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Floods, Bushfires and Sectoral Economic Output in Australia, 1978–2014*

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Using state-level annual variation in natural disasters and economic output in Australia, we estimate the direct effects of floods and bushfires on sectoral gross value added during the period 1978–2014. We find that floods exert an adverse and persistent effect on the outputs of agriculture, mining, construction and financial services sectors. For example, our estimates indicate that a state that experienced a flood in a given year encountered, on average, 5–6 per cent lower agricultural output in both that year and the following year, compared to another state with no such flood experience. Sectoral responses to bushfires are more nuanced.

I *Introduction*

Significant exogenous shocks, such as wars, famines, natural disasters, and weather extremities, directly affect countries' economic welfare by adversely impacting their output, prices, and labour markets. Among such exogenous shocks, natural disasters and weather extremities are the most common and most frequent (see Caruso & Miller, 2015). Highlighting the wide reach of natural disasters is the evidence that floods alone ravaged 3.44 billion people globally over the period 1978–2016 (Guha-Sapir *et al.*, 2016). Weather extremities mostly stem from unexpected and sizeable variations in rainfall and temperature, and have become routine in the recent era.[1] Figure 1 displays the annual average rainfall and temperature for Australia over the period 1911–2014 (Australian Bureau of Meteorology, 2012). The figure graphically illustrates that rainfall exhibits noticeably higher

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[1] It has been predicted that a once-in-20-years annual maximum daily rainfall is likely to become an event occurring once in 5–15 years by the end of the twenty-first century, particularly for high latitudes and tropical regions, and for the northern mid-latitude regions during winter (see Field, 2012).

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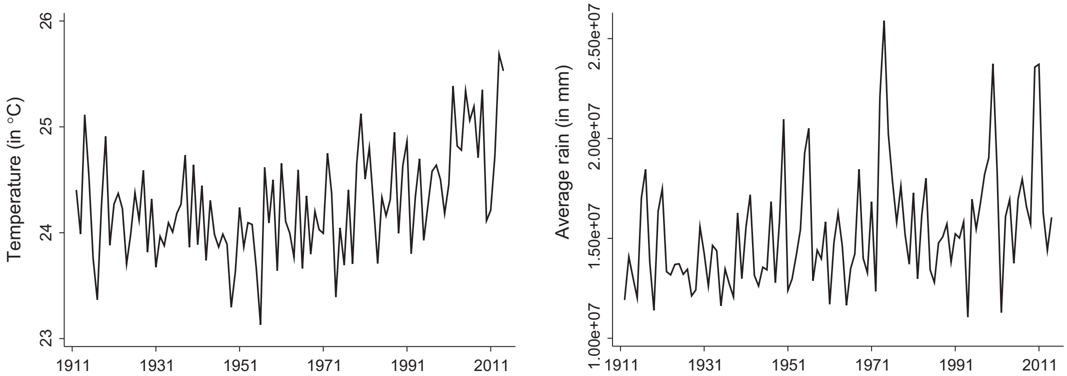
FIGURE 1
Left: Average Temperature Measured in Degrees Celsius. Right: Average Rainfall in Millimetres



Source: Authors' computations from the raw data provided by the Australian Bureau of Meteorology.

variation after the 1970s, and that average temperature rose visibly in the same period. Such alarming developments in connection with natural disasters and weather extremities have attracted growing scholarly attention regarding the macroeconomic consequences of natural disasters and their atmospheric triggers (see Dell *et al.*, 2014).

The present study provides empirical evidence on the direct effects of natural disasters and weather extremities on sectoral economic activity, using Australia as a case study. In particular, we investigate the effects of 47 major floods and 36 major bushfires on states' gross value added (GVA), using state-level annual panel data over the period 1978–2014. We measure floods and bushfires both in binary form (i.e. whether or not they occurred in a given state in a given year) as well as with their severity measures gauging the share of disaster-affected individuals in the state's total population. We also investigate the effects of extreme rain and extreme temperature on sectoral output at the state level. Weather extremities not only are exogenous triggers that can potentially lead to floods and bushfires, but also can affect economic activity in their own right.[2] Our analysis covers 10 sectors, including agriculture, mining, manufacturing, and seven different services sectors.

In a nutshell, this is the first study in the literature that systematically explores the output effects of natural disasters and weather extremities on different sections of an advanced economy. While the macroeconomic impact of natural disasters and weather extremities has been subject to investigation by several cross-country studies (see, among others, Raddatz, 2007; Noy, 2009; Capelle-Blancard & Laguna, 2010; Loayza *et al.*, 2012; Strobl, 2012; Cavallo *et al.*, 2013), hardly any study has placed the focus specifically on different sections of any single economy.[3] This information is required to understand how an economy responds to significant shocks, how long it takes for it to use its capacity to return to normal, and in which sections of the economy the normalisation occurs. Further, hardly any study

[2] Drought is another important natural disaster that requires attention, especially for a country like Australia. However, we do not study drought in this paper because their severity measures are not readily available. Droughts in Australia require a different setting to study, with long enough data, and preferably for more specific outputs (i.e. crop yield) than GVA.

[3] A notable exception for a single-country focus is Boustan *et al.* (2017), who studied the effect of natural disasters on migration, house prices and local poverty rates in US counties from 1920 to 2010. Otherwise, several other studies have placed a single economy under the microscope for a particular natural disaster, such as Hurricane Katrina or Hurricane Andrew in the USA (see, among others, Hallstrom & Smith, 2005; Vigdor, 2008). Loayza *et al.* (2012) studied the impact of natural disasters on agriculture, manufacturing and services growth in a cross-country setting. Several other studies have investigated the effects of natural disasters on other macroeconomic indicators, such as government consumption and exports, using cross-country data (e.g. Noy, 2009). Annicchiarico and Di Dio (2015) investigate the behaviour of an economy with different policy alternatives under the New Keynesian framework.

has exclusively analysed the impact of bushfires in a systematic manner.[4] Bushfires are typically considered an 'Australian disaster'.

Australia presents several empirical advantages for this analysis because, as a country that experiences numerous natural disasters every year,[5] it exhibits significant geographic and temporal variation in floods, bushfires, and extreme rain and temperature. This setting allows for a quasi-experiment with multiple shocks. Importantly, this setting is permitted over a surface area that is almost 80 per cent of the size of continental Europe, with large enough differences in weather but relatively homogeneous institutions and comparable experimental units. In addition, the six Australian states and two territories provide rich data on sector-disaggregated economic activity. Moreover, Australia offers data on the precise location and date of major bushfires and floods during the period 1978–2014. This is important because natural disasters are typically of a local nature, and Australian data at the state level can generate clear variation in terms of location and time of the shock. Finally, Australia presents century-long gridded data on rainfall for the period 1900–2014 and temperature for the period 1911–2014 at a fine geographic level (0.05 latitude and longitude degree intervals), which enables not only capturing localised weather extremities but also accurate computation of deviations from long-term climatic conditions in our sample period. This dataset also enables us to study which months of the year matter for the effects of weather extremities on sectoral output, which is a fairly novel approach in the literature, yielding important results, especially for agriculture. Our examination exploits, conditional on state-specific heterogeneity, state-specific time trends and common time effects, the variation in the timing and location of natural disasters and weather extremities across Australia to estimate the impact of exogenous natural shocks on sectoral output. Thus, our estimates capture the average deviation of sectoral GVA from its long-term trends in states and periods that faced natural disasters and weather extremities, compared to states and periods with no such shocks.

[4] Jayachandran (2009) studied the effects of the 1997 wildfire smoke on child health and mortality in Indonesia.

[5] The economic cost of natural disasters in Australia is predicted to quadruple by 2050, reaching A$33 billion per annum (Deloitte Access Economics, 2016).

Our findings reveal important effects of natural disasters on economic activity. We find that sectoral output in Australia is sensitive to natural disasters, particularly to floods. Floods play a significant role in reducing the outputs of the agricultural, mining, construction, retail and financial sectors. Critically, some effects persist over the subsequent year. For example, we find that a state that experienced a flood in a given year encountered, on average, 5–6 per cent lower agricultural output both in that year and the following year, compared to another state with no such flood experience. This estimated effect amounts to more than 2 years of lost agricultural output for Australia over the period 1978–2014. However, perhaps not paradoxically, floods exert positive effects on the outputs of some sectors, such as utilities (electricity, gas, water and waste services) and public administration and safety. Taken together, the overall impact of floods on GVA is significantly negative. Bushfires do not appear to affect overall GVA at any point in time in an economically meaningful manner. However, our empirical estimates yield that bushfires have adverse impacts on output in three of the service subgroups (construction, transportation, and the financial and insurance sector), and positive impacts on two of the service groups (utilities and retail).

Turning to weather extremities, we find that they affect the agricultural sector in Australia negatively. In particular, extreme rainfall during the months of April, May and June negatively affects agricultural output. This result is in tandem with our findings on floods, because in our sample one-third of the floods occurred during these three months. Moreover, agriculture benefits from higher-than-average rain in earlier months of the crop cycle, yet is adversely affected by hotter-than-average months and extreme heat incidents in autumn and summer in Australia. Mining output seems to be the most responsive to weather shocks owing to flooding incidents that may arise following extreme rain, higher-than-average rain, and extreme temperature. Manufacturing is the least affected by weather conditions, followed by the public sector, with nuanced differences. Taken together, this paper documents what other studies in the economics of natural disasters tend to miss: important effects of natural disasters and weather extremities on different sections of an economy.

The remainder of the paper is organised as follows. Section II provides a brief overview of the related literature. Section III describes the data sources and measurement issues. Section IV discusses the estimation framework. Section V presents the results. Section VI concludes.

II Background and the Relevant Literature

The impact of natural disasters on the real economy can work through two channels. The immediate impact of natural disasters operates through an adverse supply shock, as production is distorted, and key structures, such as roads, railways, homes, cars and business assets, are impaired. The subsequent effect of this adverse supply shock is to inhibit demand by delaying expenditure. However, as a second channel, demand is typically expected to increase as destroyed assets and infrastructure start being repaired and replenished. While consumption is expected to bounce back quickly, the replenishment and repair of damaged assets may range over an extended period. This stems from the fact that it takes time to plan new projects, re-evaluate the risks of building similar structures in the affected areas, and relocate buildings to other areas.

There is, however, conflicting empirical evidence regarding the effect of natural disasters on output. One set of evidence finds that disasters lead to substantial economic losses by destroying capital, such as railroads, buildings, roads and houses (see Barro, 2006; Cuaresma *et al.*, 2008; Noy, 2009; Cavallo *et al.*, 2010; Strobl, 2012; Felbermayr & Gröschl, 2014). Another set of evidence is consistent with the 'creative destruction' hypothesis, whereby the economy is given the opportunity to replace outdated physical resources ensuing natural disasters, which eventually boosts the economy (see Caballero & Hammour, 1994; Skidmore & Toya, 2002; Loayza *et al.*, 2012; Fomby *et al.*, 2013).

As indicated, most of the extant literature utilises cross-country datasets to examine the contemporaneous and long-term effects of natural disasters on economic output. The cross-country approach assumes a one-sector growth model framed with an aggregate production function. Such aggregate analyses highlight only the changes in gross domestic product (GDP), rather than sector-specific output, and subsequently can mask the differential effects of disasters on sectors, which could lead to the puzzling conclusion of null or ambiguous effects on overall economic growth (see Loayza *et al.*, 2012). To illustrate this point, Figure 2 plots aggregated values for the log of overall GVA, manufacturing, agriculture, mining and services outputs for some selected states of Australia. It is evident that, while nationwide aggregated values for overall GVA and some sectors appear smoother, a noticeable variation exists for sectors such as agriculture and mining when output is disaggregated for states. Further, disaster events are localised, and measuring their effects at the national level may provide insignificant estimates.

We depart from the extant literature that utilises cross-country datasets by focusing on a single country, in particular, the states and territories of Australia. We also focus on 10 different sectors, and thus deviate from the single-sector production function approach. Our study also belongs to the literature investigating the effect of weather shocks on economic activity (for a survey, see Dell *et al.*, 2014). Following this line of research, and apart from floods and bushfires, we study the effect of extreme weather conditions (extreme rain and extreme temperature) on various economic sectors in Australia. Disasters and weather shocks are inherently related, with the latter being typically the atmospheric triggers of the former. In addition, weather extremities can influence the course of the economic activity in their own right. For instance, extreme weather conditions during the sowing or harvesting months of some crops are likely to have adverse impacts on agricultural output.

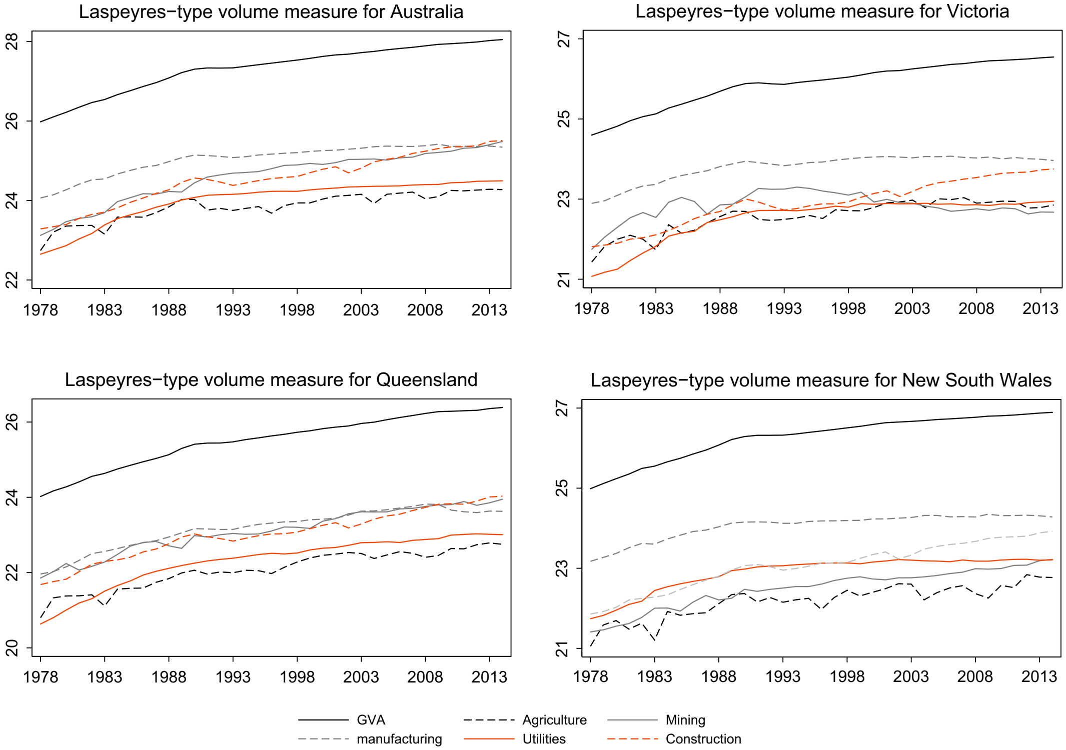
III Data and Measurement

(i) Data on Floods and Bushfires

The Australian Emergency Management Knowledge Hub provides the most extensive historical accounts of disaster events for Australia, available from the nineteenth century onwards. This dataset comes with the exact date and geographic information of the incident, as well as its intensity in terms of human fatalities and casualties.[6] We spatially identify each disaster event and overlay it with the state boundary to identify state-level data (see Figure 3). There were 47 major floods and 36 bushfires in Australia during the sample period 1978–2014. These disaster events are listed in Table A1 in the Appendix, along with their severity indicators (i.e. the number of people killed and affected). Most of the floods and bushfires during the sample period occurred in the four eastern states (Queensland, New South Wales, Victoria and Tasmania). These states accounted for 73 per cent of the Australian GDP in 2014 and nearly 80 per cent of the country's population in 2016, and hence the disasters in these states are likely to lead to significant macroeconomic impact. The most traumatic natural disasters were the 2009 'Black Saturday' bushfires in Victoria and the 2010–11 floods in Queensland,

[6] To obtain the data on natural disasters, see https://www.emknowledge.org.au/disaster-information

Figure 2
Log of the Annual Chain Laspeyres-type Volume Index for Some Selected Sectors and States. The Upper Left Panel Presents the Sum of the Nationwide Indices



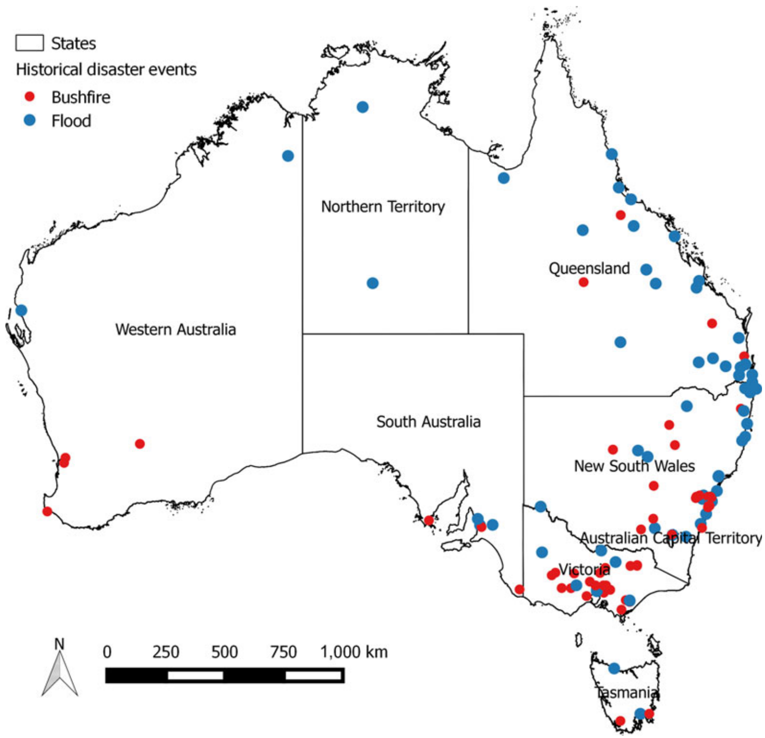
Source: Australian National Accounts.

with the former claiming a human toll of 173 and the latter killing 33 people. The number of affected people (the sum of killed, injured, evacuated and left homeless) varies widely from 0 to more than 5,000 for a given disaster.

To compute weather extremities, we use century-long gridded data of daily rainfall for the period 1900–2014 and temperature for the period 1911–2014 for Australia. It is important to note that the extreme rain and extreme temperature variables constructed using this dataset can help gauge the intensity of floods and bushfires implicitly (see Felbermayr & Gröschl, 2014). The spatial distributions of extreme temperature and extreme rainfall are displayed in Figure 4 (see below for their calculation). Strikingly, the distribution of extreme rainfall seems to map precisely into the distribution of floods, see Figure 3. Extreme rainfall is clearly concentrated on the eastern coast of Australia, suggesting that extreme rainfall could be the trigger for the floods in the sample. Neither the southern nor western coasts of Australia exhibit any extreme rainfall concentration. Meanwhile, extreme temperature is mostly concentrated in western, northern and central Australia, suggesting no link, at least visually, between extreme temperature and bushfires. As is well known, extreme temperature is hardly a sufficient condition for bushfires, which require continued heat on a certain type of landscape and, of course, an ignition.

Returning to the severity of floods and bushfires, the data indicate that the floods and bushfires in our sample resulted in a total insurance claim of

FIGURE 3
Instances of Floods and Bushfires across Australia for the Period 1978–2014



Source: Australian Institute for Disaster Resilience, https://www.emknowledge.org.au/disaster-information; last accessed 30 June 2015.

A$15.1 billion (US$14.3 billion)[7] due to destroyed houses, buildings and infrastructure (see Figure 5). These figures are highly likely to underestimate the true damage and losses due to reporting bias and other intangible damage caused by natural disasters. Nonetheless, a significant proportion of these claims were made following the 2009 ‘Black Saturday’ bushfires in Victoria and the 2010–11 floods in Queensland.[8] The availability of the exact time of the disaster allows us to match this dataset of floods and bushfires with our state-specific national accounts. In addition, with the start and end date of the disasters, we can match the state national accounts data for a given fiscal year.

[7] At 2014 constant prices and USD–AUD exchange rate on 1 July 2014.

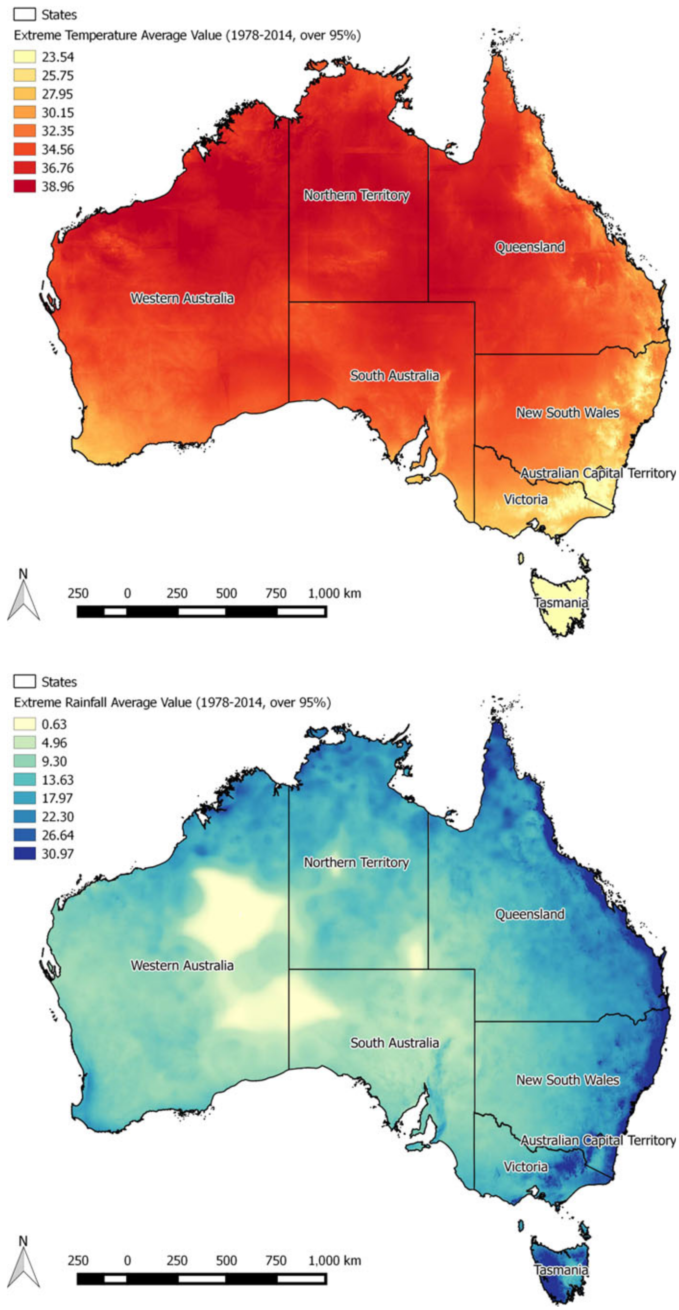
[8] We confirm that none of our empirical results in this paper are driven by these two disasters.

(ii) Data on Extreme Rainfall and Temperature

We exploit the extreme rainfall and extreme temperature incidents as potential triggers of natural disasters. The variation in the higher ends of the distributions of rainfall and temperature is likely to gauge the intensity of floods and bushfires implicitly. Weather extremities can also constitute exogenous shocks that can affect economic activity in their own right. To capture these weather variations, we trace extreme rainfall and extreme temperature on a monthly basis so as to account for seasonal variation at each node. This, in turn, allows us to investigate the extremities for which particular months are more detrimental to the sectoral output.

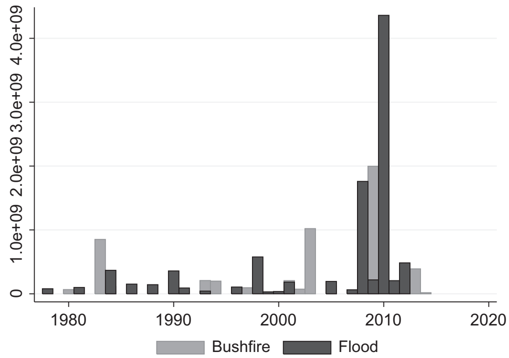
To compute weather extremities, we use the historical Gridded Climate Database of the Australian Bureau of Meteorology (2012), which stretches back to 1900 for daily rainfall, and to 1911 for daily temperature estimates. To identify

FIGURE 4
Extreme Temperature and Extreme Rainfall in Australia



Source: Authors' own calculations.

FIGURE 5
Inflation-adjusted Insurance Claims Over the Years across Australia



Source: Australian Institute for Disaster Resilience, https://www.emknowledge.org.au/disaster-information; last accessed 30 June 2015.

the intensity of weather conditions, each grid-point represents a square area with sides of about 5 km (0.05 latitude- and longitude-degree intervals). These data rely on a grid-point analysis technique using actual rainfall and temperature measures of approximately 6,000 weather stations in Australia.[9] All input station data conform to World Meteorological Organization standards and are adjusted for systematic errors in weather measurements.

Measuring total and extreme rainfall

Our total rainfall measure aims to capture rainfall variations across states and territories over month and year. We have a daily rainfall measure at a 0.05 latitude and longitude degree interval across 277,622 nodes in Australia. We first compute the monthly total rainfall for each node by summing the daily rainfall estimates within a given month during the 1900–2014 period. We then obtain the state-level monthly total rainfall by summing up the monthly total rainfall estimates of all nodes within a particular state or territory.[10] That is,

$$R^{\text{monthly}}_{m,i,t} = \sum_{d=1}^{D} \sum_{n=1}^{N} R^{\text{daily}}_{n,d,i,t},$$

where R^{daily} denotes daily rainfall, n is spatial nodes, N is the total number of nodal points in a state/territory, D is the total number of days in a particular month and R^{monthly} is the total monthly rainfall. Similarly, the yearly total rainfall is given by

$$R^{\text{yearly}}_{i,t} = \sum_{m=1}^{12} R^{\text{monthly}}_{m,i,t}.$$

It is important to note that the Australian Bureau of Statistics (ABS) provides annual sectoral output data on a fiscal year basis (e.g. July 1978 to June 1979). We compute our annual rainfall estimates using the fiscal year period that gives conformity in relation to our fiscal measures of economic performance.

We consider the 95th percentile of monthly total rainfall over a century as extreme rainfall.[11] Thus, to calculate the state-level monthly extreme rainfall volumes, we first estimate the 95th percentile of monthly total rainfall during the 1900–2014 period at nodal level. This estimate produces the threshold to identify the cut-off point for the monthly extreme rainfall of each node observed over the last 115 years. If the actual total rainfall for a particular node in a given month exceeds this historical threshold, we define such excessive rainfall as the measure of extreme rainfall intensity at that nodal level. Finally, we sum all the extreme rainfall estimates in a given year for all nodes within a state/territory of Australia. That is, we use the following formula to calculate extreme rain for a particular month m:

$$R^{\text{extreme}}_{m,i,t} = \begin{cases} R^{\text{monthly}}_{m,i,t} - R^{\text{threshold}}_{m,i}, & \text{if } R^{\text{monthly}}_{m,i,t} > R^{\text{threshold}}_{m,i}, \\ 0, & \text{otherwise,} \end{cases}$$

where time-invariant $R^{\text{threshold}}_{m,i}$ denotes the 95th percentile of monthly total rainfall that occurred in a particular

[9] This grid-point analysis technique provides better estimates for each grid square in data-sparse areas, such as central Australia. In data-rich areas (such as south-east Australia), ‘data smoothing’ will occur, resulting in grid-point values that may differ slightly from the exact rainfall amount measured at the nearby stations (see Australian Bureau of Meteorology, 2012).

[10] The Australian Capital Territory includes 98 nodes, New South Wales 30,677 nodes, the Northern Territory 46,457 nodes, Queensland 60,688 nodes, South Australia 36,725 nodes, Tasmania 2,994 nodes, Victoria 9,172 nodes, and Western Australia 90,811 nodes.

[11] Our results change only little when the 90th percentile threshold is used, or when the 95th percentile is calculated over the 1978–2014 period rather than the whole 1900–2014 period.

month during the period 1900–2014. To explain this measure differently, for each nodal point on the Australian surface, our extreme rainfall metric takes the positive difference between the actual volume of total monthly rainfall in a given year and the 95th percentile of the average monthly total rainfall observed over the last century. If the difference is negative, we set the value to zero, indicating an absence of extreme rainfall. Similarly, we compute yearly extreme rainfall by simply adding the monthly extreme rainfall estimates of all nodes in a given state/territory.

This measure captures extremities even when they occur in an area in which extremities are rare in retrospect (such as rainfall in the Northern Territory), as our comparison threshold is set at the local level that varies with every 5 km distance (0.05 degree interval). In addition, the 95th percentile threshold is applied to monthly average rainfall and temperature over the last 115 years, which captures the climatic conditions and leaves only the extreme weather shocks to be included in our measure of extreme rainfall and temperature.

Measuring average and extreme temperatures

As mentioned above, the Australian Bureau of Meteorology provides the data on daily temperature T^{daily} estimates, measured in degrees Celsius, since 1911 at 0.05 degree intervals. Using this dataset, we estimate the monthly average of daily temperature for each node in a given month during the 1911–2014 period. We then sum up the monthly averages of daily temperature of all nodes, and divide this sum by the total number of nodes in a particular state or territory. Similarly to the calculations above, monthly average temperature is given by

$$T^{\text{monthly}}_{m,i,t} = \frac{\sum_{d=1}^{D} \sum_{n=1}^{N} T^{\text{daily}}_{n,d,i,t}}{ND},$$

with which we can obtain annualised average temperature for each state/territory,

$$T^{\text{yearly}}_{i,t} = \sum_{m=1}^{12} T^{\text{monthly}}_{m,i,t}.$$

We can now write our formula to compute the monthly extremity measure T^{extreme} for temperature as follows:

$$T^{\text{extreme}}_{m,i,t} = \begin{cases} T^{\text{monthly}}_{m,i,t} - T^{\text{threshold}}_{m,i}, & \text{if } T^{\text{monthly}}_{m,i,t} > T^{\text{threshold}}_{m,i}, \\ 0, & \text{otherwise,} \end{cases}$$

where time-invariant $T^{\text{threshold}}_{m,i}$ is computed as the 95th percentile of average daily temperature that occurred in a particular month during the period 1911–2014.

(iii) Data on Australian State National Accounts

The Australian Bureau of Statistics (2014a) electronically provides annual data on the sector-specific GVA of all Australian states and territories for the period 1990–2014. These data disaggregate GVA into 19 sectors. We extend the period of this dataset backwards to 1978 using various series of the statistical yearbooks (*Australian National Accounts: State Accounts*). These yearbooks provide the sectoral decomposition of GVA into 10 sectors, rather than 19. Importantly, five sectors (agriculture, mining, manufacturing, construction and utilities) provide continuous series for the full 1978–2014 period. However, the ABS has decomposed some service sectors into multiple sectors after 1990. For example, prior to 1990, the output of the financial sector was the aggregate of two other sectors: financial and insurance services; and rental, hiring and real estate services. After 1990, these two sectors are reported separately rather than as a single financial sector.[12] Following these data considerations, we are able to undertake our

[12] The first release of annual state accounts was in May 1987, which provided sector-specific data on GVA for the period 1977/8–1985/6. Prior to the Australian and New Zealand Standard Industrial Classification 1993, the Australian System of National Accounts categorised GVA into 10 sectors; hence, the earlier statistical books on historical state accounts presented GVA data for those 10 sectors. We appended state-level sector-specific GVA with their corresponding historical accounts by normalising their base years across all series, and finally obtained data on 10 economic sectors for the period 1978–2014. To give a specific example of the appending procedure, we append the financial sector output before 1990 to the financial and insurance services services sector after 1990. We did not merge rental, hiring and real estate services with financial and insurance services before appending the finance sector output, as this merge would suffer from measurement problems owing to the nature of Laspeyres index type volume measures as various GDP components may not be chain-linked correctly. We used the largest sub-sector (according to the post-1990 classification) in the appending procedure. Thus, the sectors that are left out in our analysis, according to the post-1990 national accounts standards, are wholesale trade, accommodation and food services, information media and telecommunications, rental, hiring and real estate services, professional, scientific and technical services, administrative and support services, education and training, health care and social assistance, and other services. The five sectors and overall GVA in Figure 2 provide consistent time series over time and are not affected by the afore-mentioned decompositions.

sectoral analysis for 10 Australian economic sectors: agriculture, mining, manufacturing, and subgroups of seven services sectors, including utility (electricity, gas, water and waste services), construction, retail, transportation, finance (financial and insurance services), public administration and safety, and arts and recreation services. The share of all these sectors in overall economic activity in Australia sums to an average of 55 per cent over the sample period.[13]

We obtain state-specific population data from various versions of Australian Demographic Statistics (Australian Bureau of Statistics, 2014b). We use these data to normalise our intensity measures for flood and bushfire.

IV Estimation Strategy

Many studies document the impact of natural disasters on GDP in a one-sector framework using a cross-country setting. However, the one-sector approach can hardly paint a useful picture about which sections of the economy respond to significant shocks, how long it takes them to return to normal, and in which sectors normalisation occurs. As an example of potential disparate effects of disasters on sectors, floods may inundate mining facilities and inhibit economic activity,[14] small to mid-sized floods might assist agricultural yield by bringing in silt, alluvium and mineral deposits, whereas large floods might devastate crop yields. Thus, there are compelling reasons to undertake a sector-specific analysis of natural disasters.

An added advantage of sectoral analysis is to assist the design of disaster risk-mitigation interventions. For example, policy-makers may not require the design of risk-mitigation strategies for all economic sectors separately; rather, they can focus on the service sector for emergency response, the infrastructure sector for the post-disaster reconstruction phase, and the agriculture and mining sectors for the long-term recovery phase.

(i) Sectoral Economic Activity

We first estimate the effect of floods and bushfires on sectoral output with the following specification:

$$\begin{aligned}\log(y_{i,t}) = {} & \beta_1 Flood\_Dummy_{i,t} + \beta_2 BushFire\\ & \_Dummy_{i,t} + \beta_3 Flood\_Dummy_{i,t-1}\\ & + \beta_4 BushFire\_Dummy_{i,t-1}\\ & + \alpha_i + \rho_{i,t} + \rho_{i,t}^2 + \phi_t + \epsilon_{i,t},\end{aligned} \tag{1}$$

where y_{it} represents the outcome of interest including overall GVA, agriculture, mining, manufacturing and services, normalised by population in state/territory i for the fiscal period t. The variables *Flood_Dummy* and *BushFire_ Dummy* are binary variables and take the value 1 if there is a disaster during the corresponding fiscal period. These disaster dummies measure the average output loss in states and years that encountered a disaster, compared to a counterfactual state with no disaster shock in that year. We also include a one-year lag of the flood and bushfire variables in the model to test whether the sectoral economic effects of floods and bushfires persist in the following year. Since disasters may generate significant losses in capital, critical infrastructure, and may influence the economic incentives, their effects may last longer.[15] Ignoring this persistence would bias the estimated effects of the disasters. Our estimates are based on clustered robust standard errors.

Our baseline specification includes state-specific fixed effects, state-specific time trends, state-specific quadratic time trends, and common time-varying shocks that affect all states in a given year. State-fixed effects control for the latitude and longitude of states, which correlate with the incidence of disasters, as well as with time-invariant institutional arrangements or natural resources that might have a bearing on sectoral output. Common time-varying shocks control for nationwide effects, such as aggregate demand fluctuations or federal policy changes. State-specific time trends pick up the shocks that are peculiar to a single state, such as state labour laws, state subsidies, and their international linkages. For example, it is well known that Western Australia benefited strongly from

[13] Cyclones and disasters can inhibit data collection. We acknowledge that our results could be affected by poor measurement of economic activity, rather than being due to a decline in economic activity. We thank an anonymous reviewer for pointing this out.

[14] See Katusa (2011), who documents that the 2010–11 floods in Queensland left the mining facilities inoperable.

[15] In our robustness analysis, we include the second lag of the independent variables and do not find them to be significant.

China's remarkable growth and the associated mining boom in the post-2000 period. Controlling for state-specific time trends also enables us to relax the parallel trends assumption because it is likely that trends in economic activity in each state might differ over a long period, such as 1978–2014. Failure to control for state-specific trends may lead to biased estimates because disaster-facing states might exhibit different pre-existing trends in economic activity compared to counterfactual states. Our choice of quadratic (rather than linear) time trends stems from Figure 2, which depicts clearly that GVA follows a non-linear path over time in which output increases at a decreasing rate.[16]

Taken together, accounting for state-fixed effects, common time shocks, and state-specific quadratic time trends, our estimation captures how economic outcomes deviate from their long-term trend in a given state facing a disaster in a certain period, compared to a counterfactual state with no such disaster experience in that period. Alongside the fact that natural disasters and weather extremities are exogenous, this estimation strategy is likely to enable a causal interpretation of the coefficient estimates.

However, a potential pitfall of measuring floods and bushfires with a dummy variable is the limited ability to differentiate the size of the supply shock. For instance, some disasters lead to a substantial number of affected people, while some occur in non-residential areas. The dummy variable approach treats all disasters equally. The implication of this approach is that our estimation finds the average output loss at the state level in a disaster year compared to a non-disaster year during the sample period. To address this limitation, we also take an alternative approach and use an intensity measure,namely, the log of the total number of affected people normalised by the population of a state.[17] One can argue, however, that this intensity measure is likely to be contaminated with endogeneity. Nonetheless, using state-fixed effects, and thus capturing the within-state variation over time, could mitigate, if not entirely eliminate, the endogeneity problem.[18] The specification we use for the intensity measure is

$$\begin{aligned}\log(y_{i,t}) = {} & \beta_1 \log(Flood\_Intens_{i,t}) \\ & + \beta_2 \log(BushFire\_Intens_{i,t}) \\ & + \beta_3 \log(Flood\_Intens_{i,t-1}) \\ & + \beta_4 \log(BushFire\_Intens_{i,t-1}) \\ & + \alpha_i + \rho_{i,t} + \rho_{i,t}^2 + \phi_t + \epsilon_{i,t},\end{aligned} \tag{2}$$

where the *Flood_Intens* and *BushFire_Intens* variables are measured as described above.

(ii) The Impact of Weather Extremities

Given the potential drawbacks of binary indicators *Flood_Dummy* and *BushFire_Dummy* and the severity indicators *Flood_Intens* and *BushFire_Intens*, we now focus on weather-related shocks as potential exogenous triggers of floods and bushfires. Weather extremities are also at the centre of an emerging literature on climate economy because they can influence economic activity even without leading to a natural disaster.

Given the monthly frequency of the rainfall and temperature data, we are able to analyse extreme rain and extreme heat in a given month (extremities in January, February, March, etc.). That is, we employ the weather extremities measured for each of the 12 months, beginning with July of the previous year and ending with June of the current year, given the fiscal year in Australia. Thus, the specification takes the following form:

$$\log(y_{i,t}) = \beta_1 \log(Z_t) + \alpha_i + \rho_{i,t} + \rho_{i,t}^2 + \phi_t + \epsilon_{i,t}, \tag{3}$$

where Z_t is a measure of weather extremity in a given month. While we primarily focus on extreme rainfall and extreme temperature, we also provide the effects of average rainfall and

[16] Excluding state-specific time trends altogether from our regressions, our estimated natural disaster effects become unsurprisingly insignificant. As Figure 2 illustrates, states' GVAs have increasing trends. Combined with the sharp increase in the frequency of natural disasters towards the end of our sample period (see Appendix A), this would point to a positive correlation between natural disasters and the regression error, biasing the estimated (negative) coefficients towards zero. Controlling for state-specific time trends isolates this positive correlation. Controlling for state-specific linear (rather than quadratic) time trends clears part of the bias, and delivers statistically significant but lower point estimates for floods and insignificant estimates for bushfires.

[17] Log transformation is adopted because the share variable is highly skewed. We apply a log $(x+1)$-transformation to treat the large share of zeros in our intensity measure.

[18] Here we acknowledge that, over time, following a technological advancement, people might be warned and evacuated before a disaster hits.

TABLE 1
Descriptive Statistics

	Mean	p50	SD	p25	p75	Min	Max	Count
Flood dummy	0.12	0.00	0.32	0.00	0.00	0.00	1.00	296
Bushfire dummy	0.11	0.00	0.31	0.00	0.00	0.00	1.00	296
Agriculture/GVA (%)	3.82	3.16	2.82	1.99	4.85	0.05	13.63	290
Mining/GVA (%)	6.87	3.30	6.87	2.10	9.83	0.07	27.38	290
Manufac/GVA (%)	8.78	9.04	4.42	5.18	12.07	1.06	18.19	290
Utilities/GVA (%)	4.02	3.58	2.03	2.72	4.42	1.20	11.66	290
Construction/GVA (%)	7.69	6.30	4.02	4.48	9.55	3.28	19.84	290
Retail/GVA (%)	4.00	3.96	0.94	3.40	4.61	1.64	6.50	290
Trans comm/GVA (%)	4.91	4.66	1.56	4.07	5.69	2.13	9.64	290
Finance prop/GVA (%)	4.94	4.41	2.21	3.44	5.81	1.77	12.14	290
Public comm/GVA (%)	9.33	5.74	9.73	4.80	6.92	2.95	42.92	290
Arts recreation/GVA (%)	0.87	0.81	0.39	0.61	0.95	0.33	2.43	290
Total rain (mm)	635.75	578.37	335.54	414.56	775.18	126.81	1581.56	296
Avg temperature (°Celsius)	24.62	25.56	5.95	19.22	30.10	14.14	33.30	296
Bushfire-affected (per 1,000 ppl)	0.03	0	0.31	0	0	0	5.13	296
Flood-affected (per 1,000 ppl)	0.04	0	0.52	0	0	0	8.92	296

average temperature on economic activity to enable a complete picture.

V Results

Table 1 presents the descriptive statistics for the key variables of interest. All the statistics cover the sample of six states and two territories in Australia from 1978 to 2014. The dummy variables for floods and bushfires take the value 1 if a catastrophic event occurred in a particular state/territory in a given year, and 0 otherwise. We find that in our sample the mean score is 0.12 and 0.11 for the flood and bushfire dummies, respectively. The table shows the share of sectors in our analysis as a proportion of GVA.

(i) Floods, Bushfires and Sectoral Output

We present the results of the estimation of Equation (1) in Table 2. Table 2a presents the results with the disaster measure being the flood or bushfire dummy, while Table 2b uses the disaster intensity indicator, that is, the log of the share of affected people in the total population. Focusing on Table 2a, column 1 displays no discernible effect of floods on overall GVA, while column 2 demonstrates a negative effect of floods on the agricultural sector. In addition, floods exert a persistent negative effect on agriculture. The point estimates suggest that a state that experienced a flood in a given year faced, on average, 5.6 per cent lower agricultural output in the current year and 6.2 per cent lower output in the subsequent year. Both estimates are statistically significant at the 5 per cent level. These estimates do not point to any mechanism of effect but rather capture the net outcomes of floods. With a total of 47 major floods in our sample, the magnitude of this effect implies that Australia lost more than 2 years' worth of agricultural output during the period 1978–2014 due to floods.

Why does the persistent flood effect arise in agriculture? One explanation is related to the mechanics of national income accounting in Australia. If floods, say, occur around June (winter in Australia and end of the financial year for national accounts), then the effect may show up both in a given and subsequent fiscal year. One-third of floods in our dataset happened during the last quarter of the fiscal year. Thus, the impact of these floods on the economic activity might be picked up by next fiscal year's balance sheet. An alternative explanation is that floods may adversely influence the incentives and farming decisions of flood-affected individuals, and the resulting discouraged investment, destroyed farms, crops, livestock as well as houses, railroads, and critical infrastructure that provides access to crops and farms give rise to persistence. That the coefficient magnitudes of the contemporaneous and lagged flood effects are similar may give more weight to this explanation. Nonetheless, persistence of flood effect in agriculture highlights the fact that recovery from

TABLE 2
The Impact of Floods and Bushfires on GVA, Agriculture, Mining and Manufacturing

	(1) GVA	(2) Agric	(3) Mining	(4) Manuf
	(a) Disaster measure: disaster dummy			
Flood_t	−0.0061	−0.0564**	−0.0273	−0.0147
	(0.0059)	(0.0257)	(0.0192)	(0.0104)
Flood_{t-1}	−0.0087	−0.0621**	−0.0335	−0.0113
	(0.0068)	(0.0282)	(0.0357)	(0.0106)
Bushfire_t	−0.0042	−0.0105	−0.0559	−0.0023
	(0.0027)	(0.0158)	(0.0437)	(0.0148)
Bushfire_{t-1}	−0.0006	−0.0018	−0.0292	0.0032
	(0.0034)	(0.0181)	(0.0275)	(0.0115)
Observations	288	283	283	283
R^2	0.016	0.028	0.009	0.004
	(b) Disaster measure: disaster-affected people as a proportion of state population			
Flood_t	−0.0199***	0.0279	−0.1283***	0.0302*
	(0.0028)	(0.0189)	(0.0127)	(0.0158)
Flood_{t-1}	−0.0236***	0.0104	−0.1206***	−0.0100
	(0.0026)	(0.0151)	(0.0180)	(0.0159)
Bushfire_t	−0.0106	0.0132	−0.0759	−0.0022
	(0.0065)	(0.0442)	(0.0509)	(0.0160)
Bushfire_{t-1}	−0.0029	0.0303	0.1734*	0.0126
	(0.0073)	(0.0406)	(0.0944)	(0.0121)
Observations	288	283	283	283
R^2	0.038	0.002	0.029	0.004
State fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y
State-specific quadratic TT	Y	Y	Y	Y

Note: Standard errors in parentheses. $^*P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$. This table reports regression results for the impact of floods and bushfires on economic sectors. Panel (a) uses a dummy variable approach to measure disasters, and panel (b) uses log of share of affected people in a natural disaster in state's population as an intensity measure. The dependent variables in columns 1–4 are GVA, and agriculture, mining and manufacturing sectoral output measured in log of output in real Australian dollars scaled by state population. The standard errors are clustered by states.

floods is not rapid, and that it may take time to replenish or repair the damaged farms, buildings, roads and railways.

Turning to bushfires, we fail to identify any significant effect of bushfires on both overall GVA and the agriculture, mining and manufacturing outputs in an economically meaningful way. The first candidate to observe an effect would be the agriculture sector, yet we do not estimate such an effect. One potential explanation is that bushfires mostly occur in the months of January and February, by which time the majority of crops have already been harvested. Another explanation is that bushfires mainly occur in forests and non-agricultural lands; thus, the negative effect of bushfires on crop yields might be limited.

As indicated above, a potential pitfall of using a dummy variable approach is that it treats each disaster equally. Next, we estimate Equation (2), in which we measure the disaster intensity with the log of the share of disaster casualties in the population. The results reported in Table 2b show that floods are significantly associated with lower overall GVA, as well as lower value added in the mining sector (also with subgroups of services sectors as seen in Table 3). Further, all effects are persistent in the subsequent year. The mining result is not entirely surprising because high volumes of water may severely affect the sector following leakages to underground areas. Although facilities are typically prepared as much as possible to protect against high volumes of rainfall, during floods, important equipment

TABLE 3
The Impact of Floods and Bushfires on the Output of Services Sectors

	(1) Utility	(2) Const	(3) Retail	(4) Finance	(5) Transp	(6) Public	(7) Recrea
	Disaster measure: disaster-affected people as a proportion of state population						
Flood_t	0.0443***	−0.0317***	−0.0046	−0.0362**	0.0079**	0.0163**	−0.0119
	(0.0078)	(0.0064)	(0.0052)	(0.0146)	(0.0038)	(0.0078)	(0.0117)
Flood_{t-1}	0.0310***	−0.0149**	−0.0234***	−0.0165	0.0213***	0.0422***	−0.0293**
	(0.0092)	(0.0066)	(0.0045)	(0.0166)	(0.0039)	(0.0098)	(0.0122)
Bushfire_t	0.0269*	−0.0342***	0.0456***	−0.0225**	−0.0266*	0.0135	0.0286
	(0.0151)	(0.0120)	(0.0038)	(0.0096)	(0.0137)	(0.0093)	(0.0220)
Bushfire_{t-1}	0.0224	−0.0611***	0.0312***	0.0364***	−0.0622***	0.0013	0.0088
	(0.0339)	(0.0231)	(0.0091)	(0.0129)	(0.0106)	(0.0139)	(0.0281)
Observations	283	283	283	283	283	283	283
R^2	0.014	0.028	0.042	0.054	0.011	0.025	0.006
State fixed effects	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y	Y	Y	Y
State-specific quadratic TT	Y	Y	Y	Y	Y	Y	Y

Note: Standard errors in parentheses. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$. This table reports regression results for the impact of floods and bushfires on economic sectors. It uses the log of share of affected people in a natural disaster in state's population as an intensity measure. The dependent variables in columns 1–7 are utility (electricity, gas, water and waste services), construction, retail, transportation, finance (financial and insurance services), public administration and safety, and arts and recreation services outputs measured in log of output in real Australian dollars scaled by state population. The standard errors are clustered by states.

might be swamped and operations might be inhibited (see Floods Commission, 2012).[19] Moving on to other sectors, floods are insignificantly associated with the agricultural output using the intensity measure. Finally, we fail to find any statistically powerful flood impact on manufacturing. These disparate effects highlight the importance of analysing sectoral activity to uncover the effect of natural disasters on economic activity. Turning to bushfires, as in Table 2a, they do not exhibit any economically or statistically significant effect on sectoral output.[20]

Table 3 presents the estimates for a range of subgroups of services sectors using the intensity measure of natural disasters. Column 1 shows that both bushfires and floods increase the state level output of the electricity, gas and water sector. The effect of floods is statistically strong and persists in the subsequent year. Column 2 shows that both floods and bushfires reduce the output of the construction sector in two consecutive years. In particular, a 1 per cent increase in the intensity of bushfire decreases the per capita GVA of the construction sector by 0.03 per cent in the same year and 0.06 per cent in the following year. Though this rate may seem negligible, the total loss in construction is important. For example, construction contributed A$124.4 billion to the overall Australian GDP of A$1,461.2 billion in 2014, meaning bushfires could reduce it by A$112 million. Similarly, floods reduce the per capita GVA of construction by 0.05 per cent, potentially leading to a total loss of A$62.2 million in 2014.

Column 3 indicates that output of the retail trade sector increases following bushfires but decreases following floods. The positive effect of bushfires is also persistent, and the effects might be driven by boosted trading activity following bushfires. The negative effect of floods could emanate from the fact that floods inundate the retail trade facilities, consequently shrinking their sales. Column 4 shows that the immediate effects of both floods and bushfires on financial and insurance services are negative. However, the lagged effect of bushfires is positive. Anecdotal

[19] As anecdotal evidence, the 2010 flood in Queensland affected the Bowen Basin and left the facilities inoperable (see Forbes, 2011).

[20] One exception is a positive lagged effect on mining that is significant at the 10 per cent level. This result is surprising, with no immediate explanation available.

evidence shows that, as compared to floods, bushfires destroy houses completely (Munich Re, 2018). This may eventually result in a boost to financial and insurance services.

Column 5 indicates that bushfires and floods have opposite effects on transport, storage and communication. While bushfires decrease the output of the transport, storage and communication sector, floods increase it for two consecutive years. One possible explanation for this mixed result is that floods destroy road and rail networks of cities and urban sprawl, whereas bushfires damage the transport and communication infrastructure of rural areas. Given the lower population density, bushfire-affected communities may abandon their usual residence and resettle somewhere else. In this case, the government may sensibly choose not to rebuild the burnt road and rail infrastructure to reconnect these abandoned bushfire risk areas, restricting transport and communication services and decreasing their total revenue. In contrast, reconstruction activities following floods might trigger a creative destruction effect, boosting the total output of the transport, storage and communication sector. For instance, the 2010–11 Queensland floods damaged more than 9,100 km of the state road network and approximately 4,700 km of the rail network (World Bank, 2011). The cost of rebuilding roads and other infrastructure was around A $6.9 billion (Queensland Government, 2012).

Column 6 reports that the public administration and safety sector experiences a positive impact from floods. However, this sector does not respond to bushfires significantly. This result is quite expected: in contrast to bushfires, floods occur in areas with relatively higher population density, meaning more affected people. This scenario stretches the public administration and safety sector to mobilise its resources to the fullest, stimulating its overall level of output in the following year.

Finally, column 7 shows that floods reduce the output of the recreation, personal and other services sectors in the following year, while bushfires leave them unaffected. We believe that the negative effect arises because floods, unlike bushfires, cover not only larger geographic areas but also more densely populated urban sprawl. These flood-prone areas are generally dominated by service-oriented activities that are disrupted in the wake of such catastrophe. However, not all services are affected negatively. For example, post-disaster emergency- and recovery-related services (emergency supplies, and repair and maintenance activities) receive a boost while other services (arts and recreation, civic and personal services) become contracted in the aftermath of floods. Such opposite effects of floods on recreation, personal and other services may offset each other, resulting in an insignificant contemporaneous relationship. Once the post-disaster emergency- and recovery-related activities are completed (generally within a year), the economy may remain only with the services negatively exposed to floods. We found this dynamics in our empirical findings, such that the immediate effect of floods is insignificant while the lagged effect becomes negative (statistically significant at the 5 per cent level).

Overall, the economic significance of our findings is noteworthy, especially in the case of three sectors (retail trade, finance, and arts and recreation services), comprising one-fifth of the Australian economy. Given their sheer sizes, the mixed effects of bushfires together with the negative effect of floods on these sectors may substantially affect the overall economic performance of Australian states and territories.

To put our results in perspective, we compare our findings with those of Loayza *et al.* (2012), who estimate the effects of floods on overall GDP growth as well as agricultural, industry, and services sectors' output growth, using a cross-country dataset of 96 countries for the period 1961–2005. Loayza *et al.* (2012) find that floods, measured by the intensity metric of log(average affected/population), positively affect both overall growth and each sector's output. Their argument for the positive effect of floods on agriculture is that most of the floods in their sample could be considered as moderate floods, given that floods are localised relative to the size of the countries and that moderate floods increase agricultural yield. They attribute the positive flood effects on industry to the expansion in electricity-generating capacity and improved agriculture–non-agriculture linkages following floods, and the services growth to increased demand for commerce and retailing, transport, communications, banking and government. These effects are mostly driven by the developing countries sample, with the implication that developed countries exhibit weaker effects. Our result, that floods, measured by the intensity metric, exert insignificant effects on agriculture, accords with Loayza *et al.*'s (2012) implications for developed countries. Their reasoning for positive industry growth in developing countries is unlikely to apply to the Australian case for which we estimate an insignificant manufacturing effect. Finally, their positive finding for the services sector, though at the aggregate level, accords with our positive flood effects on the electricity, gas and water, transport, storage and communication, and public administration and safety sectors, and contrasts with our negative effects on construction, retail trade, and recreation, personal and other services.

(ii) Weather Extremities and Sectoral Output

We now examine the impact of extreme rainfall, extreme temperature, total rainfall, and average temperature on the overall GVA as well as the outputs of some key sectors.[21] Tables 4–7 provide the estimates of the effects of monthly total rainfall, monthly extreme rainfall, monthly average temperature, and monthly extreme temperature, respectively, on overall GVA and the outputs of some key sectors: agriculture, mining, manufacturing, construction, and public administration and safety.

We identify four main findings in our analysis of the effects of total rain and extreme rain on sectoral output. First, the results in Table 4 highlight that a higher total rainfall in July significantly increases the agricultural sector output of the current fiscal year. This indicates that rainfall during the grain-sowing period (typically the months of May, June and July in Australia) is important for the agricultural output of that year. Moreover, consistent with our estimates on the effect of floods in Table 2, our results in Table 5 show that extreme rain indeed has a negative effect on the sectoral output of agriculture. Extreme rain in April, May and June seems to reduce agricultural output significantly. This is in tandem with our floods data, which show that 33 per cent of all floods occurred during these months. Recall that our extreme rain is computed as the difference between average rainfall and the rainfall recorded at the 95th percentile of the entire century for the same month. Thus, extreme rain can go alongside flood incidents.

Second, Table 4 shows that higher total rain in January reduces the mining output but Table 5 reports that higher extreme rain in January increases it. This result may seem paradoxical, but it is likely to point to important nuances in mining operations in the Australian summer. There is plenty of anecdotal evidence, for example from Western Australia, suggesting that wet weather slows down mining operations due to muddy terrain and hampered shipping and loading (see Topp *et al.*, 2008). However, extreme rain is a more severe weather condition that typically inundates mining areas, and the extended flooding may cause delays in meeting contractual obligations. To satisfy contracts (which are mostly international), the sector may boost productivity in the months following the floods and increase its output beyond its trend.[22] Thus, our results may point to the degree to which weather severity may impact productivity by way of capturing heightened incentives to overcome the effects of severe weather.

Third, total rain in April and extreme rain in April and May boost construction output (see Tables 4 and 5). Considering that one-third of floods occur during this period, we are likely to capture the increased short-term recovery and reconstruction activities. In these months the government may procure construction services from the private sector to ensure timely recovery. By contrast, extreme rain in July and October has an adverse impact on the construction sector. This result may be attributed to reduced dwelling construction activity due to severe weather in the Australian winter and spring.

Fourth, both total rain and extreme rain in June are likely to boost the public administration output. Consistent with the result found in the case of the construction sector, this finding may point to increased recovery expenditures by the

[21] Our analysis using annual data on weather conditions did not yield any significant findings (results available upon request). Annual data could be too aggregate to identify any meaningful sectoral influence of weather conditions. Thus, it makes more sense to analyse the monthly weather conditions in a year, which are more likely to be influential for sectoral output.

[22] A quarterly report of the large international coal-mining company Gloucester Coal (December 2010, p. 4) notes that a higher than average number of wet weather days during the quarter impacted on operational efficiency due to the poor condition of haul roads, and to ‘maintain the overall run-of-mine production levels during the quarter, mining capacity that would have otherwise been deployed on the BRN highwall cutback was transferred from the BRN pit to the Roseville pit’. Such rescheduling of mining activities is common in the sector and attests to the fact that the sector is very responsive to weather shocks.

TABLE 4
The Impact of Monthly Total Rain on Sectoral Output

	(1) GVA	(2) Agric	(3) Mining	(4) Manuf	(5) Const	(6) Public
Jul total rain$_{t-1}$	−0.0029	0.0199**	−0.0064	−0.0098	−0.0012	0.0076
	(0.0025)	(0.0101)	(0.0189)	(0.0082)	(0.0055)	(0.0049)
Aug total rain$_{t-1}$	0.0037*	0.0002	0.0500**	0.0148	0.0062	0.0024
	(0.0022)	(0.0212)	(0.0235)	(0.0101)	(0.0075)	(0.0061)
Sep total rain$_{t-1}$	−0.0015	−0.0060	−0.0181	0.0031	0.0015	−0.0035
	(0.0023)	(0.0126)	(0.0287)	(0.0082)	(0.0060)	(0.0051)
Oct total rain$_{t-1}$	−0.0014	−0.0259	0.0168	−0.0023	0.0106	0.0111
	(0.0022)	(0.0191)	(0.0227)	(0.0133)	(0.0084)	(0.0076)
Nov total rain$_{t-1}$	−0.0007	0.0004	−0.0131	0.0012	0.0029	−0.0074**
	(0.0016)	(0.0097)	(0.0370)	(0.0091)	(0.0116)	(0.0029)
Dec total rain$_{t-1}$	−0.0044	0.0091	0.0126	0.0021	−0.0081	0.0069
	(0.0043)	(0.0179)	(0.0282)	(0.0103)	(0.0067)	(0.0060)
Jan total rain$_t$	−0.0013	0.0055	−0.0572**	−0.0233	0.0033	0.0039
	(0.0028)	(0.0097)	(0.0246)	(0.0146)	(0.0087)	(0.0030)
Feb total rain$_t$	0.0013	−0.0132	−0.0230	0.0080	0.0002	0.0006
	(0.0017)	(0.0121)	(0.0209)	(0.0090)	(0.0043)	(0.0032)
Mar total rain$_t$	−0.0025	0.0040	−0.0177	−0.0008	0.0097	0.0000
	(0.0037)	(0.0151)	(0.0172)	(0.0069)	(0.0094)	(0.0049)
Apr total rain$_t$	0.0023	0.0005	0.0004	0.0013	0.0138***	0.0062
	(0.0018)	(0.0155)	(0.0239)	(0.0062)	(0.0052)	(0.0055)
May total rain$_t$	0.0027	−0.0218*	0.0071	0.0096	0.0074	−0.0024
	(0.0021)	(0.0122)	(0.0091)	(0.0082)	(0.0064)	(0.0039)
Jun total rain$_t$	−0.0011	−0.0192	−0.0297	−0.0092	−0.0057	0.0082***
	(0.0020)	(0.0173)	(0.0187)	(0.0107)	(0.0134)	(0.0031)
Observations	288	283	283	283	283	283
R^2	0.039	0.030	0.053	0.046	0.042	0.066
State fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y	Y	Y
State-specific quadratic TT	Y	Y	Y	Y	Y	Y

Note: Standard errors in parentheses. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$. This table reports regression results for the impact of monthly total rain on economic sectors. The dependent variables in columns 1–6 are GVA, agriculture, mining, manufacturing, construction and public sector outputs measured in log of the output in real Australian dollars scaled by state population. The standard errors are clustered by states.

public sector and overtime remunerations made to public sector employees.

We now turn to the effect of average temperature and extreme temperature on economic activity using Equation (3). The results are provided in Tables 6 and 7. Recall that extreme temperature captures the extremities in the century-long data. Also note that extreme temperature in winter corresponds to relatively warmer temperatures.

Again there are four key results. First, Table 6 shows that a hotter-than-average February adversely affects the agricultural output, while a hotter-than-average June and extreme heat in June increase agricultural output (see Table 7). A relatively warmer winter might help agricultural seeding and yield, while a hotter summer seems to hamper it, which could be due to the reduced produce output.

Second, mining output is quite volatile with regard to temperature variations, especially those of extreme temperatures. Table 7 shows that seven of the 12 months exhibit significant effects on mining output due to extreme temperature. The economic implications of these intricate results are not immediately clear; however, the dependence of mining output on extreme temperature variations is salient.

Third, perhaps surprisingly, the construction sector appears to benefit from extreme heat incidents in January and February, but is negatively

TABLE 5
The Impact of Monthly Extreme Rain on Sectoral Output

	(1) GVA	(2) Agric	(3) Mining	(4) Manuf	(5) Const	(6) Public
Jul Extreme Rain$_{t-1}$	0.0035	−0.0142	−0.0061	−0.0321*	−0.0185*	0.0028
	(0.0044)	(0.0264)	(0.0379)	(0.0189)	(0.0103)	(0.0098)
Aug extreme rain$_{t-1}$	−0.0026	−0.0065	−0.0276*	−0.0105	−0.0071	−0.0034
	(0.0041)	(0.0208)	(0.0149)	(0.0226)	(0.0057)	(0.0053)
Sep extreme rain$_{t-1}$	−0.0044	−0.0176	0.0188	−0.0179	−0.0015	0.0023
	(0.0027)	(0.0151)	(0.0346)	(0.0176)	(0.0080)	(0.0068)
Oct extreme rain$_{t-1}$	0.0003	−0.0081	0.0296	0.0169***	−0.0107*	0.0056
	(0.0026)	(0.0256)	(0.0212)	(0.0063)	(0.0063)	(0.0038)
Nov extreme rain$_{t-1}$	0.0090***	0.0244	0.0119	−0.0009	0.0037	0.0084*
	(0.0022)	(0.0213)	(0.0136)	(0.0170)	(0.0135)	(0.0051)
Dec extreme rain$_{t-1}$	−0.0019	−0.0194	−0.0417	−0.0069	−0.0005	0.0048
	(0.0021)	(0.0119)	(0.0416)	(0.0075)	(0.0049)	(0.0052)
Jan extreme rain$_t$	−0.0012	0.0169	0.0376**	−0.0083	0.0081	−0.0000
	(0.0024)	(0.0171)	(0.0163)	(0.0095)	(0.0066)	(0.0022)
Feb extreme rain$_t$	−0.0040*	0.0062	−0.0179	−0.0044	−0.0074	0.0075
	(0.0021)	(0.0099)	(0.0161)	(0.0070)	(0.0058)	(0.0081)
Mar extreme rain$_t$	0.0020**	0.0318***	0.0329	0.0030	−0.0061	−0.0028
	(0.0010)	(0.0121)	(0.0205)	(0.0035)	(0.0055)	(0.0024)
Apr extreme rain$_t$	−0.0025	−0.0285**	0.0177	−0.0168	0.0250**	−0.0033
	(0.0016)	(0.0138)	(0.0139)	(0.0163)	(0.0119)	(0.0034)
May extreme rain$_t$	0.0033*	−0.0464***	−0.0283	0.0001	0.0171***	0.0060
	(0.0020)	(0.0155)	(0.0224)	(0.0069)	(0.0062)	(0.0059)
Jun extreme rain$_t$	0.0001	−0.0359***	−0.0099	−0.0008	−0.0071	0.0126***
	(0.0026)	(0.0086)	(0.0159)	(0.0126)	(0.0046)	(0.0042)
Observations	288	283	283	283	283	283
R^2	0.040	0.075	0.037	0.045	0.063	0.043
State fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y	Y	Y
State-specific quadratic TT	Y	Y	Y	Y	Y	Y

Note: Standard errors in parentheses. *$P < 0.10$, **$P < 0.05$, ***$P < 0.01$. This table reports regression results for the impact of extreme rain on economic sectors. The dependent variables in columns 1–6 are GVA, agriculture, mining, manufacturing, construction, and public administration and safety sector outputs measured in log of the output in real Australian dollars scaled by state population. The standard errors are clustered by states.

affected by extreme temperature in the spring and autumn months of October and March, respectively. Again, this result could arise due to the incentives generated by different degrees of weather severity. While moderately high temperatures may result in delays in construction in spring and autumn, an extended period of extreme temperature in the summer may lead to a boosted output in the following period to satisfy contractual obligations.[23]

Fourth, both higher-than-average temperature and extreme temperature in December consistently reduce public administration and safety output. One potential explanation is the reduced worker productivity in the public sector due to the hot weather (see Dell *et al.*, 2014 for a similar argument).

Taken together, our findings demonstrate that weather extremities have both adverse and positive outcomes, depending on the sector and the month. While agriculture benefits from higher-than-average rain in earlier months of the crop cycle, it is adversely affected by hotter-than-average months and extreme heat incidents in the Australian autumn and summer. The construction sector output is also affected by variations in

[23] In Australia, the contractor bears the responsibility for weather-related delays, and construction contracts charge delay costs for each day of the delay (see Cahill, 1996).

Table 6
The Impact of Monthly Average Temperature on Sectoral Output

	(1) GVA	(2) Agric	(3) Mining	(4) Manuf	(5) Const	(6) Public
Jul avg temp$_{t-1}$	0.0010	−0.0337	−0.1250	0.1691*	0.0346	−0.0043
	(0.0226)	(0.2388)	(0.1325)	(0.0987)	(0.1130)	(0.0834)
Aug avg temp$_{t-1}$	−0.0175	0.0615	0.2447	−0.1639	−0.1467	−0.0448
	(0.0284)	(0.2223)	(0.1923)	(0.1448)	(0.1176)	(0.0415)
Sep avg temp$_{t-1}$	0.0237	0.1813*	−0.1725	0.3705***	0.0087	−0.0952*
	(0.0244)	(0.1087)	(0.2329)	(0.1336)	(0.1370)	(0.0539)
Oct avg temp$_{t-1}$	−0.0541**	−0.1594	−0.3082	−0.4117**	−0.2168**	−0.0605*
	(0.0274)	(0.2008)	(0.4797)	(0.1826)	(0.0904)	(0.0327)
Nov avg temp$_{t-1}$	−0.0076	−0.2379	−0.5384	0.1836	0.1506*	0.0207
	(0.0476)	(0.2676)	(0.3880)	(0.1992)	(0.0889)	(0.0496)
Dec avg temp$_{t-1}$	0.0702	0.1111	0.2344	−0.2567	−0.2183	−0.0262
	(0.0702)	(0.4264)	(0.5786)	(0.1884)	(0.1515)	(0.0640)
Jan avg temp$_t$	−0.0205	0.2126	−0.0064	0.3273	−0.0488	0.0059
	(0.0350)	(0.2219)	(0.2459)	(0.2476)	(0.0737)	(0.0696)
Feb avg temp$_t$	−0.0557**	−0.4960***	0.1006	−0.0716	0.0154	−0.1575***
	(0.0246)	(0.1818)	(0.3272)	(0.1441)	(0.0582)	(0.0546)
Mar avg temp$_t$	0.0396	0.1800	0.5371**	−0.0097	−0.1626***	0.1139
	(0.0523)	(0.2343)	(0.2477)	(0.2145)	(0.0596)	(0.0739)
Apr avg temp$_t$	−0.0161	−0.1473	−0.5310*	−0.1537	−0.0434	0.0919
	(0.0478)	(0.1474)	(0.3051)	(0.1429)	(0.1764)	(0.0602)
May avg temp$_t$	0.0244	−0.1501	0.1655	0.3377***	−0.1340	0.0074
	(0.0554)	(0.2344)	(0.2429)	(0.1242)	(0.1415)	(0.0908)
Jun avg temp$_t$	−0.0308	0.5771**	−0.2596	0.0880	0.1748	−0.0685
	(0.0283)	(0.2556)	(0.3748)	(0.1526)	(0.1580)	(0.0777)
Observations	288	283	283	283	283	283
R^2	0.029	0.041	0.029	0.100	0.057	0.050
State fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y	Y	Y
State-specific quadratic TT	Y	Y	Y	Y	Y	Y

Note: Standard errors in parentheses. *P < 0.10, **P < 0.05, ***P < 0.01. This table reports regression results for the impact of average monthly temperature on selected economic sectors. The dependent variables in columns 1 –6 are GVA, agriculture, mining, manufacturing, construction, and public administration and safety sector outputs measured in log of the output in real Australian dollars scaled by state population. The standard errors are clustered by states.

weather conditions. Sometimes negative effects arise, presumably due delayed construction activities, whereas at other times output is boosted due to recovery and reconstruction. Mining output seems to be the most responsive to weather shocks. Flooding incidents that may arise following extreme rain, higher-than-average rain and, most prominently, extreme temperature all appear to affect mining output in a fiscal year. The manufacturing sector is the least affected by weather conditions.

VI Conclusion

This study is one of the first to carry out a thorough analysis of the impact of natural disasters and weather extremities on sectoral output for an advanced economy, namely, Australia. Arguably, advanced economies have a stronger capacity to respond to significant shocks than developing countries, but the ways in which their markets adjust to such shocks, how long it takes to utilise their capacity to return to normal, and in which sections of the economy the normalisation occurs are largely undocumented in the extant literature. We investigate the changes in sectoral output as a result of the aforementioned shocks using state-level annual panel data for the period 1978–2014. Australia exhibits strong spatial and temporal variation in these shocks, which

TABLE 7

The Impact of Monthly Extreme Temperature on Sectoral Output

	(1) GVA	(2) Agric	(3) Mining	(4) Manuf	(5) Const	(6) Public
Jul extreme temp$_{t-1}$	−0.0134	−0.0433	−0.4959***	−0.1018	−0.0533	0.0631
	(0.0279)	(0.0492)	(0.0652)	(0.0932)	(0.0769)	(0.0869)
Aug extreme temp$_{t-1}$	−0.0058	−0.0819	0.0552	−0.0565**	−0.0342	−0.0103
	(0.0069)	(0.0973)	(0.0531)	(0.0235)	(0.0271)	(0.0134)
Sep extreme temp$_{t-1}$	−0.0026	−0.0198	0.0299	0.0921***	0.0767	−0.0268
	(0.0184)	(0.0781)	(0.0756)	(0.0351)	(0.0527)	(0.0365)
Oct extreme temp$_{t-1}$	−0.0431**	−0.4188*	−0.2786***	0.0756	−0.0035	−0.0247
	(0.0218)	(0.2350)	(0.0841)	(0.1042)	(0.0656)	(0.0292)
Nov extreme temp$_{t-1}$	0.0007	0.0032	0.2405**	0.0582	−0.0769***	−0.0200
	(0.0209)	(0.0970)	(0.1110)	(0.0905)	(0.0253)	(0.0362)
Dec extreme temp$_{t-1}$	0.0027	−0.0303	0.2750***	−0.0117	−0.0276	−0.0472**
	(0.0126)	(0.0543)	(0.0925)	(0.0514)	(0.0268)	(0.0216)
Jan extreme temp$_t$	0.0210	−0.1286	0.0237	0.1212	0.1459**	0.0258
	(0.0216)	(0.1198)	(0.1546)	(0.0940)	(0.0604)	(0.0392)
Feb extreme temp$_t$	0.0087	0.0265	−0.1831	0.0909**	0.1587***	−0.0273
	(0.0176)	(0.1635)	(0.1266)	(0.0406)	(0.0293)	(0.0209)
Mar extreme temp$_t$	0.0320	0.0937	0.5876**	−0.0266	−0.0228	0.0196
	(0.0211)	(0.0926)	(0.2837)	(0.0230)	(0.0289)	(0.0139)
Apr extreme temp$_t$	−0.0029	−0.0536	−0.0064	−0.0224	−0.0361	0.0208
	(0.0139)	(0.0806)	(0.0718)	(0.0340)	(0.0432)	(0.0233)
May extreme temp$_t$	0.0150	−0.2136*	0.2371***	0.1970**	−0.0538	−0.0030
	(0.0222)	(0.1251)	(0.0854)	(0.0792)	(0.0409)	(0.0224)
Jun extreme temp$_t$	−0.0427**	0.3298***	−0.4048***	0.0239	0.1049***	−0.0561
	(0.0172)	(0.0438)	(0.0699)	(0.0539)	(0.0228)	(0.0349)
Observations	288	283	283	283	283	283
R^2	0.039	0.063	0.112	0.047	0.065	0.027
State fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
State-specific time trend	Y	Y	Y	Y	Y	Y
State-specific quadratic TT	Y	Y	Y	Y	Y	Y

Note: Standard errors in parentheses. *P < 0.10, **P < 0.05, ***P < 0.01. This table reports regression results for the impact of monthly extreme temperature on selected economic sectors. The dependent variables in columns 1–6 are GVA, agriculture, mining, manufacturing, construction, and public administration and safety sector outputs measured in log of the output in real Australian dollars scaled by state population. The standard errors are clustered by states.

allows for estimating a meaningful shock effect in a quasi-experimental setting. We focus on two types of natural disasters, namely, floods and bushfires, and two types of weather extremities, extreme rainfall and extreme temperature. These extremity measures are computed from a unique, long-term climatic dataset for Australia available for the period 1911–2014. Extreme weather conditions are both potential atmospheric triggers of disasters and important exogenous shocks that can influence economic activity in their own right.

Our findings indicate that the sectoral output in Australia is more sensitive to floods than bushfires. Floods exert a significant adverse impact on the agriculture, mining, construction, and financial services sectors, and their negative effects persist at least for another year. For example, our estimated effects point to a 5–6 per cent lower agricultural output both in the disaster year and the subsequent year. With 47 major floods having occurred in the sample period, these estimates suggest that Australia lost more than 2 years of agricultural output during the period 1978–2014 due to floods. Bushfires, by contrast, have no statistically significant influence on economic output.

We also study the impact of extreme rainfall and extreme temperature on sectoral output. This is inherently difficult because the variation at the highest end of the rainfall and temperature distributions may not lead to similar output reactions that would amount to a reasonable average effect to be picked up by an ordinary least squares estimator. Nevertheless, our analysis offers a relatively consistent picture of the output impact of weather extremities in Australia. We find that the Australian mining output is quite responsive to weather shocks, both rainfall and temperature, sometimes with decreased output and at other times with increased output. Also, while agriculture benefits from higher-than-average rain in earlier months of the crop cycle, it is adversely affected by hotter-than-average months and extreme heat incidents in the Australian autumn and summer. Finally, manufacturing is the least affected by weather conditions, followed by construction and public administration, which may be negatively (or sometimes positively) affected by strong variations in weather.

As to the policy implication of our results, the broad policy conclusion is that varying disaster effects call for different policy prescriptions for different types of natural disasters. However, one finding does have a specific policy implication: persistence of the flood effect in agriculture. What can be done to reduce the persistence effect? Instead of providing direct relief to farmers, governments may facilitate several risk-sharing mechanisms. For example, crop insurance programs can help avert persistence in the adverse income effects for affected farmers, which would enable them to continue their agribusinesses ensuing the year of the disaster. In this sense, countries that have adopted effective crop insurance programs (such as the USA, with its Crop Insurance Act of 1994) seem to mitigate the persistence effect.

A caveat of this paper is that we do not investigate the impact of natural disasters on government indebtedness, state indebtedness or the state budget. Federal government expenditures to recover from natural disaster and to aid disaster victims may boost the economy, depending on the fiscal multiplier. These constitute a fruitful future avenue of research.

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Appendix A

TABLE 8
Summary of Disaster Effects

Floods				Bushfires			
State	Year	Killed	Affected	State	Year	Killed	Affected
NSW	1978	6	6	ACT	2002	0	5,500
NSW	1984	0	0	ACT	2003	4	439
NSW	1986	6	6	NSW	1980	5	5
NSW	1988	0	0	NSW	1980	5	5
NSW	1990	2	1,669	NSW	1983	3	3
NSW	1996	3	13	NSW	1985	4	4
NSW	1998	1	1	NSW	1987	3	23
NSW	2001	0	3,250	NSW	1992	2	2
NSW	2005	1	3,001	NSW	1994	4	4
NSW	2008	0	0	NSW	1997	4	4
NSW**	2009	1	1	NSW	2000	4	7
NSW	2011	1	1	NSW	2002	0	5,500
NSW	2012	3	3	NSW	2002	0	0
NT	1988	3	303	NSW***	2013	2	231
NT	1998	3	5,633	QLD	1994	0	3,009
QLD	1981	1	6	QLD	2011	0	0
QLD	1989	3	3	SA	1980	0	0
QLD***	1991	14	4,041	SA	1983	38	5,288
QLD	1991	3	13	SA	2005	9	119
QLD	1996	3	13	TAS	2013	1	1,001
QLD	1998	1	1	VIC	1983	38	5,288
QLD	2000	0	10	VIC	1985	3	603
QLD	2001	2	52	VIC	1997	3	843
QLD	2005	2	2	VIC	1998	5	5
QLD	2008	0	0	VIC	2003	0	0
QLD***	2008	0	0	VIC	2006	4	10
QLD**	2009	1	1	VIC	2007	1	1,401
QLD***	2010	33	5,933	VIC	2009	173	587
QLD	2012	1	1	VIC**	2014	0	3
SA	2005	0	0	WA	2008	3	3
VIC	1990	2	1,669	WA**	2011	0	12
VIC	1991	0	220	WA	2014	1	1
VIC	1993	0	0				
VIC	1999	0	100				
VIC	2007	1	1				
VIC	2011	1	1				
VIC**	2012	0	0				
WA	2011	0	0				

Note: This table summarises the impact of floods and bushfires caused in a given year and state. The 'affected' column is computed by summing the number of people that are killed, injured, evacuated and left homeless. Year corresponds to the end date of the disaster and ** (***) indicate that there have been two (three) instances of the same disaster type in a given year for the same state.