Labour market effects of bushfires and floods in Australia: a gendered perspective*

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Abstract

We study the labour market effects of bushfires and floods within Australia over the past two decades, focusing on gender as a determinant of vulnerability. Whilst floods unambiguously lifted the labour supply of both genders (creating around 13,500 jobs per year), the likelihood of female employment is particularly vulnerable to bushfires – lowering by 1.6 percentage points (or around 5,000 jobs per year). This effect is partially explained by industry sector, with bushfires lifting overall male employment through industries including mining and transport, whilst reducing more female dominated services-sector participation. We also examine intrahousehold dynamics, finding strong evidence for an 'added worker' effect.

Keywords: labour economics, labour force participation, gender economics, natural disaster, industry sector.

JEL Classification: J01, J16, J21, Q54

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I Introduction

Climate change has been named one of the biggest threats of the 21st century (Costello et al. 2009) and is predicted to increase the frequency and severity of natural disasters. Each year natural disasters cost Australia an average of $38 billion (Deloitte Access Economics, 2021)[1] and impact around 20,000 individuals.[2] As well as the costly direct effects of natural disasters including property destruction and adverse health impacts, bushfires and floods also represent one of the most frequent and severe sources of exogenous shock for regional labour markets.

Natural disasters can generate adverse effects for local economies through: reducing firm productivity by destroying productive capital or disrupting supply chains, demolishing part of the housing stock, and dampening consumer spending as individuals save for reconstruction (Boustan et al. 2020). While these effects are generally more pronounced within developing contexts where social security systems remain underdeveloped (Belasen & Polachek 2009, Kirchberger 2017), large effects of natural disasters on employment have also been well-documented within advanced country settings including Australia (Groen & Polivka 2010, Groen et al. 2020, Ladds et al. 2017).

This paper seeks to systematically examine the effects of nearly two decades of bushfires and floods on individual labour market outcomes within Australia. In contrast to many existing studies which have commonly examined the effects of natural disasters at the state or national level (Ladds et al. 2017, Ulubaşoğlu et al. 2019),[3] our paper explores the labour market effects of these events at a finer level of geographic detail. We exploit exogenous variation in the timing and Statistical Area Level 4 (SA4-level) location of disaster occurrence, to study the effects of bushfires and floods on a range of individual labour market outcomes. Our study also incorporates a broader range of outcome measures, including both the intensive and extensive margins of employment participation and individual earnings. This allows us to provide a more nuanced analysis of the mechanisms through which natural disasters impact local labour markets.

Importantly, we are also able to assess the importance of gender as a determinant of individual labour market vulnerability following bushfires and floods. It is well documented by the international literature that women face greater economic vulnerability, including reduced levels of labour force participation, in the aftermath of natural disasters (Enarson et al. 2000, Hazeleger 2013). Whilst gendered labour market vulnerability is typically more pronounced in developing country settings, women continue to face labour

[1] http://australianbusinessroundtable.com.au/our-research

[2] According to the EM-DAT global database on natural disasters: https://www.emdat.be/

[3] An important exception is a recent paper by Johar et al. (2020), which examined the consequences of property damage due to natural disasters using individual-level longitudinal data.

market disadvantage in many developed countries. Within Australia, women have lower levels of labour force participation and are more likely to be employed in casual jobs where it may be easier for employers to reduce hours or to cut jobs in the wake of a bushfire or flood (Pennington & Stanford 2020). While gendered disadvantage in the Australian labour market has been well studied (Borland & Coelli 2016, Cassells et al. 2009), there remains a shortage of Australian studies examining the gendered effects of natural disasters. Through explicitly including a gendered focus, our study contributes critical evidence on the gendered burden of climate change.

Our paper also considers several mechanisms through which bushfires and floods may generate gendered consequences in regional labour markets. Firstly, we research if different gendered responses to natural disaster may reflect the sectoral nature of these events. We expect that demand for reconstruction services will stimulate employment and wages growth in typically male-dominated industries such as construction and engineering. In contrast, we expect job losses and reductions in hours worked to be more pronounced in sectors vulnerable to reduced discretionary spending such as hospitality and tourism where females generally account for a greater share of labour supply (Dolfman et al. 2007, Belasen & Polachek 2008).

Secondly, we examine the role of intrahousehold dynamics among mixed-sex couples in explaining the labour market effects of bushfires and floods. Natural disasters may temporarily increase domestic work, including filing insurance claims, rebuilding or relocating, and providing care to dependent children or relatives suffering from injury. Within coupled households, this may be associated with the primary carer taking time temporarily reducing their labour force participation to take on these duties. A competing hypothesis is an 'added worker' effect, whereby household members may temporarily lift their labour supply in the event that the household head loses their job. This 'added worker' response acts as a form of spousal earnings insurance, enabling the smoothing of inter-temporal household income and consumption. Given that women are more likely to have lower levels of labour force participation compared to men, prior to disaster exposure, we expect any 'added worker' effect to be most pronounced for the female labour supply reflecting a greater capacity to respond.

To identify the occurrence of bushfires and floods, we use data from the Australian Institute for Disaster Resilience (AIDR) Emergency Management Hub, which provides coverage of each natural disaster within Australia starting from the nineteenth century. Using information on disaster type, date of occurrence, and suburb-level location, we map two decades of bushfires and floods to SA4-level using geographic concordances provided by the Australian Bureau of Statistics. We then merge our disaster exposure variables with individual-level data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is an ongoing nationally representative longitudinal study of Australian households. We use detailed demographic information, as well as labour force and earnings outcomes, for financial years from 2002 to 2019.

We define individuals as being impacted by a disaster event if they report residing in a disaster-affected SA4 region at the time of bushfire or flood occurrence and remain in this region in consecutive survey years. We compare these individuals to a national cohort who do not experience a natural disaster over our study window.[4]

Our baseline specification uses a two-way fixed effects model to estimate the causal effects of bushfires and floods, controlling for covariates using fixed effects for individual, SA4 region, year, and an individual's age, as well as linear state-time trends. We use a dummy-variable for bushfire or flood exposure, and also incorporate the one- and two-year lags of these variables[5], and cluster our robust standard errors at SA4-level.

We find that bushfires and floods have different effects on Australian labour markets, highlighting the need for policymakers to adapt policy to each disaster type. We estimate that floods unambiguously lift the labour supply for both men and women, including the likelihood of employment by +1.3 ppts and by +1.8 ppts at one-year lag. In contrast, bushfires reduce the likelihood of female employment by -1.6 ppts while generating a lagged increase in the likelihood of male employment (+1.8 ppts at one-year lag and +1.6 ppts at two-year lag). A possible explanation for the contrasting effects of bushfires and floods is that floods tend to occur in areas with relatively higher population density. This may mean that floods are more likely to have a creative destruction effect with greater stimulatory spending on rebuilding and recovery.

To interpret our results in terms of their relative economic magnitude, we apply our statistically significant average treatment effects to regional labour market data provided by the ABS.[6] Over the period of our analysis, we find that floods lead to the creation of an average 13,498 jobs per year - equivalent to an additional 20 million hours or +$1.7 billion in additional GDP. Floods also boosted labour force participation by +1.1 ppts (+1.5 ppts after a one-year lag) - an additional 11,321 individuals per year. Meanwhile, in an average year, bushfires boosted male employment by 9,873 jobs or around 16.5 million hours (+$1.3 billion in additional GDP) while reducing female employment by 4,780 jobs or -6 million hours (-$495 million of foregone GDP).

[4]In our robustness checks, we relax the requirement that an individual must remain residing within a disaster-affected SA4 region in consecutive survey years, and find similar effects.

[5]In our robustness section, we replace our binary disaster variable with a severity-weighted measure of disaster occurrence and show that our results remain robust.

[6]In our analysis, we assume that employment occurs at average hours for that state, gender and year, and average total levels of labour productivity.

We find some evidence for differences in the effects of bushfires and floods across economic sectors, with fires lifting the relative likelihood of employment in mining and transport (respectively, +6.4 ppts and +6.0 ppts) which tend to be more male-dominated. Bushfires did not have a significant impact on the relative likelihood of employment in industries with a higher female composition, but generated lagged reductions at the intensive margin of employment - lowering relative average hours worked in trade (-8.5%), banking and insurance (-8.0%), and services (-6.8%). Taken together, these results are consistent with a sectoral reallocation of labour supply towards more male-dominated industries, while labour supplied to more female-dominated industries contracts along the intensive margin. This goes some way to explaining the relatively greater labour market vulnerability of women following bushfires. We also find that bushfires reduced average hours worked in transport (-12.2%) and construction (-5.9%), however this may be consistent with an expansion of the labour supply at the extensive margin in these sectors.

Floods were found to increase relative employment levels in the services sector (+5.5 ppts) and lift average hours worked in mining (+9.0%) and manufacturing (+8.6%). In contrast, floods lowered relative employment levels in the transport sector - respectively by -9.8 ppts, with this normalising after a one-year lag. These effects of floods are quite different to those of bushfires, particularly with respect to the services sector. A possible reason for this is a higher population density in flood-prone areas, compared to the more sparsely populated areas that experience bushfires. A greater population density may lead to increased demand for the services sector, such as insurance, temporary accommodation, or public administration and safety in the aftermath of a flood, which may in turn support increased employment in these industries. In contrast, demand for these services may remain relatively dampened following bushfires. This may also explain why we observe an increase in female labour force participation following a flood - with much of this likely driven by the services sector - while female employment declines following a bushfire.

Turning to intrahousehold dynamics among mixed-sex couples, we find no evidence that natural disasters increased female housework. We do however find evidence in support of an 'added worker effect', with this strongest for women. Among females whose partner had lost their job in the aftermath of a bushfire, we find a relative increase in the likelihood of labour force participation (+3.6 ppts), employment (+3.6 ppts), and average hours worked (+23.4%). Meanwhile for men, partner job loss following a bushfire was associated with relative increases in their likelihood of employment (+2.5 ppts), and lagged relative increases in both the likelihood of participation (+2.3 ppts) and average working hours (+6.6%). The 'added worker' effect was less pronounced following a flood, perhaps reflecting a lower number of individuals whose partner experienced job loss. However, partner job loss was associated with increased participation at the intensive margin - with relative average hours increased by 7.5% (13.3% for women).

Our results contribute important evidence on the labour market effects of bushfires and floods within Australia, and expand on existing literature through incorporating a wider range of indicators and estimating these effects at a finer level of geographic precision. Our paper also contributes an important perspective on the gendered burden of climate change, a topic which has critical relevance for policymakers but which has thus far been understudied within Australia. Our paper does not intend to comprehensively estimate gendered vulnerability to natural disasters, but to shed light on the relative labour market vulnerability experienced by men and women in the aftermath of these events. Finally, our paper provides new evidence into the mechanisms through which these effects of bushfires and floods are transmitted to the labour market. We highlight the sectoral nature of these effects and find evidence that mixed-sex couples may respond to natural disasters by temporarily increasing their labour supply in the event that one breadwinner loses their employment.

Our paper is organised as follows: in the next section, in Section II we briefly review the existing literature as it relates to our present study. Section III then provides an overview of our data sources, Section IV outlines the methods used, followed by results and discussion in Section V. We present our robustness checks in Section VI, and finally Section VII concludes our paper with possible directions for future research.

II Background

There is no dearth of papers which have documented the economic shocks generated by natural disasters, including dampened consumer spending, increased demand for reconstruction services following property damage, and lowered levels of productivity due to the destruction of productive capital and the disruption of supply chains (Boustan et al. 2020, Botzen et al. 2019).

Many of these papers have been conducted at the macroeconomic level using cross country panel regressions to study the effects of temperature, rainfall and increased disaster exposure on a single indicator such as gross domestic product or the unemployment rate (Dell et al. 2012, Cavallo et al. 2013, Hsiang & Jina 2014). These papers offer conflicting evidence on the effects of natural disasters, with results ranging from long lasting effects on national incomes to near immediate recovery (Botzen et al. 2019). In contrast to these studies, our paper analyses the effects of many disaster events within a single country

(Australia), which allows us to exploit heterogeneity in the timing and location of natural disasters while holding core institutional features of the economy constant.

A common feature of these cross country studies is the use of large geographic regions as a unit of analysis. Existing studies within Australia have generally been no exception, with most conducted at the national or state level (Ladds et al. 2017, Ulubaşoğlu et al. 2019). In one such recent paper, Ulubaşoğlu et al. (2019) investigated the effects of bushfires and floods on sectoral economic output using state-level variation in disaster occurrence. The authors found that bushfires did not have a significant effect on sectoral gross value added, however floods lowered output in agriculture, mining, construction and financial services. In contrast to these papers, our present study uses individuals as a unit of analysis to study the effect of natural disasters at the regional (SA4-level). This approach allows us to identify more accurately the local area effects of disaster exposure, and to provide a more nuanced analysis of the mechanisms through which these effects are transmitted in local labour markets.

Recently, a significant international literature has sought to estimate the individual level effects of large-scale single disaster events. These studies have often taken the form of event studies of specific events, in terms of their effects on existing residents (Deryugina 2017, Deryugina et al. 2018, Groen et al. 2020). One of the most studied disaster events was Hurricane Katrina in 2005 (Gallagher & Hartley 2017, Deryugina et al. 2018, Deryugina & Molitor 2018, Groen et al. 2020, Franklin & Labonne 2019). While it is important to study these major events, most disasters are not as severe as these outliers and findings from these events may overstate the average effect of a bushfire or flood. Our data allow us to study all occurrences of bushfires and floods within Australia over the past two decades, and to interpret our results in terms of the average effects of natural disasters within a given year.

A large number of studies have also focused on the labour market as an important vehicle for the transmission of natural disasters to the real economy, including floods (Xiao 2011, Xiao & Feser 2014), tornadoes (Ewing et al. 2003, 2009), wildfires (Davis et al. 2014, Nielsen-Pincus et al. 2014), and hurricanes (Belasen & Polachek 2009, Deryugina et al. 2018). Of these labour market studies, our paper is most comparable in approach to those existing studies which have been conducted at the individual level. For example, Franklin & Labonne (2019) studied the occurrence of typhoons using individual panel data from the Philippines and found that workers experienced reductions in hours worked and hourly wages, but no significant effect on layoffs. Kirchberger (2017) used an instrumental variables approach to estimate the labour market effects of earthquakes in Indonesia and provided evidence that agricultural wages rose following an earthquake as labour supply substituted into construction, thus raising the marginal product of labour in the agricultural sector. In the United States following Hurricane Katrina, Belasen & Polachek

(2009) report findings that worker earnings in affected counties increase more rapidly while employment growth occurs more slowly than in neighbouring unaffected counties.

To our knowledge, within Australia, Johar et al. (2020) is the sole attempt to focus a study on the economic effects of natural disasters at the individual level. They quantified the effects of property damage due to natural disasters on a range of individual economic and health outcomes, finding that residential destruction has no average impact on overall employment status or household income, but increases financial hardship and risk aversion. However, their analysis did not extend to consider the labour market effects of bushfires and floods for residents of the affected region, which is the focus of our present study.

Of the existing individual level studies, including the paper by Johar et al. (2020), few have explored in detail the gendered nature of these effects. Nonetheless, international literature provides clear evidence that women are often exposed to greater economic vulnerability following disaster occurrence, with many highlighting the reduced levels of female participation in the labour market (Enarson et al. 2000, Hazeleger 2013). Whilst gendered labour market vulnerability is typically more pronounced in developing country settings, women continue to face labour market disadvantage in developed countries (Borland & Coelli 2016). Within Australia, women have lower levels of labour force participation and are more likely to be employed in casual jobs where it may be easier for employers to reduce hours or to cut jobs in the wake of a bushfire or flood (Enarson et al. 2000, Pennington & Stanford 2020).

In seeking to explain varied labour market responses to natural disasters, many studies have focused on sector of employment. Typically, these studies have found that most post-disaster employment growth occurs in male-dominated industries such as construction and engineering, while job losses occur elsewhere (Dolfman et al. 2007, Belasen & Polachek 2008). Dampened discretionary consumer spending as households save for reconstruction often means that job losses and reductions in working hours are most pronounced in sectors such as hospitality and tourism, where women generally account for a greater share of the labour supply (Dolfman et al. 2007, Belasen & Polachek 2008). Whilst the sectoral nature of bushfires and floods has been studied in Australia, Ulubaşoğlu et al. (2019) use gross-value added as their dependent measure which conflates both labour and capital market effects, meaning that this may not directly link to the economic wellbeing of households in of disaster-affected regions.

Intrahousehold dynamics among mixed-sex couples may also partly explain the labour market effects of natural disasters. Natural disasters may increase domestic work temporarily, including filing insurance claims, rebuilding or relocating, and providing care to dependent children or relatives suffering from injury. Within couples, this may be associated with the primary carer taking time temporarily out of the labour force to take on these duties. Existing gender norms theory provides weight to this effect, and shows that such reductions in labour force participation are more likely to effect women (Zamarro & Prados 2021).

A competing hypothesis is that other household members may temporarily increase their labour force participation in response to job loss by the primary breadwinner. This 'added worker' response is a transitory way of smoothing intertemporal income and consumption or hedging against increased uncertainty, consistent with family utility maximisation (Mincer 1962, 1966, Ashenfelter 1980, Killingsworth & Heckman 1986). Within Australia, Gong (2011) studied the 'added worker' effect and found strong evidence that married women increased their rates of full time employment and their working hours following involuntary job loss by their partner. More recent work on 'added worker' effects suggests that household wealth dynamics are another important determinant of female labour participation (García-Pérez & Rendon 2020).

Our paper contributes to this literature by estimating the regional labour market effects of bushfires and floods within Australia, using individual-level data over nearly two decades of disaster occurrence. Importantly, we separately identify these effects for men and women, thereby providing important evidence on the gendered burden of climate change. We also shed light on potential mechanisms which may explain the relative differences in labour market vulnerability faced by men and women - including the roles of industry composition and intrahousehold dynamics.

III Data

i Natural disaster data

We use data on natural disasters from the Australian Institute for Disaster Resilience (AIDR) Emergency Management Knowledge Hub, which represents the most extensive historical accounts of disaster events for Australia.[7] These data cover each disaster beginning from the nineteenth century, including the type of disaster, date of occurrence, and a suburb-level event description. We compile this information at the suburb-level for disasters occurring within Australia between 2002 and 2019 (financial years) before mapping to SA4 regions based on geographic concordances from the Australian Bureau of Statistics (ABS). We choose to examine these effects at SA4-level as these regions are constructed to reflect the greatest degree of inter-connectivity between labour supply and demand.[8]

[7] Data is publicly accessible at https://knowledge.aidr.org.au/

[8] https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/1270.0.55.001 July%202016 Main%20Features Statistical%20Area%20Level%204%20(SA4) 10016

We observe sufficiently large variation in the timing and location of disaster occurrence at the SA4-level to exploit the exogeneity of disaster occurrence to infer the average causal effects of bushfires and floods on individual labour market outcomes.[9] Over our period of analysis, 37 SA4 regions (42%) experienced at least one bushfire and 26 SA4 regions (30%) experienced at least one flood.[10] At a state level, we find that NSW and Victoria are the most exposed to bushfires over this period while Queensland is the most exposed to floods.

ii Individual data

We merge our disaster exposure variable with individual-level data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is an ongoing nationally representative longitudinal study of Australian households. The initial HILDA survey was conducted in 2001 and included 7,682 households and 19,914 individuals in a nationally representative survey of the adult population. The number of surveyed individuals grows as subsequent waves track and record every additional household member. Each annual wave of HILDA contains detailed demographic data including on level of educational attainment, residential location, marital status, age, and gender; as well as detailed labour force and earnings data.

Importantly, HILDA has a high response rate – 96.4% in Wave 18 (financial year 2019) and a low attrition rate – for example, 75.9% of Wave 11 respondents were also included in Wave 18. These features mean that the longitudinal data provided by HILDA retains representativeness and is suitable for individual-level analysis of longitudinal labour force outcomes. Importantly, HILDA enables us to track individual labour market outcomes over a longer longitudinal period than is available in other Australian labour force data. The repeated panel nature of this data is also unique in the context of Australia. These factors allow controls for endogeneity and unobserved individual heterogeneity, which are important in analysing labour force outcomes and earnings dynamics.

We use data from Wave 1 to Wave 18 (financial years 2002 to 2019),[11] which provides an unbalanced sample of 43,770 unique individuals (387,695 person-year observations). We restrict our sample to be 19 to 65 years old, representing the working age population that is likely to have completed schooling.[12] We

[9] In our robustness section, we show that disaster occurrence is plausibly exogenous to an individual's demographic status, education, labour market and health outcomes.

[10] Excluding non-spatial SA4 special purpose codes comprising Migratory–Offshore–Shipping and No Usual Address codes for each State and Territory, there are currently 89 SA4 regions in Australia.

[11] We restrict our sample to these years so as to exclude any potential bias introduced from the COVID-19 pandemic.

[12] In Table A10 of our appendix, we show baseline results using an alternative age group of 25 to 55 years old. This more restricted age selection is to exclude university students or early retirees to ensure our results are not sensitive to the inclusion of these cohorts. From this restricted sample, our results are less precisely estimated (particularly for males), however coefficient signs are consistent. This could be explained by the fact that with a more restricted age group, male

further limit our sample to individuals who either experience only one disaster during the sample period (as our treatment group), and those who experience no natural disaster (as our control group). These restrictions give us an analysed sample of 204,922 person-year observations. Finally, since our model specification uses a lagged treatment variable, only individuals that appear in at least two consecutive years are included in the analysed samples. This brings our final sample to 154,950 observations of which 51% identified as women.

We merge our final sample from HILDA data with our consolidated disaster database based on SA4-level location and the date of disaster occurrence. Specifically, we define an individual as experiencing a natural disaster if they are residing in a natural disaster-affected SA4 region at the date of exposure. We limit our treatment group to individuals who report living in the same SA4 region in consecutive years (i.e. the survey year prior to disaster occurrence and the year post disaster occurrence).[13] Of our sample, 5,232 (around 28% of total unique individuals in the sample) lived in a disaster-affected region at some point over our period of analysis, with 2,285 (12%) experiencing a flood and 3,664 (19%) exposed to a bushfire.

Table 1 presents the lifetime (observed survey year) average values of the demographic and labour market characteristics of our sample. Those experiencing a bushfire or flood were generally slightly older and more likely to be men compared to those who did not experience a natural disaster, however had a lower educational attainment (approximately 4% less Bachelor degree attainment)[14] and were more likely to be married (approximately 4% more a married). From this, there are no clear systematic differences between those who experienced a natural disaster during our period of analysis and those who did not. We also provide summary statistics by gender and disaster exposure in Table A1 of our Appendix.

iii Mixed-sex couples sample

Out of 154,950 analysed observations, 89,896 observations are identified when our sample is restricted to mixed-sex couples. Of this restricted sample, 3,004 unique individuals (around 20% of the sample) ever experienced a bushfire during their lifetime in the survey, while 1,856 (13%) experienced a flood. In terms of individual characteristics, those who were exposed to disaster were slightly older, less educated and more likely to be married compared to partnered individuals who did not experience a disaster during the observed period. Apart from these characteristics, there are no significant differences between individuals

observations are dropped significantly compared to women.

[13] In our robustness section, we relax the requirement that individuals must reside in the disaster-affected SA4 region in consecutive years to allow for migration. We find similar results to our baseline specification.

[14] In our robustness section, we show that our results are robust to the inclusion of educational attainment in our model.

Table 1: Descriptive statistics

	(1) Had Bushfire	(2) Had Flood	(3) No Disaster
Age of Individual	42.74	42.38	41.40
	(12.19)	(12.08)	(13.87)
male	0.492	0.498	0.497
	(0.500)	(0.500)	(0.500)
Has college degree or more	0.523	0.529	0.567
	(0.499)	(0.499)	(0.495)
Married	0.669	0.671	0.626
	(0.470)	(0.470)	(0.484)
Number of Persons in Household	3.007	2.864	2.922
	(1.389)	(1.358)	(1.444)
Employed (=1)	0.742	0.743	0.750
	(0.438)	(0.437)	(0.433)
LF participate (=1)	0.776	0.774	0.784
	(0.417)	(0.418)	(0.411)
Average working hours per week	38.03	38.20	37.16
	(14.61)	(14.69)	(14.65)
Total salary weekly	0.894	0.849	0.899
	(1.023)	(0.896)	(0.974)
Household labor income	105.4	94.62	111.7
	(88.10)	(79.16)	(99.08)

Standard deviation in parentheses. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old to represent working age population. Sample must appears in two consecutive years. Financial amounts. including income and government support are shown in real (CPI adjusted in 2019) Australian dollars ('000s).

in our restricted sample who experienced a disaster compared to those who did not. See Table A2 in our Appendix for complete summary statistics for mixed-sex partnered observations.

IV Method

i Baseline model

To investigate the causal effects of bushfires and floods, we use a two-way fixed effects model, which is similar in spirit to a generalised difference-in-difference approach. This approach is commonly used to evaluate the effects of natural disasters (Cavallo et al. 2013, Hsiang & Jina 2014, Loebach & Korinek 2019, Johar et al. 2020, Ulubaşoğlu et al. 2019). Our baseline model can be written as:

$$\begin{aligned} Y_{i,s,t} =& \beta_0 + \beta_1 Fire_{i,s,t} + \beta_2 Fire_{i,s,t-1} + \beta_3 Fire_{i,s,t-2} + \beta_4 Flood_{i,s,t} + \beta_5 Flood_{i,s,t-1} + \beta_6 Flood_{i,s,t-2} \\ & + age_i + \sigma_g + \sigma_g \times \tau_t + \gamma_i + \tau_t + \epsilon_{i,s,t} \end{aligned} \quad (1)$$

where Y is the outcome of interest for individual i in period t, who resided in SA4 s. We are interested in estimating the effects of SA4-level disaster exposure both in the year that disaster occurred and in the two years following disaster occurrence, and consider these effects separately for bushfires and floods. We use dummy-coded disaster variables, $Fire$ and $Flood$, representing bushfires and floods respectively. We assign a value of 1 if an individual is residing in an SA4 region that experiences a disaster, for the full year of disaster exposure, and zero otherwise. This identification strategy relies on exploiting the exogenous variation in the time and location of disaster occurrence. This plausible exogeneity is shown in Table A4 of the Appendix, where we highlight that observed demographics, employment status, earnings, educational attainment and mental health have little explanatory power for future disaster exposure.

We control for time-invariant individual effects through individual fixed effects (γ_i), common time-varying shocks that impact all individuals in a given year through a year fixed effect (τ_t), state-level time-invariant characteristics (σ_g) and state-time trends to account for location-specific labour market trends ($\sigma \times t$) such as the resources boom which impacted regions in Western Australia throughout our period of analysis. Given that an individual's employment and earnings outcomes are expected to follow a life-cycle pattern, we also add linear controls for an individual's age. We use robust standard errors clustered at SA4-level. This follows the same approach used by most studies of natural disasters, including studies in Australia by Ulubaşoğlu et al. (2019) and Johar et al. (2020).

Our outcomes of interest include an individual's overall labour force status through dummy variables for labour market participation, employment, and unemployment; and job quality through dummy variables for whether an individual is employed full-time, or part-time. We also consider the effect of bushfires and floods on an individual's intensive margin of employment (through a log-transformed hours worked in all jobs variables) and earnings (including log-transformed variables for hourly earnings).

ii Sectoral industry effects

Next, we explore whether the labour market effects from our baseline model vary across economic sectors. To do this, we add to our baseline model an interaction term between an individual's single-digit industry of employment *industry* and SA4-level disaster exposure. The industry type categorisation follows the one-digit International Standard Industrial Classification of All Economic Activities (ISIC) that groups activities into nine broad economic sectors.[15]

[15] As adopted by ILO. For details, please see https://ilostat.ilo.org/

$$
\begin{aligned}
Y_{i,s,t} = {} & \beta_0 + \beta_1 Fire_{i,s,t} + \beta_2 Fire_{i,s,t-1} + \beta_3 Fire_{i,s,t-2} + \beta_4 Flood_{i,s,t} + \beta_5 Flood_{i,s,t-1} + \beta_6 Flood_{i,s,t-2} \\
& + \beta_7 Fire_{i,s,t} \times industry_{i,s,t} + \beta_8 Fire_{i,s,t-1} \times industry_{i,s,t-1} + \beta_9 Fire_{i,s,t-2} \times industry_{i,s,t-2} \\
& + \beta_{10} Flood_{i,s,t} \times industry_{i,s,t} + \beta_{11} Flood_{i,s,t-1} \times industry_{i,s,t-1} + \beta_{12} Flood_{i,s,t-2} \times industry_{i,s,t-2} \\
& + age_{i,t} + \sigma_s + \sigma_s \times \tau_t + \gamma_i + \tau_t + \epsilon_{i,s,t} \qquad (2)
\end{aligned}
$$

Again, the disaster variable and interaction term are estimated separately for both bushfires and floods, as is our vector of control variables. In this specification, the average treatment effect is respectively measured by the coefficients for the year of disaster occurrence, and for the two years following disaster occurrence. This treatment estimates the incremental effect of natural disasters according to an individual's industry of employment, relative to an agricultural industry reference group.

iii Intrahousehold dynamics

We also explore whether intrahousehold dynamics among mixed-sex couples could explain the relative labour market vulnerability of men and women following natural disaster. Firstly, we consider the possibility that increased domestic work take-up in the aftermath of natural disaster is associated with a temporary reduction in labour force participation. To test this effect, we use time-allocation data from HILDA, which asks individuals about their time spent on unpaid caring or domestic responsibilities. We modify equation (1) by replacing the outcome to be the number of total hours spent on domestic work (including in caring roles).

A competing hypothesis that we test for is that among mixed-sex couples, individuals may temporarily increase their labour supply in the event that their partner loses employment. To test for this 'added worker' effect, we use an interaction term which dummy codes whether an individual's partner lost their employment with SA4-level disaster exposure (separately for bushfires and floods). Our treatment effects can be interpreted as the change in an individual's labour force status if their partner lost employment (treatment), relative to the rest of the population residing in a disaster-affected region (control). Specifically, we use the following equation:

$$
\begin{aligned}
Y_{i,s,t} = {} & \beta_0 + \beta_1 Fire_{i,s,t} + \beta_2 Fire_{i,s,t-1} + \beta_3 Fire_{i,s,t-2} + \beta_4 Flood_{i,s,t} + \beta_5 Flood_{i,s,t-1} + \beta_6 Flood_{i,s,t-2} \\
& + \beta_7 Fire_{i,s,t} \times partnerlostjob_{i,s,t} + \beta_8 Fire_{i,s,t-1} \times partnerlostjob_{i,s,t} \\
& + \beta_9 Fire_{i,s,t-2} \times partnerlostjob_{i,s,t} + \beta_{10} Flood_{i,s,t} \times partnerlostjob_{i,s,t} \\
& + \beta_{11} Flood_{i,s,t-1} \times partnerlostjob_{i,s,t} + \beta_{12} Flood_{i,s,t-2} \times partnerlostjob_{i,s,t} \\
& + age_{i,t} + \sigma_s + \sigma_s \times \tau_t + \gamma_i + \tau_t + \epsilon_{i,s,t} \qquad (3)
\end{aligned}
$$

V Results

i Baseline results

Effects of Bushfires

Table 2 summarises the result of our baseline specification. Bushfires were found to have no statistically significant overall effects on an individual's labour force status, however this may be attributed to the contrasting effects for men and women. Whilst bushfires, as presented in Panel C Column (1), generated persistent increases in a male's likelihood of employment (+1.8 ppts at one-year lag, and +1.6 ppts at two-year lag), they lower the likelihood of female employment, as seen in Table 2 Panel B Column (1), by -1.6 ppts.

To provide a sense of the magnitude of these results, we apply our estimated treatment effects to SA4-level labour market data from the ABS.[16] Our approach is not intended to provide a comprehensive estimation of the costs of natural disasters to Australian labour markets, but to provide an economic interpretation of our statistically significant average treatment effects found.

We find that over the period from 2002 to 2019, bushfires led to the loss of around 86,000 female jobs - or an average of 4,780 jobs per year. Assuming these jobs were at average levels of hours and productivity,[17] this equates to an annual average of 6 million hours or $495 million in foregone GDP. Meanwhile, bushfires generated an additional 177,714 male jobs or an average of nearly 10,000 jobs per year. On average each year, this equates to an additional 16.5 million hours of male employment or

[16] Australian Bureau of Statistics (2021). RM1 - Labour force status by age, labour market region (ASGS) and sex, October 1998 onwards. Retrieved from: https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release/

[17] For each disaster, we assume that additional jobs occur at average hours for that gender, year and state/territory, based on data from the ABS. To monetise this figure, we use GDP per hour worked from OECD (https://data.oecd.org/lprdty/gdp-per-hour-worked.html) converted to 2020 Australian dollars (https://data.oecd.org/conversion/purchasing-power-parities-ppp.html). We conduct this estimation separately for each disaster in our sample, and then sum to totals.

$1.4 billion in GDP. These findings highlight the relatively more pronounced labour market vulnerability faced by women following a bushfire.

As depicted in Table 2 Panel C Column (3), bushfires also increased the likelihood of full-time employment for men, by +1.5 ppts at one-year and two-year lags; reduced the male unemployment rate by -1.1 ppts; and lifted male labour force participation (Table 2 Panel C Column (5)) by +1.0 ppts (two-year lag). These results suggest that initially additional male labour supply is mobilised from the pool of unemployed, before the overall likelihood of labour force participation is increased. We also find that bushfires reduced male consumption, with this effect statistically significant two-years on from occurrence (-29.0%, see Table 2 Panel C Column (8)).

Effects of Floods

In contrast to bushfires, we find that floods unambiguously lift the labour supply for both men and women, including the likelihood of employment by +1.3 ppts and +1.8 ppts at one-year lag (see Table 2 Panel A Column (1)). Over our period of analysis, this is equivalent to an average of 13,498 additional jobs per year - or an around 20 million hours (+$1.7 billion in additional GDP). We also find that floods lifted an individual's likelihood of participating in the labour force by +1.1 ppts and +1.5 ppts after a one-year lag (see Table 2 Panel A Column (5)) - equivalent to an average of 11,321 additional individuals participating in the labour force each year. A possible explanation for this difference in the effects of bushfires and floods is that floods tend to occur in regions with relatively higher population density, which may be more likely to experience greater stimulatory spending on rebuilding and recovery - and thereby 'creative destruction'.

The effect of floods on employment was more pronounced for men than for women, with the male likelihood of employment increased by +1.6 ppts and +1.9 ppts after a one-year lag (see Table 2 Panel C Column (1)), equivalent to a total male employment effect of around 7,529 additional jobs per year. In contrast, floods lead to a lagged increase in female employment of +1.8% (Table 2 Panel B Column (1)), or an average of nearly 4,000 female jobs per year.

We observe gendered differences in the mobilisation of this additional labour supply, with male jobs more likely to be filled from the male pool of unemployed while females were more likely to enter employment from outside the labour force. This is reflected in the reduced likelihood of male unemployment (-1.0 ppts, Table 2 Panel C Column (4)) and an increased likelihood of female participation (+2.0%, or 4,406 additional females, as seen in Table 2 Panel B Column (5)). Meanwhile, floods did not significantly impact either the male likelihood of participation (see Table 2 Panel C Column (5)) or the female likelihood of unemployment (see Table 2 Panel B Column (4)). The increase in female labour force participation is consistent with initial increases in female hourly earnings (+2.4%) inducing employment growth as women are encouraged to enter the labour market (see Table 2 Panel B Column (7)).

We also find gendered differences in the take-up of part-time employment following floods. Whilst floods increased the male likelihood of full-time employment after a one-year lag (+2.6 ppts), female employment was more likely to be part-time (+1.9 ppts), as seen in Table 2 Panel C Column (3) and Panel B Column (2) respectively. However, both men and women experienced a decline in their average hours worked two-years on from flood exposure, with this effect largest among women - -3.9% compared to -1.6% for men (see Table 2 Panels B and C Column (6)).

Table 2: Indirect effects of natural disasters on labor market outcomes

	(1) Employed (=1)	(2) Part-time (=1)	(3) Full-time (=1)	(4) Unemployed (=1)	(5) LF participate (=1)	(6) Log working hours	(7) (Log) Hourly wage	(8) LR person consumption
Panel A. Overall								
Fire	-0.004	0.000	-0.004	0.001	-0.003	-0.010	-0.004	-0.026
	(0.007)	(0.005)	(0.007)	(0.004)	(0.006)	(0.009)	(0.010)	(0.078)
Flood	0.013**	0.013*	-0.000	-0.003	0.011*	0.003	0.002	-0.027
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.011)	(0.008)	(0.073)
Fire t-1	0.010	0.005	0.006	-0.004	0.006	-0.007	-0.006	-0.010
	(0.007)	(0.006)	(0.006)	(0.003)	(0.007)	(0.010)	(0.008)	(0.071)
Flood t-1	0.018***	0.007	0.012*	-0.004	0.015***	-0.010	-0.009	0.075
	(0.005)	(0.007)	(0.006)	(0.003)	(0.005)	(0.009)	(0.011)	(0.105)
Fire t-2	0.005	-0.007	0.012**	-0.003	0.002	0.002	0.004	-0.189***
	(0.006)	(0.006)	(0.006)	(0.003)	(0.006)	(0.007)	(0.007)	(0.063)
Flood t-2	0.009	0.016*	-0.008	-0.003	0.006	-0.028***	0.016*	-0.041
	(0.007)	(0.009)	(0.009)	(0.004)	(0.005)	(0.009)	(0.009)	(0.104)
N	154,950	154,950	154,950	154,950	154,950	114,738	103,409	154,950
Adj. R2	0.589	0.421	0.606	0.205	0.590	0.585	0.654	0.538
Panel B. Female								
Fire	-0.016**	-0.005	-0.012	0.007	-0.009	-0.021	0.014	-0.067
	(0.008)	(0.008)	(0.010)	(0.006)	(0.006)	(0.018)	(0.010)	(0.115)
Flood	0.010	0.013	-0.004	-0.000	0.010	0.004	0.024*	-0.026
	(0.011)	(0.013)	(0.010)	(0.004)	(0.011)	(0.015)	(0.014)	(0.097)
Fire t-1	0.003	0.004	-0.001	0.001	0.004	-0.019	-0.004	0.132
	(0.008)	(0.009)	(0.009)	(0.005)	(0.009)	(0.014)	(0.011)	(0.094)
Flood t-1	0.018**	0.019*	-0.002	0.003	0.020**	-0.016	-0.005	0.058
	(0.008)	(0.011)	(0.011)	(0.005)	(0.008)	(0.013)	(0.012)	(0.196)
Fire t-2	-0.005	-0.015	0.010	-0.001	-0.006	-0.004	-0.001	-0.101
	(0.010)	(0.009)	(0.009)	(0.004)	(0.010)	(0.013)	(0.009)	(0.102)
Flood t-2	0.015	0.024	-0.010	-0.005	0.010	-0.039**	0.021	-0.016
	(0.011)	(0.016)	(0.013)	(0.006)	(0.008)	(0.019)	(0.015)	(0.144)
N	80,567	80,567	80,567	80,567	80,567	55,391	51,089	80,567
Adj. R2	0.564	0.387	0.528	0.166	0.557	0.531	0.603	0.547
Panel C. Male								
Fire	0.009	0.004	0.005	-0.007	0.002	0.000	-0.021	0.017
	(0.010)	(0.007)	(0.009)	(0.005)	(0.009)	(0.007)	(0.013)	(0.117)
Flood	0.016**	0.013*	0.004	-0.005	0.011	0.003	-0.019*	-0.035
	(0.008)	(0.007)	(0.012)	(0.005)	(0.007)	(0.011)	(0.011)	(0.138)
Fire t-1	0.018**	0.004	0.015***	-0.011**	0.007	0.003	-0.007	-0.174
	(0.009)	(0.007)	(0.005)	(0.004)	(0.008)	(0.010)	(0.012)	(0.117)
Flood t-1	0.019**	-0.006	0.026**	-0.010*	0.009	-0.005	-0.012	0.101
	(0.009)	(0.008)	(0.012)	(0.005)	(0.009)	(0.011)	(0.014)	(0.132)
Fire t-2	0.016**	0.001	0.015**	-0.006	0.010*	0.007	0.009	-0.290***
	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.008)	(0.013)	(0.110)
Flood t-2	0.001	0.007	-0.006	0.000	0.002	-0.016*	0.010	-0.068
	(0.009)	(0.008)	(0.008)	(0.005)	(0.007)	(0.009)	(0.019)	(0.123)
N	74,383	74,383	74,383	74,383	74,383	59,347	52,320	74,383
Adj. R2	0.612	0.374	0.604	0.244	0.625	0.550	0.690	0.518
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

ii Sectoral industry effects

Effects of bushfires

We find that bushfires and floods have different sectoral effects for labour markets, as summarised in Table 3. For example, we find that relative to agricultural employment, bushfires lifted the likelihood of employment in the mining (+6.4 ppts) and transport (+6.0 ppts) sectors (see Table 3 Column(1)). These industries tend to be male dominated, with men accounting for more than three quarters of employment. This goes some way to explaining why bushfires increase male employment whilst reducing female employment, consistent with a potential sectoral reallocation favouring male labour.

Consistent with this relative restructuring of labour supply toward male-dominated sectors, we find that bushfires reduce participation in female-dominated sectors at the intensive margin of employment. As seen in Table 3 Column (4), relative average hours were reduced in the trade sector (-8.5%, -10.5% at one-year lag), the services sector (-6.8% at one-year lag), and the banking and insurance sector (-8.0% at one-year lag). We also find that bushfires persistently reduced the relative likelihood of full-time employment in trade (-9.5 ppts, -8.5 ppts at one-year lag) and services (-3.7 ppts, -5.2 ppts at one-year lag) as seen in Table 3 Column (3). These results were not accompanied by an increase in employment to these sectors, suggesting that labour supply to these sectors contracts along the intensive margin following bushfire exposure. These results may also reflect a preference among female workers to change to part-time hours following a bushfire.

We also find that bushfires reduced relative average hours worked in transport (-12.2% at one-year lag) and construction (-5.9% at one-year lag), however this is perhaps consistent with an expansion of labour supply in these sectors occurring at part-time hours (see Table 3 Column (2) and Column(4)). Individuals employed in manufacturing, traditionally also a male-dominated sector, also became relatively less likely to work full-time (-6.0 ppts, see Table 3 Column(3)) and more likely to work part-time (+7.1 ppts, see Table 3 Column(2)).

We find that bushfires were also associated with an increase in the hourly returns to labour supply in several sectors, with these displaying no definite pattern across gender composition. Specifically, as depicted in Table 3 Column (5), bushfires increased average hourly earnings in the trade (+10.4%, +12.7% at one-year lag), services (+10.3%), banking and insurance (+12.8% at one-year lag), mining (+17.1% at one-year lag), and manufacturing (+9.9% at one-year lag).

Effects of floods

Floods were found to increase the relative likelihood of employment, as depicted in Table 3 Column (1), in the services sector (+5.5 ppts at one-year lag). It is likely that women accounted for much of this employment growth, with the services sector traditionally having a higher share of female employment representation than other sectors in our analysis.

Floods had mixed effects on more male-dominated sectors. We find that floods reduced the relative likelihood of employment (-9.5 ppts) in the transport sector, however normalisation occurred after a one-year lag (see Table 3 Column (1)). Meanwhile, floods were found to increase relative average hours worked in both the mining (+9.0%) and manufacturing (+8.6%) sectors (see Table 3 Column (4)), while increasing the likelihood of full-time employment, as seen in Table 3 Column (3), in manufacturing (+8.7 ppts), and transport (+8.7 ppts at one-year lag).

Floods were also found to generate a lagged increase in relative hourly returns to labour in both the construction (+11.9%) and trade (+15.9%) sectors (see Table 3 Column (5)). This is perhaps consistent with labour supply shortages in these industries.

The sectoral effects of floods found are quite different to those of bushfires, most notably for the services sector. A possible reason for this is a higher population density in flood-prone areas, compared to the more sparsely populated areas that experience bushfires. A higher population density may lead to increased demand for services, such as insurance, temporary accommodation, or public administration and safety in the aftermath of a flood, which may in turn support increased employment in these sectors. In contrast, demand for these services may remain relatively dampened following bushfires. This may also explain why we observe an increase in female labour force participation following a flood - with much of this likely driven by the services sector - while female employment declines following a bushfire.

Table 3: Indirect effects of natural disasters on labor market by industry

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed (=1)	Part-time (=1)	Full-time (=1)	Log working hours	(Log) Hourly wage	LR person consumption
Energy × Fire	-0.025	-0.006	-0.023	0.081	-0.100	-0.566
	(0.121)	(0.039)	(0.123)	(0.074)	(0.073)	(0.736)
Mining × Fire	0.064*	0.021	0.044	-0.018	0.025	-0.232
	(0.036)	(0.037)	(0.046)	(0.057)	(0.094)	(0.695)
Manufacturing × Fire	0.014	0.071**	-0.060*	-0.010	0.078	0.064
	(0.029)	(0.035)	(0.033)	(0.044)	(0.058)	(0.510)
Construction × Fire	0.009	0.044	-0.039	-0.033	0.069	0.100
	(0.025)	(0.032)	(0.031)	(0.048)	(0.057)	(0.344)
Trade × Fire	-0.010	0.082***	-0.095***	-0.085**	0.104**	0.126
	(0.023)	(0.029)	(0.028)	(0.034)	(0.052)	(0.291)
Transport × Fire	0.060*	0.057	-0.014	-0.072	0.026	0.067
	(0.034)	(0.039)	(0.045)	(0.058)	(0.068)	(0.529)
Bank/Insurance × Fire	-0.019	-0.020	-0.022	-0.047	0.033	-0.084
	(0.041)	(0.032)	(0.039)	(0.059)	(0.086)	(0.574)
Services × Fire	0.017	0.050*	-0.037*	-0.022	0.103*	0.188
	(0.018)	(0.026)	(0.022)	(0.039)	(0.055)	(0.298)
Energy × Fire t-1	-0.021	0.020	-0.044	-0.044	0.105	-0.817
	(0.034)	(0.034)	(0.057)	(0.037)	(0.063)	(0.680)
Mining × Fire t-1	-0.014	0.019	-0.030	0.006	0.171*	0.623
	(0.049)	(0.025)	(0.062)	(0.046)	(0.086)	(0.802)
Manufacturing × Fire t-1	0.022	0.039	-0.029	-0.042	0.099*	0.442
	(0.023)	(0.027)	(0.033)	(0.034)	(0.059)	(0.543)
Construction × Fire t-1	0.019	0.038	-0.022	-0.059*	0.074	0.310
	(0.021)	(0.030)	(0.033)	(0.032)	(0.068)	(0.603)
Trade × Fire t-1	-0.019	0.065***	-0.085***	-0.105***	0.127**	0.301
	(0.026)	(0.024)	(0.032)	(0.030)	(0.061)	(0.572)
Transport × Fire t-1	0.034	0.089**	-0.055	-0.122***	0.109	1.030
	(0.031)	(0.037)	(0.052)	(0.045)	(0.068)	(0.655)
Bank/Insurance × Fire t-1	-0.019	-0.018	0.002	-0.080*	0.128*	0.282
	(0.033)	(0.046)	(0.059)	(0.045)	(0.068)	(0.748)
Services × Fire t-1	0.001	0.051**	-0.052*	-0.068***	0.089	0.773
	(0.021)	(0.023)	(0.030)	(0.021)	(0.058)	(0.531)
Energy × Fire t-2	-0.025	-0.021	-0.006	0.025	-0.036	0.323
	(0.055)	(0.068)	(0.074)	(0.035)	(0.089)	(0.595)
Mining × Fire t-2	-0.033	0.025	-0.057	-0.017	0.087	0.229
	(0.052)	(0.052)	(0.058)	(0.058)	(0.086)	(0.857)
Manufacturing × Fire t-2	-0.011	0.035	-0.048	-0.023	-0.026	-0.158
	(0.029)	(0.035)	(0.034)	(0.043)	(0.059)	(0.541)
Construction × Fire t-2	0.009	0.016	-0.010	-0.025	-0.001	0.102
	(0.035)	(0.035)	(0.033)	(0.042)	(0.066)	(0.474)
Trade × Fire t-2	-0.006	0.021	-0.030	-0.047	-0.014	-0.081

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed (=1)	Part-time (=1)	Full-time (=1)	Log working hours	(Log) Hourly wage	LR person consumption
	(0.032)	(0.033)	(0.034)	(0.040)	(0.059)	(0.445)
Transport × Fire t-2	0.002	0.026	-0.027	-0.024	-0.062	0.202
	(0.039)	(0.049)	(0.045)	(0.049)	(0.055)	(0.555)
Bank/Insurance × Fire t-2	-0.071	-0.032	-0.038	-0.016	0.014	0.202
	(0.058)	(0.048)	(0.054)	(0.062)	(0.080)	(0.543)
Services × Fire t-2	-0.007	0.006	-0.015	-0.001	-0.032	0.119
	(0.027)	(0.026)	(0.032)	(0.039)	(0.052)	(0.435)
Energy × Flood	-0.004	-0.041	0.035	0.019	0.048	0.681
	(0.032)	(0.053)	(0.040)	(0.055)	(0.050)	(1.119)
Mining × Flood	-0.037	-0.085	0.047	0.090*	-0.021	0.197
	(0.053)	(0.053)	(0.038)	(0.048)	(0.069)	(1.217)
Manufacturing × Flood	0.004	-0.085*	0.087***	0.086*	-0.076	0.142
	(0.038)	(0.049)	(0.026)	(0.047)	(0.071)	(0.512)
Construction × Flood	-0.010	-0.051	0.037	0.023	-0.033	0.298
	(0.045)	(0.052)	(0.051)	(0.046)	(0.057)	(0.946)
Trade × Flood	-0.003	-0.031	0.025	0.015	-0.030	0.401
	(0.035)	(0.050)	(0.042)	(0.059)	(0.057)	(0.592)
Transport × Flood	-0.095*	-0.064	-0.033	0.017	-0.031	-0.023
	(0.050)	(0.062)	(0.043)	(0.049)	(0.068)	(0.931)
Bank/Insurance × Flood	-0.007	0.043	-0.050	-0.033	0.065	0.540
	(0.052)	(0.066)	(0.070)	(0.063)	(0.084)	(0.906)
Services × Flood	0.008	-0.011	0.016	-0.002	-0.008	0.545
	(0.032)	(0.044)	(0.029)	(0.041)	(0.066)	(0.600)
Energy × Flood t-1	-0.005	-0.032	0.023	0.020	0.167	1.394
	(0.064)	(0.061)	(0.090)	(0.077)	(0.111)	(0.867)
Mining × Flood t-1	0.008	-0.024	0.031	0.033	0.051	0.837
	(0.048)	(0.057)	(0.060)	(0.064)	(0.115)	(1.066)
Manufacturing × Flood t-1	0.045	-0.017	0.061	-0.011	0.095	-0.168
	(0.043)	(0.054)	(0.041)	(0.060)	(0.086)	(0.588)
Construction × Flood t-1	0.020	-0.048	0.063	-0.006	0.119*	0.439
	(0.030)	(0.051)	(0.045)	(0.060)	(0.071)	(0.617)
Trade × Flood t-1	0.015	-0.009	0.020	-0.021	0.159**	0.536
	(0.029)	(0.048)	(0.044)	(0.045)	(0.076)	(0.588)
Transport × Flood t-1	0.062	-0.029	0.087*	-0.014	0.127	0.767
	(0.039)	(0.056)	(0.048)	(0.067)	(0.102)	(0.691)
Bank/Insurance × Flood t-1	-0.000	0.024	-0.026	-0.089	-0.026	1.047
	(0.042)	(0.053)	(0.067)	(0.081)	(0.121)	(0.873)
Services × Flood t-1	0.055**	0.010	0.042	-0.015	0.095	0.836
	(0.022)	(0.049)	(0.048)	(0.058)	(0.074)	(0.590)
Energy × Flood t-2	-0.036	0.031	-0.051	-0.066	0.141	0.993
	(0.109)	(0.071)	(0.117)	(0.128)	(0.135)	(1.179)
Mining × Flood t-2	-0.137	0.110	-0.231*	-0.083	0.222	1.488
	(0.101)	(0.115)	(0.121)	(0.184)	(0.229)	(1.092)

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed (=1)	Part-time (=1)	Full-time (=1)	Log working hours	(Log) Hourly wage	LR person consumption
Manufacturing × Flood t-2	-0.006	0.046	-0.032	-0.018	0.107	-1.233
	(0.051)	(0.070)	(0.068)	(0.115)	(0.114)	(0.785)
Construction × Flood t-2	-0.004	0.027	-0.014	-0.016	0.112	-1.129
	(0.039)	(0.064)	(0.060)	(0.129)	(0.127)	(0.732)
Trade × Flood t-2	0.010	0.045	-0.018	-0.035	0.134	-0.547
	(0.044)	(0.060)	(0.067)	(0.099)	(0.114)	(0.718)
Transport × Flood t-2	0.013	0.056	-0.044	-0.059	0.126	-1.099
	(0.051)	(0.080)	(0.083)	(0.121)	(0.139)	(0.848)
Bank/Insurance × Flood t-2	0.015	0.100	-0.062	-0.031	0.146	-0.829
	(0.061)	(0.075)	(0.075)	(0.145)	(0.148)	(0.692)
Services × Flood t-2	-0.007	0.028	-0.020	-0.027	0.102	-0.813
	(0.041)	(0.070)	(0.065)	(0.115)	(0.117)	(0.616)
N	98,267	98,267	98,267	90,286	81,392	98,267
Adj. R2	0.266	0.482	0.546	0.600	0.668	0.535

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

iii Intrahousehold dynamics

Effect on domestic work

We find no evidence to suggest that natural disasters increase the total time spent by females on domestic duties (see Table A3 in the Appendix). However, our survey data are collected annually so it is possible that any short-term effect on female housework is transitory and has normalised by the time our sample is next observed. We do however find that floods contemporaneously increased male time spent on domestic work by 1.065 hours per week with this effect statistically significant.

Evidence for an 'added worker' effect

In contrast to our hypotheses that women may temporarily take time out of the labour force to take on additional domestic responsibilities, we find strong evidence of an 'added worker' effect - whereby household members were more likely to increase their labour supply if their partner had lost their job following natural disaster exposure.

Our overall results, as depicted in Table 4 Panel A, are consistent with an 'added worker' effect at the intensive margin of employment, with relative average hours lifted after a fire by 18.7% and after a flood by 7.5% among those whose partners had lost their job (see Table 4 column(6)). We also find that floods had a lagged effect of increasing the relative likelihood of full-time employment (+10.6 ppts, see Table 4 Column (3)) after a one-year lag and of employment (+2.3 ppts, see Table 4 Panel A Column (1)) after a two-year lag.

As expected, the evidence of an 'added worker' effect was most pronounced for females. This may reflect a lower level of female labour force participation prior to disaster occurrence, translating to a greater ability to respond through increasing labour supply. The 'added worker' effect was strongest for women following a bushfire, as reported in Table 4 Panel B, with results indicating this effect at both the extensive and intensive margins of participation. Among females whose partner had lost their job in the aftermath of a bushfire, we find a relative increase in the likelihood of labour force participation (+3.6 ppts, see Table 4 Panel B Column (5)), employment (+3.6 ppts, see Table 4 Panel B Column (1)), and average hours worked (+23.4%, see Table 4 Panel B Column (6)).

Meanwhile for males following a bushfire, partner job loss was associated with a lagged increase in relative participation levels at both the extensive and intensive margins, as summarised in Table 4 Panel C. At the extensive margin, we find that bushfires lifted the relative male likelihood of employment by +2.5 ppts (see Table 4 Column (1)) and of participation by +2.3 ppts after a one-year lag (see Column

(5)). We also find these effects at the intensive margin, with males relatively more likely to be employed full-time (+4.7 ppts at one-year and two-year lags, see Column (3)) and relative average working hours increased by 6.6% (one-year lag, see Table 4 Column (6)).

The 'added worker' effect was not as pronounced following floods, perhaps reflecting a lower likelihood of partner job loss. However, we do find that women whose partner lost their job following a flood experienced a relative increase in their average hours worked, by 13.3% (Table 4 Panel B Column (6)). Meanwhile, males observed lagged relative increases in their likelihood of full-time employment (+12.7 ppts at one-year lag) and employment (+2.6 ppts at two-year lag), as seen in Table 4 Column (3) and (1) of Table 4 Panel C respectively.

Table 4: Partner sample only: Added worker effect of natural disasters on labor market outcomes

	(1) Employed (=1)	(2) Part-time (=1)	(3) Full-time (=1)	(4) Unemployed (=1)	(5) LF participate (=1)	(6) Log working hours	(7) (Log) Hourly wage	(8) LR person consumption
Panel A. Overall								
Partner lost job × Fire	0.019	0.023	-0.004	0.000	0.019	0.187***	-0.063	-0.082
	(0.012)	(0.070)	(0.071)	(0.000)	(0.012)	(0.057)	(0.055)	(0.855)
Partner lost job × Flood	-0.059	0.013	-0.072	0.002	-0.057	0.075**	-0.118	-0.549
	(0.067)	(0.058)	(0.073)	(0.001)	(0.067)	(0.034)	(0.077)	(0.810)
Partner lost job × Fire t-1	-0.001	-0.040	0.038	-0.001	-0.001	0.005	0.094*	0.110
	(0.029)	(0.051)	(0.043)	(0.001)	(0.029)	(0.056)	(0.049)	(0.665)
Partner lost job × Flood t-1	0.010	-0.097	0.106*	-0.000	0.010	0.061	0.041	-1.416***
	(0.010)	(0.062)	(0.063)	(0.001)	(0.010)	(0.055)	(0.089)	(0.497)
Partner lost job × Fire t-2	0.007	0.013	-0.006	0.000	0.007	0.057	-0.008	-0.351
	(0.005)	(0.040)	(0.040)	(0.001)	(0.005)	(0.048)	(0.033)	(0.806)
Partner lost job × Flood t-2	0.023**	0.105	-0.079	0.000	0.023**	-0.016	0.039	0.332
	(0.010)	(0.077)	(0.079)	(0.001)	(0.010)	(0.059)	(0.092)	(0.972)
N	89,896	89,896	89,896	89,896	89,896	86,067	86,067	89,896
Adj. R2	0.676	0.566	0.572	0.175	0.685	0.586	0.652	0.548
Panel B. Female								
Partner lost job × Fire	0.036**	0.114	-0.079	0.001	0.036**	0.234**	-0.080	-2.188**
	(0.018)	(0.135)	(0.129)	(0.001)	(0.018)	(0.101)	(0.082)	(1.038)
Partner lost job × Flood	-0.072	-0.089	0.017	0.001	-0.070	0.133**	-0.086	-0.439
	(0.069)	(0.117)	(0.115)	(0.002)	(0.069)	(0.058)	(0.111)	(1.246)
Partner lost job × Fire t-1	-0.018	-0.043	0.025	0.001	-0.017	-0.039	0.089*	-0.197
	(0.048)	(0.088)	(0.073)	(0.001)	(0.048)	(0.098)	(0.053)	(1.041)
Partner lost job × Flood t-1	0.006	-0.058	0.063	-0.000	0.005	0.055	-0.073	-0.793
	(0.011)	(0.158)	(0.158)	(0.001)	(0.011)	(0.090)	(0.122)	(0.961)
Partner lost job × Fire t-2	0.004	0.046	-0.042	-0.000	0.004	0.104	0.008	-0.933
	(0.006)	(0.070)	(0.070)	(0.001)	(0.007)	(0.066)	(0.041)	(1.349)
Partner lost job × Flood t-2	0.025	0.082	-0.053	0.000	0.025	0.054	0.004	1.778
	(0.020)	(0.121)	(0.129)	(0.001)	(0.020)	(0.094)	(0.092)	(1.307)
N	45,855	45,855	45,855	45,855	45,855	44,504	44,504	45,855
Adj. R2	0.565	0.517	0.517	0.103	0.575	0.544	0.604	0.558
Panel C. Male								
Partner lost job × Fire	0.005	-0.022	0.029	-0.000	0.005	0.160***	-0.061	1.244
	(0.017)	(0.074)	(0.080)	(0.000)	(0.017)	(0.054)	(0.073)	(1.224)
Partner lost job × Flood	-0.038	0.092	-0.131	0.001	-0.037	0.045	-0.134**	-0.807
	(0.072)	(0.067)	(0.099)	(0.002)	(0.072)	(0.035)	(0.066)	(1.968)
Partner lost job × Fire t-1	0.025**	-0.023	0.047**	-0.002	0.023*	0.066*	0.100	0.279
	(0.012)	(0.023)	(0.022)	(0.002)	(0.012)	(0.038)	(0.062)	(1.072)
Partner lost job × Flood t-1	0.018	-0.110**	0.127**	-0.000	0.017	0.066	0.129	-2.024***
	(0.014)	(0.054)	(0.063)	(0.001)	(0.015)	(0.051)	(0.085)	(0.694)
Partner lost job × Fire t-2	0.008	-0.038***	0.047**	0.001	0.009	0.009	-0.033	0.375
	(0.012)	(0.014)	(0.018)	(0.001)	(0.012)	(0.032)	(0.041)	(1.004)
Partner lost job × Flood t-2	0.026*	0.085	-0.057	-0.000	0.026*	-0.038	0.066	-0.906
	(0.013)	(0.088)	(0.088)	(0.001)	(0.014)	(0.067)	(0.142)	(1.313)
N	44,041	44,041	44,041	44,041	44,041	41,563	41,563	44,041
Adj. R2	0.734	0.503	0.570	0.235	0.742	0.555	0.692	0.527
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

VI Robustness

i Exogeneity of treatment assignment

The validity of our results relies on the assumption that disaster occurrence is exogenous. Residing in a bushfire-exposed area or a flood-exposed area should not be determined by other individual characteristics, household characteristics, or potential labour market outcomes. A violation of this requirement would suggest some kind of endogenous treatment or selection bias.

To test the exogeneity of our treatment assignment, we adapt the approach used by Johar et al. (2020), by regressing a linear probability model of treatment assignment on several key individual characteristics, household characteristics and potential outcomes. Similar to the main equation (1) and the approach used by Johar et al. (2020), we also control for year fixed effects, state fixed effects, linear state-time trends and individual fixed effects.

The results are summarised in Table A4 of our Appendix. Overall, we do not find that any of the covariates correlate with the probability of being exposed to a bushfire or flood. This suggests that our treatment is exogenous and provides a degree of confidence that there is no selection bias into the treatment group.

ii Placebo

We also employ several robustness checks to address potential concerns over the validity of our results. The first of these is a placebo test, in which we replace the disaster exposure variables in our baseline equation with their one- and two-year lead indicators. This can be thought of as a test of conditional parallel pre-trends of our outcome measures between those who later experienced a disaster and those who did not. If our model and group selection is correctly specified, we would expect the results of this test to be statistically insignificant.

From Tables A5 in our Appendix, we find that this assumption is satisfied for our key variables on individual labour market status using our overall sample - which provides a level of confidence in causally interpreting these results.

However, our placebo test picks up several potential biases for the male and female samples. The affected results include: the likelihood of female participation following a bushfire, the likelihood of male full-time employment and average working hours following a bushfire, and the likelihood of male part-time employment following a flood. This may suggest anticipation effects associated with bushfires, with males increasing their working hours and women reducing their labour force participation. Such anticipation effects may violate the parallel pre-trends assumption for these outcomes. Of these, we only find statistically significant treatment effects for male full-time employment following a bushfire, and male part-time employment following a flood.

iii Allowing migration following disaster exposure

Our third robustness check varies our treatment assignment by relaxing the requirement that individuals reside in the disaster-affected region in consecutive survey years. While our baseline model can be interpreted as capturing the effect of natural disasters on individuals who continue residing in the disaster-affected region, several studies have shown that disasters can induce significant migration (Boustan et al. 2017). The inclusion of migrants in our model may vary our estimated treatment effects.

Table A9 in the Appendix summarises the results. We find that results from this treatment assignment support our identified treatment effects, however are generally smaller in magnitude. This suggests that the labour market response induced by natural disasters is most pronounced for the immediate affected region. In this specification, we also identify a number of new statistically significant results - including an increased likelihoods of labour force participation and employment two-years on from a fire, reduced average working hours one-year on from a flood, and an increased likelihood of male full-time employment following a bushfire.

iv Controlling for other covariates

As our next robustness check, we separately incorporate several covariates into our baseline model. These covariates are several potentially important confounding factors to an individual's labour force status and earnings.

Firstly, there is the possibility of a sorting mechanism whereby individuals with lower levels of education may tend to live in disaster-prone regions. To test this, we include a categorical variable measuring an individual's highest level of educational attainment in our baseline model. From our results, as presented in Table A6 of the Appendix, we find that our results are robust to the inclusion of this control. We do find smaller magnitudes of the treatment effects except for the effect of fires on male consumption, however the signs on these coefficients remain consistent with our baseline effects.

Secondly, given our focus on labour market outcomes for individuals, occupation may play an explanatory role in determining the effect of natural disasters on individuals. To account for this, we include a control for an individual's broad level occupational group. Since our results from the interaction between industry sector and disaster type are significant in Table 3, we expect that controlling for occupation would also alter several results compared to the baseline results. From our results, as presented in Table A7 in the Appendix, we find that, overall, inclusion of occupation type variables leads to several treatment effects becoming not statistically significant - including for the likelihood of being employed, and of working part-time or full-time. These changes could be observed for both male and female samples. The results suggest the importance of examining detailed industry-specific treatment effects as discussed in Section 3.2.

Lastly, we also run a version of our baseline model to control for disaster severity, to ensure that our results are not driven by small-scale disaster events that have little impact on regional populations. We define our measure of disaster severity as the number of HILDA respondents reporting direct property damage within a disaster-affected SA4 region per 1,000 respondents. Given the availability of self-reported property damage from HILDA, we limit our sample period to 2010 to 2019 financial years. This also helps to ensure that our baseline results are not driven by the choice of sample time period, although this means that this specification is not directly comparable to our baseline. As presented in Table A8 in the Appendix, we find that overall our baseline results are generally robust over this specification. We do find the contemporaneous effects of bushfires on the likelihood of female employment and of floods on average hourly female wages lose their statistical significance. However, after controlling for severity, we find that bushfires generated a significant lagged decrease in female consumption.

VII Conclusion

In our paper, we study the labour market effects of bushfires and floods within Australia over the past two decades, focusing on the relative vulnerability of men and women. We find that the effects of bushfires and floods differ, necessitating that policymakers adapt their policy to each disaster type. Whilst we find that floods unambiguously lift labour supply among both men and women, bushfires have different consequences for men and women. Importantly, we find that the labour force status of women is most vulnerable to bushfires - which lower the likelihood of female employment by -1.6 ppts or equivalent to 4,780 female jobs or 6 million hours of lost work per year.

We find that these differences across gender can partially be explained by different responses across industry sector, with bushfires increasing the relative likelihood of employment in male-dominated industries including mining and transport. On the other hand, bushfires are associated with a relative reduction in the average hours worked in industries with a higher female composition including trade, banking and insurance, and services. These results are consistent with a structural reallocation of labour supply towards male-dominated sectors, while labour supplied to more female-dominated sectors contracts along the intensive margin. The sectoral analysis of these effects contributes important evidence for policymakers seeking to appropriately design and target disaster-recovery support.

In contrast to bushfires, we find that floods generate persistent increases in both the male and female labour supply - lifting both the likelihood of employment (+1.3 ppts, +1.8 ppts at one-year lag) and of labour force participation (+1.1 ppts, +1.5 ppts at one-year lag). This equates to an annual average of an additional 13,498 jobs or potentially 20 million hours, and an average of 11,321 additional individuals participating in the labour force each year. A possible reason for this difference between bushfires and floods is that floods tend to occur in regions with higher density population, which potentially supports creative destruction through additional spending on rebuilding and related services such as insurance, temporary accommodation, and public safety. We find that the services sector experienced the strongest relative employment growth of any industry following floods (+5.5 ppts), with much of this employment growth likely to be contributed by women. We also document gendered differences in the mobilisation of this additional labour supply, with males more likely to enter employment from the pool of unemployed while females entered employment from outside the labour force.

As well as highlighting the important gendered and sectoral dimensions of natural disasters, our paper also contributes new evidence on the role played by intrahousehold dynamics among mixed-sex couples. We find no evidence that natural disasters increase female domestic work, however find evidence consistent with an 'added worker' effect following disaster occurrence - whereby partnered individuals are likely to increase their labour supply in the event that one breadwinner loses his or her job. We find this effect is strongest following bushfires, with increased participation at both the extensive and intensive margins, while it is only observed at the intensive margin following floods. We also find that the 'added worker' response is strongest for women, perhaps consistent with lower levels of labour force participation and a greater ability to respond through increasing their labour supply.

Our paper contributes to other labour market studies on natural disasters, documenting these effects within the Australian economy at a finer level of geographic detail and incorporating a wider range of indicators than in existing studies. Importantly, we contribute an important perspective on the gendered burden of climate change in terms of the relative labour market vulnerability faced by men and women, a topic which has critical relevance for policymakers but which has thus far been understudied within Australia. Our findings provide insight into the design and targeting of post-disaster policy supports - highlighting in particular the vulnerability of women in the aftermath of bushfires. We also provide new evidence into the mechanisms through which the effects of bushfires and floods are transmitted to the labour market. We shed light on the importance of industry sector, including the relative vulnerability of the services, trade and banking and insurance sectors following bushfires and the transport sector following floods. We also provide novel estimates that suggest members of mixed-sex couples may respond to natural disasters by temporarily increasing their labour supply in the event that one breadwinner loses their employment.

With climate change amplifying both the frequency and significance of natural disasters, this remains a critical and rich area for further research. One such topic warranting further exploration is the persistence of these effects for both individuals and affected communities within Australia, in terms of long-term recovery or scarring effects. Such research should not only be limited to the labour market, but also extend to individual health, migration, and human capital outcomes. Secondly, whilst our paper contributes initial evidence on the sectoral nature of these effects, more work is required to more precisely capture these effects for affected communities. Further research on these topics will add to understanding on these issues, enabling improvements to post-disaster policy supports and increasing the resilience of disaster-prone Australian communities.

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A Appendix

Table A1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Had Bushfire		Had Flood		Never had disaster	
	Male	Female	Male	Female	Male	Female
Age of Individual	42.87	42.60	41.91	42.84	40.68	42.12
	(12.14)	(12.23)	(12.02)	(12.12)	(13.89)	(13.82)
Has college degree or higher	0.571	0.477	0.552	0.507	0.602	0.533
	(0.495)	(0.499)	(0.497)	(0.500)	(0.490)	(0.499)
Number of person in household	2.991	3.022	2.826	2.900	2.898	2.946
	(1.438)	(1.340)	(1.409)	(1.305)	(1.470)	(1.416)
Married	0.647	0.691	0.662	0.681	0.618	0.634
	(0.478)	(0.462)	(0.473)	(0.466)	(0.486)	(0.482)
Employed (=1)	0.799	0.687	0.813	0.674	0.815	0.685
	(0.401)	(0.464)	(0.390)	(0.469)	(0.388)	(0.464)
Part-time (=1)	0.0934	0.334	0.106	0.313	0.130	0.324
	(0.291)	(0.472)	(0.308)	(0.464)	(0.336)	(0.468)
Full-time (=1)	0.704	0.352	0.707	0.361	0.684	0.360
	(0.456)	(0.478)	(0.455)	(0.480)	(0.465)	(0.480)
Unemployed (=1	0.0366	0.0309	0.0345	0.0269	0.0384	0.0304
	(0.188)	(0.173)	(0.182)	(0.162)	(0.192)	(0.172)
LF participate (=1)	0.835	0.718	0.848	0.701	0.854	0.716
	(0.371)	(0.450)	(0.359)	(0.458)	(0.354)	(0.451)
Hours worked	43.62	31.73	43.09	32.36	41.88	31.60
	(12.97)	(13.76)	(13.41)	(14.01)	(13.68)	(13.78)
Hourly wage	30.58	26.94	29.88	26.28	30.85	27.99
	(24.91)	(21.81)	(21.52)	(21.12)	(24.82)	(37.42)
Do fair share of homework	0.763	0.922	0.763	0.922	0.741	0.893
	(0.425)	(0.268)	(0.425)	(0.268)	(0.438)	(0.310)
Do more than fair share	0.169	0.518	0.180	0.513	0.169	0.462
	(0.375)	(0.500)	(0.384)	(0.500)	(0.375)	(0.499)

Standard deviation in parentheses. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old to represent working age population. Sample must appears in two consecutive years. Financial amounts. including income and government support are shown in real (CPI adjusted in 2019) Australian dollars ('000s).

Table A2: Descriptive statistics - Partnered sample

	(1) Had Bushfire	(2) Had Flood	(3) No Disaster
Age of Individual	43.84	43.46	42.75
	(11.81)	(11.74)	(13.26)
male	0.492	0.497	0.496
	(0.500)	(0.500)	(0.500)
Has college degree or higher	0.544	0.549	0.602
	(0.498)	(0.498)	(0.489)
Married	0.685	0.687	0.655
	(0.464)	(0.464)	(0.475)
Number of person in household	2.978	2.850	2.887
	(1.377)	(1.351)	(1.433)
Employed (=1)	0.746	0.749	0.762
	(0.435)	(0.433)	(0.426)
LF participate (=1)	0.777	0.777	0.792
	(0.416)	(0.416)	(0.406)
Hours worked	38.18	38.37	37.60
	(14.33)	(14.49)	(14.31)
Total weekly salary	0.919	0.868	0.942
	(1.049)	(0.900)	(0.990)
Household labor income	106.2	95.46	112.5
	(89.54)	(80.01)	(98.85)
Person consumption	20.75	20.56	20.55
	(29.01)	(25.74)	(28.70)

Standard deviation in parentheses. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old to represent working age population. Sample must appears in two consecutive years. Financial amounts. including income and government support are shown in real (CPI adjusted in 2019) Australian dollars ('000s).

Table A3: Indirect effects of natural disasters on division of labor within HH

	(1) Do fair share of homework	(2) Do more than fair share
Panel A. Overall		
Fire	0.002	-0.006
	(0.006)	(0.008)
Flood	0.009	-0.010
	(0.006)	(0.006)
Fire t-1	-0.013**	0.001
	(0.005)	(0.006)
Flood t-1	0.004	-0.008
	(0.005)	(0.007)
Fire t-2	-0.011*	0.004
	(0.006)	(0.006)
Flood t-2	0.001	-0.000
	(0.007)	(0.008)
N	134,422	154,950
Adj. R2	0.497	0.481
Panel B. Female		
Fire	-0.009	-0.020**
	(0.008)	(0.010)
Flood	-0.001	-0.016
	(0.007)	(0.010)
Fire t-1	-0.008	0.007
	(0.007)	(0.009)
Flood t-1	0.003	-0.014
	(0.004)	(0.012)
Fire t-2	-0.012*	0.005
	(0.006)	(0.011)
Flood t-2	-0.005	-0.001
	(0.008)	(0.012)
N	71,680	80,567
Adj. R2	0.428	0.437
Panel C. Male		
Fire	0.016	0.010
	(0.011)	(0.011)
Flood	0.020**	-0.002
	(0.009)	(0.006)
Fire t-1	-0.018**	-0.005
	(0.009)	(0.010)
Flood t-1	0.004	-0.001
	(0.009)	(0.008)
Fire t-2	-0.009	0.004
	(0.011)	(0.008)
Flood t-2	0.007	0.001
	(0.010)	(0.010)
N	62,742	74,383
Adj. R2	0.482	0.369
Fixed effects	Yes	Yes

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

Table A4: Robusness: Johar specification

	(1) Fire	(2) Flood
Married	0.002	0.001
	(0.002)	(0.001)
highedu	-0.004	0.000
	(0.002)	(0.001)
Number of Persons in Household	0.001	0.000
	(0.001)	(0.000)
Employed (=1)	0.002	-0.003
	(0.005)	(0.004)
Full-time (=1)	0.000	-0.001
	(0.001)	(0.001)
LF participate (=1)	-0.001	-0.000
	(0.003)	(0.001)
Depressed	-0.000	-0.001
	(0.006)	(0.003)
Log working hours	-0.000	0.002
	(0.001)	(0.001)
(Log) Hourly wage	-0.001	0.000
	(0.001)	(0.000)
LR person consumption	0.000	0.000
	(0.000)	(0.000)
Prob-F	0.642	0.713
N	204,912	204,912
Mean	0.022	0.014

Standard errors in parentheses. Replace missing values to zeroes to avoid collinearity problem between reported wages and employment status. * p <0.10, ** p <0.05, *** p <0.01. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

Table A5: Placebo check: indirect effects of natural disasters on labor market outcomes

	(1) Employed (=1)	(2) Part-time (=1)	(3) Full-time (=1)	(4) Unemployed (=1)	(5) LF participate (=1)	(6) Log working hours	(7) (Log) Hourly wage	(8) LR person consumption
Panel A. Overall								
P_Fire	-0.003	-0.006	0.003	-0.002	-0.006	0.003	-0.006	0.002
	(0.005)	(0.004)	(0.005)	(0.003)	(0.005)	(0.009)	(0.009)	(0.091)
P2_Fire	-0.006	-0.005	-0.001	0.004	-0.002	-0.005	0.006	-0.104
	(0.006)	(0.006)	(0.006)	(0.003)	(0.006)	(0.008)	(0.007)	(0.066)
P_Flood	-0.003	-0.002	-0.003	-0.003	-0.006	0.014	0.000	0.017
	(0.008)	(0.006)	(0.007)	(0.005)	(0.005)	(0.009)	(0.009)	(0.082)
P2_Flood	-0.002	-0.005	0.003	0.000	-0.002	0.005	0.004	0.098
	(0.007)	(0.008)	(0.008)	(0.003)	(0.006)	(0.011)	(0.012)	(0.093)
N	154,952	154,952	154,952	154,952	154,952	114,946	104,229	154,952
Adj. R2	0.556	0.409	0.587	0.210	0.553	0.578	0.651	0.557
Panel B. Female								
P_Fire	-0.012	-0.006	-0.007	-0.001	-0.013*	-0.010	-0.013	0.009
	(0.008)	(0.009)	(0.006)	(0.004)	(0.007)	(0.018)	(0.012)	(0.111)
P2_Fire	-0.009	-0.009	-0.001	0.007	-0.002	-0.011	0.006	-0.107
	(0.009)	(0.010)	(0.010)	(0.005)	(0.009)	(0.016)	(0.011)	(0.091)
P_Flood	-0.007	0.003	-0.011	-0.002	-0.010	0.026	-0.006	0.012
	(0.010)	(0.012)	(0.011)	(0.006)	(0.007)	(0.017)	(0.014)	(0.152)
P2_Flood	-0.002	0.002	-0.005	0.000	-0.002	0.008	0.011	0.039
	(0.009)	(0.014)	(0.012)	(0.005)	(0.008)	(0.020)	(0.016)	(0.151)
N	80,568	80,568	80,568	80,568	80,568	55,412	51,375	80,568
Adj. R2	0.537	0.373	0.505	0.176	0.525	0.520	0.598	0.583
Panel C. Male								
P_Fire	0.007	-0.009	0.015**	-0.005	0.002	0.015*	0.003	-0.013
	(0.006)	(0.006)	(0.008)	(0.005)	(0.006)	(0.008)	(0.014)	(0.100)
P2_Fire	-0.003	-0.003	-0.001	0.001	-0.003	0.001	0.007	-0.113
	(0.009)	(0.008)	(0.008)	(0.005)	(0.007)	(0.009)	(0.009)	(0.104)
P_Flood	0.002	-0.007	0.007	-0.004	-0.002	0.005	0.006	0.026
	(0.009)	(0.009)	(0.014)	(0.005)	(0.008)	(0.012)	(0.016)	(0.151)
P2_Flood	-0.002	-0.014*	0.012	0.001	-0.001	0.004	-0.003	0.152
	(0.009)	(0.008)	(0.010)	(0.005)	(0.008)	(0.013)	(0.015)	(0.109)
N	74,384	74,384	74,384	74,384	74,384	59,534	52,854	74,384
Adj. R2	0.571	0.363	0.583	0.242	0.580	0.550	0.689	0.526
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

Table A6: Robustness check: control for education

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed (=1)	Part-time (=1)	Full-time (=1)	Unemployed (=1)	LF participate (=1)	Log working hours	(Log) Hourly wage	LR person consumption
Panel A. Overall								
Fire	-0.003	-0.000	-0.003	0.001	-0.003	-0.009	-0.003	-0.021
	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)	(0.009)	(0.010)	(0.079)
Flood	0.014**	0.014*	-0.001	-0.003	0.010	0.003	0.002	-0.035
	(0.006)	(0.008)	(0.008)	(0.003)	(0.006)	(0.010)	(0.008)	(0.077)
Fire t-1	0.008	0.003	0.006	-0.004	0.004	-0.006	-0.006	-0.013
	(0.006)	(0.006)	(0.006)	(0.004)	(0.007)	(0.009)	(0.008)	(0.070)
Flood t-1	0.018***	0.008	0.010	-0.004	0.014***	-0.011	-0.009	0.064
	(0.006)	(0.006)	(0.006)	(0.003)	(0.005)	(0.009)	(0.011)	(0.103)
Fire t-2	0.003	-0.009	0.012**	-0.003	-0.000	0.004	0.005	-0.186***
	(0.007)	(0.006)	(0.006)	(0.003)	(0.006)	(0.007)	(0.007)	(0.065)
Flood t-2	0.010	0.019*	-0.009	-0.002	0.008	-0.028***	0.016*	-0.042
	(0.008)	(0.010)	(0.009)	(0.004)	(0.005)	(0.009)	(0.009)	(0.106)
N	149,256	149,256	149,256	149,256	149,256	114,738	103,409	149,256
Adj. R2	0.584	0.427	0.618	0.210	0.583	0.596	0.654	0.532
Panel B. Female								
Fire	-0.015*	-0.006	-0.009	0.008	-0.007	-0.021	0.014	-0.063
	(0.008)	(0.008)	(0.010)	(0.006)	(0.007)	(0.018)	(0.010)	(0.114)
Flood	0.009	0.014	-0.006	-0.000	0.008	0.002	0.024*	-0.026
	(0.012)	(0.013)	(0.010)	(0.004)	(0.012)	(0.014)	(0.014)	(0.101)
Fire t-1	0.003	0.002	0.001	0.001	0.004	-0.016	-0.004	0.129
	(0.008)	(0.010)	(0.009)	(0.005)	(0.009)	(0.013)	(0.011)	(0.092)
Flood t-1	0.017**	0.022**	-0.005	0.003	0.020**	-0.017	-0.005	0.064
	(0.008)	(0.011)	(0.012)	(0.005)	(0.009)	(0.013)	(0.012)	(0.193)
Fire t-2	-0.008	-0.018*	0.010	-0.002	-0.010	-0.002	-0.001	-0.110
	(0.010)	(0.009)	(0.009)	(0.004)	(0.010)	(0.012)	(0.009)	(0.103)
Flood t-2	0.017	0.029*	-0.013	-0.005	0.012	-0.041**	0.021	0.004
	(0.012)	(0.016)	(0.014)	(0.006)	(0.009)	(0.020)	(0.016)	(0.146)
N	78,736	78,736	78,736	78,736	78,736	55,391	51,089	78,736
Adj. R2	0.567	0.393	0.541	0.168	0.559	0.544	0.604	0.543
Panel C. Male								
Fire	0.009	0.004	0.005	-0.008	0.002	0.001	-0.020	0.023
	(0.008)	(0.007)	(0.009)	(0.006)	(0.007)	(0.007)	(0.013)	(0.124)
Flood	0.017**	0.014*	0.004	-0.006	0.011	0.004	-0.019*	-0.058
	(0.008)	(0.007)	(0.012)	(0.005)	(0.006)	(0.010)	(0.011)	(0.143)
Fire t-1	0.014*	0.003	0.012**	-0.011**	0.003	0.004	-0.007	-0.183
	(0.008)	(0.007)	(0.005)	(0.005)	(0.007)	(0.010)	(0.012)	(0.123)
Flood t-1	0.019**	-0.006	0.025**	-0.011*	0.008	-0.005	-0.012	0.072
	(0.007)	(0.009)	(0.010)	(0.006)	(0.006)	(0.010)	(0.014)	(0.128)
Fire t-2	0.015**	-0.000	0.015**	-0.005	0.010*	0.010	0.009	-0.274**
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.008)	(0.013)	(0.116)
Flood t-2	0.003	0.007	-0.005	0.001	0.004	-0.015	0.010	-0.091
	(0.009)	(0.008)	(0.008)	(0.005)	(0.007)	(0.009)	(0.019)	(0.120)
N	70,520	70,520	70,520	70,520	70,520	59,347	52,320	70,520
Adj. R2	0.589	0.385	0.603	0.251	0.598	0.561	0.691	0.511
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

Table A7: Robustness check: control for occupation

	(1) Employed (=1)	(2) Part-time (=1)	(3) Full-time (=1)	(4) Unemployed (=1)	(5) LF participate (=1)	(6) Log working hours	(7) (Log) Hourly wage	(8) LR person consumption
Panel A. Overall								
Fire	0.000	0.009	-0.009	-0.001	-0.001	-0.012	-0.006	-0.024
	(0.008)	(0.008)	(0.008)	(0.004)	(0.006)	(0.008)	(0.011)	(0.100)
Flood	0.001	0.005	-0.004	0.000	0.001	-0.004	0.001	0.010
	(0.007)	(0.010)	(0.009)	(0.004)	(0.006)	(0.011)	(0.008)	(0.119)
Fire t-1	0.005	0.005	0.001	-0.003	0.002	-0.009	-0.006	-0.062
	(0.005)	(0.007)	(0.007)	(0.004)	(0.004)	(0.008)	(0.009)	(0.118)
Flood t-1	0.006	0.005	0.002	0.001	0.007	-0.010	-0.014	0.039
	(0.008)	(0.010)	(0.009)	(0.003)	(0.007)	(0.009)	(0.011)	(0.127)
Fire t-2	0.009	-0.001	0.010	-0.003	0.006	0.004	0.009	-0.215**
	(0.006)	(0.008)	(0.008)	(0.002)	(0.006)	(0.008)	(0.009)	(0.100)
Flood t-2	-0.003	0.010	-0.015	-0.000	-0.003	-0.033***	0.010	-0.140
	(0.009)	(0.015)	(0.014)	(0.004)	(0.007)	(0.010)	(0.008)	(0.108)
N	98,267	98,267	98,267	98,267	98,267	90,286	81,392	98,267
Adj. R2	0.266	0.482	0.546	0.199	0.249	0.600	0.668	0.535
Panel B. Female								
Fire	-0.009	0.015	-0.023*	0.009	-0.000	-0.024	0.014	-0.084
	(0.010)	(0.014)	(0.012)	(0.006)	(0.006)	(0.016)	(0.012)	(0.121)
Flood	0.007	0.014	-0.008	0.002	0.009	-0.011	0.021	-0.002
	(0.011)	(0.016)	(0.012)	(0.005)	(0.010)	(0.017)	(0.014)	(0.113)
Fire t-1	-0.000	0.008	-0.008	-0.004	-0.005	-0.012	-0.000	0.082
	(0.009)	(0.013)	(0.013)	(0.006)	(0.008)	(0.014)	(0.013)	(0.121)
Flood t-1	0.009	0.017	-0.008	-0.002	0.007	-0.012	-0.011	-0.017
	(0.012)	(0.018)	(0.014)	(0.005)	(0.011)	(0.013)	(0.015)	(0.231)
Fire t-2	0.002	-0.003	0.006	-0.002	-0.000	0.001	0.006	-0.108
	(0.011)	(0.015)	(0.015)	(0.004)	(0.010)	(0.014)	(0.012)	(0.144)
Flood t-2	0.005	0.016	-0.013	-0.004	0.002	-0.039*	0.008	-0.223
	(0.012)	(0.025)	(0.022)	(0.006)	(0.009)	(0.021)	(0.012)	(0.168)
N	47,722	47,722	47,722	47,722	47,722	42,691	39,466	47,722
Adj. R2	0.260	0.414	0.491	0.186	0.242	0.548	0.620	0.554
Panel C. Male								
Fire	0.009	0.003	0.005	-0.010**	-0.001	-0.001	-0.026**	0.037
	(0.010)	(0.008)	(0.010)	(0.004)	(0.008)	(0.007)	(0.013)	(0.158)
Flood	-0.004	-0.004	0.001	-0.001	-0.005	0.004	-0.016	0.021
	(0.008)	(0.009)	(0.013)	(0.005)	(0.006)	(0.010)	(0.010)	(0.188)
Fire t-1	0.010	0.003	0.009	-0.003	0.007	-0.005	-0.012	-0.203
	(0.007)	(0.007)	(0.006)	(0.004)	(0.006)	(0.010)	(0.011)	(0.181)
Flood t-1	0.004	-0.007	0.011	0.004	0.007	-0.006	-0.016	0.095
	(0.009)	(0.010)	(0.014)	(0.004)	(0.008)	(0.009)	(0.014)	(0.117)
Fire t-2	0.015***	0.001	0.015**	-0.004	0.012**	0.009	0.011	-0.317*
	(0.006)	(0.007)	(0.007)	(0.004)	(0.005)	(0.009)	(0.012)	(0.171)
Flood t-2	-0.010	0.004	-0.015	0.003	-0.008	-0.025***	0.011	-0.071
	(0.010)	(0.009)	(0.010)	(0.005)	(0.008)	(0.008)	(0.016)	(0.138)
N	50,545	50,545	50,545	50,545	50,545	47,595	41,926	50,545
Adj. R2	0.268	0.431	0.470	0.214	0.248	0.557	0.700	0.509
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

Table A8: Robustness check: control for severity

	(1) Employed (=1)	(2) Part-time (=1)	(3) Full-time (=1)	(4) Unemployed (=1)	(5) LF participate (=1)	(6) Log working hours	(7) (Log) Hourly wage	(8) LR person consumption
Panel A. Overall								
Fire	-0.002	0.003	-0.005	-0.001	-0.003	-0.012	-0.012	-0.032
	(0.006)	(0.006)	(0.008)	(0.005)	(0.006)	(0.012)	(0.011)	(0.089)
Flood	0.015	0.001	0.013	-0.012***	0.003	-0.000	0.013	-0.006
	(0.012)	(0.012)	(0.010)	(0.004)	(0.010)	(0.015)	(0.015)	(0.116)
Fire t-1	0.008	0.008	0.001	-0.004	0.005	-0.009	-0.009	-0.011
	(0.006)	(0.005)	(0.006)	(0.004)	(0.006)	(0.010)	(0.008)	(0.081)
Flood t-1	0.024***	0.012	0.013	-0.008*	0.016*	-0.016	-0.016	0.256
	(0.009)	(0.011)	(0.008)	(0.005)	(0.008)	(0.013)	(0.014)	(0.156)
Fire t-2	0.008	-0.002	0.010*	-0.003	0.005	-0.003	0.003	-0.244***
	(0.007)	(0.007)	(0.006)	(0.003)	(0.007)	(0.008)	(0.007)	(0.065)
Flood t-2	0.004	0.008	-0.005	-0.002	0.002	-0.028**	0.014	-0.061
	(0.009)	(0.009)	(0.010)	(0.005)	(0.007)	(0.013)	(0.012)	(0.153)
N	105,241	105,241	105,241	105,241	105,241	78,098	70,663	105,241
Adj. R2	0.636	0.472	0.648	0.236	0.639	0.629	0.662	0.548
Panel B. Female								
Fire	-0.014	0.002	-0.016	0.003	-0.011	-0.030	0.001	-0.112
	(0.009)	(0.010)	(0.012)	(0.007)	(0.009)	(0.022)	(0.010)	(0.110)
Flood	0.013	0.007	0.003	-0.009	0.004	-0.012	0.010	-0.033
	(0.018)	(0.020)	(0.011)	(0.007)	(0.017)	(0.022)	(0.025)	(0.119)
Fire t-1	0.001	0.010	-0.008	-0.000	0.001	-0.020	-0.009	0.069
	(0.009)	(0.009)	(0.010)	(0.005)	(0.009)	(0.015)	(0.011)	(0.098)
Flood t-1	0.024**	0.030*	-0.006	0.002	0.026**	-0.026	-0.011	0.383
	(0.011)	(0.015)	(0.014)	(0.007)	(0.013)	(0.020)	(0.019)	(0.240)
Fire t-2	-0.001	-0.007	0.006	-0.001	-0.002	-0.011	0.005	-0.194**
	(0.010)	(0.010)	(0.008)	(0.005)	(0.010)	(0.012)	(0.010)	(0.097)
Flood t-2	0.013	0.015	-0.003	-0.004	0.009	-0.044*	0.029	-0.035
	(0.013)	(0.017)	(0.014)	(0.008)	(0.011)	(0.024)	(0.019)	(0.216)
N	54,829	54,829	54,829	54,829	54,829	37,907	35,083	54,829
Adj. R2	0.617	0.445	0.585	0.197	0.611	0.585	0.611	0.528
Panel C. Male								
Fire	0.012	0.003	0.009	-0.005	0.007	0.004	-0.025*	0.062
	(0.010)	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)	(0.015)	(0.146)
Flood	0.018	-0.005	0.024*	-0.016**	0.002	0.011	0.018	0.025
	(0.011)	(0.011)	(0.012)	(0.006)	(0.010)	(0.013)	(0.017)	(0.198)
Fire t-1	0.016*	0.005	0.013**	-0.008*	0.008	0.000	-0.009	-0.103
	(0.009)	(0.007)	(0.005)	(0.005)	(0.007)	(0.010)	(0.013)	(0.116)
Flood t-1	0.027**	-0.007	0.035**	-0.019*	0.008	-0.003	-0.019	0.133
	(0.011)	(0.015)	(0.016)	(0.010)	(0.011)	(0.014)	(0.018)	(0.192)
Fire t-2	0.018**	0.002	0.016*	-0.006	0.012*	0.005	-0.000	-0.296***
	(0.008)	(0.006)	(0.008)	(0.005)	(0.006)	(0.009)	(0.013)	(0.102)
Flood t-2	-0.005	-0.001	-0.004	0.000	-0.005	-0.011	-0.002	-0.095
	(0.012)	(0.010)	(0.012)	(0.005)	(0.010)	(0.011)	(0.017)	(0.162)
N	50,412	50,412	50,412	50,412	50,412	40,191	35,580	50,412
Adj. R2	0.653	0.420	0.643	0.272	0.669	0.593	0.698	0.550
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.

Table A9: Robustness: Allowing migration

	(1) Employed (=1)	(2) Part-time (=1)	(3) Full-time (=1)	(4) Unemployed (=1)	(5) LF participate (=1)	(6) Log working hours	(7) (Log) Hourly wage	(8) LR person consumption
Panel A. Overall								
Fire_exp	0.006	0.002	0.004	-0.002	0.003	-0.003	-0.007	0.021
	(0.006)	(0.005)	(0.005)	(0.003)	(0.006)	(0.008)	(0.008)	(0.069)
Flood_exp	0.012**	0.003	0.008*	-0.001	0.011**	-0.004	-0.008	-0.007
	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.010)	(0.010)	(0.078)
L1_Fire_exp	0.009	-0.007	0.016***	-0.004	0.004	0.008	0.004	-0.153***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.006)	(0.007)	(0.006)	(0.054)
L1_Flood_exp	0.006	0.010	-0.005	-0.000	0.005	-0.020**	0.012	-0.024
	(0.007)	(0.009)	(0.010)	(0.004)	(0.006)	(0.010)	(0.008)	(0.094)
L2_Fire_exp	0.011*	0.002	0.009	-0.001	0.009*	0.009	0.007	-0.080
	(0.006)	(0.006)	(0.007)	(0.003)	(0.005)	(0.007)	(0.008)	(0.072)
L2_Flood_exp	0.006	0.010	-0.004	0.002	0.008	-0.009	0.004	-0.011
	(0.007)	(0.008)	(0.009)	(0.004)	(0.007)	(0.012)	(0.008)	(0.076)
N	154,950	154,950	154,950	154,950	154,950	114,738	103,409	154,950
Adj. R2	0.589	0.421	0.606	0.205	0.590	0.585	0.654	0.538
Panel B. Female								
Fire_exp	-0.000	0.001	-0.000	0.001	0.001	-0.013	-0.007	0.101
	(0.007)	(0.008)	(0.007)	(0.004)	(0.008)	(0.013)	(0.010)	(0.088)
Flood_exp	0.013*	0.015*	-0.003	0.005	0.018**	-0.006	-0.014	0.020
	(0.007)	(0.009)	(0.007)	(0.005)	(0.007)	(0.017)	(0.013)	(0.164)
L1_Fire_exp	0.001	-0.013	0.015*	-0.002	-0.001	0.007	-0.004	-0.095
	(0.009)	(0.009)	(0.008)	(0.004)	(0.009)	(0.012)	(0.008)	(0.089)
L1_Flood_exp	0.009	0.017	-0.009	-0.000	0.009	-0.029	0.016	-0.017
	(0.011)	(0.016)	(0.014)	(0.005)	(0.010)	(0.020)	(0.015)	(0.152)
L2_Fire_exp	0.004	-0.003	0.008	0.005	0.009	0.011	-0.002	-0.099
	(0.010)	(0.011)	(0.009)	(0.004)	(0.009)	(0.015)	(0.011)	(0.126)
L2_Flood_exp	0.006	0.016	-0.011	0.002	0.007	-0.027	-0.009	0.067
	(0.013)	(0.013)	(0.011)	(0.004)	(0.013)	(0.020)	(0.015)	(0.095)
N	80,567	80,567	80,567	80,567	80,567	55,391	51,089	80,567
Adj. R2	0.564	0.387	0.528	0.166	0.557	0.531	0.603	0.547
Panel C. Male								
Fire_exp	0.011	0.001	0.010*	-0.007	0.004	0.005	-0.006	-0.071
	(0.009)	(0.007)	(0.006)	(0.005)	(0.007)	(0.009)	(0.010)	(0.099)
Flood_exp	0.010	-0.009	0.020*	-0.007	0.003	-0.001	-0.002	-0.031
	(0.007)	(0.008)	(0.010)	(0.005)	(0.007)	(0.010)	(0.012)	(0.120)
L1_Fire_exp	0.016***	-0.000	0.016***	-0.007	0.009**	0.008	0.012	-0.219**
	(0.006)	(0.005)	(0.006)	(0.005)	(0.004)	(0.007)	(0.011)	(0.086)
L1_Flood_exp	0.001	0.002	-0.001	-0.001	0.001	-0.012	0.007	-0.035
	(0.010)	(0.006)	(0.009)	(0.005)	(0.007)	(0.009)	(0.016)	(0.096)
L2_Fire_exp	0.017**	0.007	0.011	-0.008	0.010*	0.009	0.016	-0.069
	(0.008)	(0.007)	(0.010)	(0.005)	(0.006)	(0.008)	(0.010)	(0.101)
L2_Flood_exp	0.007	0.003	0.004	0.002	0.009	0.008	0.016*	-0.102
	(0.009)	(0.009)	(0.009)	(0.005)	(0.008)	(0.012)	(0.009)	(0.157)
N	74,383	74,383	74,383	74,383	74,383	59,347	52,320	74,383
Adj. R2	0.612	0.374	0.604	0.244	0.625	0.550	0.690	0.518
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and SA4 location, and SA4-year linear time trends. Standard errors are clustered at state level.

Table A10: Indirect effects of natural disasters on labor market outcomes - Sample restricted to 25 - 55 years old

	(1) Employed (=1)	(2) Part-time (=1)	(3) Full-time (=1)	(4) Unemployed (=1)	(5) LF participate (=1)	(6) Log working hours	(7) (Log) Hourly wage	(8) LR person consumption
Panel A. Overall								
Fire	-0.004	-0.005	0.001	0.002	-0.002	0.001	-0.013	0.030
	(0.006)	(0.006)	(0.007)	(0.004)	(0.006)	(0.007)	(0.010)	(0.086)
Flood	0.017**	0.005	0.011	-0.008*	0.010	0.015	0.001	0.032
	(0.007)	(0.011)	(0.009)	(0.004)	(0.008)	(0.011)	(0.008)	(0.089)
Fire t-1	0.010	0.006	0.004	-0.000	0.009	0.002	-0.000	0.016
	(0.007)	(0.006)	(0.007)	(0.004)	(0.007)	(0.008)	(0.008)	(0.072)
Flood t-1	0.015*	-0.004	0.018**	-0.008**	0.007	0.001	0.001	0.125
	(0.008)	(0.010)	(0.008)	(0.003)	(0.008)	(0.009)	(0.010)	(0.126)
Fire t-2	0.004	-0.007	0.010	-0.002	0.002	0.004	0.011	-0.180**
	(0.007)	(0.007)	(0.007)	(0.003)	(0.007)	(0.008)	(0.008)	(0.071)
Flood t-2	0.012	0.017	-0.007	-0.004	0.008	-0.025**	0.015*	-0.017
	(0.010)	(0.013)	(0.010)	(0.004)	(0.008)	(0.012)	(0.008)	(0.141)
N	103,977	103,977	103,977	103,977	103,977	81,925	73,973	103,977
Adj. R2	0.575	0.453	0.629	0.195	0.569	0.611	0.672	0.540
Panel B. Female								
Fire	-0.015	-0.012	-0.001	0.005	-0.010	-0.003	-0.003	-0.022
	(0.010)	(0.010)	(0.011)	(0.005)	(0.009)	(0.016)	(0.012)	(0.125)
Flood	0.019	0.005	0.012	-0.007	0.012	0.022	0.022	0.085
	(0.016)	(0.020)	(0.013)	(0.006)	(0.015)	(0.016)	(0.017)	(0.118)
Fire t-1	0.007	0.013	-0.006	0.002	0.010	-0.015	-0.001	0.207*
	(0.010)	(0.011)	(0.010)	(0.006)	(0.010)	(0.014)	(0.013)	(0.122)
Flood t-1	0.015*	0.010	0.005	-0.001	0.014	-0.003	0.010	0.201
	(0.009)	(0.016)	(0.015)	(0.006)	(0.012)	(0.018)	(0.013)	(0.202)
Fire t-2	-0.001	-0.009	0.006	-0.004	-0.005	-0.002	0.014	-0.047
	(0.011)	(0.013)	(0.011)	(0.006)	(0.012)	(0.014)	(0.011)	(0.127)
Flood t-2	0.018	0.032	-0.016	-0.006	0.012	-0.037	0.022	0.060
	(0.014)	(0.021)	(0.017)	(0.006)	(0.013)	(0.025)	(0.015)	(0.154)
N	54,220	54,220	54,220	54,220	54,220	39,607	36,452	54,220
Adj. R2	0.539	0.403	0.545	0.161	0.524	0.546	0.616	0.553
Panel C. Male								
Fire	0.007	0.003	0.004	-0.002	0.005	0.003	-0.022	0.086
	(0.007)	(0.008)	(0.011)	(0.005)	(0.007)	(0.007)	(0.017)	(0.144)
Flood	0.015	0.007	0.008	-0.009	0.006	0.006	-0.019*	-0.032
	(0.010)	(0.009)	(0.011)	(0.006)	(0.009)	(0.011)	(0.010)	(0.185)
Fire t-1	0.012	-0.003	0.016*	-0.004	0.008	0.018	0.001	-0.209*
	(0.009)	(0.007)	(0.009)	(0.005)	(0.008)	(0.011)	(0.014)	(0.122)
Flood t-1	0.014	-0.016*	0.031***	-0.015**	-0.000	0.004	-0.007	0.058
	(0.012)	(0.009)	(0.012)	(0.007)	(0.011)	(0.010)	(0.012)	(0.164)
Fire t-2	0.010	-0.004	0.014**	-0.002	0.009	0.007	0.008	-0.339***
	(0.007)	(0.006)	(0.007)	(0.005)	(0.006)	(0.008)	(0.014)	(0.124)
Flood t-2	0.005	0.002	0.002	-0.002	0.003	-0.013*	0.007	-0.101
	(0.009)	(0.010)	(0.009)	(0.007)	(0.007)	(0.007)	(0.016)	(0.187)
N	49,757	49,757	49,757	49,757	49,757	42,318	37,521	49,757
Adj. R2	0.617	0.361	0.600	0.233	0.631	0.546	0.713	0.516
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. Sample is drawn from HILDA Wave 1 to Wave 18. We restrict sample to be between 19 to 65 years old (working age population and who have completed schooling) who appear in at least two consecutive years. Regressions control for covariates using fixed effects for individual, age, year, and state, and state-year linear time trends. Standard errors are clustered at SA4 level.