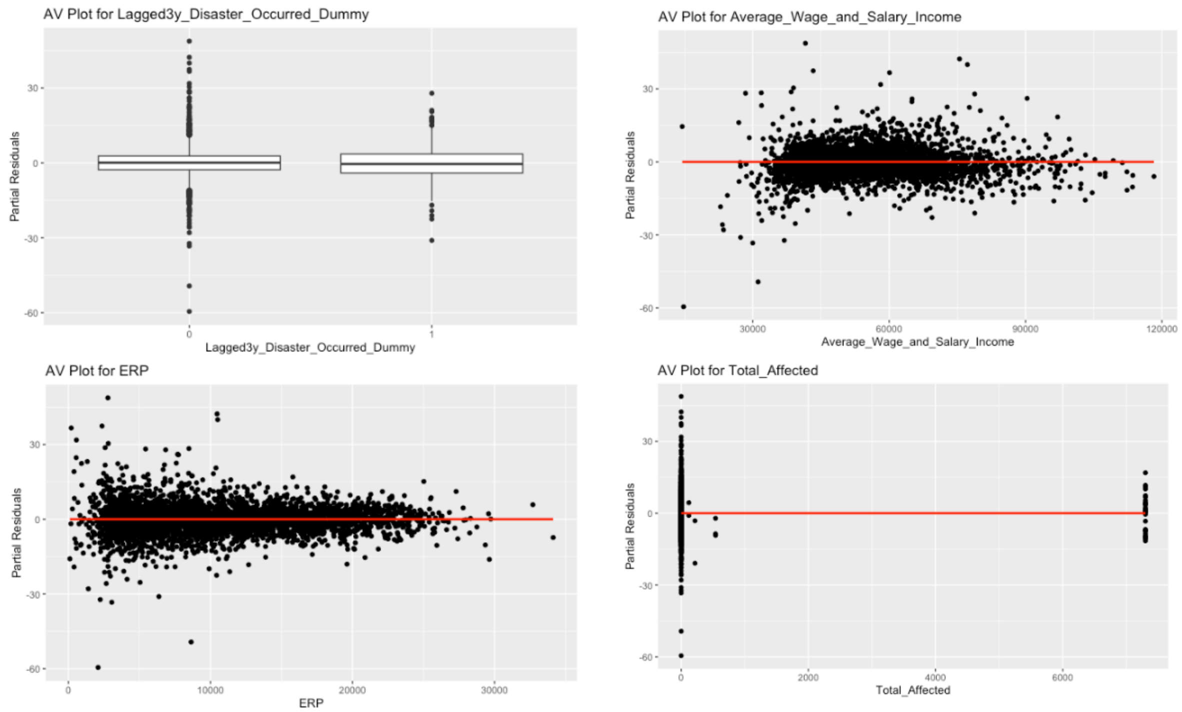
Appendix Figure 7: A1 Model AV Plots: One-year Percentage Change in Income vs One-Year Lagged Disaster Occurrence [26]



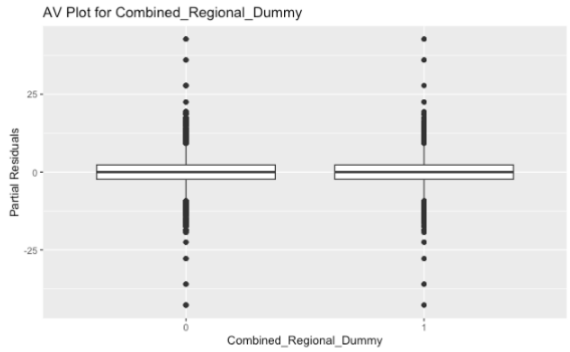
Percentage_Change_in_Average Wage & Salary Income ~
ERP + Average Wage & Salary Income + Lagged1y_Disaster_Occurred_Dummy + Total_Affected + Major_Cities_Dummy + Combined_Regional_Dummy + Remote_Very_Remote_Dummy + Education1_Certificate_I_and_II + Education2_Certificate_III_and_IV Education3_Advanced_Diploma_and_Diploma + Education4_Bachelor_Degree + Education5_Postgraduate_Degree + Unemployment_Rate + factor(Year)



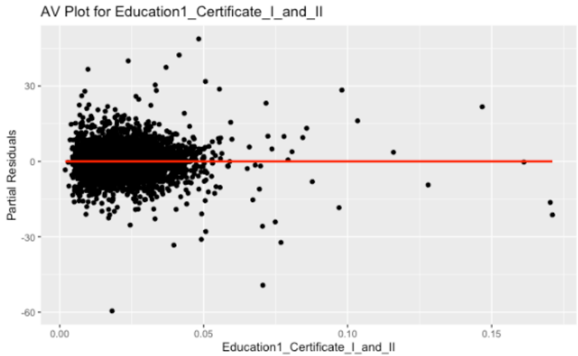
Appendix Figure 8: A2 Model AV Plots: Three-year Percentage Change in Income vs Three-year Lagged Disaster Occurrence[27]

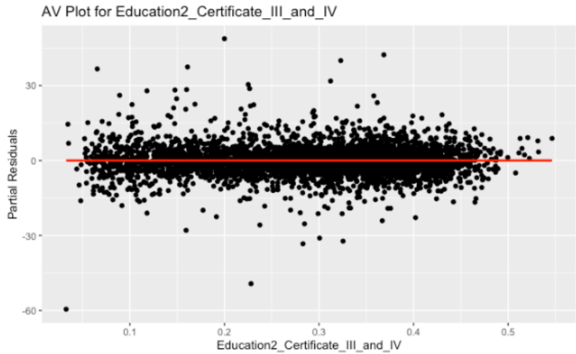


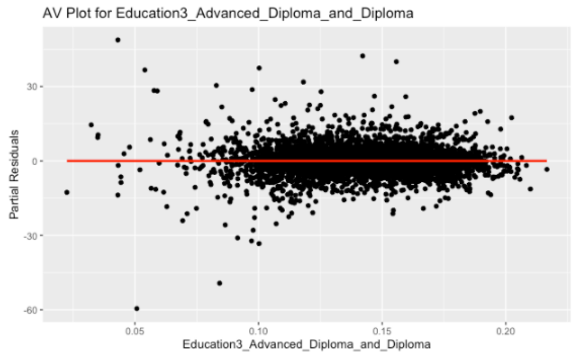
[27] average_wage_3y_pct_change ~
ERP + Average Wage & Salary Income + Lagged3y_Disaster_Occurred_Dummy + Total_Affected + Major_Cities_Dummy + Combined_Regional_Dummy + Remote_Very_Remote_Dummy + Education1_Certificate_I_and_II + Education2_Certificate_III_and_IV + Education3_Advanced_Diploma_and_Diploma + Education4_Bachelor_Degree + Education5_Postgraduate_Degree + Unemployment_Rate + factor(Year)

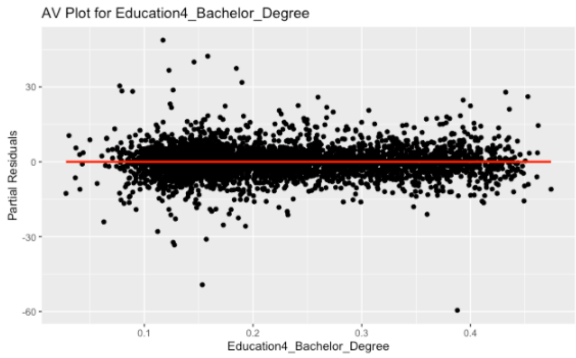

AV Plot for Combined_Regional_Dummy
Partial Residuals
25
0
-25
0
1
Combined_Regional_Dummy

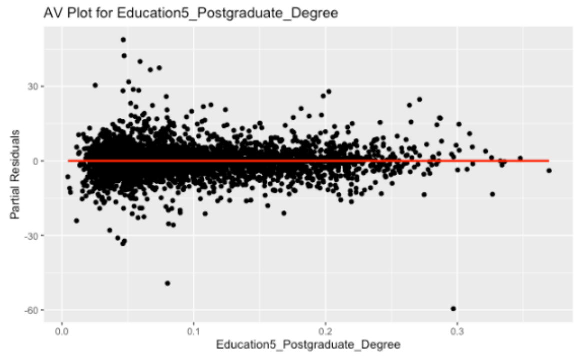

AV Plot for Remote_Very_Remote_Dummy
Partial Residuals
25
0
-25
0
1
Remote_Very_Remote_Dummy

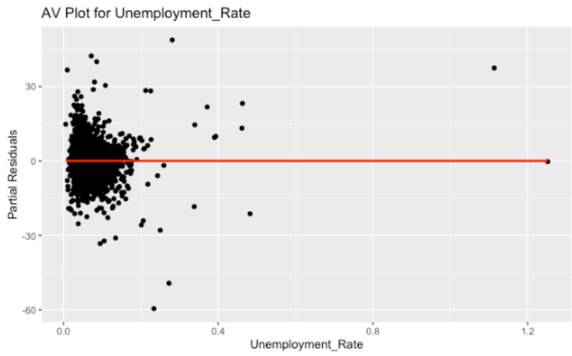

AV Plot for Education1_Certificate_I_and_II
Partial Residuals
30
0
-30
-60
0.00
0.05
0.10
0.15
Education1_Certificate_I_and_II


AV Plot for Education2_Certificate_III_and_IV
Partial Residuals
30
0
-30
-60
0.1
0.2
0.3
0.4
0.5
Education2_Certificate_III_and_IV

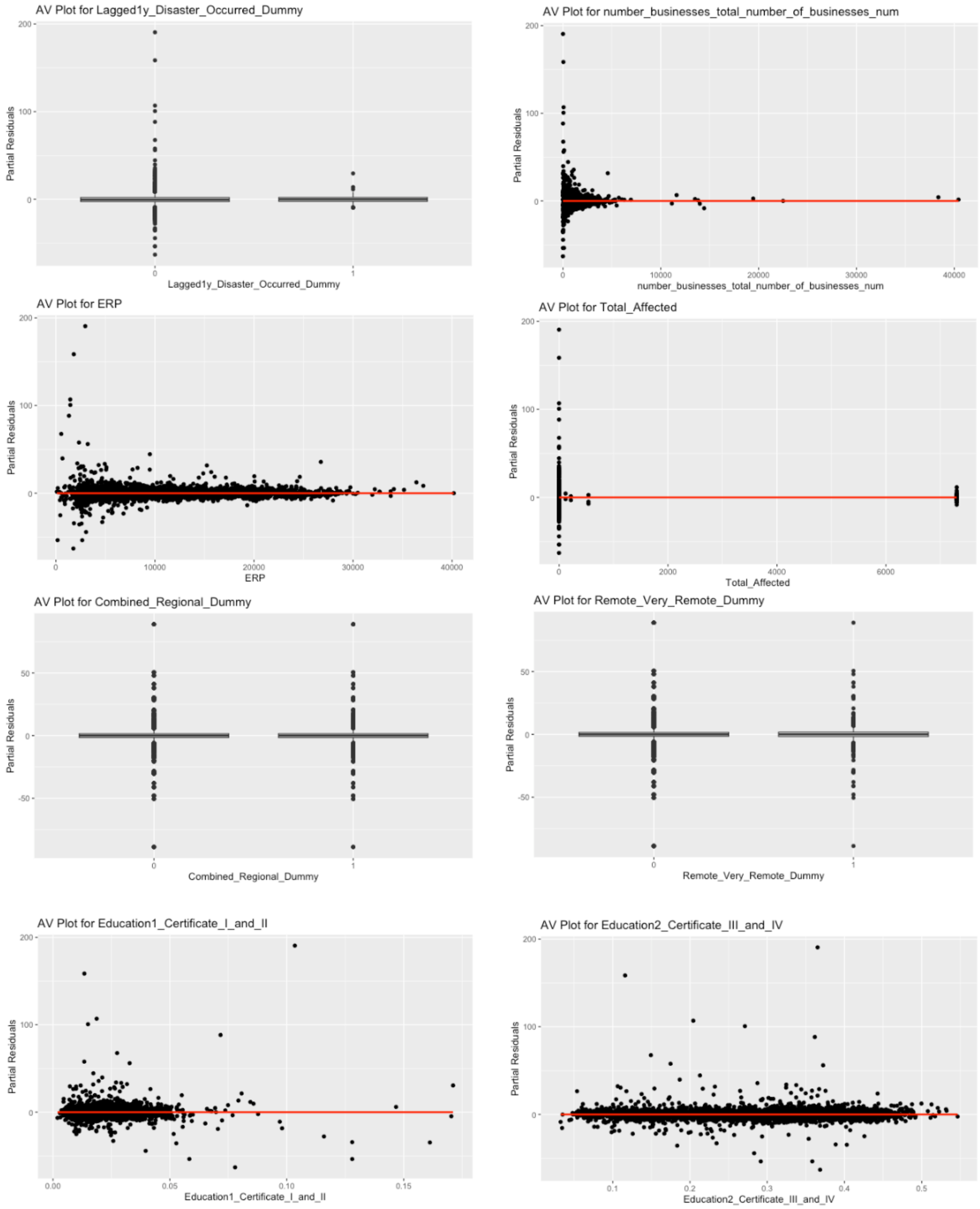

AV Plot for Education3_Advanced_Diploma_and_Diploma
Partial Residuals
30
0
-30
-60
0.05
0.10
0.15
0.20
Education3_Advanced_Diploma_and_Diploma


AV Plot for Education4_Bachelor_Degree
Partial Residuals
30
0
-30
-60
0.1
0.2
0.3
0.4
Education4_Bachelor_Degree


AV Plot for Education5_Postgraduate_Degree
Partial Residuals
30
0
-30
-60
0.0
0.1
0.2
0.3
Education5_Postgraduate_Degree


AV Plot for Unemployment_Rate
Partial Residuals
30
0
-30
-60
0.0
0.4
0.8
1.2
Unemployment_Rate

Appendix Figure 9: B1 Model AV Plots: One-Year Percentage Change in Total Number of Businesses vs One-Year Lagged Disaster Occurrence[28]



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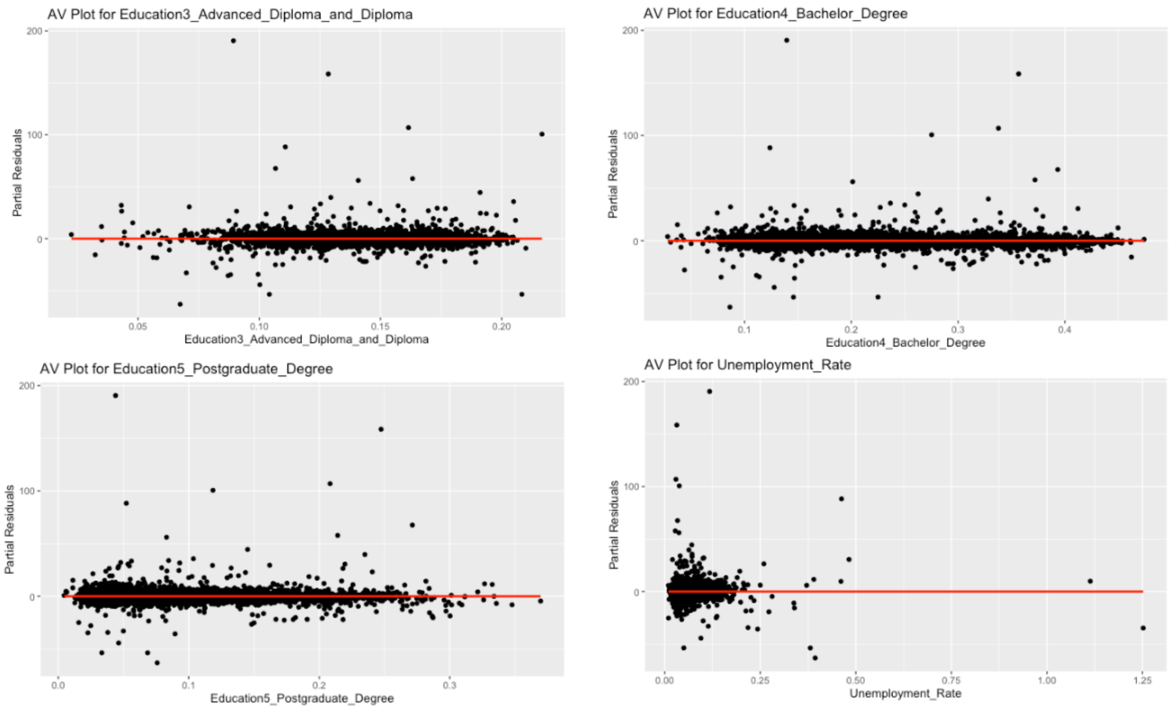
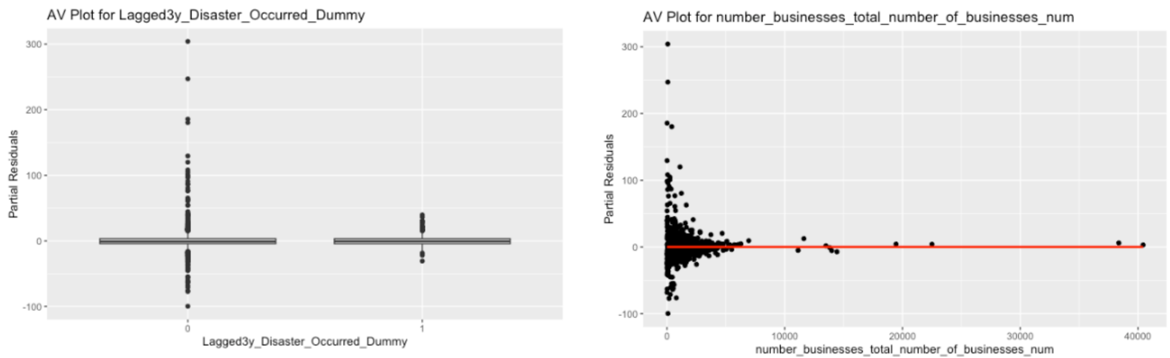
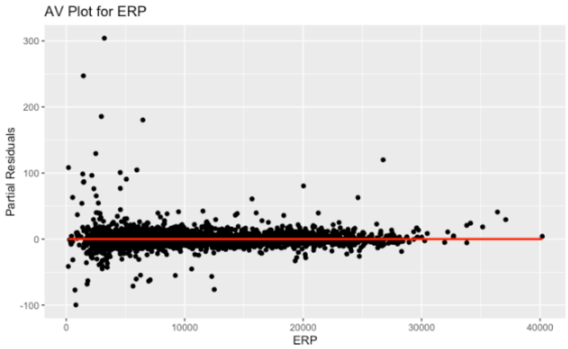
[28] Percentage_Change_Number_Businesses ~
ERP + number_businesses_total_number_of_businesses_num + Lagged1y_Disaster_Occurred_Dummy + Total_Affected + Major_Cities_Dummy + Combined_Regional_Dummy + Remote_Very_Remote_Dummy + Education1_Certificate_I_and_II + Education2_Certificate_III_and_IV + Education3_Advanced_Diploma_and_Diploma + Education4_Bachelor_Degree + Education5_Postgraduate_Degree + Unemployment_Rate + factor(Year)

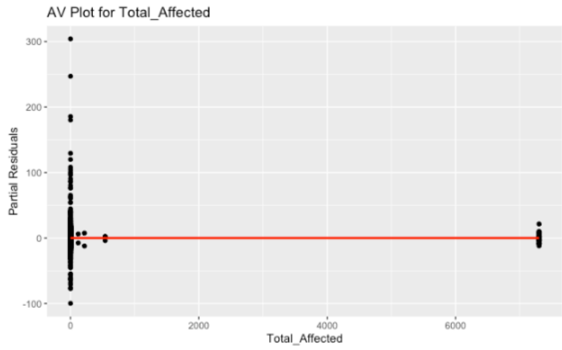


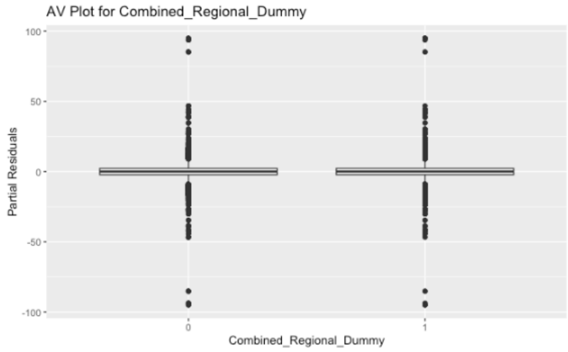
Appendix Figure 10: B2 Model AV Plots: Three-Year Percentage Change in Total Number of Businesses vs Three-Year Lagged Disaster Occurrence[29]

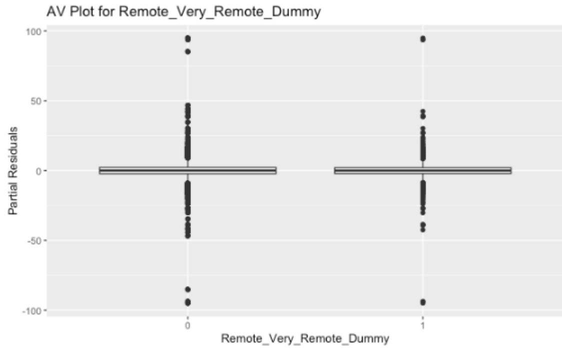


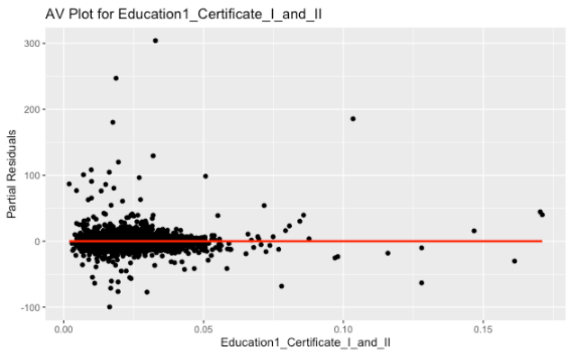
[29] number_businesses_3y_pct_change ~
ERP + number_businesses_total_number_of_businesses_num +
Lagged3y_Disaster_Occurred_Dummy + Total_Affected +
Major_Cities_Dummy + Combined_Regional_Dummy +
Remote_Very_Remote_Dummy + Education1_Certificate_I_and_II +
Education2_Certificate_III_and_IV + Education3_Advanced_Diploma_and_Diploma +
Education4_Bachelor_Degree + Education5_Postgraduate_Degree +
Unemployment_Rate + factor(Year)

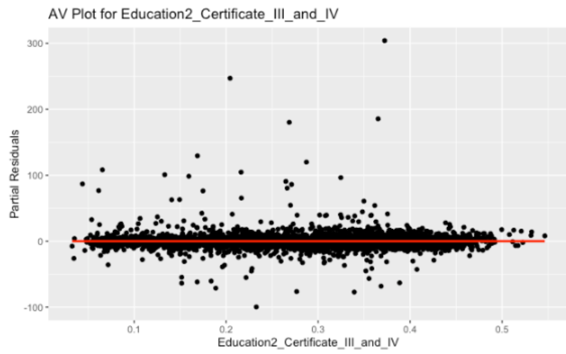

AV Plot for ERP
Partial Residuals
ERP

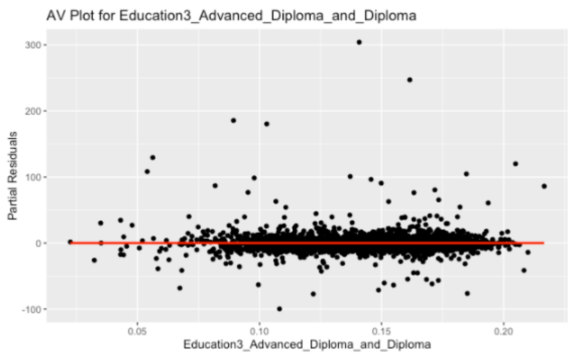

AV Plot for Total_Affected
Partial Residuals
Total_Affected

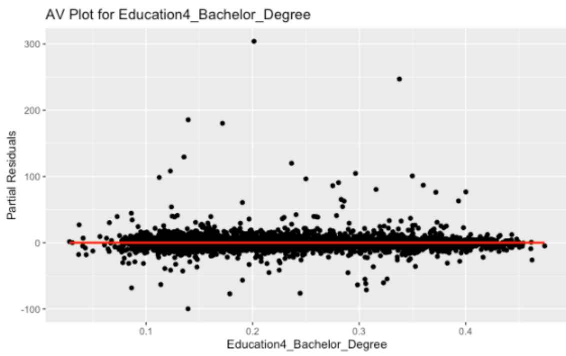

AV Plot for Combined_Regional_Dummy
Partial Residuals
Combined_Regional_Dummy

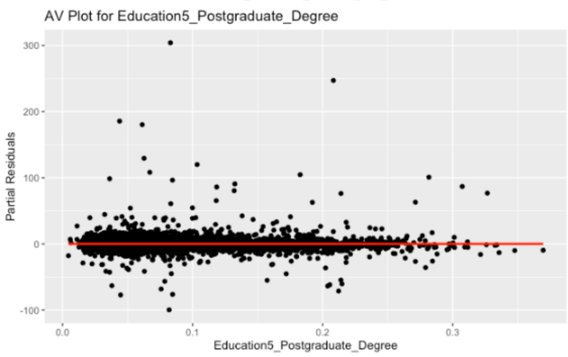

AV Plot for Remote_Very_Remote_Dummy
Partial Residuals
Remote_Very_Remote_Dummy

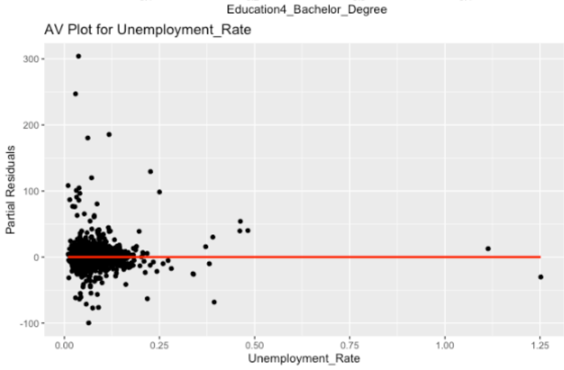

AV Plot for Education1_Certificate_I_and_II
Partial Residuals
Education1_Certificate_I_and_II


AV Plot for Education2_Certificate_III_and_IV
Partial Residuals
Education2_Certificate_III_and_IV

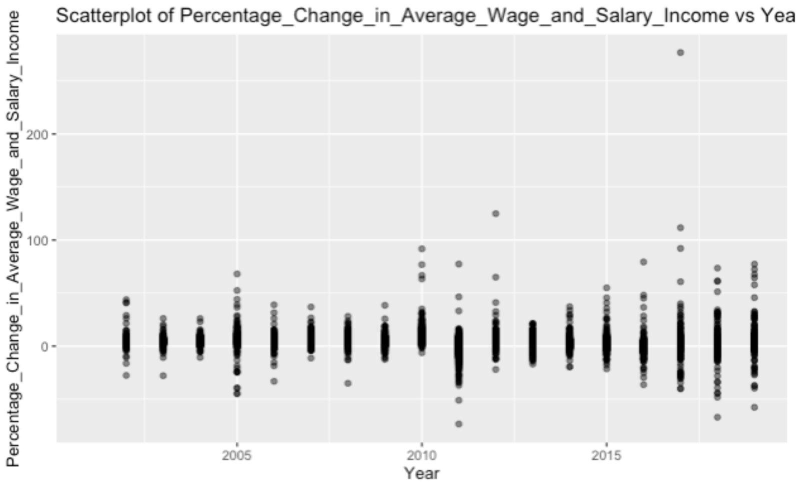

AV Plot for Education3_Advanced_Diploma_and_Diploma
Partial Residuals
Education3_Advanced_Diploma_and_Diploma


AV Plot for Education4_Bachelor_Degree
Partial Residuals
Education4_Bachelor_Degree

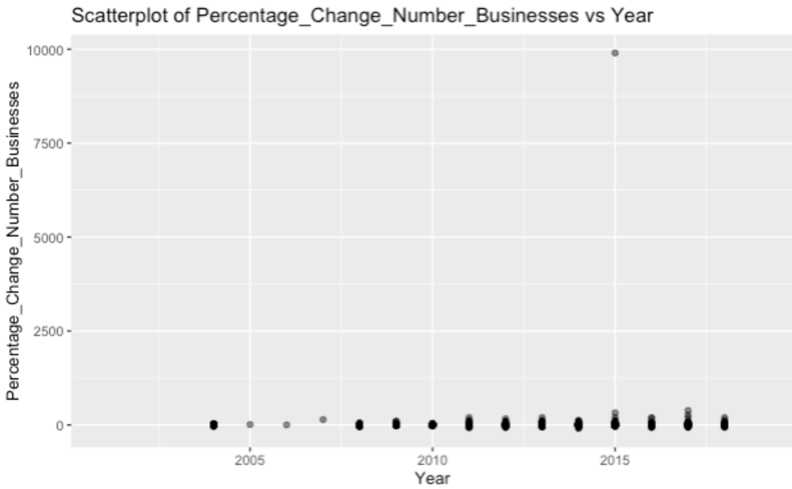

AV Plot for Education5_Postgraduate_Degree
Partial Residuals
Education5_Postgraduate_Degree


AV Plot for Unemployment_Rate
Partial Residuals
Unemployment_Rate

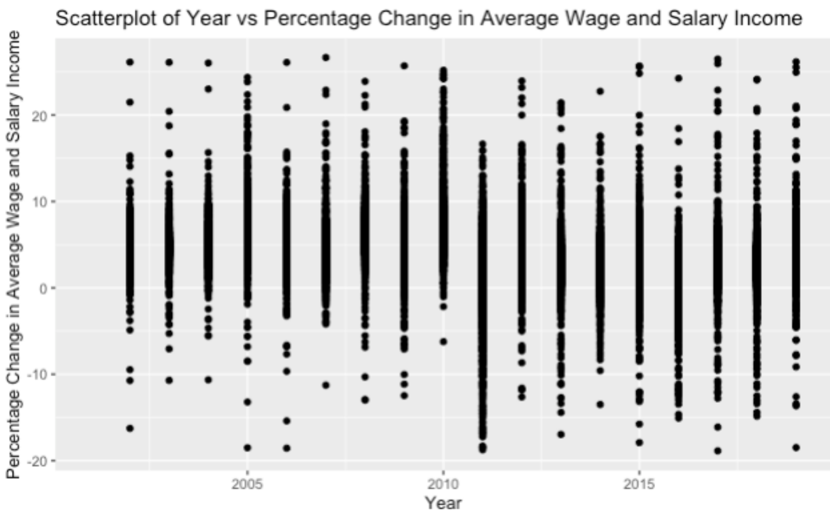
Appendix Figure 11: A1 Model Outliers



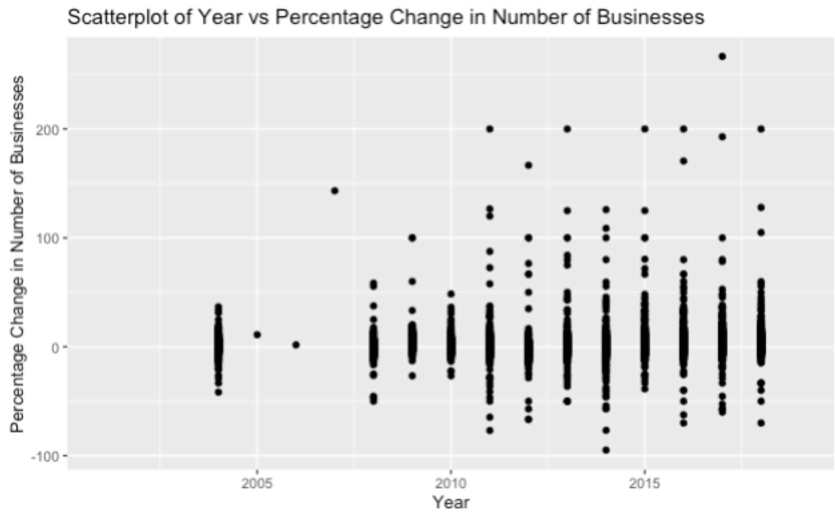
Appendix Figure 12: B1 Model Outliers



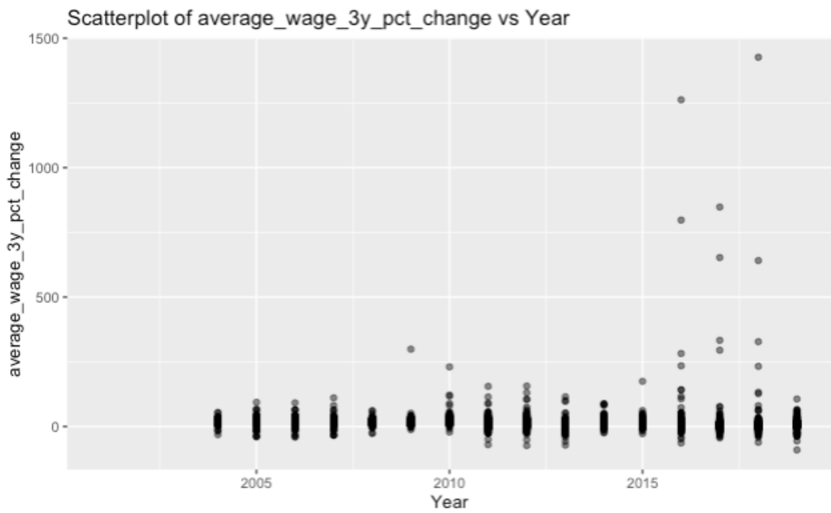
Appendix Figure 13: A1 Model Outliers Removed



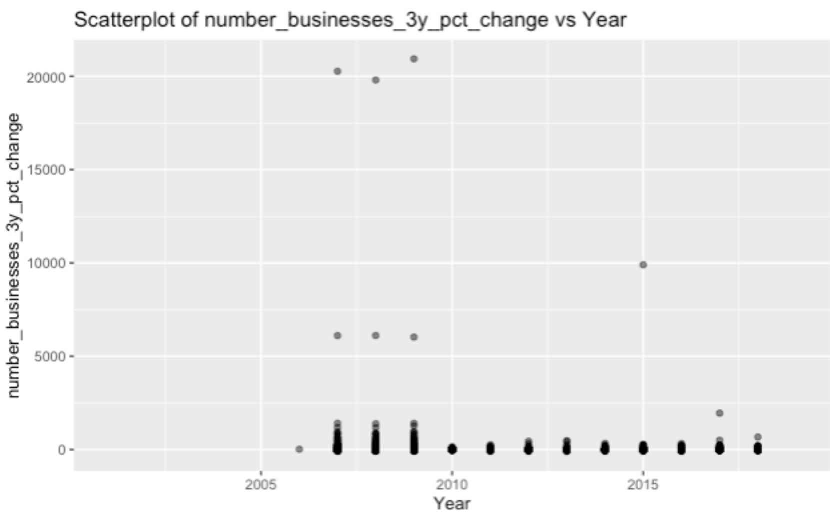
Appendix Figure 14: B1 Model Outliers Removed



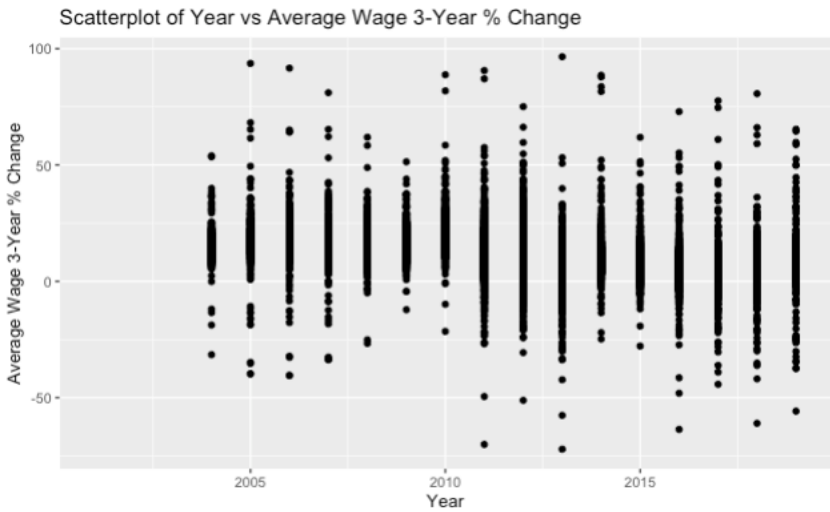
Appendix Figure 15: A2 Model Outliers



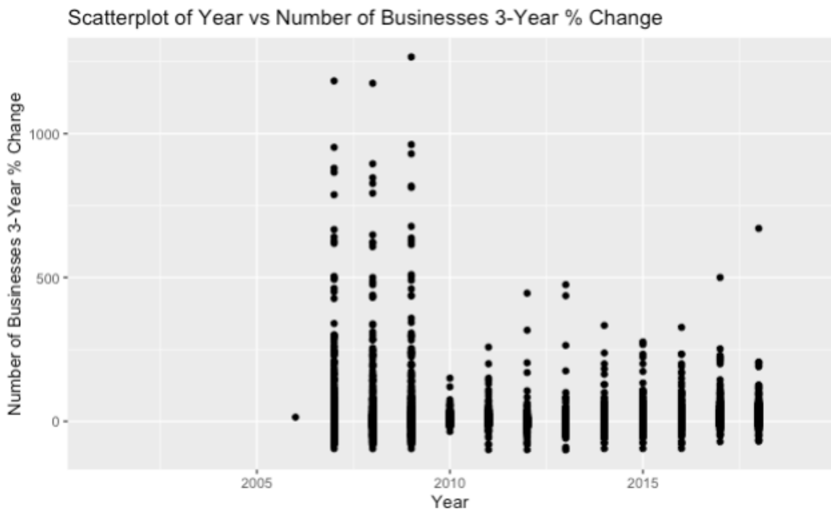
Appendix Figure 16: B2 Model Outliers



Appendix Figure 17: A2 Model Outliers Removed

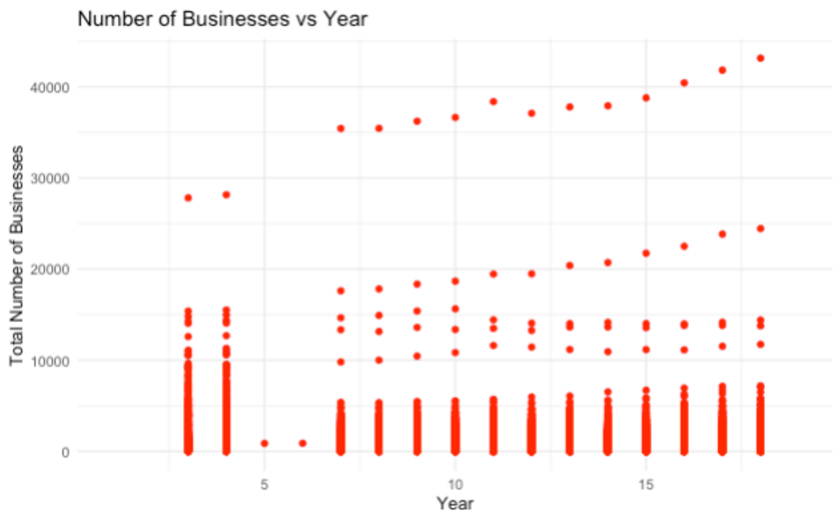


Appendix Figure 18: B2 Model Outliers Removed

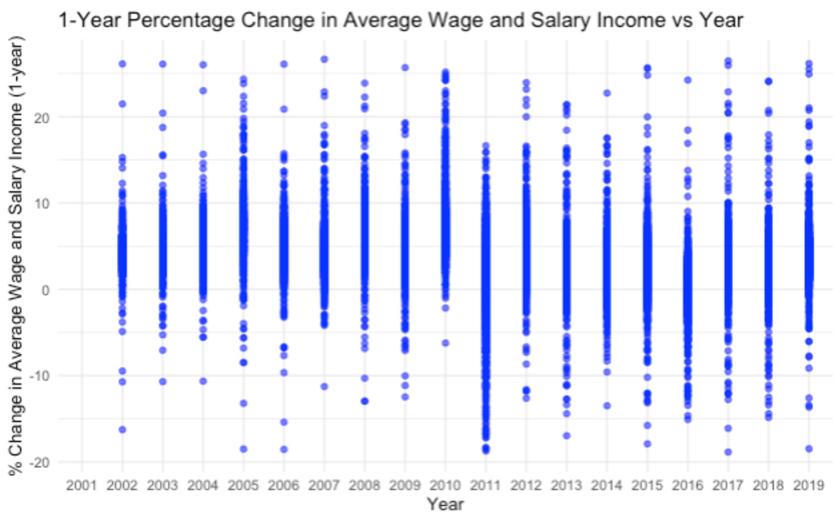


Appendix Figure 19: Descriptive Overview - Average Income vs Year

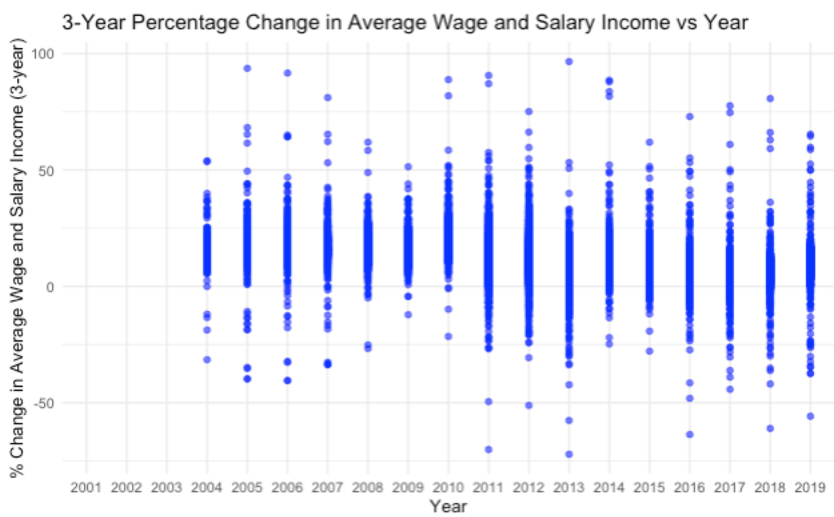
Appendix Figure 20: Descriptive Overview - Number of Businesses vs Year



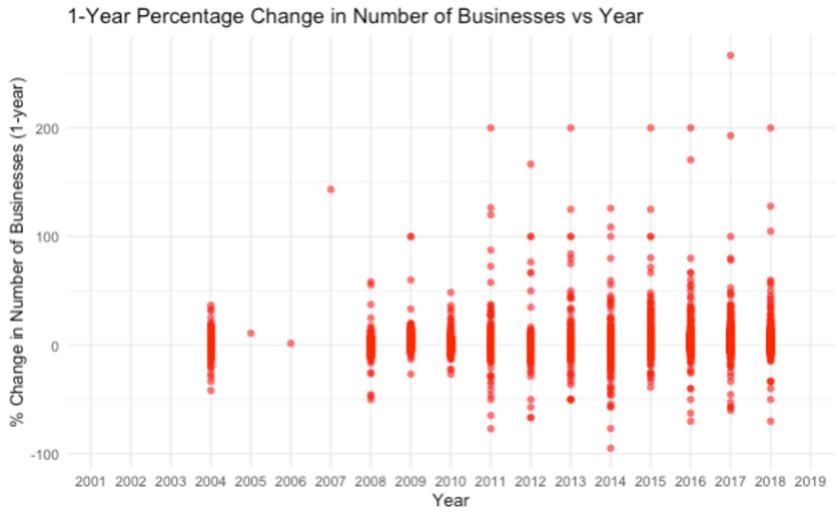
Appendix Figure 21: Descriptive Overview - 1-Year % Change Income vs Year



Appendix Figure 22: Descriptive Overview - 3-Year % Change Income vs Year

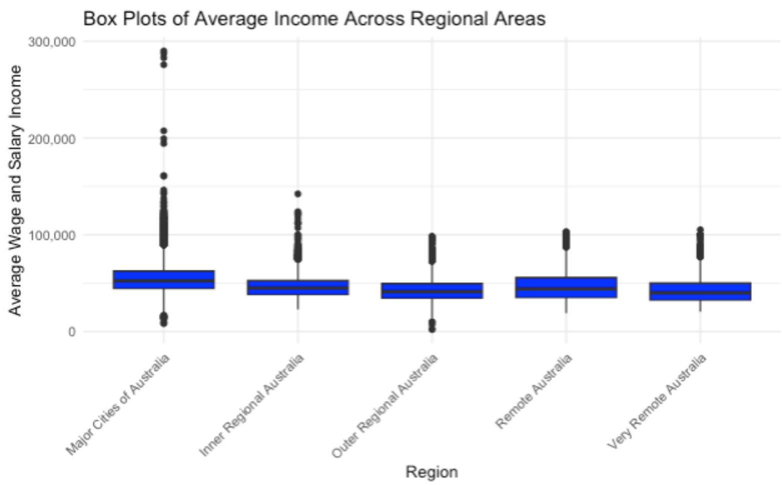


Appendix Figure 23: Descriptive Overview - 1-Year % Change Businesses vs Year

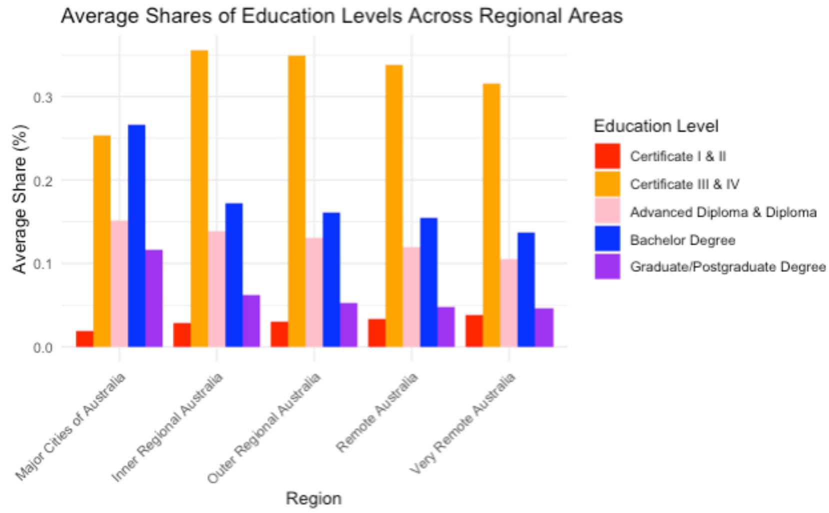


Appendix Figure 24: Descriptive Overview - 3-Year % Change Businesses vs Year

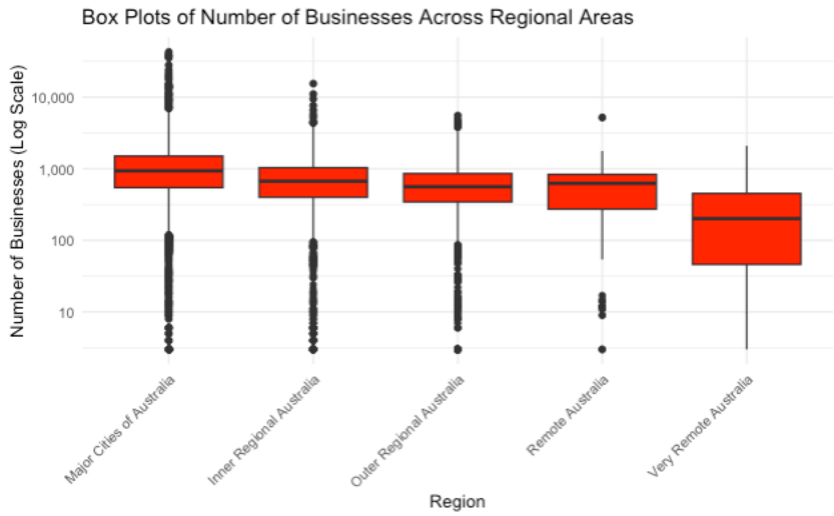
Appendix Figure 25: Descriptive Overview - Average Income vs Regionality



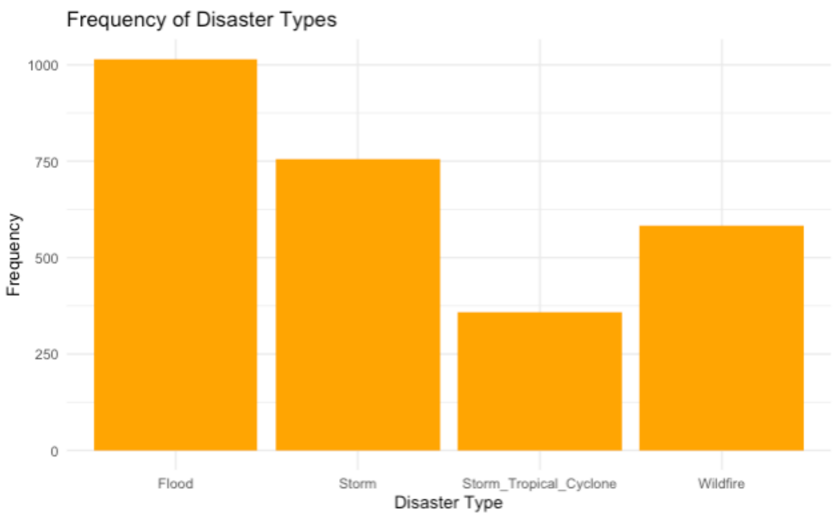
Appendix Figure 26: Average Education vs Regionality



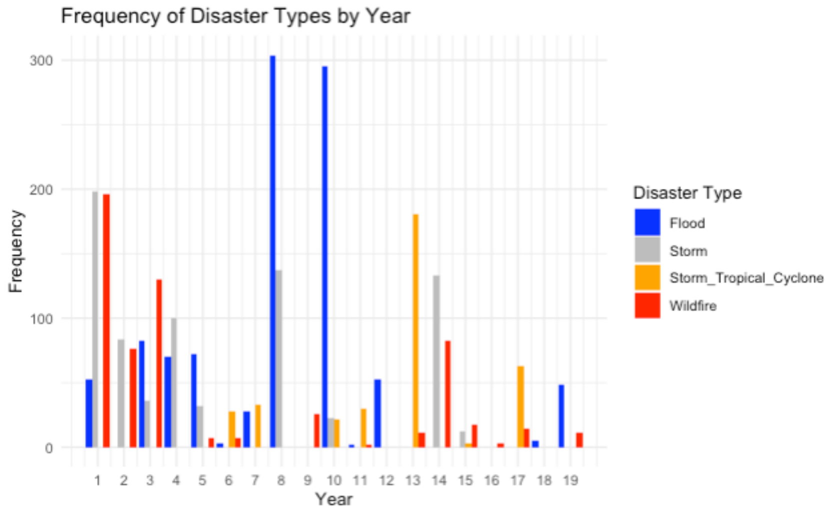
Appendix Figure 27: Number of Businesses vs Regionality



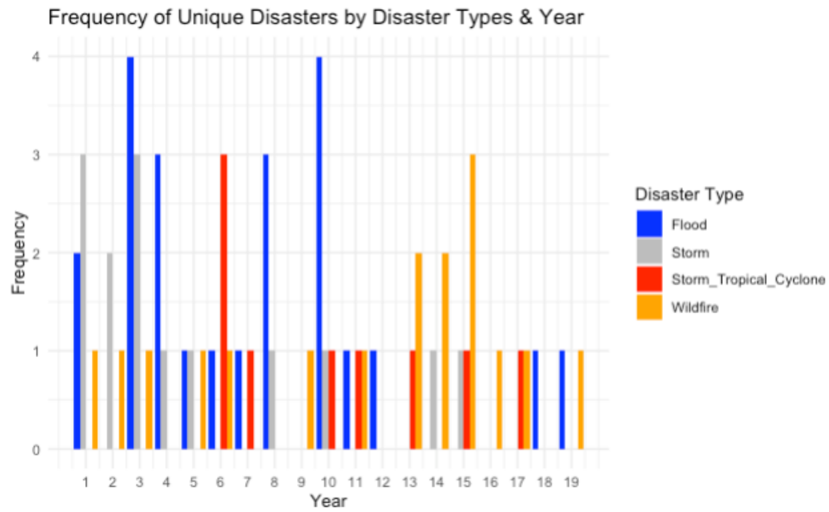
Appendix Figure 28: Descriptive Overview - Disaster Type Frequencies



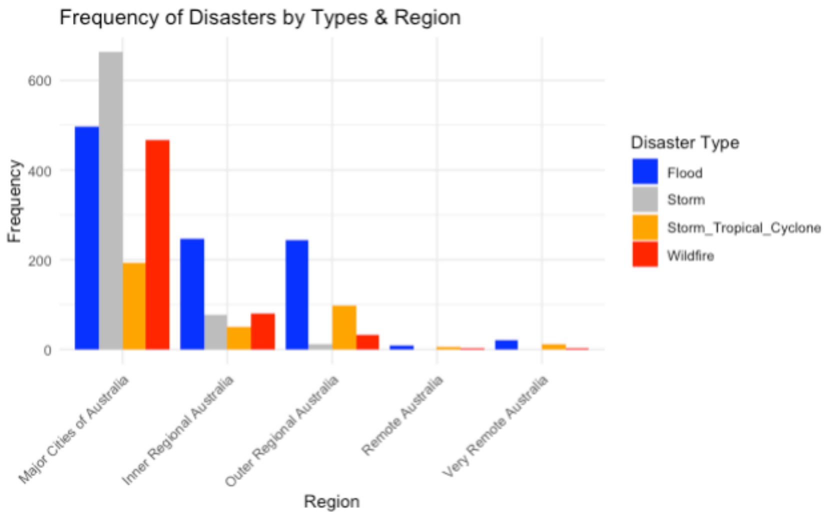
Appendix Figure 29: Descriptive Overview - Disaster Type Frequencies vs Year



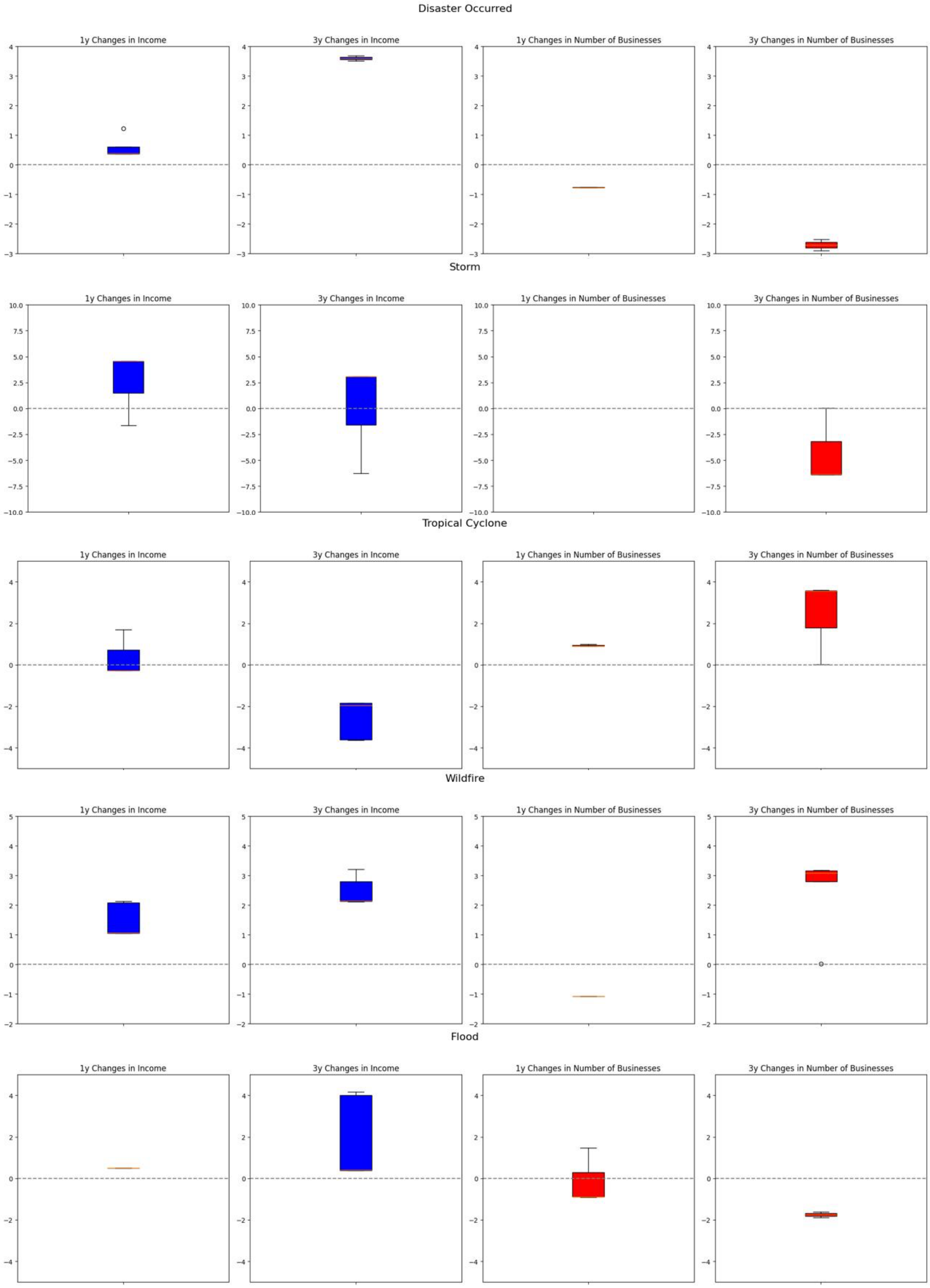
Appendix Figure 30: Descriptive Overview - Disaster Type Frequencies (Unique Disasters) vs Year



Appendix Figure 31: Descriptive Overview - Frequency of Disasters by Type & Region



Appendix Figure 32: Boxplots of Statistically Significant Disaster Coefficients



Tables with Full Results of Regression Analysis

Appendix Table 4: A1.1 – 1y Changes in Income – Disaster Occurred

Dependent Variable **1y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001’’’	-0.0001’**	-0.0001***	-0.0001***	-0.0001	-0.0001	-0.0001
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.0001)	(-0.0001)	(-0.0001)
Average_Wage_and_Salary_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0003***	0.0003***	0.0003***
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00005)	(-0.00005)	(-0.00005)
Lagged1y_Disaster_Occurred_Dummy	**0.369*****	**0.365*****	**1.230****	**0.393*****	0.239	0.202	
	(-0.069)	(-0.069)	(-0.515)	(-0.07)	(-0.278)	(-0.279)	
Major_Cities_Dummy		-0.314					
		(-0.437)					
Inner_Regional_Dummy		0.1					
		(-0.417)					
Outer_Regional_Dummy		-0.496					
		(-0.406)					
Remote_Very_Remote_Dummy		1.333					
		(-0.895)					
I(Lagged1y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			**-0.874***				**0.687***

	(-0.522)				(-0.388)
I(Lagged1y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)	-0.837				-0.292
	(-0.534)				(-0.409)
I(Lagged1y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)	**-1.003***				-0.697
	(-0.536)				(-0.512)
I(Lagged1y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)					-1.711
					(-1.534)
Total_Affected		-0.00001***		-0.0003**	
		(0)		(-0.0001)	
I(Lagged1y_Disaster_Occurred_Dummy * Total_Affected)					
Education1_Certificate_I_and_II			-74.899**	-74.693**	-75.539**
			(-31.554)	(-31.683)	(-31.663)
Education2_Certificate_III_and_IV			0.154	0.58	0.816
			(-6.931)	(-6.939)	(-6.912)
Education3_Advanced_Diploma_and_Diploma			44.535***	43.242***	43.728***
			(-10.952)	(-10.94)	(-10.915)
Education4_Bachelor_Degree			25.733***	26.836***	26.297***
			(-8.232)	(-8.227)	(-8.209)

Education5_Postgraduate_Degree					-20.561*	-20.690*	-16.54
					(-11.066)	(-11.082)	(-11.268)
Unemployment_Rate					-15.737	-16.863	-15.418
					(-10.195)	(-10.858)	(-10.107)
Year2003-2019	***	***	***	***	-	-	-
Year2016					-2.712***	-2.764***	-2.765***
					(-0.4)	(-0.401)	(-0.399)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	32,694	32,694	32,694	32,694	4,062	4,062	4,062
R^2	0.296	0.296	0.296	0.296	0.069	0.072	0.071
Adjusted R^2	0.243	0.243	0.243	0.243	-0.998	-0.995	-0.997
F Statistic	638.300*** (df = 20; 30422)	532.216*** (df = 24; 30418)	555.311*** (df = 23; 30419)	608.263*** (df = 21; 30421)	14.104*** (df = 10; 1891)	13.279*** (df = 11; 1890)	11.168*** (df = 13; 1888)

Appendix Table 5: A1_2 – 1y Changes in Income – Storm

Dependent Variable **1y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001***	-0.0001***	-0.00005***	-0.0001***	-0.0002*	-0.0002*	-0.0002*
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.0001)	(-0.0001)	(-0.0001)
Average_Wage_and_Salary_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0003***	0.0003***	0.0003***
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00005)	(-0.00005)	(-0.00005)
Lagged1y_Disaster_Dummy_Storm	0.012	0.003	**-1.622***	-0.004	**4.594***	**4.554***	
	(-0.12)	(-0.12)	(-0.428)	(-0.12)	(-0.923)	(-0.926)	
Major_Cities_Dummy		-0.214					
		(-0.437)					
Inner_Regional_Dummy		0.138					
		(-0.417)					
Outer_Regional_Dummy		-0.503					
		(-0.407)					
Remote_Very_Remote_Dummy		1.309					
		(-0.896)					
I(Lagged1y_Disaster_Dummy_Storm * Major_Cities_Dummy)			**1.691***				**4.701***
			(-0.449)				(-0.953)

I(Lagged1y_Disaster_Dummy_Storm * Inner_Regional_Dummy)	**1.564*****				**1.801*****
	(-0.502)				(-0.231)
I(Lagged1y_Disaster_Dummy_Storm * Outer_Regional_Dummy)					
I(Lagged1y_Disaster_Dummy_Storm * Remote_Very_Remote_Dummy)					
Total_Affected		-0.00001*		-0.0003**	
		(0)		(-0.0001)	
I(Lagged1y_Disaster_Dummy_Storm * Total_Affected)					
Education1_Certificate_I_and_II			-75.545**	-75.392**	-75.255**
			(-31.402)	(-31.518)	(-31.411)
Education2_Certificate_III_and_IV			-0.11	0.282	-0.179
			(-6.92)	(-6.923)	(-6.922)
Education3_Advanced_Diploma_and_Diploma			44.119***	42.865***	44.227***
			(-10.873)	(-10.859)	(-10.876)
Education4_Bachelor_Degree			29.150***	30.162***	29.166***
			(-8.15)	(-8.141)	(-8.15)
Education5_Postgraduate_Degree			-22.381**	-22.307**	-22.499**
			(-11.01)	(-11.032)	(-11.013)

Unemployment_Rate					-14.296	-15.384	-14.261
					(-9.487)	(-10.118)	(-9.47)
Year2003-2019	***	***	***	***	-	-	-
Year2016					-2.623***	-2.670***	-2.619***
					(-0.393)	(-0.394)	(-0.393)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	32,694	32,694	32,694	32,694	4,062	4,062	4,062
R2	0.295	0.295	0.295	0.295	0.079	0.082	0.08
Adjusted R2	0.242	0.242	0.242	0.242	-0.977	-0.973	-0.978
F Statistic	636.394*** (df = 20; 30422)	530.673*** (df = 24; 30418)	578.792*** (df = 22; 30420)	606.244*** (df = 21; 30421)	16.318*** (df = 10; 1891)	15.279*** (df = 11; 1890)	14.856*** (df = 11; 1890)

Appendix Table 6: A1.3 1y Changes in Income – Tropical Cyclone

Dependent Variable **1y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.00005***	-0.0001***	-0.00005***	-0.0001***	-0.0001	-0.0001	-0.0001
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.0001)	(-0.0001)	(-0.0001)
Average_Wage_and_Salary_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0003***	0.0003***	0.0003***
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00005)	(-0.00005)	(-0.00005)
Lagged1y_Disaster_Dummy_Tropical_Cyclone_Storm	**-0.268***	**-0.271***	**1.697***	-0.191	-0.107	-0.197	
	(-0.151)	(-0.151)	(-0.961)	(-0.169)	(-0.978)	(-0.985)	
Major_Cities_Dummy		-0.208					
		(-0.437)					
Inner_Regional_Dummy		0.133					
		(-0.417)					
Outer_Regional_Dummy		-0.505					
		(-0.407)					
Remote_Very_Remote_Dummy		1.309					
		(-0.895)					
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone_Storm * Major_Cities_Dummy)			**-2.393****				
			(-0.98)				
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone_Storm * Inner_Regional_Dummy)			**-2.119***				-1.163

	(-1.085)				(-1.285)
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone_Storm * Outer_Regional_Dummy)	-1.46				2.081
	(-0.983)				(-1.432)
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone_Storm * Remote_Very_Remote_Dummy)					-2.152
					(-2.559)
Total_Affected		0		-0.0003**	
		(0)		(-0.0001)	
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone_Storm * Total_Affected)					
Education1_Certificate_I_and_II			-74.479**	-74.293**	-74.476**
			(-31.623)	(-31.755)	(-31.681)
Education2_Certificate_III_and_IV			0.348	0.764	0.033
			(-6.939)	(-6.946)	(-6.948)
Education3_Advanced_Diploma_and_Diploma			44.493***	43.184***	44.466***
			(-10.965)	(-10.95)	(-10.968)
Education4_Bachelor_Degree			25.982***	27.070***	25.647***
			(-8.231)	(-8.221)	(-8.237)
Education5_Postgraduate_Degree			-21.863**	-21.797*	-22.227**
			(-11.127)	(-11.154)	(-11.157)
Unemployment_Rate			-15.968	-17.137	-16.181
			(-10.45)	(-11.152)	(-10.598)

Year2003-2019	***	***	***	***	-	-	-
Year2016					-2.751***	-2.802***	-2.757***
					(-0.399)	(-0.401)	(-0.401)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	32,694	32,694	32,694	32,694	4,062	4,062	4,062
R2	0.295	0.295	0.295	0.295	0.069	0.072	0.07
Adjusted R2	0.242	0.242	0.243	0.242	-0.999	-0.995	-0.999
F Statistic	636.599*** (df = 20; 30422)	530.849*** (df = 24; 30418)	554.478*** (df = 23; 30419)	606.321*** (df = 21; 30421)	14.044*** (df = 10; 1891)	13.242*** (df = 11; 1890)	11.896*** (df = 12; 1889)

Appendix Table 7: A1.4 – 1y Changes in Income – Wildfire

Dependent Variable **1y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001	-0.0001	-0.0001
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.0001)	(-0.0001)	(-0.0001)
Average_Wage_and_Salary_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0003***	0.0003***	0.0003***
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00005)	(-0.00005)	(-0.00005)
Lagged1y_Disaster_Dummy_Wildfire	**1.056*****	**1.048*****	0.217	**1.061*****	**2.087***	**2.125***	
	(-0.128)	(-0.129)	(-0.639)	(-0.128)	(-1.117)	(-1.12)	
Major_Cities_Dummy		-0.323					
		(-0.436)					
Inner_Regional_Dummy		0.041					
		(-0.418)					
Outer_Regional_Dummy		-0.515					
		(-0.406)					
Remote_Very_Remote_Dummy		1.34					
		(-0.892)					
I(Lagged1y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			1.061				1.972
			(-0.656)				(-1.755)

I(Lagged1y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)	0.348				2.225
	(-0.732)				(-1.488)
I(Lagged1y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)	-0.135				**2.169*****
	(-0.775)				(-0.258)
I(Lagged1y_Disaster_Dummy_Wildfire * Remote_Very_Remote_Dummy)					
Total_Affected		-0.00001**		-0.0003**	
		(0)		(-0.0001)	
I(Lagged1y_Disaster_Dummy_Wildfire * Total_Affected)					
Education1_Certificate_I_and_II			-76.588**	-76.473**	-76.664**
			(-31.48)	(-31.599)	(-31.489)
Education2_Certificate_III_and_IV			0.088	0.492	0.105
			(-6.95)	(-6.954)	(-6.955)
Education3_Advanced_Diploma_and_Diploma			44.708***	43.392***	44.710***
			(-10.98)	(-10.966)	(-10.98)
Education4_Bachelor_Degree			25.664***	26.751***	25.658***
			(-8.234)	(-8.224)	(-8.233)
Education5_Postgraduate_Degree			-20.678*	-20.584*	-20.672*
			(-11.144)	(-11.17)	(-11.141)

Unemployment_Rate					-15.904	-17.031	-15.895
					(-10.249)	(-10.911)	(-10.248)
Year2003-2019	***	***	***	***	-	-	-
Year2016					-2.791***	-2.840***	-2.791***
					(-0.401)	(-0.403)	(-0.401)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	32,694	32,694	32,694	32,694	4,062	4,062	4,062
R2	0.296	0.296	0.296	0.296	0.07	0.073	0.07
Adjusted R2	0.243	0.243	0.243	0.243	-0.996	-0.992	-0.998
F Statistic	639.444*** (df = 20; 30422)	533.171*** (df = 24; 30418)	556.349*** (df = 23; 30419)	609.179*** (df = 21; 30421)	14.329*** (df = 10; 1891)	13.509*** (df = 11; 1890)	11.929*** (df = 12; 1889)

Appendix Table 8: A1.5 – 1y Changes in Income – Flood

Dependent Variable **1y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001	-0.0001	-0.0001
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.0001)	(-0.0001)	(-0.0001)
Average_Wage_and_Salary_Income	0.0001***	0.0001***	0.0001***	0.0001***	0.0003***	0.0003***	0.0003***
	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00001)	(-0.00005)	(-0.00005)	(-0.00005)
Lagged1y_Disaster_Dummy_Flood	**0.498***	**0.495***	1.049	**0.489***	-0.433	-0.471	
	(-0.117)	(-0.117)	(-0.672)	(-0.117)	(-0.298)	(-0.299)	
Major_Cities_Dummy		-0.233					
		(-0.437)					
Inner_Regional_Dummy		0.164					
		(-0.417)					
Outer_Regional_Dummy		-0.486					
		(-0.407)					
Remote_Very_Remote_Dummy		1.319					
		(-0.897)					
I(Lagged1y_Disaster_Dummy_Flood * Major_Cities_Dummy)			-0.607				-0.142
			(-0.691)				(-0.415)
I(Lagged1y_Disaster_Dummy_Flood * Inner_Regional_Dummy)			-0.413				-0.585

	(-0.692)				(-0.427)
I(Lagged1y_Disaster_Dummy_Flood * Outer_Regional_Dummy)	-0.66				**-1.541*****
	(-0.703)				(-0.483)
I(Lagged1y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)					-1.432
					(-1.661)
Total_Affected		-0.00001		-0.0003**	
		(0)		(-0.0001)	
I(Lagged1y_Disaster_Dummy_Flood * Total_Affected)					
Education1_Certificate_I_and_II			-74.537**	-74.384**	-75.490**
			(-31.589)	(-31.715)	(-31.603)
Education2_Certificate_III_and_IV			0.52	0.952	1.108
			(-6.964)	(-6.971)	(-6.954)
Education3_Advanced_Diploma_and_Diploma			44.407***	43.057***	44.021***
			(-10.98)	(-10.966)	(-10.97)
Education4_Bachelor_Degree			26.645***	27.815***	26.793***
			(-8.261)	(-8.253)	(-8.259)
Education5_Postgraduate_Degree			-23.978**	-24.090**	-20.776*
			(-11.122)	(-11.146)	(-11.311)

Unemployment_Rate					-15.82	-16.96	-15.38
					(-10.178)	(-10.84)	(-10.054)
Year2003-2019	***	***	***	***	-	-	-
Year2016					-2.795***	-2.848***	-2.833***
					(-0.403)	(-0.404)	(-0.402)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	32,694	32,694	32,694	32,694	4,062	4,062	4,062
R2	0.295	0.296	0.295	0.295	0.07	0.072	0.071
Adjusted R2	0.243	0.243	0.243	0.243	-0.998	-0.993	-0.999
F Statistic	637.887*** (df = 20; 30422)	531.905*** (df = 24; 30418)	554.742*** (df = 23; 30419)	607.610*** (df = 21; 30421)	14.200*** (df = 10; 1891)	13.408*** (df = 11; 1890)	11.067*** (df = 13; 1888)

Appendix Table 9: A2.1 – 3y Changes in Income – Disaster Occurred

Dependent Variable 3y Percentage Change in Average Wage & Salary Income	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001**	-0.0001**	-0.0001**	-0.0001**	-0.0003	-0.0003	-0.0003
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Average_Wage_and_Salary_Income	0.0005***	0.0005***	0.0005***	0.0005***	0.001***	0.001***	0.001***
	(-0.00004)	(-0.00004)	(-0.00004)	(-0.00004)	(-0.0001)	(-0.0001)	(-0.0001)
Lagged3y_Disaster_Occurred_Dummy	0.162	0.152	0.427	0.111	**3.512***	**3.682***	
	(-0.138)	(-0.139)	(-0.901)	(-0.138)	(-0.57)	(-0.585)	
Major_Cities_Dummy		-1.707					
		(-1.057)					
Inner_Regional_Dummy		0.469					
		(-0.941)					
Outer_Regional_Dummy		-2.424***					
		(-0.908)					
Remote_Very_Remote_Dummy		5.442**					
		(-2.598)					
I(Lagged3y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			-0.288				**2.859***
			(-0.915)				(-0.702)
I(Lagged3y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)			0.282				**6.443***

	(-0.948)				(-1.111)
I(Lagged3y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)	-0.835				**2.800****
	(-0.958)				(-1.208)
I(Lagged3y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)					0.678
					(-2.473)
Total_Affected		-0.00004***		-0.0003	
		(-0.00001)		(-0.0002)	
I(Lagged3y_Disaster_Occurred_Dummy * Total_Affected)					
Education1_Certificate_I_and_II			-219.725***	-220.098***	-216.956***
			(-66.892)	(-67.018)	(-67.069)
Education2_Certificate_III_and_IV			-1.87	-1.412	-2.069
			(-15.824)	(-15.842)	(-15.858)
Education3_Advanced_Diploma_and_Diploma			79.587***	78.904***	78.733***
			(-21.809)	(-21.818)	(-21.67)
Education4_Bachelor_Degree			44.382**	45.111**	43.907**
			(-21.314)	(-21.334)	(-21.266)
Education5_Postgraduate_Degree			-125.578***	-125.817***	-126.484***
			(-26.433)	(-26.44)	(-26.345)
Unemployment_Rate			-11.86	-12.446	-11.137
			(-14.201)	(-14.464)	(-14.035)

Year2003-2019	***	***	***	***	-	-	-
Year2016					-10.670***	-10.678***	-10.635***
					(-0.982)	(-0.983)	(-0.983)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	28,414	28,414	28,414	28,414	4,086	4,086	4,086
R2	0.391	0.392	0.392	0.392	0.378	0.378	0.38
Adjusted R2	0.339	0.339	0.339	0.339	-0.326	-0.327	-0.324
F Statistic	934.697*** (df = 18; 26151)	765.811*** (df = 22; 26147)	801.431*** (df = 21; 26148)	887.404*** (df = 19; 26150)	116.454*** (df = 10; 1915)	105.955*** (df = 11; 1914)	90.249*** (df = 13; 1912)

Appendix Table 10: A2.2 – 3y Changes in Income – Storm

Dependent Variable 3y Percentage Change in Average Wage & Salary Income	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001**	-0.0001**	-0.0001**	-0.0001**	-0.0003	-0.0003	-0.0003
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Average_Wage_and_Salary_Income	0.0005***	0.0005***	0.0005***	0.0005***	0.001***	0.001***	0.001***
	(-0.00004)	(-0.00004)	(-0.00004)	(-0.00004)	(-0.0001)	(-0.0001)	(-0.0001)
Lagged3y_Disaster_Dummy_Storm	-0.274	-0.293	**-6.270*** **	-0.415	**3.072*** **	**3.085*** **	
	(-0.279)	(-0.28)	(-1.622)	(-0.28)	(-0.687)	(-0.687)	
Major_Cities_Dummy		-1.578					2.706***
		(-1.061)					(-0.761)
Inner_Regional_Dummy		0.548					5.992***
		(-0.943)					(-0.833)
Outer_Regional_Dummy		-2.422***					
		(-0.911)					
Remote_Very_Remote_Dummy		5.423**					
		(-2.602)					
I(Lagged3y_Disaster_Dummy_Storm * Major_Cities_Dummy)			**6.226*** **				
			(-1.652)				
I(Lagged3y_Disaster_Dummy_Storm * Inner_Regional_Dummy)			**5.419*** **				

			(-1.716)				
I(Lagged3y_Disaster_Dummy_Storm * Outer_Regional_Dummy)							
I(Lagged3y_Disaster_Dummy_Storm * Remote_Very_Remote_Dummy)							
Total_Affected				-0.00004***		0.0001	
				(-0.00001)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Storm * Total_Affected)							
Education1_Certificate_I_and_II					-216.311***	-216.582***	-213.842***
					(-68.116)	(-68.064)	(-68.327)
Education2_Certificate_III_and_IV					-1.414	-1.558	-1.943
					(-16.015)	(-16.015)	(-16.053)
Education3_Advanced_Diploma_and_Diploma					77.208***	77.774***	76.427***
					(-21.924)	(-21.927)	(-21.93)
Education4_Bachelor_Degree					46.922**	46.541**	46.861**
					(-21.383)	(-21.404)	(-21.379)
Education5_Postgraduate_Degree					-122.127***	-122.166***	-122.722***
					(-26.514)	(-26.506)	(-26.537)
Unemployment_Rate					-14.26	-13.966	-14.348
					(-15.007)	(-15.013)	(-15.039)

Year2005-2019	***	***	***	***	-	-	-
Year2016					-11.183***	-11.164***	-11.178***
					(-0.973)	(-0.973)	(-0.972)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	28,414	28,414	28,414	28,414	4,086	4,086	4,086
R2	0.391	0.392	0.392	0.392	0.373	0.373	0.373
Adjusted R2	0.339	0.339	0.339	0.339	-0.338	-0.339	-0.338
F Statistic	934.687*** (df = 18; 26151)	765.822*** (df = 22; 26147)	842.175*** (df = 20; 26149)	887.547*** (df = 19; 26150)	113.743*** (df = 10; 1915)	103.382*** (df = 11; 1914)	103.546*** (df = 11; 1914)

Appendix Table 11: A2.3 – 3y Changes in Income – Tropical Cyclone

Dependent Variable **3y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001**	-0.0001**	-0.0001*	-0.0001*	-0.0003*	-0.0003*	-0.0003*
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Average_Wage_and_Salary_Income	0.0005***	0.0005***	0.0005***	0.0005***	0.001***	0.001***	0.001***
	(-0.00004)	(-0.00004)	(-0.00004)	(-0.00004)	(-0.0001)	(-0.0001)	(-0.0001)
Lagged3y_Disaster_Dummy_Tropical_Cyclone_Storm	**-1.834*** **	**-1.840*** **	0.352	**-1.959*** **	**-3.611*** **	**-3.629*** **	
	(-0.3)	(-0.3)	(-1.461)	(-0.302)	(-0.74)	(-0.741)	
Major_Cities_Dummy		-1.571					
		(-1.056)					
Inner_Regional_Dummy		0.509					
		(-0.94)					
Outer_Regional_Dummy		-2.406***					
		(-0.907)					
Remote_Very_Remote_Dummy		5.457**					
		(-2.602)					
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Major_Cities_Dummy)			**-3.230** **				**-3.619*** **
			(-1.524)				(-0.788)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Inner_Regional_Dummy)			-1.671				-2.75

	(-1.766)				(-2.174)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Outer_Regional_Dummy)	-1.128				**-10.133*****
	(-1.511)				(-1.365)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Remote_Very_Remote_Dummy)					**-8.560*****
					(-1.387)
Total_Affected		-0.00004***		0.0001	
		(-0.00001)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone_Storm * Total_Affected)					
Education1_Certificate_I_and_II			-213.618***	-213.920***	-210.887***
			(-67.287)	(-67.217)	(-67.636)
Education2_Certificate_III_and_IV			-0.896	-1.063	-1.376
			(-15.533)	(-15.529)	(-15.695)
Education3_Advanced_Diploma_and_Diploma			69.766***	70.393***	69.133***
			(-21.438)	(-21.437)	(-21.501)
Education4_Bachelor_Degree			41.791**	41.317*	42.119**
			(-21.089)	(-21.111)	(-21.1)
Education5_Postgraduate_Degree			-103.778***	-103.732***	-103.776***
			(-26.121)	(-26.102)	(-26.378)
Unemployment_Rate			-11.628	-11.269	-11.778
			(-14.499)	(-14.492)	(-14.59)

Year2005-2019	***	***	***	***	-	-	-
Year2016					-10.943***	-10.919***	-10.919***
					(-0.952)	(-0.952)	(-0.962)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	28,414	28,414	28,414	28,414	4,086	4,086	4,086
R2	0.392	0.392	0.392	0.393	0.376	0.376	0.376
Adjusted R2	0.339	0.34	0.34	0.34	-0.331	-0.332	-0.332
F Statistic	936.863*** (df = 18; 26151)	767.605*** (df = 22; 26147)	803.647*** (df = 21; 26148)	889.800*** (df = 19; 26150)	115.386*** (df = 10; 1915)	104.888*** (df = 11; 1914)	88.789*** (df = 13; 1912)

Appendix Table 12: A2.4 – 3y Changes in Income – Wildfire

Dependent Variable **3y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001**	-0.0001**	-0.0001**	-0.0001**	-0.0003*	-0.0003*	-0.0003*
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Average_Wage_and_Salary_Income	0.0005***	0.0005***	0.0005***	0.0005***	0.001***	0.001***	0.001***
	(-0.00004)	(-0.00004)	(-0.00004)	(-0.00004)	(-0.0001)	(-0.0001)	(-0.0001)
Lagged3y_Disaster_Dummy_Wildfire	**2.134***	**2.123***	-0.849	**2.145***	1.789	1.779	
	(-0.29)	(-0.291)	(-1.554)	(-0.29)	(-1.28)	(-1.28)	
Major_Cities_Dummy		-1.907*					
		(-1.055)					
Inner_Regional_Dummy		0.315					
		(-0.956)					
Outer_Regional_Dummy		-2.412***					
		(-0.902)					
Remote_Very_Remote_Dummy		5.497**					
		(-2.588)					
I(Lagged3y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			**3.170**				**2.924***
			(-1.591)				(-0.784)

I(Lagged3y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)	2.504				**3.298*****
	(-1.665)				(-1.186)
I(Lagged3y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)	2.658				-1.117
	(-1.937)				(-3.61)
I(Lagged3y_Disaster_Dummy_Wildfire * Remote_Very_Remote_Dummy)					
Total_Affected		-0.00004***		0.0001	
		(-0.00001)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Wildfire * Total_Affected)					
Education1_Certificate_I_and_II			-202.929***	-203.091***	-202.154***
			(-67.539)	(-67.498)	(-67.588)
Education2_Certificate_III_and_IV			-4.343	-4.465	-4.843
			(-15.913)	(-15.916)	(-16.028)
Education3_Advanced_Diploma_and_Diploma			69.983***	70.397***	70.141***
			(-21.859)	(-21.86)	(-21.869)
Education4_Bachelor_Degree			46.033**	45.737**	46.119**
			(-21.343)	(-21.365)	(-21.348)
Education5_Postgraduate_Degree			-119.707***	-119.727***	-120.291***
			(-26.511)	(-26.504)	(-26.553)

Unemployment_Rate					-12.705	-12.474	-12.749
					(-14.698)	(-14.727)	(-14.709)
Year2005-2019	***	***	***	***	-	-	-
Year2016					-11.329***	-11.314***	-11.328***
					(-0.961)	(-0.96)	(-0.961)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	28,414	28,414	28,414	28,414	4,086	4,086	4,086
R2	0.392	0.393	0.392	0.393	0.369	0.369	0.369
Adjusted R2	0.34	0.34	0.34	0.34	-0.346	-0.346	-0.347
F Statistic	937.835*** (df = 18; 26151)	768.357*** (df = 22; 26147)	803.887*** (df = 21; 26148)	890.463*** (df = 19; 26150)	112.017*** (df = 10; 1915)	101.800*** (df = 11; 1914)	93.302*** (df = 12; 1913)

Appendix Table 13: A2.5 – 3y Changes in Income – Flood

Dependent Variable **3y Percentage Change in Average Wage & Salary Income**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	-0.0001**	-0.0001**	-0.0001**	-0.0001**	-0.0004**	-0.0003*	-0.0003*
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Average_Wage_and_Salary_Income	0.0005***	0.0005***	0.0005***	0.0005***	0.001***	0.001***	0.001***
	(-0.00004)	(-0.00004)	(-0.00004)	(-0.00004)	(-0.0001)	(-0.0001)	(-0.0001)
Lagged3y_Disaster_Dummy_Flood	**0.378***	**0.376***	0.685	**0.403***	**4.016*****	**4.175*****	
	(-0.217)	(-0.217)	(-1.34)	(-0.217)	(-0.602)	(-0.619)	
Major_Cities_Dummy		-1.658					
		(-1.058)					
Inner_Regional_Dummy		0.518					
		(-0.941)					
Outer_Regional_Dummy		-2.415***					
		(-0.909)					
Remote_Very_Remote_Dummy		5.441**					
		(-2.601)					
I(Lagged3y_Disaster_Dummy_Flood* Major_Cities_Dummy)			-0.564				**3.825*****
			(-1.364)				(-0.768)

I(Lagged3y_Disaster_Dummy_Flood * Inner_Regional_Dummy)	0.495				**5.550*****
	(-1.409)				(-1.318)
I(Lagged3y_Disaster_Dummy_Flood * Outer_Regional_Dummy)	-0.556				**3.464*****
	(-1.431)				(-1.226)
I(Lagged3y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)					1.726
					(-2.351)
Total_Affected		-0.00004***		-0.0003	
		(-0.00001)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Flood * Total_Affected)					
Education1_Certificate_I_and_II			-216.241***	-216.287***	-218.580***
			(-66.152)	(-66.282)	(-66.276)
Education2_Certificate_III_and_IV			-1.808	-1.338	-0.306
			(-15.283)	(-15.283)	(-15.342)
Education3_Advanced_Diploma_and_Diploma			72.061***	70.891***	72.684***
			(-21.405)	(-21.403)	(-21.211)
Education4_Bachelor_Degree			38.467*	39.055*	38.235*
			(-21.024)	(-21.027)	(-20.956)
Education5_Postgraduate_Degree			-104.963***	-104.326***	-106.424***
			(-25.783)	(-25.809)	(-26.106)
Unemployment_Rate			-8.842	-9.378	-8.392

					(-13.703)	(-13.934)	(-13.602)
Year2005-2019	***	***	***	***	-	-	-
Year2016					-10.320***	-10.324***	-10.289***
					(-0.962)	(-0.963)	(-0.974)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	28,414	28,414	28,414	28,414	4,086	4,086	4,086
R2	0.392	0.392	0.392	0.392	0.382	0.383	0.383
Adjusted R2	0.339	0.339	0.339	0.339	-0.318	-0.318	-0.318
F Statistic	934.837*** (df = 18; 26151)	765.933*** (df = 22; 26147)	801.497*** (df = 21; 26148)	887.615*** (df = 19; 26150)	118.488*** (df = 10; 1915)	107.837*** (df = 11; 1914)	91.296*** (df = 13; 1912)

Appendix Table 14: B1.1 - 1y Changes in Number of Businesses – Disaster Occurred

Dependent Variable **1y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.0004***	0.0004***	0.0004***	0.0004***	0.0002	0.0002	0.0003
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Lagged1y_Disaster_Occurred_Dummy	(-0.017)	(-0.016)	0.604	(-0.036)	**-0.780****	**-0.751****	
	(-0.16)	(-0.16)	(-0.68)	(-0.163)	(-0.348)	(-0.356)	
number_businesses_total_number_of_businesses_num	0.001***	0.001***	0.001***	0.001***	0.004**	0.004**	0.004**
	(-0.0004)	(-0.0004)	(-0.0004)	(-0.0004)	(-0.002)	(-0.002)	(-0.002)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-0.808)					
		(-1.385)					
Outer_Regional_Dummy		(-0.097)					
		(-0.768)					
Remote_Very_Remote_Dummy		1.003					
		(-1.133)					
I(Lagged1y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			(-0.773)				**-1.889*****
			(-0.71)				(-0.414)

I(Lagged1y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)	(-0.389)				**1.667*****
	(-0.735)				(-0.516)
I(Lagged1y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)	(-0.407)				0.531
	(-0.747)				(-0.664)
I(Lagged1y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)					0.003
					(-2.541)
Total_Affected		0.00001		0.0003*	
		(-0.00001)		(-0.0002)	
I(Lagged1y_Disaster_Occurred_Dummy * Total_Affected)					
Education1_Certificate_I_and_II			121.394	121.026	120.128
			(-141.017)	(-141.167)	(-141.109)
Education2_Certificate_III_and_IV			37.926	37.538	37.46
			(-25.393)	(-25.484)	(-25.452)
Education3_Advanced_Diploma_and_Diploma			59.640**	60.839***	61.197***
			(-23.244)	(-23.031)	(-23.214)
Education4_Bachelor_Degree			63.995***	63.210***	63.054***
			(-17.045)	(-17.143)	(-17.011)
Education5_Postgraduate_Degree			(-36.799)	(-36.906)	-46.847*
			(-23.923)	(-23.903)	(-24.575)

Unemployment_Rate					(-45.312)	(-44.632)	(-45.498)
					(-33.888)	(-34.095)	(-33.817)
Year2005 - 2018	***	***	***	***			
Year2016					2.379^{***}	2.407^{***}	2.499^{***}
					(-0.683)	(-0.675)	(-0.68)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	23,864	23,864	23,864	23,864	4,189	4,189	4,189
R2	0.096	0.096	0.096	0.096	0.112	0.112	0.116
Adjusted R2	0.002	0.001	0.001	0.001	(-0.848)	(-0.848)	(-0.842)
F Statistic	135.319^{***} (df = 17; 21599)	115.019^{***} (df = 20; 21596)	115.063^{***} (df = 20; 21596)	127.822^{***} (df = 18; 21598)	25.306^{***} (df = 10; 2013)	23.132^{***} (df = 11; 2012)	20.273^{***} (df = 13; 2010)

Appendix Table 15: B1.2 - 1y Changes in Number of Businesses – Storm

Dependent Variable **1y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.0004***	0.0004***	0.0004***	0.0004***	0.0002	0.0002	0.0002
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Lagged1y_Disaster_Dummy_Storm	0.21	0.211	0.039	0.234	-1.184	-1.152	
	(-0.385)	(-0.385)	(-1.122)	(-0.386)	(-0.893)	(-0.9)	
number_businesses_total_number_of_businesses_num	0.001***	0.001***	0.001***	0.001***	0.004**	0.004**	0.004**
	(-0.0004)	(-0.0004)	(-0.0004)	(-0.0004)	(-0.002)	(-0.002)	(-0.002)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-0.841)					
		(-1.388)					
Outer_Regional_Dummy		(-0.099)					
		(-0.768)					
Remote_Very_Remote_Dummy		1.003					
		(-1.133)					
I(Lagged1y_Disaster_Dummy_Storm * Major_Cities_Dummy)			0.182				-1.366
			(-1.182)				(-0.902)

I(Lagged1y_Disaster_Dummy_Storm * Inner_Regional_Dummy)							**4.461*****
							(-0.551)
I(Lagged1y_Disaster_Dummy_Storm * Outer_Regional_Dummy)							
I(Lagged1y_Disaster_Dummy_Storm * Remote_Very_Remote_Dummy)							
Total_Affected				0.00001		0.0003*	
				(-0.00001)		(-0.0001)	
I(Lagged1y_Disaster_Dummy_Storm * Total_Affected)							
Education1_Certificate_I_and_II					121.184	120.809	120.734
					(-141.085)	(-141.225)	(-141.097)
Education2_Certificate_III_and_IV					37.46	37.073	37.592
					(-25.317)	(-25.398)	(-25.32)
Education3_Advanced_Diploma_and_Diploma					60.354***	61.584***	60.119**
					(-23.353)	(-23.151)	(-23.361)
Education4_Bachelor_Degree					62.561***	61.786***	62.578***
					(-16.95)	(-17.023)	(-16.95)
Education5_Postgraduate_Degree					(-33.083)	(-33.341)	(-32.923)
					(-23.8)	(-23.796)	(-23.807)

Unemployment_Rate					(-45.16)	(-44.455)	(-45.199)
					(-33.916)	(-34.106)	(-33.925)
Year2005 - 2018	***	***	***	***			
Year2016					2.430***	2.457***	2.424***
					(-0.695)	(-0.688)	(-0.695)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	23,864	23,864	23,864	23,864	4,189	4,189	4,189
R2	0.096	0.096	0.096	0.096	0.111	0.112	0.111
Adjusted R2	0.002	0.001	0.001	0.002	(-0.85)	(-0.849)	(-0.85)
F Statistic	135.335*** (df = 17; 21599)	115.033*** (df = 20; 21596)	127.811*** (df = 18; 21598)	127.840*** (df = 18; 21598)	25.107*** (df = 10; 2013)	22.966*** (df = 11; 2012)	22.858*** (df = 11; 2012)

Appendix Table 16: B1.3 - 1y Changes in Number of Businesses – Tropical Cyclone

Dependent Variable **1y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.0004***	0.0004***	0.0004***	0.0004***	0.0002	0.0002	0.0002
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Lagged1y_Disaster_Dummy_Tropical_Cyclone	**0.901*****	**0.901*****	(-0.872)	**1.003*****	1.345	1.406	
	(-0.29)	(-0.29)	(-1.306)	(-0.35)	(-1.626)	(-1.644)	
number_businesses_total_number_of_businesses_num	0.001***	0.001***	0.001***	0.001***	0.004**	0.004**	0.004**
	(-0.0004)	(-0.0004)	(-0.0004)	(-0.0004)	(-0.002)	(-0.002)	(-0.002)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-0.799)					
		(-1.38)					
Outer_Regional_Dummy		(-0.086)					
		(-0.768)					
Remote_Very_Remote_Dummy		1.012					
		(-1.134)					
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Major_Cities_Dummy)			1.256				
			(-1.359)				
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Inner_Regional_Dummy)			**2.931***			2.122	

	(-1.504)			(-2.24)	
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Outer_Regional_Dummy)	**2.643***			**2.739***	
	(-1.433)			(-1.664)	
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Remote_Very_Remote_Dummy)				**-5.050***	
				(-2.853)	
Total_Affected		(-0.00001)	0.0003*		
		(-0.00001)	(-0.0002)		
I(Lagged1y_Disaster_Dummy_Tropical_Cyclone * Total_Affected)					
Education1_Certificate_I_and_II			119.955	119.084	
			(-141.414)	(-141.564)	(-141.77)
Education2_Certificate_III_and_IV			37.013	36.612	37.023
			(-25.372)	(-25.457)	(-25.357)
Education3_Advanced_Diploma_and_Diploma			60.862***	62.130***	60.571***
			(-23.299)	(-23.092)	(-23.333)
Education4_Bachelor_Degree			63.145***	62.337***	62.832***
			(-16.918)	(-17.002)	(-16.943)
Education5_Postgraduate_Degree			(-33.378)	(-33.659)	(-34.113)
			(-23.873)	(-23.871)	(-23.907)

Unemployment_Rate					(-44.3)	(-43.561)	(-44.018)
					(-34.127)	(-34.325)	(-34.197)
Year2005 - 2018	***	***	***	***			
Year2016					2.439***	2.467***	2.456***
					(-0.69)	(-0.684)	(-0.687)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	23,864	23,864	23,864	23,864	4,189	4,189	4,189
R2	0.096	0.096	0.097	0.096	0.111	0.112	0.112
Adjusted R2	0.002	0.002	0.002	0.002	(-0.85)	(-0.849)	(-0.85)
F Statistic	135.643*** (df = 17; 21599)	115.295*** (df = 20; 21596)	115.506*** (df = 20; 21596)	128.114*** (df = 18; 21598)	25.098*** (df = 10; 2013)	22.966*** (df = 11; 2012)	21.073*** (df = 12; 2011)

Appendix Table 17: B1.4 - 1y Changes in Number of Businesses – Wildfire

Dependent Variable **1y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.0004^{***}	0.0004^{***}	0.0004^{***}	0.0004^{***}	0.0002	0.0002	0.0002
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Lagged1y_Disaster_Dummy_Wildfire	**-1.078****	**-1.076****	-1.426	**-1.082****	-0.866	-0.899	
	(-0.443)	(-0.443)	(-1.646)	(-0.443)	(-0.996)	(-0.993)	
number_businesses_total_number_of_businesses_num	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.004^{**}	0.004^{**}	0.004^{**}
	(-0.0004)	(-0.0004)	(-0.0004)	(-0.0004)	(-0.002)	(-0.002)	(-0.002)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-0.8)					
		(-1.383)					
Outer_Regional_Dummy		(-0.056)					
		(-0.754)					
Remote_Very_Remote_Dummy		0.959					
		(-1.129)					
I(Lagged1y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			0.394				-0.914
			(-1.737)				(-1.128)

I(Lagged1y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)	0.355				0.147
	(-1.837)				-1.492
I(Lagged1y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)					**-7.555*****
					(-0.936)
I(Lagged1y_Disaster_Dummy_Wildfire * Remote_Very_Remote_Dummy)					
Total_Affected		0.00001		0.0003*	
		(-0.00001)		(-0.0001)	
I(Lagged1y_Disaster_Dummy_Wildfire * Total_Affected)					
Education1_Certificate_I_and_II			121.556	121.208	121.513
			(-141.325)	(-141.454)	(-141.423)
Education2_Certificate_III_and_IV			37.32	36.936	37.434
			(-25.293)	(-25.37)	(-25.287)
Education3_Advanced_Diploma_and_Diploma			60.510***	61.749***	60.461***
			(-23.379)	(-23.18)	(-23.376)
Education4_Bachelor_Degree			63.231***	62.434***	63.203***
			(-16.935)	(-17.017)	(-16.937)
Education5_Postgraduate_Degree			(-33.468)	(-33.747)	(-33.54)
			(-23.789)	(-23.787)	(-23.787)

Unemployment_Rate					(-44.859)	(-44.153)	(-44.849)
					(-33.708)	(-33.89)	(-33.717)
Year2005 - 2018	***	***	***	***			
Year2016					2.447***	2.475***	2.450***
					(-0.703)	(-0.696)	(-0.703)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	23,864	23,864	23,864	23,864	4,189	4,189	4,189
R2	0.096	0.096	0.096	0.096	0.111	0.111	0.111
Adjusted R2	0.002	0.002	0.002	0.002	(-0.85)	(-0.85)	(-0.851)
F Statistic	135.642*** (df = 17; 21599)	115.293*** (df = 20; 21596)	121.356*** (df = 19; 21597)	128.128*** (df = 18; 21598)	25.059*** (df = 10; 2013)	22.926*** (df = 11; 2012)	20.926*** (df = 12; 2011)

Appendix Table 18: B1.5 - 1y Changes in Number of Businesses – Floods

Dependent Variable **1y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.0004***	0.0004***	0.0004***	0.0004***	0.0002	0.0002	0.0002
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0002)	(-0.0002)	(-0.0002)
Lagged1y_Disaster_Dummy_Flood	-0.232	-0.231	**1.465****	-0.214	**-0.908*****	**-0.878****	
	(-0.177)	(-0.177)	(-0.681)	(-0.178)	(-0.347)	(-0.349)	
number_businesses_total_number_of_businesses_num	0.001***	0.001***	0.001***	0.001***	0.004**	0.004**	0.004**
	(-0.0004)	(-0.0004)	(-0.0004)	(-0.0004)	(-0.002)	(-0.002)	(-0.002)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-0.82)					
		(-1.385)					
Outer_Regional_Dummy		(-0.107)					
		(-0.768)					
Remote_Very_Remote_Dummy		0.995					
		(-1.134)					
I(Lagged1y_Disaster_Dummy_Flood * Major_Cities_Dummy)			**-1.833****				**-2.042*****
			(-0.722)				(-0.465)

I(Lagged1y_Disaster_Dummy_Flood * Inner_Regional_Dummy)	**-1.407****				**1.752*****
	(-0.717)				(-0.479)
I(Lagged1y_Disaster_Dummy_Flood * Outer_Regional_Dummy)	**-1.950*****				0.256
	(-0.73)				(-0.624)
I(Lagged1y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)					**5.165****
					(-2.134)
Total_Affected		0.00001		0.0003*	
		(-0.00001)		(-0.0001)	
I(Lagged1y_Disaster_Dummy_Flood * Total_Affected)					
Education1_Certificate_I_and_II			120.201	119.873	122.406
			(-140.901)	(-141.033)	(-140.715)
Education2_Certificate_III_and_IV			37.63	37.253	36.71
			(-25.28)	(-25.364)	(-25.314)
Education3_Advanced_Diploma_and_Diploma			59.936**	61.126***	62.127***
			(-23.364)	(-23.156)	(-23.353)
Education4_Bachelor_Degree			64.448***	63.650***	63.464***
			(-17.128)	(-17.223)	(-17.085)
Education5_Postgraduate_Degree			(-37.161)	(-37.271)	-47.122*
			(-24.235)	(-24.213)	(-24.865)

Unemployment_Rate					(-44.757)	(-44.094)	(-45.652)
					(-33.677)	(-33.868)	(-33.773)
Year2005 - 2018	***	***	***	***			
Year2016					2.360***	2.388***	2.497***
					(-0.688)	(-0.681)	(-0.693)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	23,864	23,864	23,864	23,864	4,189	4,189	4,189
R2	0.096	0.096	0.096	0.096	0.112	0.112	0.116
Adjusted R2	0.002	0.001	0.001	0.002	(-0.848)	(-0.848)	(-0.842)
F Statistic	135.357*** (df = 17; 21599)	115.051*** (df = 20; 21596)	115.127*** (df = 20; 21596)	127.851*** (df = 18; 21598)	25.318*** (df = 10; 2013)	23.144*** (df = 11; 2012)	20.255*** (df = 13; 2010)

Appendix Table 19: B2.1 - 3y Changes in Number of Businesses – Disaster Occurred

Dependent Variable **3y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.001***	0.001**	0.001**	0.001***	0.001	0.001	0.001
	(-0.001)	(-0.001)	(-0.0005)	(-0.001)	(-0.0005)	(-0.0005)	(-0.0005)
Lagged3y_Disaster_Occurred_Dummy	0.549	0.568	11.766	0.492	**-2.515***	**-2.902***	
	(-0.764)	(-0.764)	(-13.053)	(-0.778)	(-0.584)	(-0.583)	
number_businesses_total_number_of_businesses_num	0.016***	0.016***	0.016***	0.016***	0.024***	0.024***	0.024***
	(-0.005)	(-0.005)	(-0.005)	(-0.005)	(-0.007)	(-0.007)	(-0.007)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-2.75)					
		(-2.093)					
Outer_Regional_Dummy		28.388*					
		(-15.771)					
Remote_Very_Remote_Dummy		91.36					
		(-69.315)					
I(Lagged3y_Disaster_Occurred_Dummy * Major_Cities_Dummy)			(-13.002)				**-5.987***
			(-13.052)				(-0.749)
I(Lagged3y_Disaster_Occurred_Dummy * Inner_Regional_Dummy)			(-8.573)				(-0.123)
			(-13.087)				(-1.274)

I(Lagged3y_Disaster_Occurred_Dummy * Outer_Regional_Dummy)			(-10.783)				0.759
			(-13.333)				(-1.007)
I(Lagged3y_Disaster_Occurred_Dummy * Remote_Very_Remote_Dummy)							**6.289****
							(-2.809)
Total_Affected				(-0.00002)		0.001***	
				(-0.00002)		(-0.0002)	
I(Lagged3y_Disaster_Occurred_Dummy * Total_Affected)							
Education1_Certificate_I_and_II					116.123	117.121	133.866
					(-160.993)	(-160.835)	(-160.174)
Education2_Certificate_III_and_IV					(-15.73)	(-16.81)	(-21.972)
					(-31.188)	(-31.326)	(-31.684)
Education3_Advanced_Diploma_and_Diploma					151.451***	152.937***	146.790***
					(-29.791)	(-29.703)	(-30.158)
Education4_Bachelor_Degree					103.598***	102.080***	101.196***
					(-22.557)	(-22.593)	(-22.525)
Education5_Postgraduate_Degree					-87.929**	-87.536**	-90.788**
					(-38.274)	(-38.18)	(-38.11)
Unemployment_Rate					-96.361**	-94.974**	-92.553**
					(-38.145)	(-38.132)	(-37.81)

Year2005 - 2018	-	-	-	-			
Year2016					(-0.146)	(-0.137)	(-0.055)
					(-0.824)	(-0.823)	(-0.822)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	20,316	20,316	20,316	20,316	4,070	4,070	4,070
R2	0.092	0.095	0.092	0.092	0.202	0.203	0.21
Adjusted R2	(-0.022)	(-0.018)	(-0.022)	(-0.022)	(-0.613)	(-0.612)	(-0.6)
F Statistic	121.473*** (df = 15; 18061)	104.895*** (df = 18; 18058)	101.577*** (df = 18; 18058)	113.882*** (df = 16; 18060)	50.918*** (df = 10; 2013)	46.618*** (df = 11; 2012)	40.987*** (df = 13; 2010)

Appendix Table 20: B2.2 - 3y Changes in Number of Businesses – Storm

Dependent Variable **3y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.001^{**}	0.001^{**}	0.001^{**}	0.001^{**}	0.001	0.001	0.001
	(-0.001)	(-0.001)	(-0.0005)	(-0.0005)	(-0.0005)	(-0.0005)	(-0.0005)
Lagged3y_Disaster_Dummy_Storm	-0.693	-0.699	45.999	-0.793	**-6.400*****	**-6.369*****	
	(-1.317)	(-1.317)	(-94.694)	(-1.327)	(-0.738)	(-0.734)	
number_businesses_total_number_of_businesses_num	0.016^{***}	0.016^{***}	0.016^{***}	0.016^{***}	0.024^{***}	0.024^{***}	0.024^{***}
	(-0.005)	(-0.005)	(-0.005)	(-0.005)	(-0.007)	(-0.007)	(-0.007)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-2.513)					
		(-2.021)					
Outer_Regional_Dummy		28.380^{*}					
		(-15.773)					
Remote_Very_Remote_Dummy		91.352					
		(-69.316)					
I(Lagged3y_Disaster_Dummy_Storm * Major_Cities_Dummy)			-47.839				**-6.212*****
			-94.694				(-0.795)

I(Lagged3y_Disaster_Dummy_Storm * Inner_Regional_Dummy)	-36.361				**-7.907*****
	(-95.061)				(-1.439)
I(Lagged3y_Disaster_Dummy_Storm * Outer_Regional_Dummy)					
I(Lagged3y_Disaster_Dummy_Storm * Remote_Very_Remote_Dummy)					
Total_Affected		(-0.00002)		0.0003	
		(-0.00002)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Storm * Total_Affected)					
Education1_Certificate_I_and_II			133.493	133.002	132.121
			(-159.874)	(-160.035)	(-160.199)
Education2_Certificate_III_and_IV			(-20.84)	(-21.169)	(-20.573)
			(-31.437)	(-31.532)	(-31.493)
Education3_Advanced_Diploma_and_Diploma			145.140***	146.371***	145.563***
			(-30.282)	(-30.117)	(-30.351)
Education4_Bachelor_Degree			101.692***	100.944***	101.721***
			(-22.438)	(-22.499)	(-22.441)
Education5_Postgraduate_Degree			-88.764**	-89.036**	-88.450**
			(-37.854)	(-37.842)	(-37.873)

Unemployment_Rate					-92.367**	-91.720**	-92.310**
					(-37.497)	(-37.668)	(-37.483)
Year2005 - 2018	-	-	-	-			
Year2016					(-0.2)	(-0.172)	(-0.207)
					(-0.844)	(-0.836)	(-0.845)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	20,316	20,316	20,316	20,316	4,070	4,070	4,070
R2	0.092	0.095	0.092	0.092	0.21	0.211	0.21
Adjusted R2	(-0.022)	(-0.019)	(-0.021)	(-0.022)	(-0.596)	(-0.597)	(-0.597)
F Statistic	121.464*** (df = 15; 18061)	104.886*** (df = 18; 18058)	107.583*** (df = 17; 18059)	113.879*** (df = 16; 18060)	53.608*** (df = 10; 2013)	48.784*** (df = 11; 2012)	48.736*** (df = 11; 2012)

Appendix Table 21: B2.3 - 3y Changes in Number of Businesses – Tropical Cyclone

Dependent Variable **3y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.001***	0.001**	0.001***	0.001***	0.001*	0.001*	0.001*
	(-0.001)	(-0.001)	(-0.001)	(-0.0005)	(-0.0005)	(-0.0005)	(-0.0005)
Lagged3y_Disaster_Dummy_Tropical_Cyclone	0.298	0.237	-2.019	0.203	**3.599***	**3.566***	
	(-1.399)	(-1.398)	(-6.521)	(-1.412)	(-0.827)	(-0.833)	
number_businesses_total_number_of_businesses_num	0.016***	0.016***	0.016***	0.016***	0.024***	0.024***	0.024***
	(-0.005)	(-0.005)	(-0.005)	(-0.005)	(-0.007)	(-0.007)	(-0.007)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-2.656)					
		(-2.051)					
Outer_Regional_Dummy		28.375*					
		(-15.773)					
Remote_Very_Remote_Dummy		91.347					
		(-69.316)					
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Major_Cities_Dummy)			3.971				**4.081***
			(-6.567)				(-0.916)

I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Inner_Regional_Dummy)	4.157				1.103
	(-6.737)				(-1.356)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Outer_Regional_Dummy)	-1.728				**-5.936****
	(-8.046)				(-2.891)
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Remote_Very_Remote_Dummy)					**10.109*****
					(-2.077)
Total_Affected		-0.00002		0.0003	
		(-0.00002)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Tropical_Cyclone * Total_Affected)					
Education1_Certificate_I_and_II			114.714	114.251	113.38
			(-160.629)	(-160.769)	(-161.151)
Education2_Certificate_III_and_IV			(-17.213)	(-17.569)	(-15.909)
			(-31.257)	(-31.357)	(-31.449)
Education3_Advanced_Diploma_and_Diploma			157.697***	158.943***	158.537***
			(-29.952)	(-29.799)	(-30.006)
Education4_Bachelor_Degree			106.239***	105.406***	105.987***
			(-22.926)	(-22.997)	(-22.985)
Education5_Postgraduate_Degree			-106.234***	-106.387***	-109.121***
			(-38.36)	(-38.337)	(-38.727)

Unemployment_Rate					-97.103**	-96.386**	-96.920**
					(-38.107)	(-38.285)	(-38.061)
Year2005 - 2018	-	-	-	-			
Year2016					0.008	0.037	0.063
					(-0.838)	(-0.831)	(-0.845)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	20,316	20,316	20,316	20,316	4,070	4,070	4,070
R2	0.092	0.095	0.092	0.092	0.203	0.204	0.204
Adjusted R2	(-0.022)	(-0.019)	(-0.022)	(-0.022)	(-0.61)	(-0.61)	(-0.611)
F Statistic	121.458*** (df = 15; 18061)	104.881*** (df = 18; 18058)	101.270*** (df = 18; 18058)	113.871*** (df = 16; 18060)	51.411*** (df = 10; 2013)	46.795*** (df = 11; 2012)	39.727*** (df = 13; 2010)

Appendix Table 22: B2.4 - 3y Changes in Number of Businesses – Wildfire

Dependent Variable **3y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.001^{***}	0.001^{**}	0.001^{***}	0.001^{***}	0.001^{*}		0.001^{*}
	(-0.001)	(-0.001)	(-0.001)	(-0.0005)	(-0.0005)		(-0.0005)
Lagged3y_Disaster_Dummy_Wildfire	**3.176****	**3.085****	8.456	**3.160****	**3.210*****	**2.805****	
	(-1.283)	(-1.281)	(-12.339)	(-1.283)	(-1.221)	(-1.217)	
number_businesses_total_number_of_businesses_num	0.016^{***}	0.016^{***}	0.016^{***}	0.016^{***}	0.024^{***}	0.028^{***}	0.024^{***}
	(-0.005)	(-0.005)	(-0.005)	(-0.005)	(-0.007)	(-0.006)	(-0.007)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-2.682)					
		(-2.061)					
Outer_Regional_Dummy		28.347^{*}					
		(-15.773)					
Remote_Very_Remote_Dummy		91.319					
		(-69.316)					
I(Lagged3y_Disaster_Dummy_Wildfire * Major_Cities_Dummy)			-6.637				0.945
			(-12.419)				(-1.238)

I(Lagged3y_Disaster_Dummy_Wildfire * Inner_Regional_Dummy)	-1.004				3.123
	(-12.662)				(-3.031)
I(Lagged3y_Disaster_Dummy_Wildfire * Outer_Regional_Dummy)	-14.224				**7.052***
	(-14.325)				(-1.505)
I(Lagged3y_Disaster_Dummy_Wildfire * Remote_Very_Remote_Dummy)					
Total_Affected		(-0.00002)		0.0003*	
		(-0.00002)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Wildfire * Total_Affected)					
Education1_Certificate_I_and_II			104.179	96.893	103.116
			(-160.223)	(-159.538)	(-160.288)
Education2_Certificate_III_and_IV			(-13.85)	(-19.042)	(-13.288)
			(-31.256)	(-32.04)	(-31.419)
Education3_Advanced_Diploma_and_Diploma			158.435***	169.853***	158.240***
			(-30.012)	(-31.478)	(-29.993)
Education4_Bachelor_Degree			102.212***	104.343***	102.017***
			(-22.638)	(-22.234)	(-22.645)
Education5_Postgraduate_Degree			-94.512**	-87.065**	-93.582**
			(-38.271)	(-39.689)	(-38.387)

Unemployment_Rate					-95.316**	-93.227**	-95.245**
					(-37.655)	(-37.25)	(-37.645)
Year2005 - 2018	-	-	-	-			
Year2016					0.167	0.341	0.16
					(-0.844)	(-0.836)	(-0.845)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	20,316	20,316	20,316	20,316	4,070	4,116	4,070
R2	0.092	0.095	0.092	0.092	0.199	0.195	0.199
Adjusted R2	(-0.022)	(-0.018)	(-0.022)	(-0.022)	(-0.62)	(-0.645)	(-0.621)
F Statistic	121.521*** (df = 15; 18061)	104.931*** (df = 18; 18058)	101.335*** (df = 18; 18058)	113.930*** (df = 16; 18060)	49.929*** (df = 10; 2013)	48.790*** (df = 10; 2014)	41.611*** (df = 12; 2011)

Appendix Table 23: B2.5 - 3y Changes in Number of Businesses – Flood

Dependent Variable **3y Percentage Change in Total Number of Businesses**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Model Type	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model	Fixed Effects Model
ERP	0.001**	0.001**	0.001**	0.001***	0.001*	0.001*	0.001*
	(-0.001)	(-0.001)	(-0.0005)	(-0.0005)	(-0.0005)	(-0.0005)	(-0.0005)
Lagged3y_Disaster_Dummy_Flood	0.548	0.633	20.095	0.521	**-1.614****	**-1.893*****	
	(-1.049)	(-1.049)	(-21.786)	(-1.051)	(-0.736)	(-0.723)	
number_businesses_total_number_of_businesses_num	0.016***	0.016***	0.016***	0.016***	0.024***	0.024***	0.024***
	(-0.005)	(-0.005)	(-0.005)	(-0.005)	(-0.007)	(-0.007)	(-0.007)
Major_Cities_Dummy							
Inner_Regional_Dummy		(-2.62)					
		(-2.046)					
Outer_Regional_Dummy		28.406*					
		(-15.772)					
Remote_Very_Remote_Dummy		91.378					
		(-69.316)					
I(Lagged3y_Disaster_Dummy_Flood * Major_Cities_Dummy)			-22.201				**-4.225*****
			(-21.75)				(-0.911)

I(Lagged3y_Disaster_Dummy_Flood * Inner_Regional_Dummy)	-18.862				1.369
	(-21.774)				(-1.25)
I(Lagged3y_Disaster_Dummy_Flood * Outer_Regional_Dummy)	-17.38				0.794
	(-21.917)				(-1.041)
I(Lagged3y_Disaster_Dummy_Flood * Remote_Very_Remote_Dummy)					4.619
					(-2.912)
Total_Affected		(-0.00002)		0.0005^{***}	
		(-0.00002)		(-0.0002)	
I(Lagged3y_Disaster_Dummy_Flood * Total_Affected)					
Education1_Certificate_I_and_II			109.084	109.225	114.26
			(-161.017)	(-160.962)	(-160.791)
Education2_Certificate_III_and_IV			(-14.727)	(-15.524)	(-16.027)
			(-31.189)	(-31.295)	(-31.453)
Education3_Advanced_Diploma_and_Diploma			156.775^{***}	158.582^{***}	158.800^{***}
			(-29.779)	(-29.688)	(-29.856)
Education4_Bachelor_Degree			104.995^{***}	104.037^{***}	105.995^{***}
			(-22.925)	(-22.939)	(-23.036)
Education5_Postgraduate_Degree			-97.123^{**}	-98.104^{**}	-114.099^{***}
			(-38.212)	(-38.196)	(-38.846)

Unemployment_Rate					-97.445**	-96.519**	-95.318**
					(-38.625)	(-38.591)	(-38.155)
Year2005 - 2018	-	-	-	-			
Year2016					(-0.016)	(-0.001)	0.227
					(-0.818)	(-0.817)	(-0.817)
Note:	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied	Newey-West standard errors applied
Observations	20,316	20,316	20,316	20,316	4,070	4,070	4,070
R2	0.092	0.095	0.092	0.092	0.2	0.201	0.205
Adjusted R2	(-0.022)	(-0.018)	(-0.021)	(-0.022)	(-0.617)	(-0.616)	(-0.608)
F Statistic	121.465*** (df = 15; 18061)	104.890*** (df = 18; 18058)	101.698*** (df = 18; 18058)	113.878*** (df = 16; 18060)	50.335*** (df = 10; 2013)	45.979*** (df = 11; 2012)	39.991*** (df = 13; 2010)