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Let's Get Physical: Impacts of Climate Change Physical Risks on Provincial Employment

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Abstract

We analyze 40 years' worth of natural disaster shocks in Canada, using a local projection framework to assess their impact on provincial labour markets. We find that disasters decrease hours worked within a week and lower wage growth in the medium run. The impact is driven by periods of employment slack, which suggests that disasters act as a catalyst for already weak local economies. We also find a more tempered response over time, possibly due to adaptation or stronger federal financial support. Finally, we document substantial heterogeneity across disaster types. Overall, our study highlights that natural disasters can detrimentally affect vulnerable workers through the income channel.

Topics: Climate change; Regional economic developments; Labour markets
JEL codes: C33, E24, J3, Q54

Résumé

Nous analysons les chocs causés par des catastrophes naturelles au Canada sur une période de 40 ans en utilisant un cadre de projection locale pour évaluer leurs répercussions sur les marchés du travail provinciaux. Nous constatons que les catastrophes ont pour effet de réduire le nombre d'heures travaillées dans la semaine qui les suit et qu'elles freinent la croissance des salaires à moyen terme. Les effets sont amplifiés en période de capacités inutilisées sur le marché du travail, ce qui porte à croire que les catastrophes jouent un rôle de catalyseur pour les économies locales qui sont déjà affaiblies. Nous notons également une réaction plus modérée au fil du temps, possiblement en raison d'une adaptation du marché du travail ou d'un soutien financier fédéral plus important. Enfin, nous décrivons une grande hétérogénéité entre les types de catastrophes. Dans l'ensemble, notre étude montre que les catastrophes naturelles peuvent nuire aux travailleurs vulnérables par l'entremise du canal du revenu.

Sujets : Changements climatiques; Évolution économique régionale; Marchés du travail
Codes JEL : C33, E24, J3, Q54

1 Introduction

The frequency and severity of natural disasters are increasing (Imada et al., 2018; Walsh et al., 2018; Knutson et al., 2018), a trend likely to continue due to anthropogenic climate change (Intergovernmental Panel on Climate Change (IPCC), 2007, 2013). Hence, against the backdrop of accelerating climate change, it is crucial to enhance our understanding of how natural disasters affect the macroeconomy.

In Canada, 2023 showcased the potential impact of physical risks of climate change due to the significant number of devastating natural disasters. Most notably, the record-breaking wildfire season burned an area more than twice the previous record, leading to the evacuation of approximately 200,000 people.[1] It also resulted in a significant deterioration in air quality, even in northern US cities. Not long after, Nova Scotia experienced severe flash floods due to extreme rainfall, which brought an amount of rain equivalent to three months' worth in under 24 hours.[2] Out west, Hurricane Hilary maintained tropical storm status while tracking across Southern California, generating flash floods. The remnants of the tropical storm then moved across the Prairies in Canada, a nearly unprecedented occurrence. A year like 2023 underscores the urgency to better understand the consequences of such events on the macroeconomy, beyond the economic loss arising from the destruction of physical assets.

In this paper, we build a panel of natural disasters (wildfires, floods, winter storms and other storms) in Canada over 1980–2019 to study the labour market impact on the intensive margin, the extensive margin and real wages. In a panel local projection (Jordá (2005)) and smooth local projection (Auerbach and Gorodnichenko, 2012; Choi et al., 2024), we investigate the dynamic impacts and state-dependent responses for horizons as short as 1 week up to 30 months after the disasters. Our approach has several advantages. First, the use of disaster-level data allows us to draw causal inference, as provincial macroeconomic conditions in the short run are unlikely to impact the frequency and location of extreme weather events. Mitigating actions by government authorities may reduce the odds and duration of

[1] See CBC article, September 4, 2023.
[2] See CBC article, July 22, 2023.

some events, like floods (new dams) or wildfires (construction zoning), but the occurrence of an extreme disaster in a given month and province is largely exogenous. A significant impact on the labor market would suggest that the possible adaptation of local economies over time does not fully compensate for the increased severity and frequency of disasters. Second, weekly or monthly impulse responses over a panel of provinces allows for a clearer quantification of economic impacts as opposed to either country-level or annual analyses (e.g., Tran and Wilson (2023) and Zeenat Fouzia et al. (2020) use U.S. county data but at the annual frequency). Most natural disasters are localized in terms of space and time: in our sample, natural disasters last on average 7 days and mostly affect a single province.[3]

We summarize our main findings as follows. First, disasters affect the local labour market negatively, mainly through changes in hours worked and wage growth, rather than employment rate. Following a shock, hours worked decrease temporarily, while wage growth tends to decline for up to a year afterward. This decline could be attributed to factors such as migration outflows (as observed in Coulombe and Rao (2023) for wildfires in the US) or sectoral adjustments during the recovery phase post-disaster. Furthermore, focusing on the immediate aftermath, we analyze weekly responses of employment and hours worked by exploiting the unique timing of the labour survey. Our findings reveal that weekly hours worked decrease sharply by up to 45 minutes immediately after the shock. This is in line with Graff Zivin and Neidell (2014), who find that daily maximum temperatures above 85°F induce a reduction of hours worked by as much as an hour.

Second, the negative impact on hours worked and real wage growth is mostly concentrated in states with high employment slack. That is, in regions where the labour market is already weak and the economy is sluggish, disasters can exacerbate these conditions: natural disasters act as a catalyst for a painful adjustment of the labour market. However, provincial economic recovery efforts supported by the federal government effectively attenuate part of the longer-term negative labour market impacts. This is in line with the companion work of Dahlhaus et al. (2024), who find that disaster financial assistance from the federal gov-

[3] One could also look at the impact at the finer 3-digit Forward Sortation Area (about 1600 of them) like Duprey et al. (2021), but employment data are not available at this local level.

ernment dampens the negative drag on GDP growth associated with a large provincial debt burden.

Third, we find that the responses of employment have become rather neutral after the year 2000, contrasting with the more negative responses observed in the preceding two decades. This suggests that either the labour market has gradually adapted to cope with increasingly severe and frequent natural disasters, or government support has intensified to limit the aggregate labour market effects. This finding contrasts with the conclusions of Kim et al. (2022), who found limited evidence of adaptation to extreme weather events in the US.

Finally, our findings indicate substantial heterogeneity in the impacts across disasters. The largest disasters in Canadian history have a severe and persistent impact on the labour market. Hours worked typically increase in response to wildfires, whereas storms show the least pronounced effects. Severe winter storms, however, are associated with an increase in the employment rate. Floods have an immediate negative impact on the labour market, with both employment and hours worked decreasing within the first week and throughout the subsequent month. Real wage growth consistently shows a negative response across all disaster types, especially in the absence of federal government assistance. Furthermore, most disaster-specific responses are amplified by periods of labour market slack. The heterogeneous responses across disaster types is partly explained by sectoral shifts in employment, as explored by Meier et al. (2023) for wildfires in Southern Europe.

Our findings have the following important policy implications. First, when assessing the overall impacts of natural disasters, the effect on local labour markets should not be overlooked. Natural disasters can detrimentally affect vulnerable workers through the income channel, especially when it materializes at the same time as other shocks that had already weakened the economy. Income losses, in turn, can be one of the main drivers of households' defaults, possibly further amplifying losses for the overall financial system. Thus (climate) stress-tests should also consider the impact on job losses and disrupted income streams, as well as the joint occurrence of negative macroeconomic shocks and natural disasters. Second, disaster relief funding and its design is important for policy makers. Federal funding is most needed when provinces face an already weak provincial labour market. On the one hand, federal funding can alleviate some of the longer-term effects of disasters on wage growth. However, it may hide a sectoral reallocation. For instance, those living in wildfire-prone areas working in retail industries are more likely to lose their jobs, while part-time workers in the construction sector are more likely to benefit from the recovery phase after a wildfire. Third, policy makers have reasons to remain concerned about the macroeconomic impact of natural disasters, given the risk of increased frequency and magnitude, even as mitigation policies may provide some partial offset. The disruptive effect we quantify for the largest disasters in Canadian history is a cautionary tale for the decades to come, should Canada continue to experience record-breaking disasters.

The rest of the paper is organized as the follows. Section 2 reviews related studies and highlights our contribution. Section 3 describes the natural disaster dataset derived from the Canadian Disaster Database. Section 4 presents the panel local projection model. Section 5 shows the results for the extensive and intensive margins of employment, explores the possible state-dependence and discusses possible evidence of adaptation over time. Finally, section 6 concludes.

2 Related literature

The literature on the economic effects of climate change focuses a lot on the impact of abnormal temperatures, often in cross-country studies (e.g., Dell et al. 2012, Burke et al. 2015, Cipollini et al. 2023). For instance, Kiley (2021) uses a panel quantile regression on 125 countries and finds that temperature anomalies increase the possibility of severe per capita GDP contractions. Berg et al. (2023) use a local projection framework that allows heterogeneity across countries and find that higher temperatures damage the growth of high-income countries while their impacts on low- and middle-income countries vary. Colacito et al. (2019) find a negative impact of extreme temperatures on output in a panel of US states. Other papers take a broader view of extreme weather events beyond temperatures by looking at precipitation (e.g. Damania et al. 2020) or composite weather indices capturing other dimensions like wind and precipitation in addition to heat (e.g., Kim et al. 2022).

Extreme heat can also be related to employment. Kim et al. (2022) use a smooth transition vector autoregressive model to highlight the time-varying effects over several decades. The macroeconomic impacts of extreme weather data become significant over time, with lower industrial production and consumption growth and higher unemployment and inflation rates. Wilson (2019) uses local weather data and finds that it can nowcast the surprise component of monthly employment reports. Graff Zivin and Neidell (2014) use within-county temperature variations and estimate the time allocation between labour and leisure when temperature is high. They find that daily maximum temperatures above 85°F induce workers to reduce labour time as much as an hour, but this effect is limited by persistent labour demand. Our work complements these papers by looking at the effect of natural disasters (instead of weather data) on hours worked, employment and wages over time for horizons as short as 1 week after a disaster. For instance, we find that weekly hours worked can decrease by 45 minutes on impact.

Another strand of the literature focuses more on the economic effect of natural disasters, for instance droughts (Gallic and Vermandel 2020) or storms (Groen et al. 2016). Several studies focus on the most extreme disasters, for instance Hurricane Katrina in 2005 on business establishments (Jarmin and Miranda, 2009), systemic banking risks (Raykov and Silva-Buston, 2020), household finances (Gallagher and Hartley, 2017), employment and income of affected individuals (Deryugina et al., 2018). Billings et al. (2022) focus on Hurricane Harvey to understand the implications of flood losses for households with differing access to insurance and credit. Ho et al. (2023) look at mortgage arrears after the impact of the 2016 wildfire that destroyed most of the Fort McMurray city. In our paper, we also estimate the labour market impact for the largest disasters in our dataset, although this is not the main focus of our paper as we cover a total of 558 individual disasters.

We contribute to the literature on natural disasters by focusing specifically on the labour market impact of a wide range of natural disasters (wildfires, floods and summer and winter storms). So far, few mostly contemporaneous papers explore the impact on regional labour market dynamics. Tran and Wilson (2023) and Zeenat Fouzia et al. (2020) study the effect of US natural disasters on county-level labour market data at the annual frequency. Tran and

Wilson (2023) find that total and per capita income increase over the long run, driven by a boost first in employment followed by wages. Zeenat Fouzia et al. (2020) further analyze the heterogeneous impact of disasters on local employment and wages depending on the demand and supply channels. Coulombe and Rao (2023) use a local projection framework combined with data derived from satellite imagery to study the effect of wildfires on monthly employment across US counties. They find fire exposure causes lower employment in the short to medium run, with medium-run effects driven by migration. They also find that the labour market effects of wildfires are amplified during periods of high labour market slack. Meier et al. (2023) use satellite imagery for Southern Europe since 2011 to explore the impact of wildfires on annual GDP and employment growth. They find a sectoral shift in employment, with tourism-related jobs declining and jobs in construction and real estate-related services increasing. After hurricanes in the case of Puerto Rico, Barattieri et al. (2023) find an average employment drop of 0.5% for up to 12 months.

We differ from those natural disaster and employment papers in at least three broad ways. First, our paper has the best combined coverage of disaster types, time horizon (starting in 1980) and granularity by relying on data up to the weekly frequency of labour, with possible splits by sectors. Second, we also distinguish the intensive and extensive margins of employment by adding the impact of natural disasters on hours worked, which can vary significantly (as suggested by Graff Zivin and Neidell (2014) in the case of extreme heat), especially within a week of a disaster occurrence. Third, we further explore the state-dependence of the labour market response during periods of slack across a broad range of disaster types, suggesting that disasters are a catalyst for already weak local economies. Fourth, the long time series allows us to explore changes in the employment impact over time to discuss the possible role of adaptation (in the spirit of Kim et al. 2022) despite the increasing frequency of disasters.

Our work is also the first one to focus on the employment impact of a broad range of natural disasters affecting Canada. It complements Ho et al. (2023), who focus on the impact of the largest Canadian wildfire on households' mortgage arrears. Similar data and methods are also used in companion work to assess the impact of natural disasters on sectoral Canadian inflation (Duprey and Fernandes, 2024) as well as Canadian GDP as a function of provincial fiscal space (Dahlhaus et al., 2024).

3 Data

3.1 Natural disaster series

To study the effect of natural disasters on labour markets, we leverage 558 unique disaster events that occurred between 1980 and 2019 recorded in the Canadian Disaster Database (CDD) maintained by Public Safety Canada.[4] The CDD selectively includes only particularly severe disasters, defined as events that cause devastation in a community "in a way that exceeds or overwhelms that community's ability to cope" (Ministers Responsible For Emergency Management, 2017). This level of devastation is reached when a disaster meets at least one of the following criteria:

- the death of 10 or more people,
- the injuring of 100 or more people,
- the community's evacuation or homelessness,
- an appeal for national or international assistance,
- significant damage or interruptions that affect the community's ability to recover, or
- historical significance.

This dataset also provides information on the type of disaster, which we use to classify events into four categories:

- wildfires,
- floods (which include storm surges and other flooding events),
- storms (which include severe storms, thunderstorms, hurricanes, and tornadoes), and
- winter storms.

Table 1: Distribution of panel observations across months, 1980–2019

	Wildfire			**Flood**			**Storm**			**Winter Storm**		
	Binary	Cost		Binary	Cost		Binary	Cost		Binary	Cost	
	N	*N*	Mean	*N*	*N*	Mean	*N*	*N*	Mean	*N*	*N*	Mean
Jan	0	0		9	7	\$9	6	3	\$23	12	5	\$163
Feb	1	0		19	10	\$1	4	1	\$7	23	12	\$416
Mar	1	0		11	6	\$4	4	1	\$111	22	8	\$26
Apr	0	0		36	22	\$15	5	4	\$38	11	6	\$54
May	18	6	\$100	43	26	\$52	9	6	\$47	3	1	\$3
Jun	25	8	\$493	33	25	\$88	21	17	\$72	0	0	
Jul	27	9	\$38	33	26	\$212	34	25	\$60	0	0	
Aug	23	11	\$50	17	13	\$65	44	37	\$85	0	0	
Sep	18	10	\$30	9	7	\$30	33	27	\$58	0	0	
Oct	6	5	\$21	14	11	\$6	22	11	\$46	2	0	
Nov	1	1	\$1	8	4	\$33	16	7	\$45	4	0	
Dec	0	0		10	7	\$13	8	5	\$39	14	0	
Total	**120**	**50**	**\$117**	**242**	**164**	**\$66**	**206**	**144**	**\$63**	**91**	**32**	**\$198**

Notes: *N* denotes the number of observations in our panel. If a disaster is spread over multiple months or across provinces, it will count as multiple observations. For events with available data on cost, we report the average cost in millions of Canadian dollars (2012 constant price) and the average cost as a percentage of monthly provincial GDP. Cost refers to total cost from insurance and government assistance programs. Total cost in the last row is the weighted average across months. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category. Floods include storm surges and other flooding events.

We construct a monthly panel dataset for 10 Canadian provinces spanning 1980 to 2019 using the CDD.[5] Since the CDD identifies the region affected by the disaster and not the province, we first map each event to its affected province. Where a disaster spans multiple provinces, we assume that each province is affected, and thus we create two explanatory variables.

The first is a binary dummy variable indicating a disaster occurrence in a region each month (Figure 1). In some rare cases, multiple disasters may affect the same province in 1 month; however, our binary dummy does not indicate the number of disasters.[6] From 558

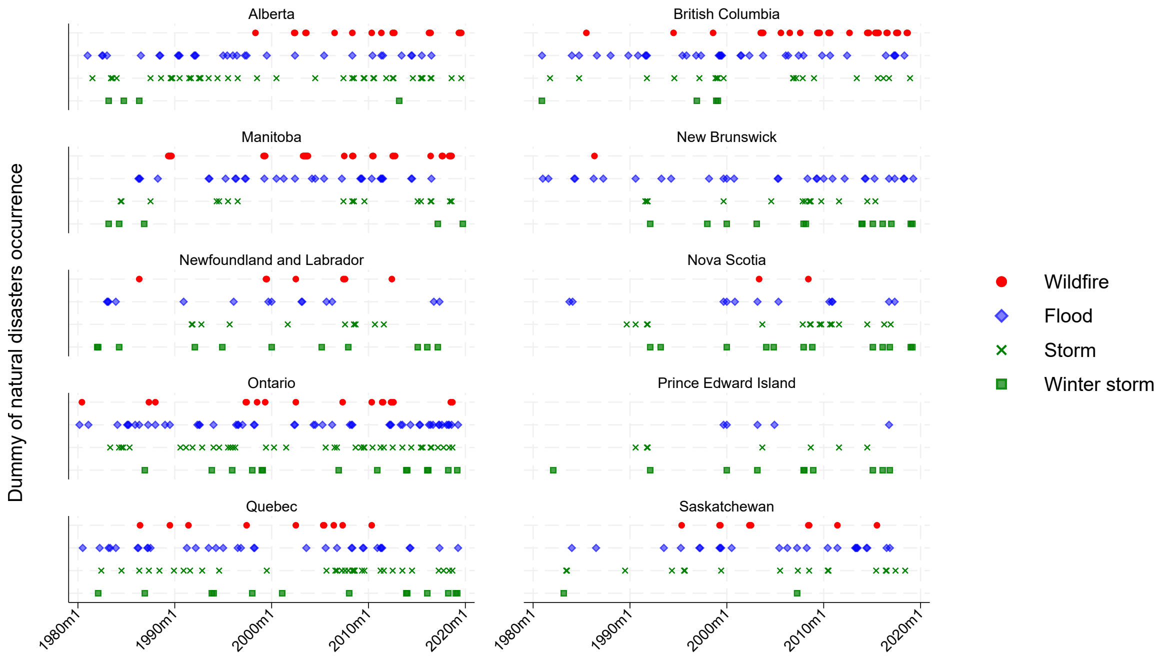
[4]Version downloaded on September 9, 2023.

[5]We exclude the Northwest Territories, Yukon and Nunavut from our analysis as too few disasters that meet the criteria of the CDD are observed in the territories.

[6]We do not attempt to exploit the number of disasters occurring in a month as a proxy for disaster intensity, as these events are infrequent. In fact, there are only 29 (respectively 6) instances of two (respectively three) disasters of the same type recorded in the same month and province over the 40-year period under study. Only 10 events have two simultaneous disasters of different types within the same month and province, mostly floods

unique disasters events, we generate 659 month–province observations (Table 1).

Figure 1: Time series of natural disaster dummy variables by province, 1980–2019



Notes: Month and province with at least one natural disaster per category. The same disaster may be counted as occurring in multiple months and provinces if it lasts longer than a month and affects multiple provinces. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category. Floods include storm surges and other flooding events.

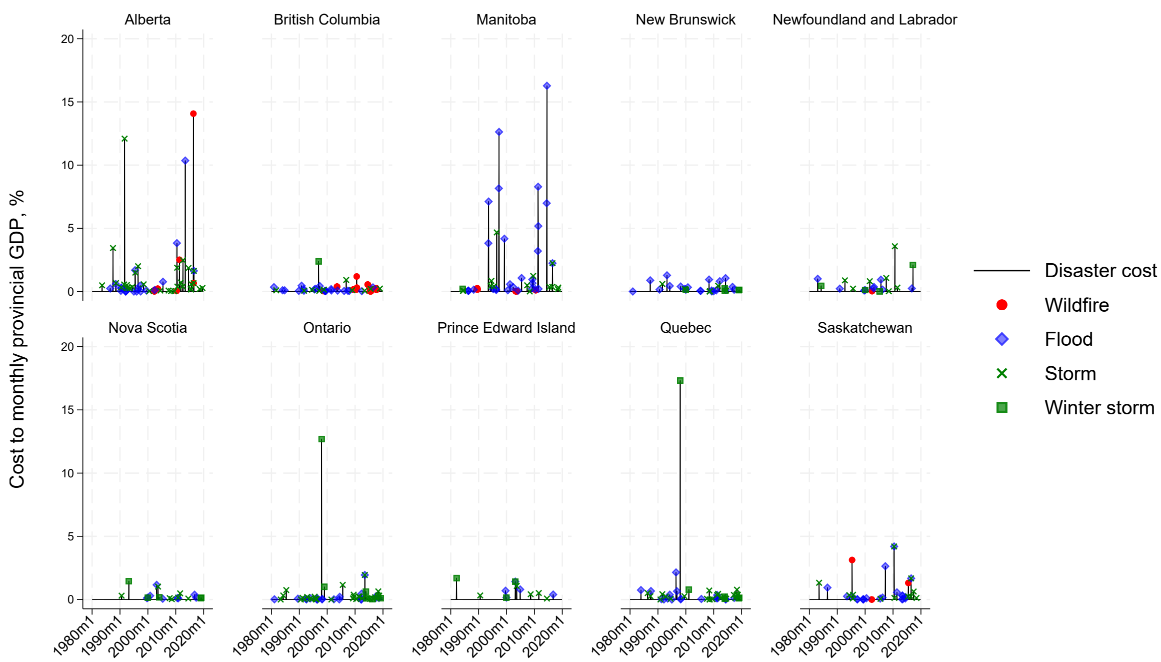
The second variable we construct is a continuous cost variable (Figure 2). This provides a proxy of the disaster intensity to evaluate the effect of disaster size on labour markets. Disaster costs comprise the insurance payouts, costs associated with damages incurred by municipalities and provinces, as well as financial assistance provided through provincial and federal Disaster Financial Assistance Arrangements (DFAA) and non-governmental organizations.[7] When a disaster affects multiple provinces, we allocate costs based on the

and storms occurring alongside each other.

[7]In the event of a large-scale natural disaster, the Government of Canada provides financial assistance to provincial and territorial governments through the Disaster Financial Assistance Arrangements (DFAA). When response and recovery costs exceed what individual provinces or territories could reasonably be expected to bear on their own, the DFAA provides the Government of Canada with a fair and equitable means of assisting provincial and territorial governments. See the DFAA webpage.

population size of each affected province.[8] Similarly, if a disaster spans multiple months, we split costs proportionally to the number of days the disaster was ongoing within each month. Since only 331 of the 558 disasters in the CDD recorded cost, our second variable yields 390 observations (Table 1). We finally normalize the disaster costs by monthly provincial GDP.[9]

Figure 2: Relative cost of natural disasters in each province, 1980–2019



Notes: Time series of natural disaster cost as a percentage of monthly provincial GDP per province. The cost of a disaster impacting different provinces and over multiple months is allocated based on the population in each affected province and on the number of days within each month. Symbols indicate the type of disaster in each month/province with cost reported. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category. Floods include storm surges and other flooding events.

Our provincial dummy and cost variables in Figures 1 and 2 illustrate the heterogeneous exposure of Canadian provinces to various disaster types. This heterogeneity arises from Canada's vast geography, which encompasses diverse climate zones. For instance, provinces such as British Columbia, Alberta, Manitoba, Saskatchewan, Ontario, Quebec and Newfoundland and Labrador are located in the boreal forest (Figure 3). The occurrence of wild-

[8] Provincial population data are from Statistics Canada Table 17-10-0009-01.

[9] We construct monthly provincial GDP by interpolating quarterly provincial GDP that is sourced from the Conference Board of Canada. For the interpolation, we use monthly aggregate industrial production for the period prior to 1997 and national monthly GDP thereafter. The industrial production index is from FRED (CANPROINDMISMEI series). National monthly GDP is taken from Statistics Canada Table 36-10-0434-02.

fire is common in the boreal forest, which happens more frequently in these provinces. While flood affects all provinces to some extent, some, like Manitoba, face significant exposure to large and costly floods due to the relatively flat landscape of the Prairies (Figure 2).

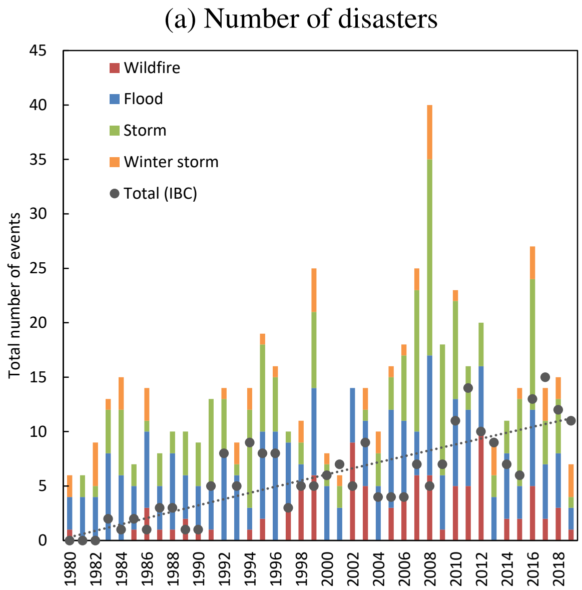
Figure 3: Location of the boreal forest across Canadian provinces

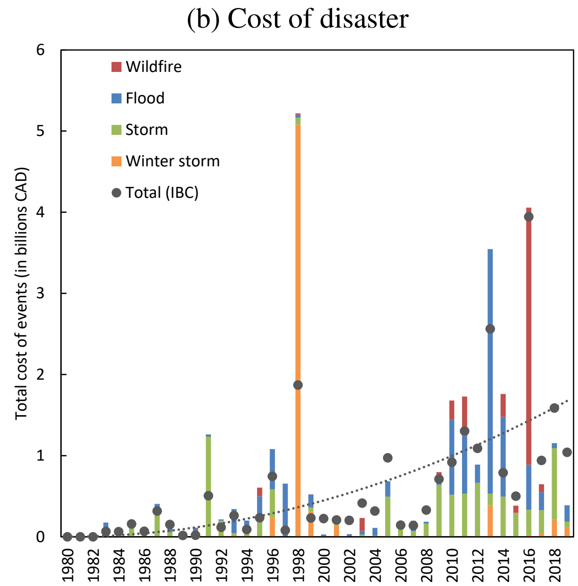
Source: Boreal forest map produced by the Canadian Forest Service. Image and shapefiles available on Natural Resource Canada's (NRCAN) website: https://natural-resources.canada.ca/our-natural-resources/forests/sustainable-forest-management/boreal-forest/13071.

Several stylized facts emerge from our data. First, perhaps unsurprisingly, we note the seasonal patterns associated with each type of disaster. Wildfires, floods, and storms predominately occur during the spring and summer months, while winter storms are isolated to the winter months. Second, floods and storms emerge as the most frequent types of disasters in our dataset.[10] Nonetheless, when examining the average cost, wildfires and winter storms are the more costly events. For instance, the top two disasters during this period were the 2016 Fort McMurray wildfires, costing approximately $4.4 billion in damages, and the 1998

[10]Public Safety Canada identifies floods as the most common natural disaster in Canada. See Backgrounder: Floods (2023).

Figure 4: Annual number and cost of disaster events in Canada since 1980





Notes: Cost includes insurance costs and federal assistance programs (e.g., DFAA). Storms include thunderstorms, hurricanes, and tornadoes; floods includes storm surges. IBC data do not include federal government emergency funding.
Source: Canadian Disaster Database (CDD) as defined by the Ministers Responsible For Emergency Management (2017) and Insurance Bureau of Canada (2021).

ice storm in eastern Canada, with an approximate cost of $2.6 billion (Insurance Bureau of Canada, 2021, in 2021 dollar terms). Third, when plotting the average frequency and cost of damages across the different disaster types between 1980 and 2019, we observe that the frequency and severity of disasters have been increasing over the 40-year period under study, as shown in Figure 4. This is likely attributable to climate change, which raises temperatures thereby increasing the frequency and severity of extreme weather events (Intergovernmental Panel on Climate Change (IPCC), 2007, 2013).

Additional summary statistics of our provincial disaster data by type are provided in Table 2. Relative to provincial GDP, winter storms and floods tend to be costlier on average. Moreover, floods tend to trigger the most government assistance as a percent of GDP. In terms of evacuations, wildfires displace the most people. Finally, winter storms cause the most disruption to critical infrastructure, such as utilities.

Table 2: Summary statistics of variables used to proxy for natural disaster intensity

	N	Mean	SD	P50	P75	P95	Max
Cost per monthly provincial GDP, percent							
Wildfire	50	0.58	1.98	0.16	0.27	2.52	13.67
Flood	164	0.86	2.82	0.14	0.46	3.83	23.25
Storm	144	0.51	1.17	0.25	0.52	1.33	12.10
Winter storm	34	1.68	3.31	0.29	1.45	11.82	12.86
Disaster Financial Assistance Arrangements payments per monthly provincial GDP, percent							
Wildfire	35	0.20	0.33	0.16	0.23	1.32	1.57
Flood	123	0.54	1.37	0.14	0.37	2.15	9.05
Storm	44	0.24	0.57	0.05	0.13	1.02	3.57
Winter storm	15	0.61	0.72	0.18	1.49	1.96	1.96
Number of evacuated persons							
Wildfire	78	5,026	13,229	1,075	3,200	25,000	90,000
Flood	126	2,073	9,251	494	1,333	4,000	100,000
Storm	33	1,192	5,186	180	600	1,700	30,000
Winter storm	24	1,126	2,664	50	369	6,764	10,342
Number of persons affected by utilities disruptions							
Wildfire	4	1,799	1,116	1,948	2,500	3,000	3,000
Flood	15	383,842	1,048,268	115,994	154,197	4,150,761	4,150,761
Storm	57	308,132	665,308	75,000	261,919	1,560,000	3,684,211
Winter storm	35	1,110,464	3,333,538	47,237	286,000	7,615,063	18,300,000

Notes: *N* report the total number of disaster shock observations across months and provinces in each category for which data are available. “SD” is the standard deviation. “P50”, “P75” and “P95” refer to percentiles.

3.2 Labour market data

To evaluate how provincial employment reacts to natural disasters, we rely on two surveys conducted by Statistics Canada: the Labour Force Survey (LFS) and the Survey of Employment, Payrolls and Hours (SEPH).[11]

LFS offers monthly provincial employment rates and average weekly hours worked, starting in 1980 and 1986, respectively.[12,13] This survey is administered to a representative

[11] When needed, data are seasonally adjusted using the X12 seasonal adjustment procedure.

[12] The employment rate is sourced from Table 14-10-0022-01, and hours worked are from Table 14-10-0036-01 of Statistics Canada’s LFS.

[13] Hours worked in the survey data has outliers, possibly due to holidays occasionally falling in the reference week or other factors (Cociuba et al. 2018). We hence trim the hours worked series as follows. When hours worked for a given week deviate by more than two hours above or below the average of the previous and

sample of working-age Canadians who are not institutionalized. Survey respondents provide detailed information on their employment status and hours worked for the week containing the 15th in a month, i.e., the reference week. The timing of the survey brings a challenge and an opportunity. On one hand, if a disaster occurs after the reference week in a given month, the labour market variable in that month's observation will not reflect any changes caused by the disaster by construction. To address this timing challenge, we rearrange our disaster data such that a month is defined as starting after the reference week in a month and ending after that in the next month. On the other hand, the timing of the survey during a specific reference week allows for a more detailed assessment of the weekly impact of natural disasters because we have information on the start day of the disaster.

From this survey, we also construct a continuous measure of monthly provincial employment gap, defined as the percentage difference between the actual monthly provincial employment rate and the Hodrick-Prescott filtered trend of provincial employment (using a smoothing parameter of 14,400 for monthly data). Figure 5 shows the employment gap series for each province. We use this as an indicator of labour market slack when investigating state-dependent labour market responses to natural disasters.

The other source of our labour data is the SEPH, which provides data on monthly provincial wage growth since 2001.[14] This survey collects administrative employment data on a monthly basis across a set of establishments. We transform the nominal data into real wages using monthly provincial CPI.[15]

Note that we can also leverage both surveys' breakdown between the production and service sectors to investigate the sectoral impacts of natural disasters.[16] Results using sectoral

subsequent observation, we replace it with the value of the previous observation. This is equivalent to trimming about 5% of the observations. However, we do not trim if a spike occurs in the same province/month as a natural disaster, to account for the possibility that unusual changes in hours worked might indeed be driven by natural disasters.

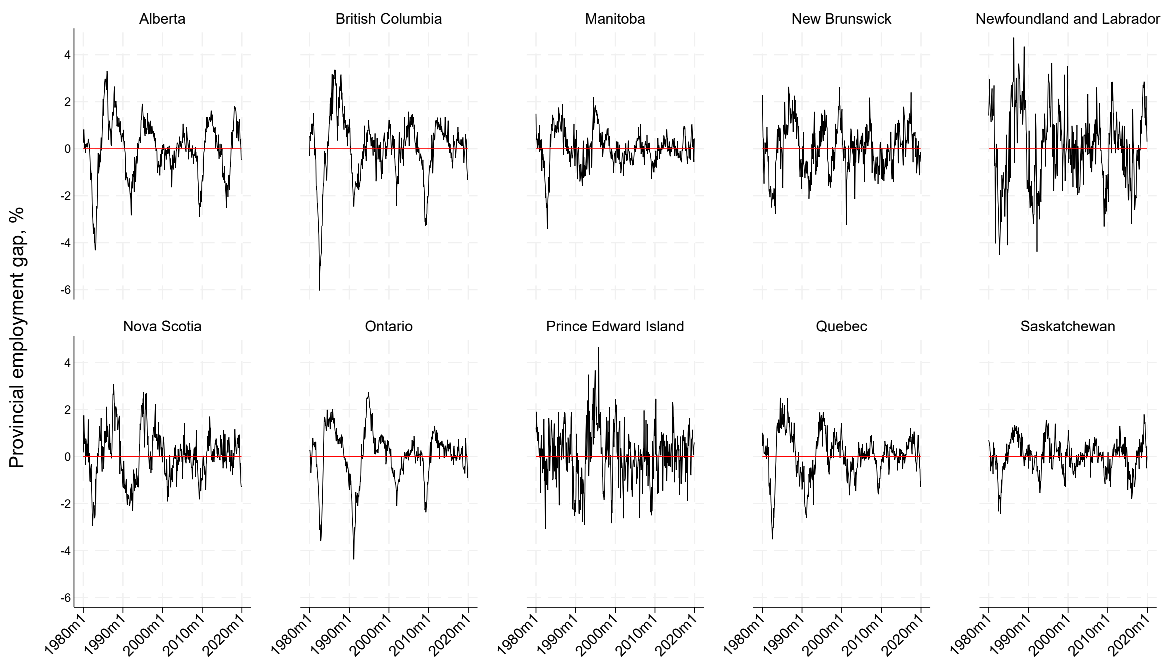
[14]The monthly average of weekly nominal earnings (including overtime) is sourced from Table 14-10-0223-01 of Statistics Canada's SEPH. More details on the survey design can be found on Statistics Canada's website dedicated to the SEPH: https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=2612.

[15]Monthly provincial CPI is sourced from Statistics Canada Table 18-10-0004-01.

[16]Sectoral breakdown in Table 14-10-0022-01 and Table 14-10-0036-01 of the LFS, and Table 14-10-0223-01 of the SEPH. The most granular sectoral breakdown has missing entries or high volatility and is thus used only to confirm the narrative of our findings for each disaster type.

labour market data are presented in Appendix A.

Figure 5: Provincial employment gap



Notes: Provincial employment gap is defined as the percentage difference between the actual monthly provincial employment rate and the Hodrick-Prescott filtered trend with smoothing parameter 14,400 for monthly data.

4 Methodology

We assess the impact of natural disasters using the local projection framework of Jordá (2005). This framework has been extended to apply to a panel setting (see Tran and Wilson 2023 and Miyamoto et al. 2019, for instance). We first present our baseline specification before highlighting various extensions to explore alternative sources of heterogeneity.

In all our models, the dependent variable is either the change of the monthly provincial employment rate, average weekly hours worked, or real wage growth between a month h of interest and the month prior to the start of a disaster ($\Delta Y_{i,t+h:t-1} \equiv Y_{i,t+h} - Y_{i,t-1}$).

4.1 Baseline models

4.1.1 Monthly effects of natural disasters

In our baseline setup, the main variable of interest is a binary dummy $\mathbb{1}(disaster)_{i,t}$ that denotes an occurrence of a disaster of any type in a given month and province (Figure 1):

$$\begin{aligned} \Delta Y_{i,t+h:t-1} \quad = \quad & c + \alpha_h \mathbb{1}(disaster)_{i,t} + \sum_{p=-12,\ p\neq 0}^{h} \alpha_h^p \mathbb{1}(disaster)_{i,t+p} \\ & + \sum_{\tau=1}^{3} \psi_h^\tau \Delta Y_{i,t-\tau} + \sum_{\tau=1}^{3} \phi_h^\tau GDP_{i,t-\tau} + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h}. \end{aligned} \tag{1}$$

Equation (1) is estimated using a monthly panel of 10 Canadian provinces (indexed by i) for each horizon h=$0,\ldots,30$. Hence, the coefficient α_hs quantifies the average dynamic impact of a disaster on one of our three labour market variables over time. If multiple disasters occur back to back in a short period of time, they may bias the effect. Therefore, we control for the possibility that other disasters may have occurred several months prior to the disaster of interest (p=$-12,\ldots,-1$) or in between a month after the impact and the investigated horizon (i.e., p=$1,\ldots,h$).[17] We also include three lags of the dependent variable and provincial GDP growth to capture past provincial economic conditions. We include province (η_i), month (η_m) and province/month fixed effects ($\eta_{i,m}$) to remove province-specific effects and any remaining seasonality in the labour market. We also add a year fixed effect (η_y) to control for any common changes in employment volatility over time or possible effects of slow-moving temperature changes.[18] The provincial monthly error term for horizon h is denoted as $\epsilon_{i,t+h}$. We use heteroskedastic robust standard errors.[19]

Our identification strategy hinges on the assumption that the occurrence of a significant

[17] Disasters that happened more than 12 months prior to the disasters of interest are not controlled, since our main results do not show much effect lingering beyond 12 months on labour markets. Excluding those controls has little impact on our results.

[18] We can also control for provincial temperatures by using data from Vincent et al. (2020) on daily maximal temperatures averaged over the month and over the weather stations in each province. Controlling for the deviation from the pre-1990 provincial monthly average temperatures did not change any results.

[19] The lagged dependent variables used as a control already correct for possible autocorrelation in the residuals. Thus heteroskedastic and autocorrelation robust standard errors (Newey-West HAC) lead to similar results.

natural disaster in a given month is mostly unpredictable conditional on available information such as provincial economic states and seasonal patterns. As seen from Table 1, one expects winter storms in the winter and wildfires, storms and floods in the spring and summer, such that the provincial economy is likely prepared to some degree to face a potential disaster. Such seasonal preparations would be captured by months fixed effects. Our results capture the effect of the occurrence of a more severe than usual disaster in a given month and province, which can be considered as exogenous. Indeed, our dataset covers only natural disasters that are significant enough to meet the CDD criterion.

4.1.2 Weekly effects of natural disasters

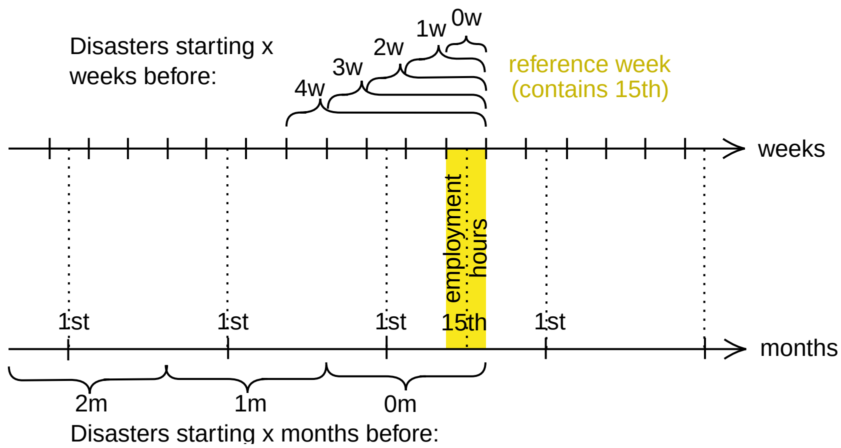
We can gain additional insights about the response of employment rates and hours worked within the first month (i.e., $h = 0$) by exploiting the design of the LFS. Although the LFS is a monthly survey, it is conducted during the reference week that includes the 15th of a month. As illustrated in Figure 6, we can sort disaster occurrences by their proximity to the reference week. Using this information, we investigate the weekly effects of a disaster.

We estimate one equation per week $w = 0, ..., 4$:

$$\begin{aligned}\Delta Y_{i,t:t-1} \quad = \quad & c + \alpha_w \mathbb{1}(disaster)^w_{i,t} + \sum_{p=-12}^{-1} \alpha^p_w \mathbb{1}(disaster)_{i,t+p} \\ & + \sum_{\tau=1}^{3} \psi^\tau_w \Delta Y_{i,t-\tau} + \sum_{\tau=1}^{3} \phi^\tau_w GDP_{i,t-\tau} + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h}, \quad (2)\end{aligned}$$

where $\mathbb{1}(disaster)^w_{i,t}$ is a dummy variable that takes 1 if a disaster occurs w weeks prior to the reference week of month t for province i. Thus $\alpha_{w=0}$ captures the effect of a disaster happening within the reference week, $\alpha_{w=1}$ that of a disaster happening one week prior to the reference week, etc. Hence, $\{\alpha_w\}^4_{w=0}$ represents weekly impulse responses after a disaster.

Figure 6: Weekly versus monthly impulse response functions



Note: This diagram demonstrates how the Labour Force Survey (LFS) design is exploited to estimate weekly responses of employment rate and hours worked to a disaster. We identify how many weeks before the reference week (i.e., the week including the 15th of a month) a disaster happened, noted as "0w" – "4w" above.

4.2 Heterogeneity by economic states

We explore possible state-dependent effects of disasters on the labour market using a smooth-transition panel local projection model (Auerbach and Gorodnichenko, 2012; Choi et al., 2024). Suppose $z_{i,t}$ denotes a variable determining the state of the provincial economy. We construct a logistic function F as follows:

$$F(z_{i,t}) \equiv \frac{\exp\left(-\gamma[\frac{z_{i,t}-c_z}{\sigma_z}]\right)}{1+\exp\left(-\gamma[\frac{z_{i,t}-c_z}{\sigma_z}]\right)}, \tag{3}$$

where c_z and σ_z denote the sample average and standard deviation of $z_{i,t}$. The transition parameter γ determines the speed of transition between states. This function can be understood as representing the probability of being in a high or low $z_{i,t}$ state, with the smooth-transition local projection model represented as follows:

$$\begin{aligned}\Delta Y_{i,t+h:t-1} \quad = \quad & F(z_{i,t-1})\left\{c^P + \alpha_h^P \mathbb{1}(disaster)_{i,t}\right\} + (1 - F(z_{i,t-1}))\left\{c^N + \alpha_h^N \mathbb{1}(disaster)_{i,t}\right\} \\ & + \sum_{p=-12,\, p\neq 0}^{h} \alpha_h^p \mathbb{1}(disaster)_{i,t+p} + \sum_{\tau=1}^{3} \psi_h^\tau Y_{i,t-\tau} + \sum_{\tau=1}^{3} \phi_h^\tau GDP_{i,t-\tau} \\ & + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h}. \end{aligned} \tag{4}$$

We use the provincial employment gap as a proxy for labour market slack to capture transitions between different states of the economy. We set $c_z = 0$ as the mean employment gap, which is theoretically zero. Note that this model can be understood as a generalization of a model that interacts a dummy variable for positive or negative output gap with the natural disaster dummy. If $\gamma \to \infty$, then $F \to 0$ when $z_{i,t} > c_z$ or $F \to 1$ when $z_{i,t} < c_z$: with $c_z = 0$, this is equivalent to having a dummy variable that is 0 when the labour market slack is positive and 1 when it is negative. The benefit of using the smooth transition is to ensure that our state-dependence results are not driven by observations that have a marginally positive or negative labour market slack. Those very similar states would otherwise be arbitrarily classified into a binary state when using a dummy variable. Still, our results are quantitatively similar when using a dummy variable for positive or negative labour market slack instead of the smooth transition. As we use monthly data, we set $\gamma = 3$, but alternative $\gamma >> 0$ parameters also yield similar results. If $\gamma \to 0$, then $F \to 1/2$ irrespective of the value of $z_{i,t}$ and the model is uninformative about the state dependence and collapses to Equation (1).

4.3 Heterogeneity by disaster intensity

We extend Equation (1), which uses a binary disaster dummy, to also capture disaster intensity. As in Figure 2, disaster severity is proxied by total incurred cost normalized by the level of monthly provincial GDP, $cost^d_{i,t}$:[20]

$$\begin{aligned}\Delta Y_{i,t+h:t-1} &= c + \alpha_h \mathbb{1}(disaster)_{i,t} + \beta_h cost_{i,t} + \sum_{p=-12,\, p\neq 0}^{h} \alpha_h^p \mathbb{1}(disaster)_{i,t+p} \\ &+ \sum_{\tau=1}^{3} \psi_h^\tau Y_{i,t-\tau} + \sum_{\tau=1}^{3} \phi_h^\tau GDP_{i,t-\tau} + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h} \qquad (5)\end{aligned}$$

The combination of fitted parameters $\{\hat{\alpha}_h, \hat{\beta}_h\}$ across horizons in Equation (5) allows for the computation of marginal impacts of disasters with total costs of various magnitudes. For instance, the effect of a disaster with a median cost $p50$ or a cost in the ninety-fifth percentile $p95$ at a given horizon h can be written as $\hat{\alpha}_h + \hat{\beta}_h \cdot p50$ and $\hat{\alpha}_h + \hat{\beta}_h \cdot p95$, respectively.

Alternatively, we employ another measure of disaster intensity based on the use of Disaster Financial Assistance Arrangements (DFAA) after a disaster. The DFAA is a federal program established in 1970 to provide financial assistance to provincial and territorial governments. It is triggered in the event of large-scale natural disasters when response and recovery costs exceed what individual provinces or territories could reasonably be expected to bear on their own. Therefore, we divide natural disasters into those with or without DFAA subsidies ($\mathbb{1}(disaster)^P_{i,t}$ and $\mathbb{1}(disaster)^{NP}_{i,t}$) and estimate the following model:

$$\begin{aligned}\Delta Y_{i,t+h:t-1} &= \alpha_h^P \mathbb{1}(disaster)^P_{i,t} + \alpha_h^{NP} \mathbb{1}(disaster)^{NP}_{i,t} + \sum_{p=-12,\, p\neq 0}^{h} \alpha_h^p \mathbb{1}(disaster)_{i,t+p} \\ &+ \sum_{\tau=1}^{3} \psi_h^\tau \Delta Y_{i,t-\tau} + \sum_{\tau=1}^{3} \phi_h^\tau GDP_{i,t-\tau} + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h}. \qquad (6)\end{aligned}$$

As a robustness check in Appendix C and D, we use another alternative measures of disaster intensity such as the number of evacuated persons and the number of persons affected by utility disruptions, and investigate if disasters have non-linear effects by their intensity for

[20]Not all reported disasters have an estimated cost. Our specification implicitly assumes that the cost of those disasters without a reported cost is small and thus was not systematically recorded. Similar results are obtained if we control for this missing information by splitting the disaster dummy variables with or without recorded costs.

different types of disasters.

4.4 Heterogeneity over time

Adaptation to past natural disasters as well as worsening anthropogenic climate change can raise challenges to empirical studies of natural disaster shocks. Both can lead to structural changes, which may affect the response of economic variables to shocks over time.[21] On the one hand, adaptation may reduce the effect of disaster shocks. For instance, lakeside residents may choose to adopt sump pumps to mitigate flooding, firms may relocate factories out of floodplains, and governments may build dams and reservoirs to prevent damage. Such actions would reduce the economic impact of a flood. On the other hand, climate change can potentially increase the severity of natural disasters. Essentially, rising temperatures affect extreme weather patterns over time (Intergovernmental Panel on Climate Change (IPCC), 2013), which could further complicate a possibly non-linear effect of disasters. While the effects of adaption and climate change move in opposite directions and may have offsetting impacts, it is not clear, a priori, which effect would dominate.

While disentangling the source of time variations in response to disasters is not feasible, we consider the net effect of these structural influences on labour markets over time. To do so, we split our sample into two and estimate Equation (5) for the sub-sample periods of pre- and post-2000.[22] We want to compare the distribution of fitted values in both sub-samples to document any shift over time that may suggest a change in the relative importance in the adaptation or climate change effects. We compute the Canada-wide fitted values as follows. We first use point estimates of the coefficients $\{\alpha_h, \beta_h\}_{h=0}^{H}$ from Equation (5) to simulate monthly time series of fitted disaster impacts by province. The impact in a given month is the sum of the effect of a disaster occurring in that month and the delayed effect of disasters

[21] Similarly, economists have highlighted time variations in the monetary policy transmission mechanism that resulted in observed changes in the Phillips Curve (Korobilis 2013 and references therein), or more generally found strong empirical support for parameter instability after a large shock (Aastveit et al. 2017 and Strachan and Van Dijk 2013).

[22] Because data on provincial wages are available only post-2000, we restrict our analysis to the employment rate and hours worked for both sub-samples.

that have occurred in the previous 12 months. We then aggregate the outcome to the national level by taking the population-weighted average impact across provinces.

4.5 Heterogeneity by disaster type

Lastly, we extend our baseline Equation (1) to explore the heterogeneity across disaster types of Figure 1. We include separate dummy variables for each disaster type such that $\mathbb{1}(disaster)_{i,t}^{d}$ is now also indexed by $d=1,\ldots,4$ for each of the four types of disasters: wildfire, flood, storm and winter storm.

$$\begin{aligned}\Delta Y_{i,t+h:t-1} \quad = \quad & c+\sum_{d=1}^{4}\left\{\alpha_h^d \mathbb{1}(disaster)_{i,t}^{d}+\sum_{p=-12,\,p\neq 0}^{h}\alpha_h^{d,p}\mathbb{1}(disaster)_{i,t+p}^{d}\right\} \\ & +\sum_{\tau=1}^{3}\psi_h^{\tau}\Delta Y_{i,t-\tau}+\sum_{\tau=1}^{3}\phi_h^{\tau}GDP_{i,t-\tau}+\eta_i+\eta_y+\eta_m+\eta_{i,m}+\epsilon_{i,t+h}.\end{aligned} \tag{7}$$

5 Results

Table 3 provides a brief summary of our key results; hours worked, and to a lesser extent the employment rate, may decrease within a few weeks, but real wages persistently decrease over a year. Those impacts are mostly concentrated in the periods of labour market slack, such that disasters may work as a catalyst for already weak provincial labour markets. Reassuringly, we find some evidence of adaptation to natural disasters over time.

Table 3: Summary of key results

	Employment rate	Hours worked	Real wages	Adaptation?
Overall		↓ 4w	↓ 1y	Yes
Wildfire		↑ 3m	↓ 1y	Yes
Flood	↓ 4w	↓ 4w	↓ 3y	No
Storm	(h)	↓ 3-6m	(h)	Yes
Winter storm	↓ 13m	(h)	↓ 6m,↑ 1y	Yes

Notes: The cells for the first three columns display the direction of the average effect with an arrow and the relevant horizon for significance in weeks, months or years. A red cell indicates that the effect is mostly concentrated in periods of high labour market slack. A red cell with "(h)" means that the effect is significant only during states of high labour market slack but not when estimating an average effect. The last column indicates if there is some evidence of adaptation over time to make the labour markets more resilient.

5.1 Results from the baseline model

Figure 7 presents estimated impulse responses of the provincial employment rate, average weekly hours worked and real wage growth after a natural disaster. We plot both weekly and monthly responses obtained from Equations (1) and (2).

Figure 7: Impacts of natural disasters on labour markets

Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals using Equations (1) and (2). Note that the weekly impulse response function is possible due to the unique design of the Labor Force Survey, but this is not the data source for the real wage growth, hence panel C is not available.

Two findings stand out. First, hours worked significantly declines immediately after a disaster for up to one month (Figure 7-B, -E), while the response of employment is muted overall (Figure 7-A, -D). The former likely stems from property damage, infrastructure disruptions and evacuations. Second, we observe a substantial negative impact on real wage growth, by approximately 50 basis points in the latter half of the year post-disaster (Figure 7-F).[23] This reflects potential reductions in annual salary increases due to unexpected costs

[23]The decline in real wage growth is not driven by changes in inflation. Duprey and Fernandes (2024) show that natural disasters in Canada impact inflation for some disasters, when the economy is particularly weak, and through specific components like shelter and energy. However, the overall effect of inflation is insignificant, suggesting that inflation may not be the main driver of the real wage decline.

like repairing physical assets. Additionally, it may involve shifts in labour market composition or the migration of higher-earning individuals from affected areas.

5.2 State dependence of labour market response to disasters

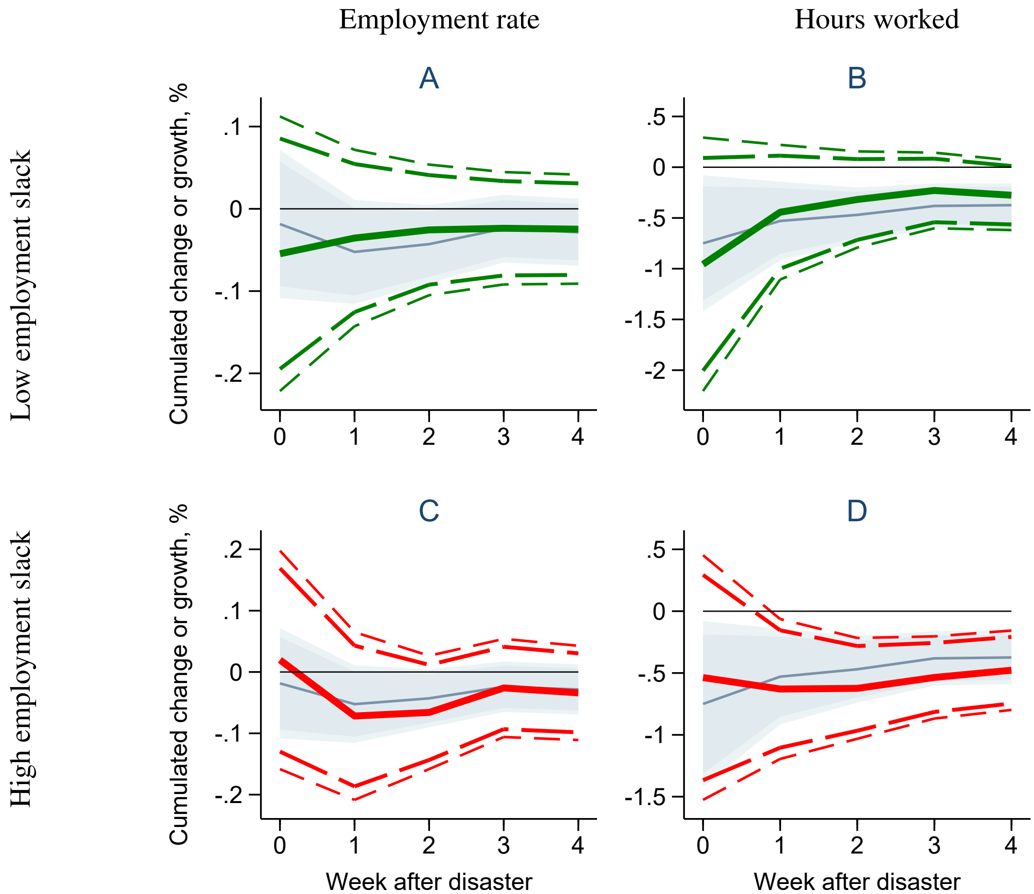
Based on the state-dependent model (Equation (4)), we find that natural disasters disproportionately affect the labour market during periods of high employment slack, likely catalyzing painful economic adjustments during downturns. Conversely, tight labour markets demonstrate greater resilience to natural disasters overall.

Figure 8: State-dependent adjustment of labour markets: monthly responses

Notes: State-dependent impacts of a natural disaster on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals using Equation (4).

Figure 8 shows state-dependent impulse responses, which contrasts to the baseline results from Section 5.1 where state dependence was not considered (grey line). Notably, the lower wage growth as well as lower hours worked observed in the baseline is driven by the responses in the high employment slack state (Figure 8-F, -E). Similarly, we observe a decline in hours worked one to four weeks after a natural disaster, particularly in the high employment slack state (Figure 9). Finally, we find that the insignificant impact on overall employment in the baseline is due to counteracting forces in both states; during periods of low employment slack, full-time employment may increase while part-time employment may decrease; in contrast, during periods of high employment slack, full-time employment may decrease while part-time employment may increase (Figure B.5).

Figure 9: State-dependent adjustment of labour markets in the first four weeks



Notes: Weekly state-dependent responses of employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) to a natural disaster, with the 90 and 95% confidence intervals. Responses are obtained from an extended version of Equation (2) to incorporate state dependence as in Equation (4).

5.3 Size-dependence of labour market response to disasters

Figure 10 depicts the marginal effects of a disaster shock across different disaster severity, leveraging Equation (5). Specifically, Panels D to F plot the marginal effect for a median cost disaster, and Panels G to I for disaster with costs in the 95th percentile.

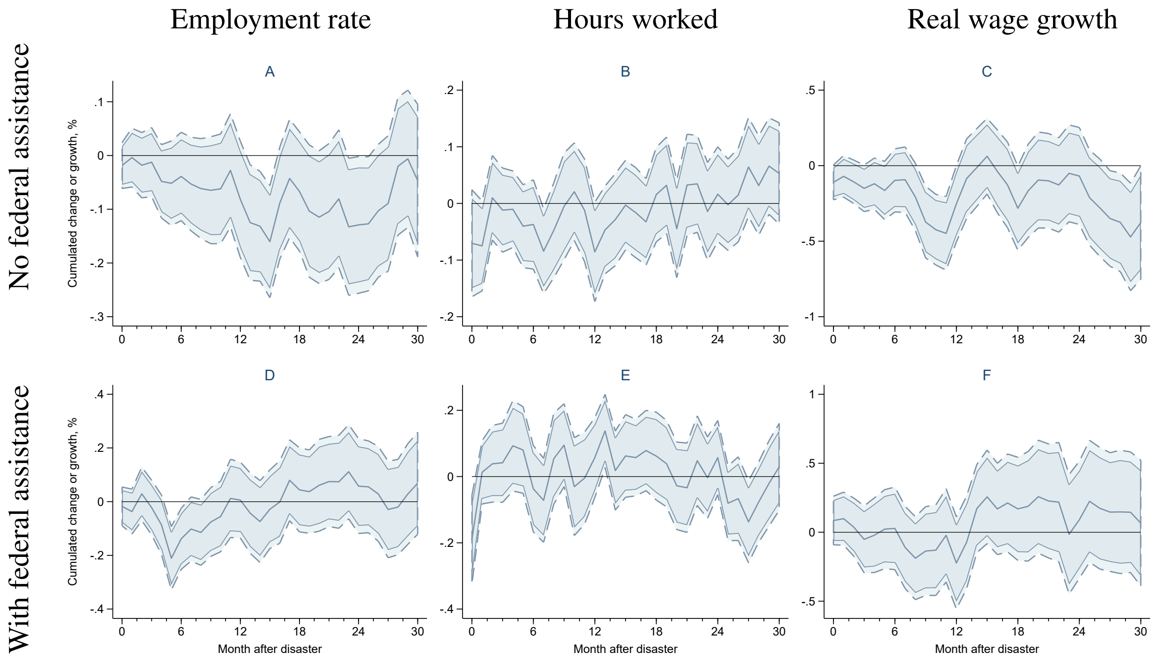
One important finding that stands out is that larger disasters produce stronger and more persistent effects on wage growth (Figure 10-F). For disasters of median costs, real wage

Figure 10: Size-dependent adjustment of labour markets to a disaster

Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Effects of a disaster with a recorded cost at the median (top row) or at the 95th percentile of the distribution (bottom row) based on Equation (5).

growth decreases by 50 basis points in the year following the event, while it decreases by 80 basis points for disasters with the largest costs. Interestingly, the effect on hours worked is no longer significant for the largest disasters (Figure 10-H) while we observe a positive and temporary increase of about 20 basis points in the employment rate about a year after the event (Figure 10-G). This could reflect some re-hiring to replace workers who were displaced following the disaster. However, despite a small rebound in employment, the downward pressure on wages persists even three years later, with wage growth being reduced by more than 100 basis points. Reallocation and/or migration may be a likely driver of this decrease; for instance, Coulombe and Rao (2023) document the migration out of US counties after wildfires, potentially resulting in changes to the composition of the local labour market.

Figure 11: Impact of federal government support after a natural disaster



Notes: State-dependent impacts of a natural disaster on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with natural disaster dummy variables split between disasters that led to federal government funding via the DFAA program (bottom row) or not (top row), Equation (6).

Next, we examine another measure of disaster intensity by grouping disasters into those with or without federal assistance (i.e., DFAA) and split the binary disaster dummy into two subgroups (Equation (6)). Figure 11 reports the resulting impulse responses. On one hand, natural disasters that qualify for the DFAA tend to be more extreme and result in a larger reduction in employment by 20 basis points within the first six months (Figure 11-D) and a larger reduction in hours worked on impact (Figure 11-E). On the other hand, natural disasters that qualify for the DFAA may benefit from additional resources for the recovery and reconstruction and avoid any decrease in real wages in the medium run (Figure 11-F). This is in line with Dahlhaus et al. (2024), who find that large provincial debt may weaken the economic recovery following a disaster unless federal funding assistance is available. Putting this result together with our findings from Section 5.2, the availability of federal

DFAA program funds may substantially dampen the effect of natural disasters even during a period of high employment slack.

We further explore the size-dependent impacts of disasters by focusing individually on the three most severe disasters that happened during our sample period: the 2016 Fort McMurray wildfire, the 2013 Alberta floods, and the 1998 ice storm in Appendix E. Absent adaptation to natural disasters, this analysis can also provide insights on how future disasters will affect the labour market as climate change intensifies.[24]

5.4 Time dependence of labour market responses to disasters

Over time, two opposing forces may shape the labour market impact of natural disasters. On one hand, climate change may increase the frequency and severity of natural disasters, exacerbating their impact. On the other hand, provincial economies may adapt by increasing government spending and enhancing resilience. While we cannot definitively separate the effects of these opposing forces over time, we can infer which factor predominates in different periods by analyzing our model across sub-sample periods. Specifically, we display the range of possible fitted impacts aggregated across Canada and discuss possible shifts in the distribution of impacts that could indicate a change in the labour market responses to a natural disaster in our two sub-samples.

If worsening disaster severity or higher frequency predominates, the labour market impact would intensify. This would be evidenced by either a wider distribution of impacts over time or a leftward shift, reflecting the overall negative impact of natural disasters. Alternatively, if adaptation prevails, impacts are likely to diminish over time. This could be represented by the following possible patterns in the distribution of impacts in the most recent sub-sample: a narrowing and centring of the impact distribution around zero, indicating successful mitigation of labour market disruptions and reduced volatility; a shift of the distribution rightward towards zero, suggesting adaptation is lessening negative impacts; or a

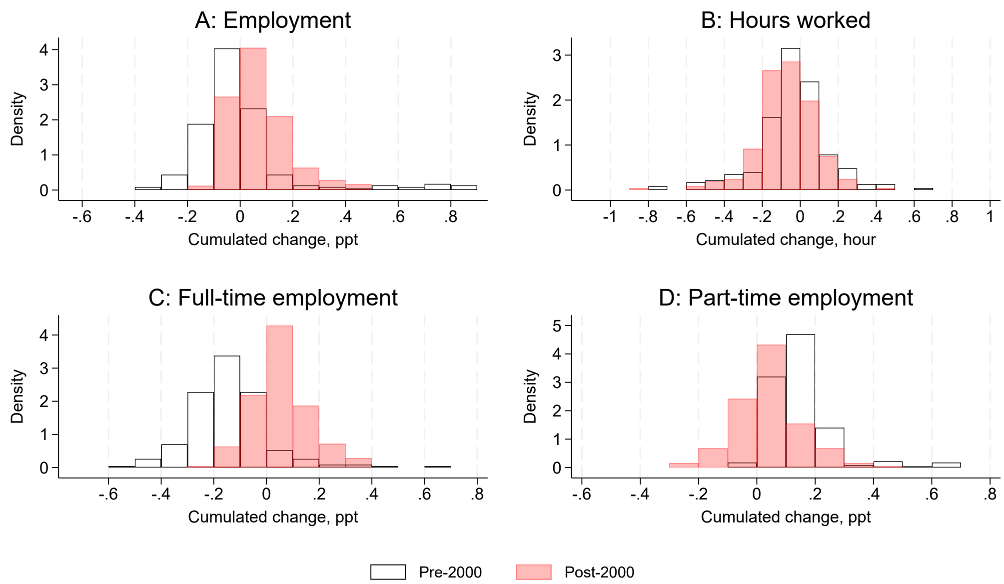
[24] While our findings demonstrate that disasters may have asymmetric impacts on the labour market depending on their severity, it is also important to verify that our baseline findings are not driven by one extremely large disaster. Therefore, we check the robustness of our findings in Appendix F by re-estimating our baseline model while removing one disaster at a time from our dataset.

rightward shift into positive effects, indicating potential overcompensation by labour markets in response to increasing disaster severity and heightened recovery efforts.

Figure 12 presents the distribution of simulated impacts in two reference periods, i.e., pre- and post-2000. Bars represent the frequency of simulated monthly effects for all disasters in the two sub-sample periods, aggregated over time and over all provinces.[25] This analysis does not consider the significance of the impact but instead focuses on the range of possible fitted values. Post-2000, we find that employment responses shift closer to zero with a smaller variance (Figure 12-A). Full-time employment used to be negatively impacted by natural disasters pre-2000, but the effect post-2000 is largely centred on zero (Figure 12-C). Part-time employment used to respond positively to natural disasters per-2000, but the effect post-2000 is also largely centred on zero (Figure 12-D). Overall, the evolution of the range of possible impacts in the last 20 years of our sample suggests adaptation, making the labour market more resilient despite the increasing severity and frequency of natural disasters. Businesses may cope better and rely less on the extensive margin (but marginally more on the intensive margin) for possible labour adjustments after natural disasters. However an alternative explanation could be a stronger impact of government financial assistance, as suggested by the dampening effect of DFAA federal funding on the labour market impact (Figure 11). Indeed, DFAA payments have been increasing over time. Still, our results are somewhat in contrast to the US, where Kim et al. (2022) find limited support for adaptation with economic indicators responding much more negatively in recent years.

[25] This exercise is not conducted for real wage growth, as the series is available from 2000 only. Similar results are obtained when our baseline model using a binary disaster dummy, i.e., Equation (1), is used, and not distinguishing disaster intensity is incorporated, as shown in Appendix G.

Figure 12: Impact of natural disasters pre- and post-2000



Notes: Simulated impacts of all types of natural disasters before and after 2000. The effects of each disaster are fitted for 0 to 12 months, based on Equation (5), and then aggregated at the Canada-wide level.

5.5 Type dependence of labour market response to disasters

Lastly, we display effects across disaster types in Figures 14, 15, 16 and 17. Panels A to C show the results from the model with only the natural disaster dummy variables estimated with Equation (1). The remaining panels depict the marginal effects of the disaster across different disaster severity, leveraging Equation (5) and disaster cost percentiles from Table 2. Appendix A reports impacts disaggregated further by the production and service sectors.

We find important divergences in labour market response across disaster types. For instance, wildfires and floods appear to follow the general patterns from Sections 5.1 and 5.3. However, storms have more muted effects, suggesting more localized impacts, while large winter storms lead to positive effects on employment.

5.5.1 Effect of wildfires

Wildfires lead to an increase in hours worked within six months and a 50 basis point reduction on wage growth within 12 months (Figure 14-B, -C). The increase in hours worked is driven by periods of high employment slack (Figure B.1-E). This is primarily because of an increase in hours worked in the goods sector due to the forestry/mining/oil sector that tends to be the critical industries for provinces most exposed to wildfires. Conversely, the impact on real wage growth is driven more by periods of low employment slack (Figures B.1-C). This is likely a specific sectoral reallocation of jobs in provinces specialized in resource extraction that are most exposed to wildfires (see Figure 3 for the overlap between boreal forests and provinces relying on resource extraction). When the local labour market is slack, we observe relatively more jobs in less attractive (but better paying) sectors like forestry/mining/oil and transportation in isolated areas that are physically demanding. When the local labour market is tight, we observe relatively more jobs in the business support sector that may be easier office jobs in cities with relatively lower salary compensations.

The employment effect for the largest wildfires is further amplified, although government support may partly ease the labour market impact. Employment decreases by 25 basis points within six months (Figure 14-G). The initial decrease in employment is compensated by a persistent increase in hours worked up to two years after the largest disasters (Figure 14-H). This pattern of lower employment rate but higher hours worked is observed only for wildfires that require federal assistance (Figure C.1-D and -E). Interestingly, wildfires that are severe enough to require federal assistance are associated with a short run increase in real wages (Figure C.1-F) while real wages decrease in the absence of federal assistance (Figure C.1-C). This suggests that recovery efforts supported by the federal government effectively attenuate part of the negative labour market impact. This is in line with Dahlhaus et al. (2024), who find that large provincial debt may weaken the economic recovery after wildfires unless federal funding assistance is available. Similarly, for the most severe wildfires associated with the 95th percentile of evacuations, although the overall employment rate does not vary (Figure D.1-F), the short-run decrease in full-time employment is compensated by a short-run increase in part-time employment.

These effects are mostly driven by the service sector (Figure A.2-A, -B, -C) with positive pressure on hours worked in the transportation sector partly compensated by a decrease in hours worked in the business support, wholesale and retail category. Although we observe no significant response on the production sector overall (Figure A.1-A, -B, -C), further sectoral decomposition suggests positive pressure on employment in the forestry/mining/oil, utilities and construction sectors, positive pressure on hours worked in the forestry/mining/oil sector, compensated by a sharp decrease in hours worked in the agricultural sector. This sectoral effect is consistent with provinces most exposed to wildfires being located in the boreal forests with industries heavily focused on resource extraction relying on labour input at the intensive margin despite possible migration outflows after wildfires.

Lastly, our analysis shows that the degree of adaptation over time also varies by disaster type, as shown in Appendix H. In the case of wildfires, evidence supports adaptation over time; post-2000, the simulated impacts of both employment and hours worked tend to centre on zero (Figures H.1-iA, -iiA). In other words, wildfires occurring in the past 20 years have generally had less pronounced impacts on the labour market compared to those in the preceding two decades, where the simulated effects were more widely dispersed.

5.5.2 Effect of floods

In the first few weeks after a flood, the employment rate is immediately reduced by 10 basis points (Figure 13-A) while hours worked decrease by up to one hour (Figure 13-B). Both of those effects on the intensive and extensive margins of employment dissipate a month after the flood (Figure 15-A, -B). After six months, real wage growth is persistently negative with a 60 basis point decrease recovering only after three years (Figure 15-C).

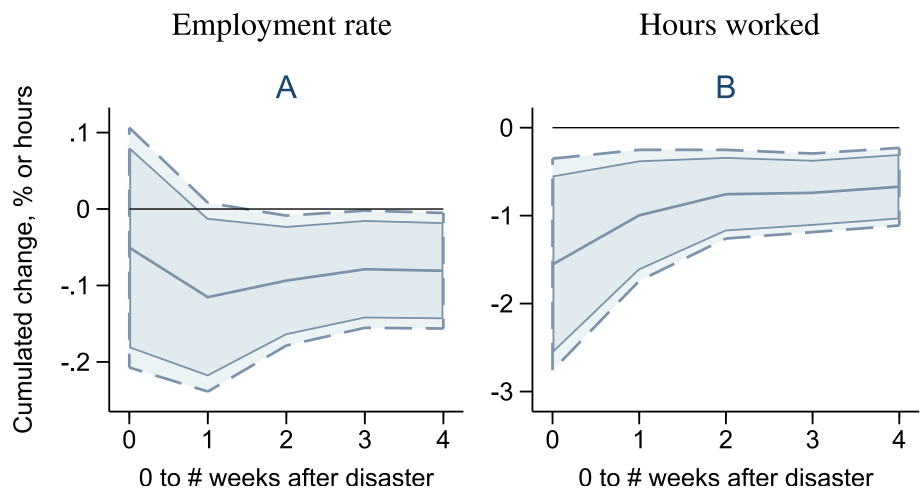
Those effects are primarily driven by periods of high provincial employment slack. Hours worked and real wages are persistently reduced (up to one year and three years, respectively) when floods occur during periods of employment slack (Figure B.2-E and -F).

For the largest disasters, the negative effect on the employment rate may persist up to six months (Figure 15-G). The effect is also amplified for alternative measures of severity like the number of evacuations (Figure D.2). The effect on wage growth is amplified only when there is no call for federal assistance (Figure C.2-C and -F). In general, floods receive more federal assistance funding than other disasters (Table 2). This suggests that recovery efforts supported by the federal government effectively attenuate part of the longer-term negative labour market impacts. This is also in line with Dahlhaus et al. (2024), who find that large provincial debt may weaken the economic recovery after floods unless federal funding assistance is available.

The short-run decrease in hours worked is mainly observed in the production sector (Figure A.1-D), mainly driven by the agricultural, forestry/mining, construction and manufacturing sectors, while hours worked increase on impact in the utilities sector. Conversely, the short-run decrease in the employment rate and decrease in wages is mainly observed in the service sector (Figure A.2-E, -F), with a lower employment rate in the food/accommodation sector that recovers within a year. The impact on the service sector may be related to flooding being more likely to occur in more densely populated areas, as most Canadian urban centres are along rivers. The employment rate also decreases on impact in the agricultural sector, with an increase in the construction sector after three months to support repairs.

Unlike other disasters, floods since 2000 have shown less adaptation, marked by increased variability in employment impacts and a negative skew in hours worked (Figures H.1-iB, -iiB). Specifically, floods have notably reduced hours worked post-2000, contrasting with the previous two decades where their effects were centred on zero. Despite their higher frequency compared to other disasters, the relatively minor impacts of floods on average may have limited efforts and government support for adaptation.

Figure 13: Weekly impacts of a flood



Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals using Equation (2).

5.5.3 Effect of storms

Storms, excluding winter storms, are the least intense type of disaster among all our measures of disaster intensity (i.e., cost as a percent of provincial GDP, DFAA payments as a percent of provincial GDP, number of evacuees and number of people affected by utilities disruption; see Table 2 for more details). Hence, it comes as no surprise that the overall effect of storms is relatively insignificant (Figure 16).

As such, any significant effect of storms on the labour market should be concentrated in some specific dimensions. First, the effect is more specific to some sectors. The slight decrease in hours worked a few months after the storm (Figure 16-E) is mostly observed in the utilities, forestry/mining/oil and service sectors (Figure A.2-H). Only for the accommodation/food sector do we observe an increase in hours worked within a month, possibly driven by power cuts and temporary accommodation. Second, larger storms appear to have a significant impact when their intensity is ranked using the number of affected persons rather than monetary cost. Storms have the smallest average cost as a percentage of provincial GDP and the smallest associated variance (Table 2), and thus no significant effects are observed using the disaster cost (Figure 16-G to I). However, when the number of affected persons is used instead, a large negative response of hours worked is estimated (Figure D.3). Third, their effect becomes significant when conditioned on labour market slack: both the employment rate and real wages decrease briefly when storms occur during periods of high employment slack (Figures B.3-D and -F). Conversely, real wages tend to temporarily increase during periods of low employment slack (Figure B.3-C).

In terms of its impacts over time, storms show improved adaptation post-2000 similar to the case of wildfires and winter storms, although their impacts on hours worked shift slightly more negatively (Figures H.1-iC, -iiC).

5.5.4 Effect of winter storms

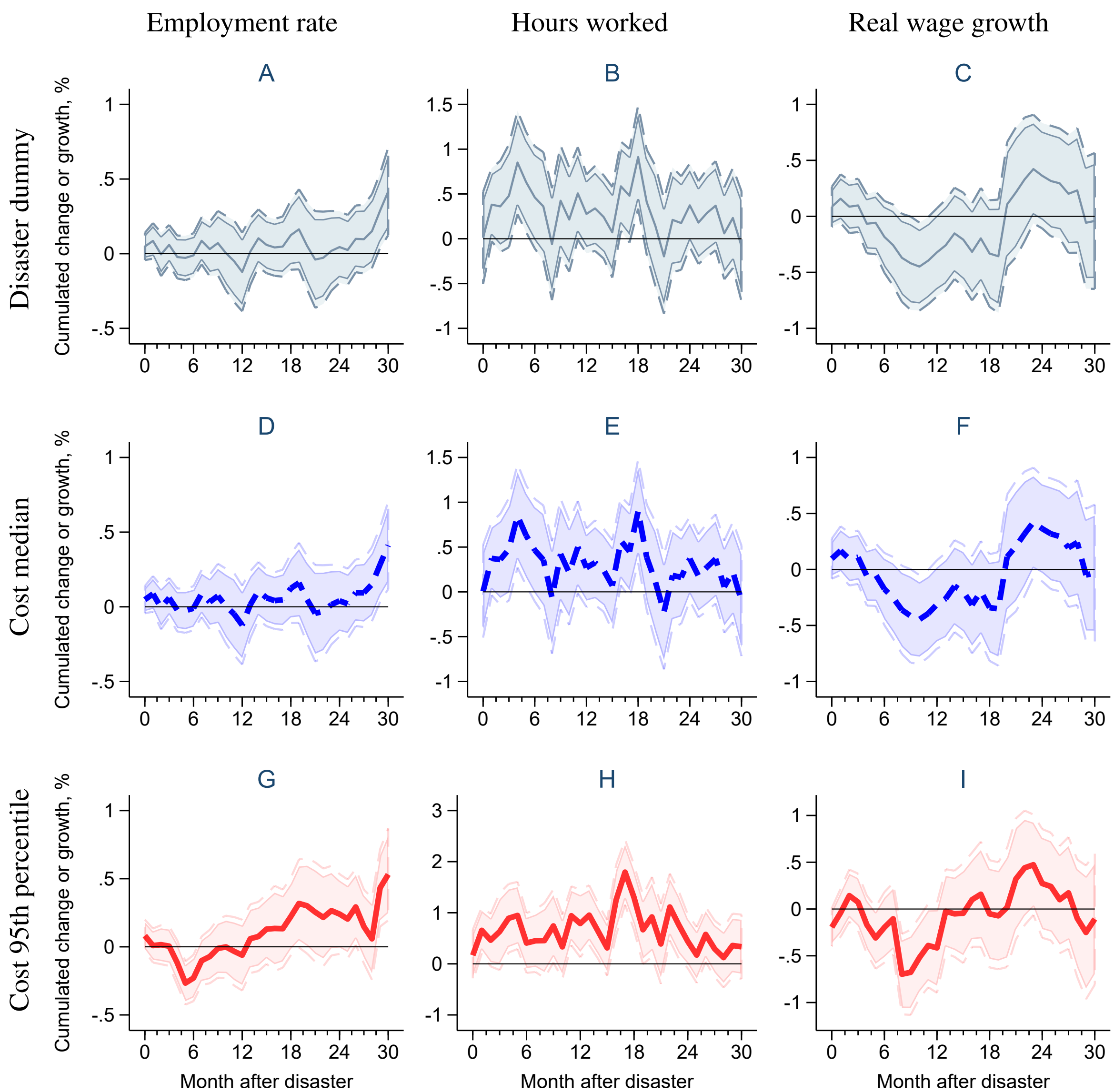
Winter storms may marginally decrease real wages within a year before being more than offset by stronger growth one year after (Figure 17-C and -F). This pattern is more noticeable in the service sector (Figure A.2-L) for winter storms with the median recorded number of affected persons (Figure D.4) and for those that do not require federal-level assistance (Figure C.4).

State dependence in the responses of the labour market tends to be strong for winter storms. The change in real wages occurs only in periods of employment slack (Figure B.4-F) during which hours worked also decrease (Figure B.4-E), driven by persistently lower hours worked in the agricultural sector and the wholesale/retail sectors.

The effect of winter storms also depends on disaster size. Similar to the effect observed for the largest winter storm, i.e., the 1998 ice storm (Figure E.1), winter storms with larger costs drive up the employment rate (Figure 17-G). The higher employment rate is due mainly to the service sector, especially for transportation, possibly due to government spending for repairs to damaged infrastructure. As expected, hours worked also spike in the utilities sector, which may be particularly strained by severe winter storms.

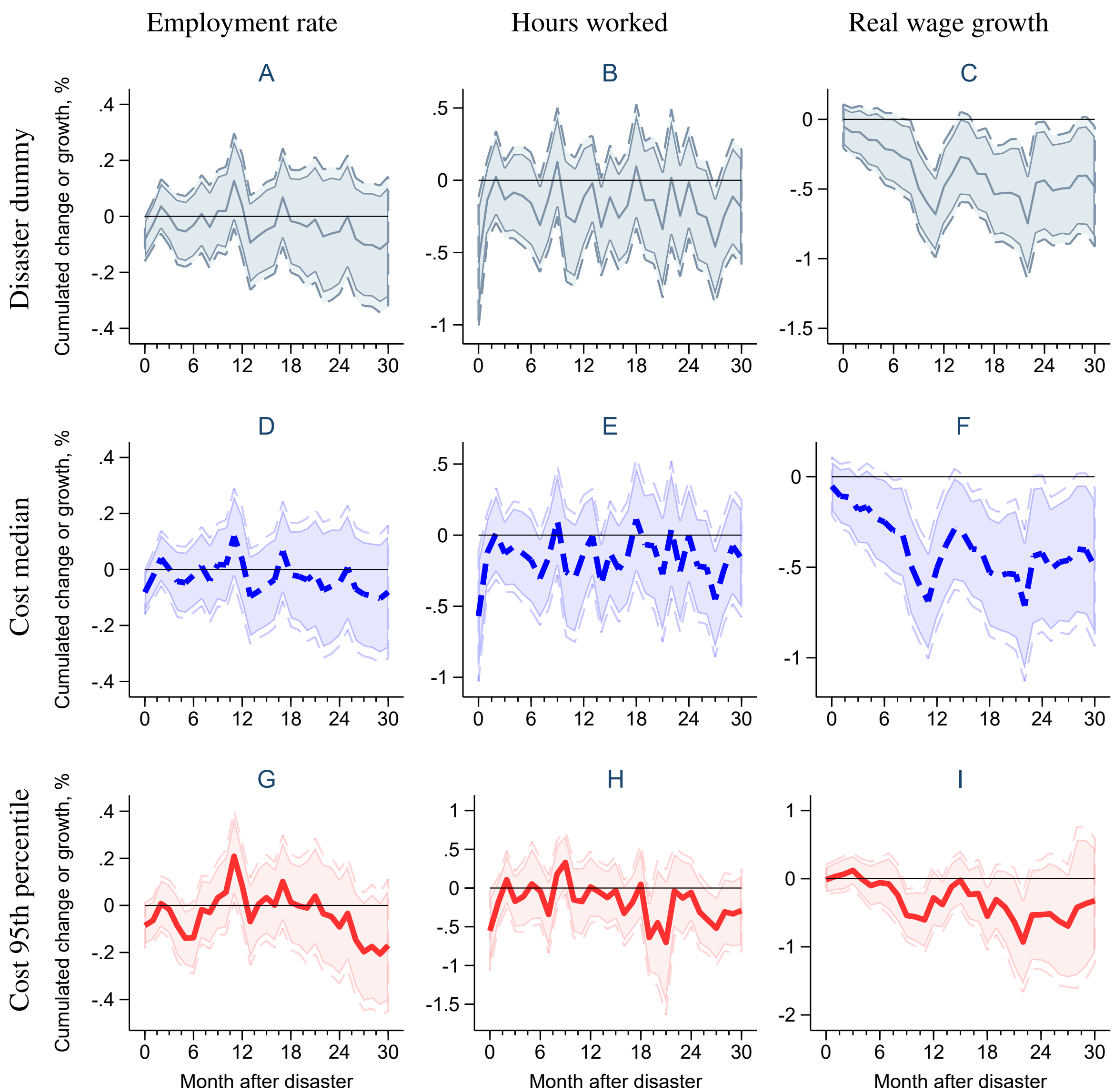
Winter storms also demonstrate significant changes in their simulated impacts over time, particularly indicating evidence of adaptation. Post-2000, the simulated impact distributions of both employment and hours worked notably shift towards the positive range (Figures H.1-iD, -iiD). This shift into positive territory may also be influenced by substantial government support for clean-up operations.

Figure 14: Impact of a wildfire on the provincial labour market



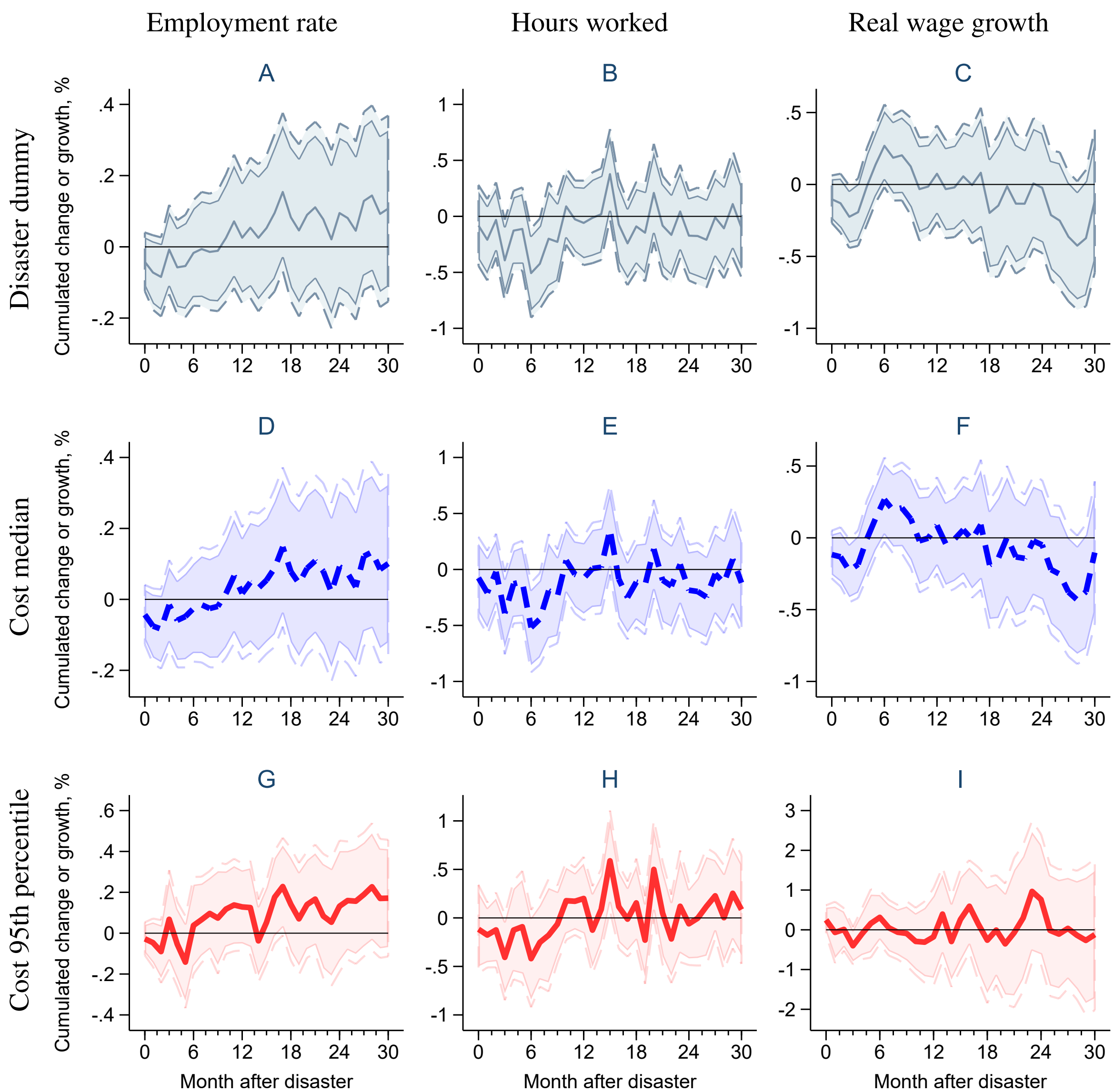
Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. The first row displays responses from the model with the natural disaster dummy variables, using Equation (1). The second row displays the effects of a disaster with the recorded cost at the median level, and the third row shows the effects with the recorded cost at the 95th percentile, using Equation (5).

Figure 15: Impact of a flood on the provincial labour market



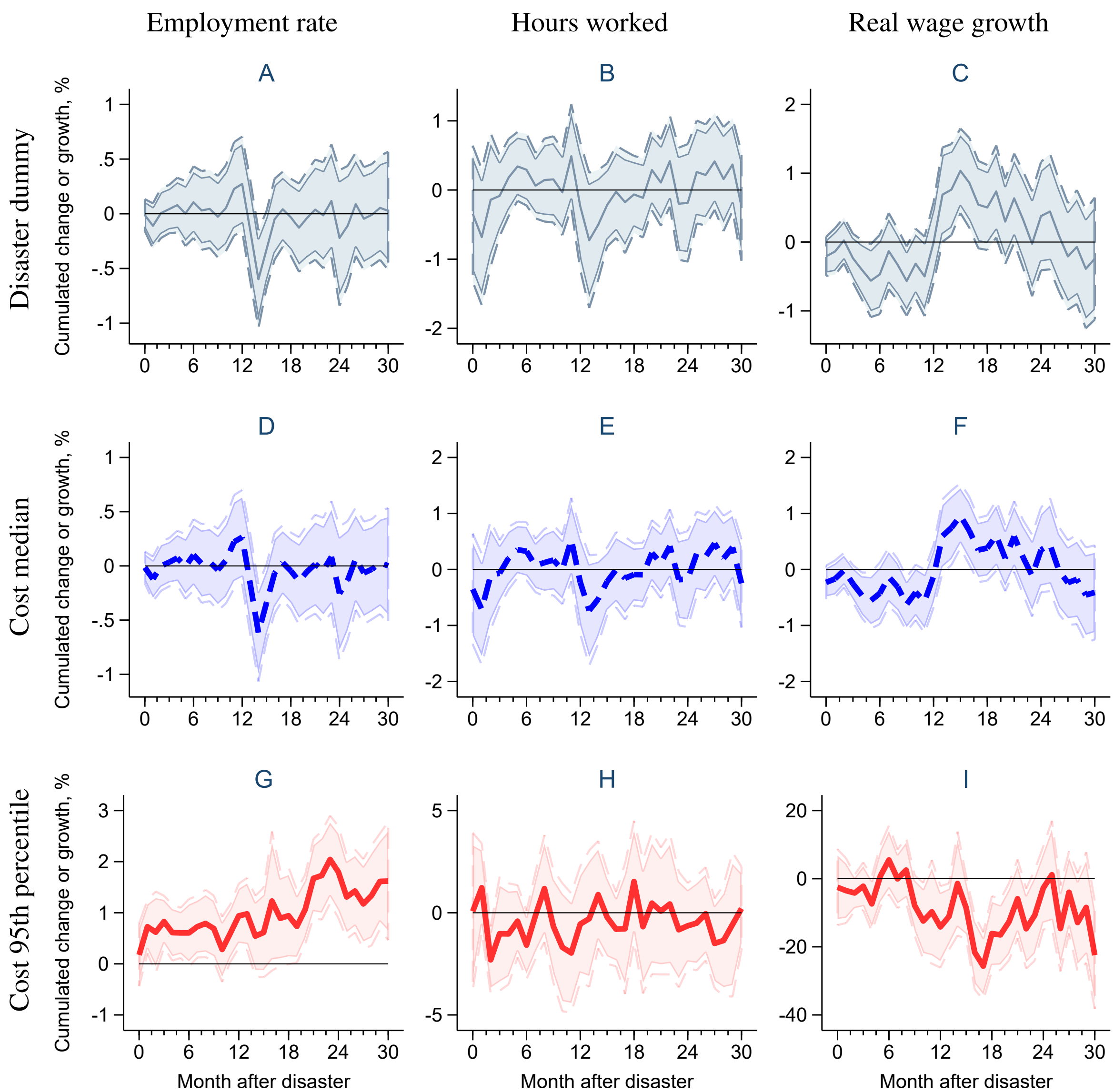
Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. The first row displays responses from the model with the natural disaster dummy variables, using Equation (1). The second row displays the effects of a disaster with the recorded cost at the median level, and the third row shows the effects with the recorded cost at the 95th percentile, using Equation (5).

Figure 16: Impact of a storm on the provincial labour market



Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. The first row displays responses from the model with the natural disaster dummy variables, using Equation (1). The second row displays the effects of a disaster with the recorded cost at the median level, and the third row shows the effects with the recorded cost at the 95th percentile, using Equation (5). Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure 17: Impact of a winter storm on the provincial labour market



Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. The first row displays responses from the model with the natural disaster dummy variables, using Equation (1). The second row displays the effects of a disaster with the recorded cost at the median level, and the third row shows the effects with the recorded cost at the 95th percentile, using Equation (5).

6 Conclusion

This paper investigates how natural disasters affect the local labour market in 10 Canadian provinces, focusing on employment, hours worked and real wage growth. We construct a monthly provincial panel of disasters spanning the period from 1980 to 2019 by exploiting the Canadian disaster database, which records weather events causing significant damages. We use a panel local projection setup extended to account for the heterogeneity across economic states, disaster intensity, disaster type and changes over time.

We find the following. First, disasters initially reduce hours worked within a week, with effects fading quickly, while wage growth declines half a year later. Second, most of the effects occur during periods of high employment slack. This suggests that natural disasters act as a catalyst for painful labour market readjustments in already weak labour markets, although federal assistance can dampen some of this effect. Third, in the second half of our sample, the labour market displays a more muted response to disasters, possibly indicating either an adaptation to more frequent and severe events over time or a stronger impact of government support. Finally, we observe substantial heterogeneity across disaster intensity and disaster types, although wage growth tends to be weaker across all disasters.

Our findings have two main policy implications. First, when assessing the overall impact of natural disasters, the effect on local labour markets should not be overlooked: natural disasters can detrimentally affect vulnerable workers through the income channel, especially when it materializes at the same time as other shocks that had already weakened the economy. In addition, income losses can be one of the main drivers of household defaults, possibly further amplifying losses for the overall economy. Second, disaster relief funding and its design is important for policy makers. On the one hand, federal funding can alleviate some of the longer-term effects of disasters on wage growth. However it may hide a sectoral reallocation. For instance, those living in wildfire-prone areas working in retail industries are more likely to lose their job, while part-time workers in the construction sector likely benefit from the recovery phase after a wildfire. Finally, policy makers have reasons to remain concerned about the macroeconomic impact of natural disasters given the risk of increased frequency and magnitude, even as mitigation policies may provide some partial offset. The disruptive effect we quantify for the largest disasters in Canadian history is a cautionary tale for the decades to come should Canada continue to experience record-breaking disasters.

We use a panel of extreme events to explore the labour market impacts of natural disasters. While our method offers broadly applicable results compared to case studies, it relies on a historical dataset and cannot accurately project future labour market responses, especially given accelerating climate change. Therefore, interpretations of our findings should consider uncertainties surrounding potential structural changes in the economy due to climate change.

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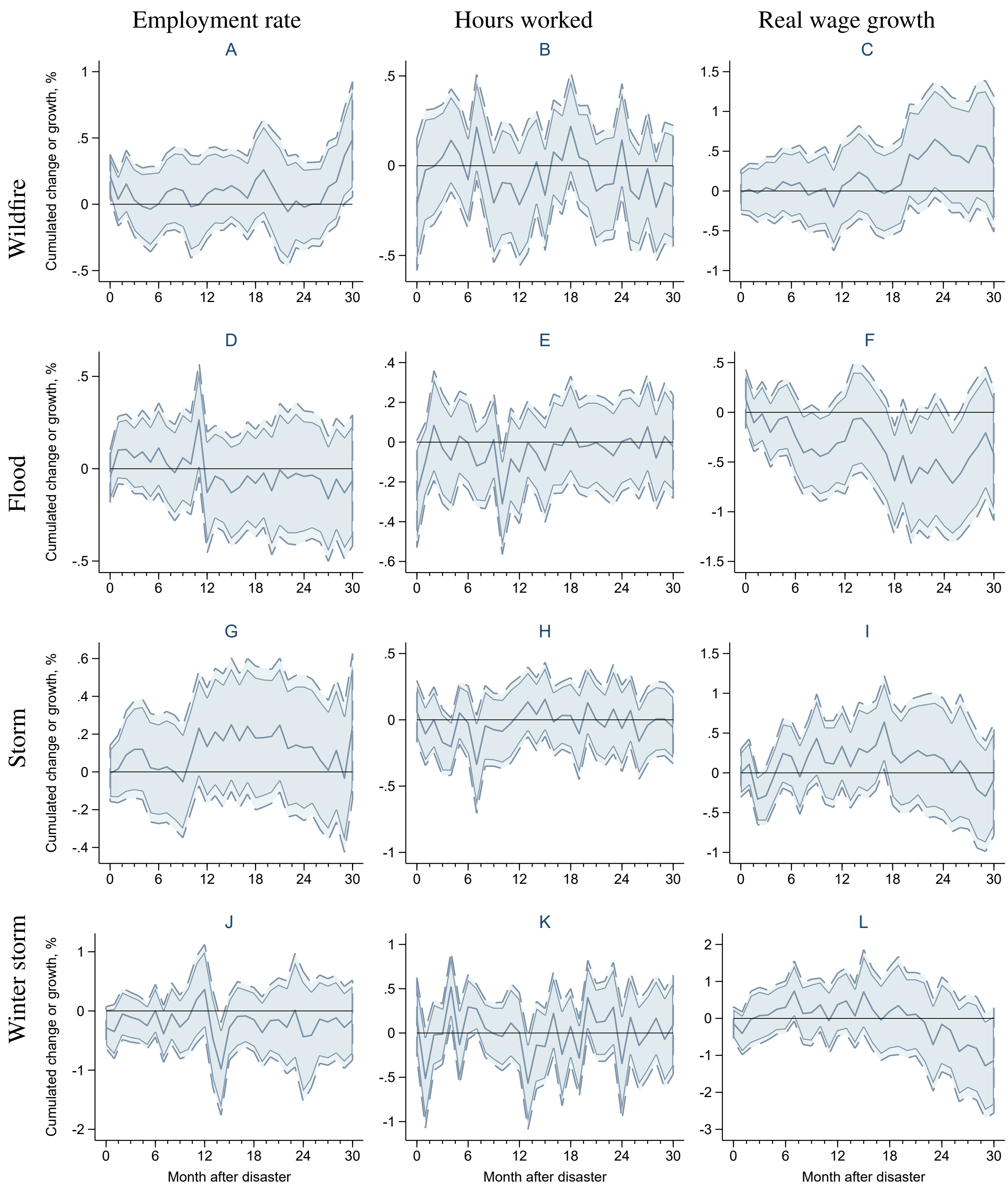
A Appendix: Production versus service sectors

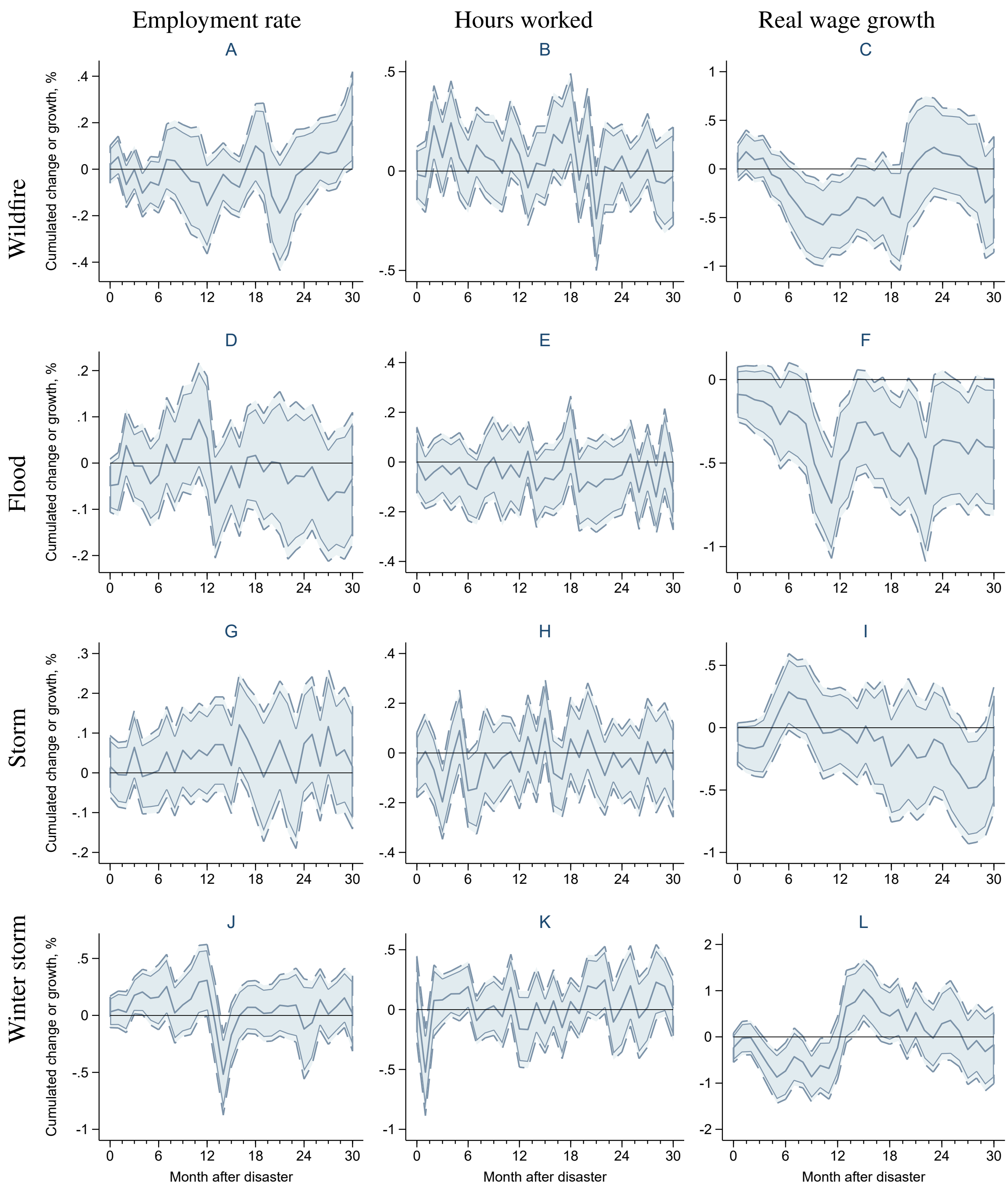
To evaluate the sectoral impacts of natural disasters, we re-estimate Equation (7) using the sectoral employment rate, hours worked and real wage growth for the production and service sectors in Figures A.1 and A.2, respectively.

Figure A.1: Responses of the production sector



Notes: Impact on the production sector's employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence interval, using Equation (1). Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure A.2: Responses of the service sector



Notes: Impact on the service sector's employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence interval, using Equation (1). Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

B Appendix: State-dependent responses—additional results

Figure B.1: State-dependent adjustment of labour markets: Wildfires

Notes: State-dependent impacts of wildfires on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) in low or high employment slack states (top and bottom panels, respectively) for 0 to 30 months ahead with the 90 and 95% confidence intervals, based on Equation (4).

Figure B.2: State-dependent adjustment of labour markets: Floods

Notes: State-dependent impacts of floods on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) in low or high employment slack states (top and bottom panels, respectively) for 0 to 30 months ahead with the 90 and 95% confidence intervals, based on Equation (4).

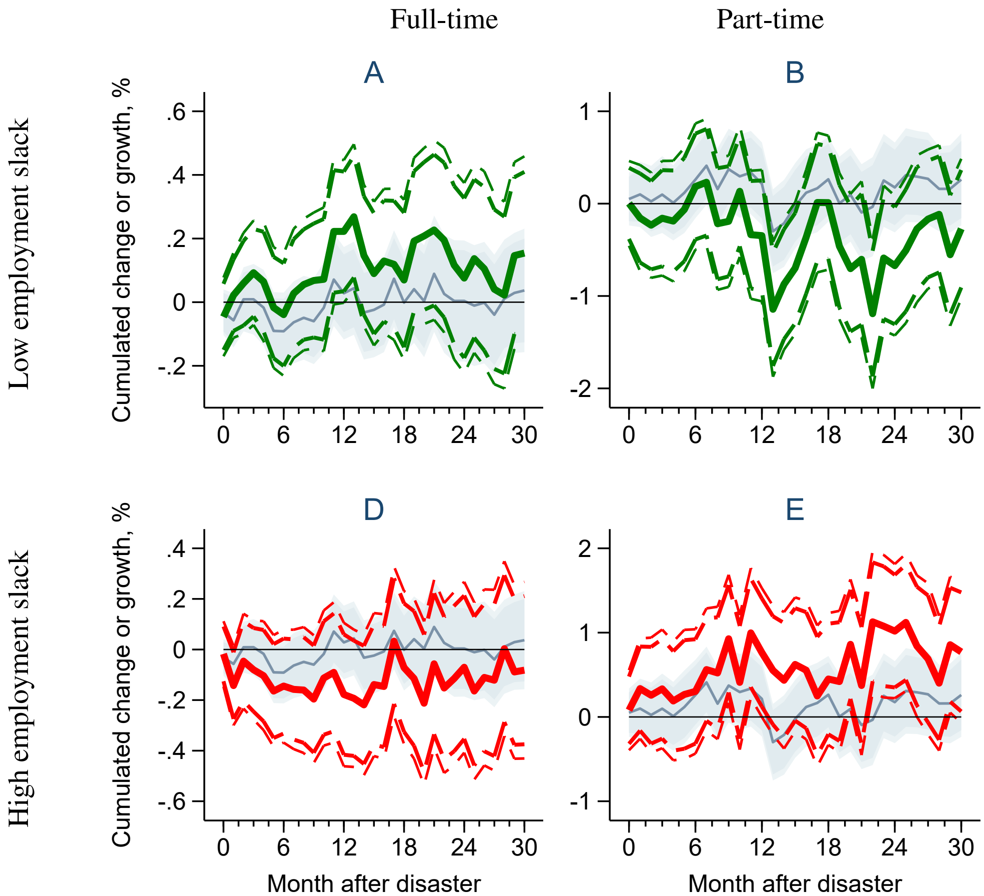
Figure B.3: State-dependent adjustment of labour markets: Storms

Notes: State-dependent impacts of storms on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) in low or high employment slack states (top and bottom panels, respectively) for 0 to 30 months ahead with the 90 and 95% confidence intervals, based on Equation (4).

Figure B.4: State-dependent adjustment of labour markets: Winter storms

Notes: State-dependent impacts of winter storms on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) in low or high employment slack states (top and bottom panels, respectively) for 0 to 30 months ahead with the 90 and 95% confidence intervals, based on Equation (4).

Figure B.5: State-dependent responses of full- and part-time employment



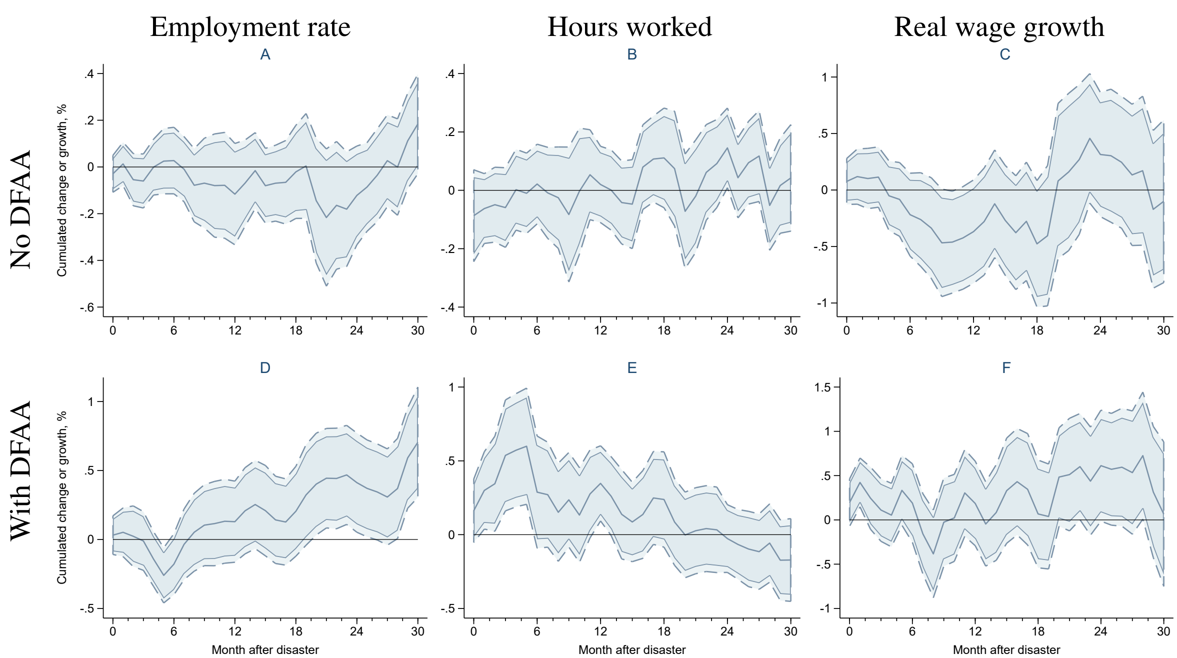
Notes: State-dependent impacts of a natural disaster on full- and part-time employment (left and right panels, respectively) in low or high employment slack states (top and bottom panels, respectively) for 0 to 30 months ahead with the 90 and 95% confidence intervals, based on Equation (4).

C Appendix: DFAA as a measure of disaster intensity

We divide the natural disasters into those with or without subsidies (P or NP) from the Disaster Financial Assistance Arrangements (DFAA). The DFAA is a federal program established in 1970 to provide financial assistance to provincial and territorial governments. It is triggered in the event of large-scale natural disasters when response and recovery costs exceed what individual provinces or territories could reasonably be expected to bear on their own. This is one alternative proxy for the importance of the disaster. The coefficients of interest are $\alpha_h^{P,d}$ and $\alpha_h^{NP,d}$ in the following equation:

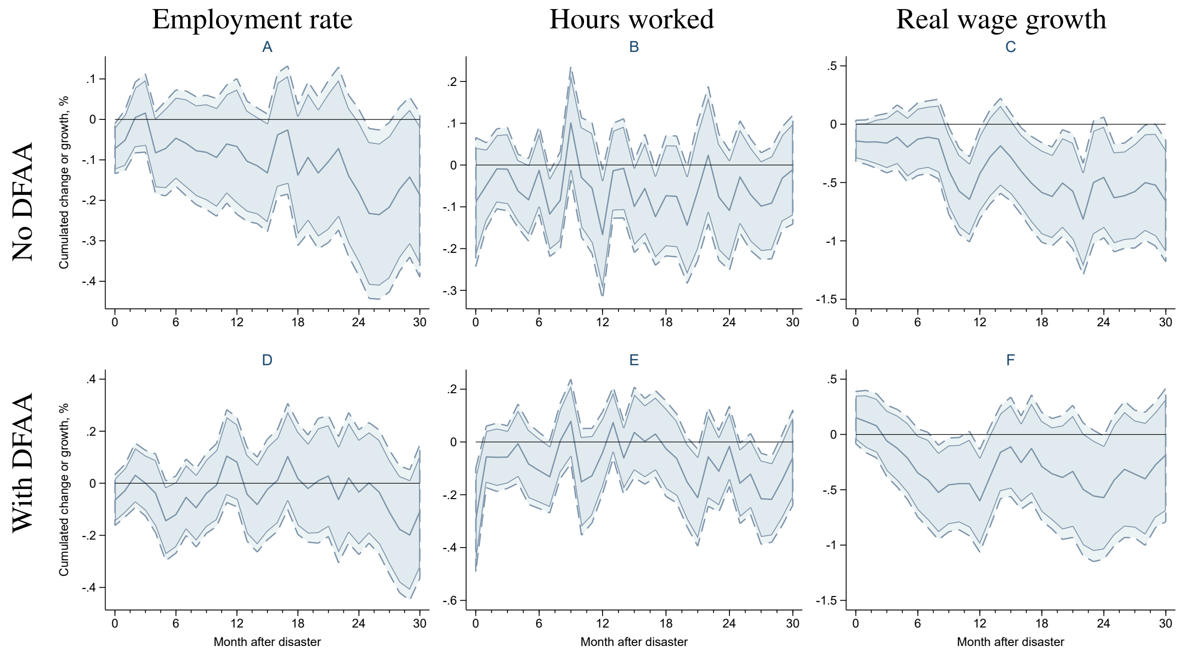
$$\begin{aligned}\Delta Y_{i,t+h:t-1} &= \sum_{d=1}^{4}\left\{\alpha_h^{P,d}\mathbb{1}(disaster)_{i,t}^{P,d} + \alpha_h^{NP,d}\mathbb{1}(disaster)_{i,t}^{NP,d} + \sum_{p=-12,\, p\neq 0}^{h}\alpha_h^{d,p}\mathbb{1}(disaster)_{i,t+p}^{d}\right\} \\ &+ \sum_{\tau=1}^{3}\psi_h^{\tau}\Delta Y_{i,t-\tau:t-\tau-1} + \sum_{\tau=1}^{3}\phi_h^{\tau}GDP_{i,t-\tau} + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h}. \end{aligned} \tag{8}$$

Figure C.1: Impacts of wildfires depending on the size of federal government support



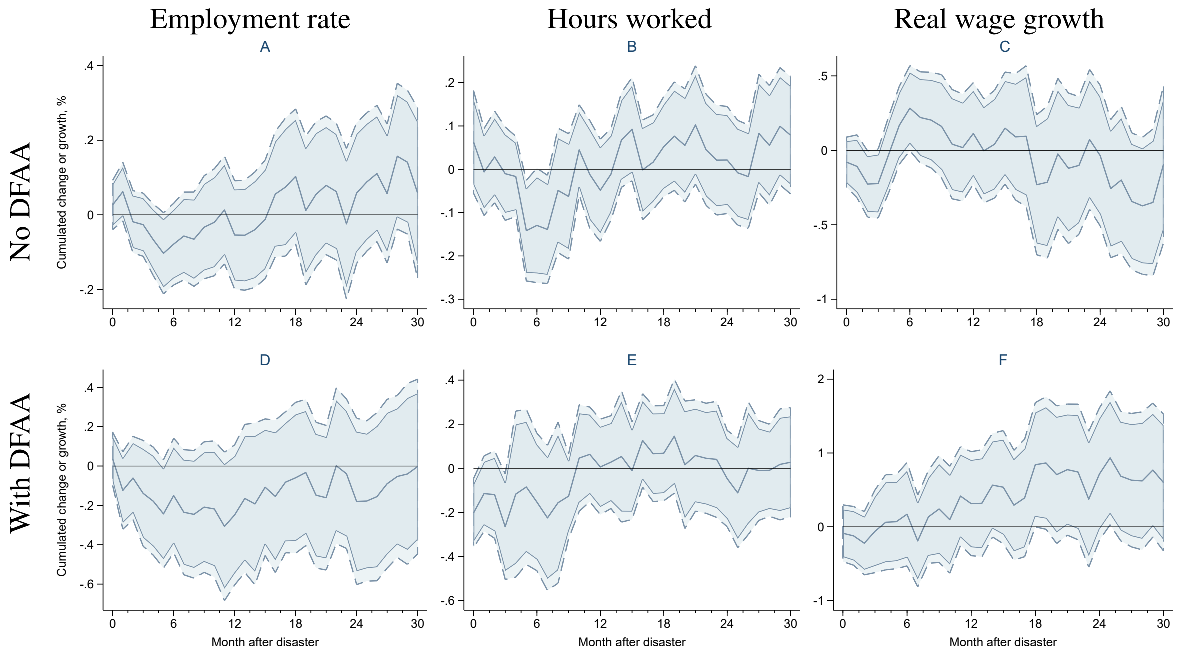
Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with natural disaster dummy variables split between disasters that led to federal government funding via the DFAA program or not using Equation (8).

Figure C.2: Impacts of floods depending on the size of federal government support



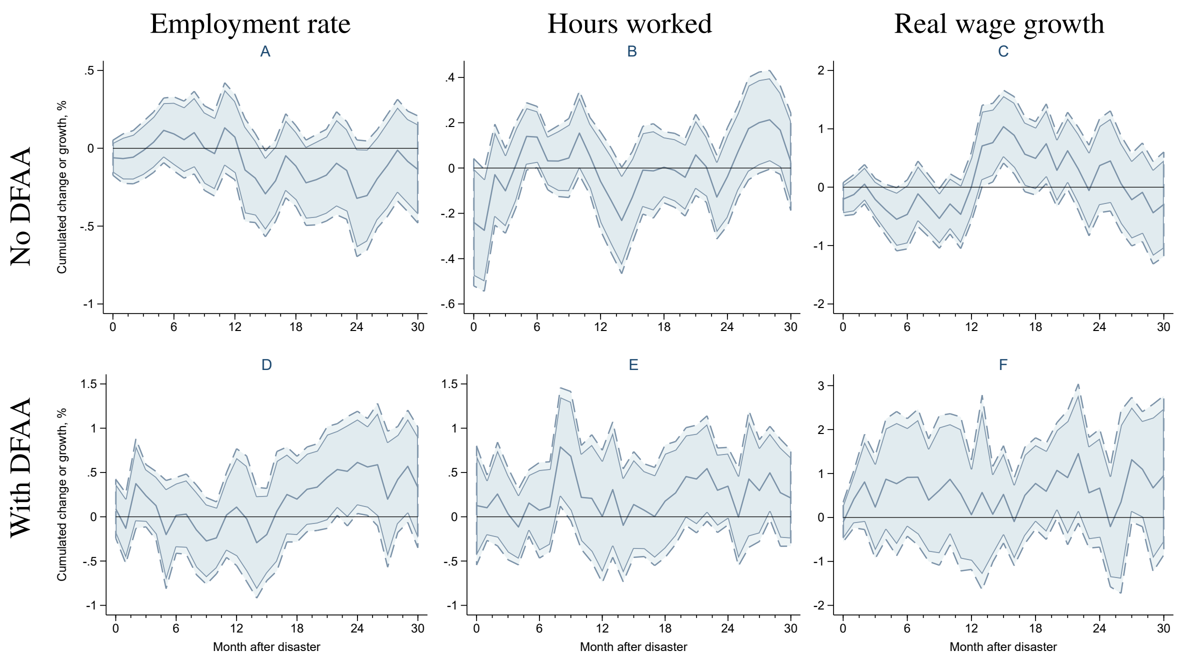
Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with natural disaster dummy variables split between disasters that led to federal government funding via the DFAA program or not using Equation (8).

Figure C.3: Impacts of storms depending on the size of federal government support



Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with natural disaster dummy variables split between disasters that led to federal government funding via the DFAA program or not using Equation (8). Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure C.4: Impacts of winter storms depending on the size of federal government support



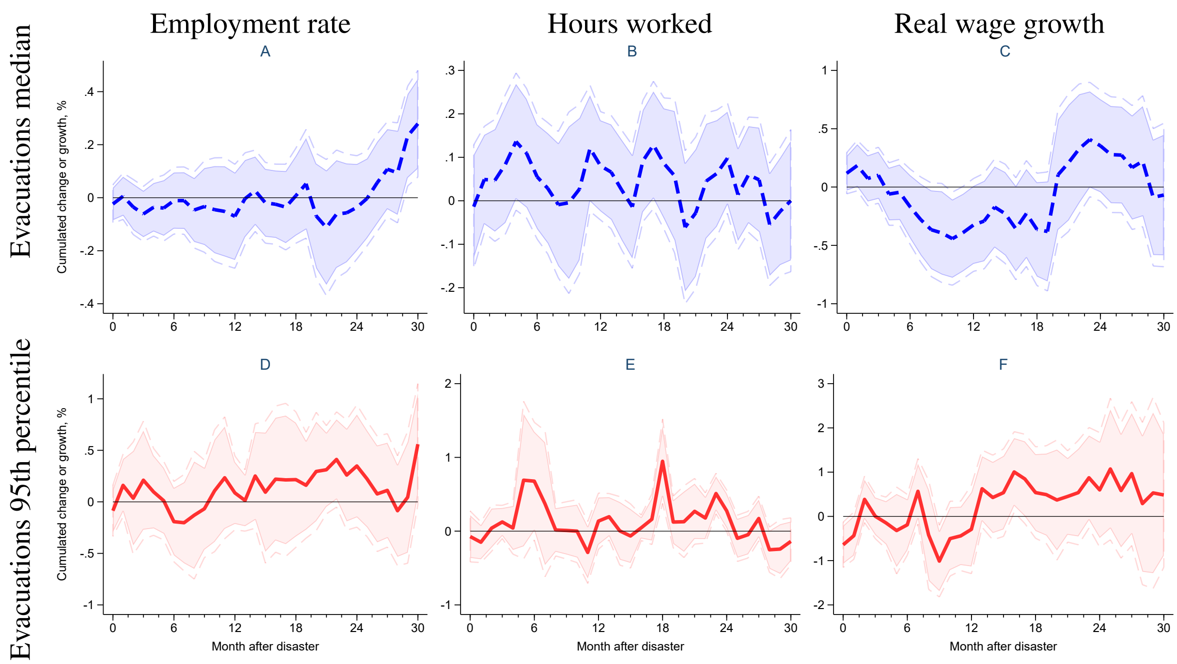
Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with natural disaster dummy variables split between disasters that led to federal government funding via the DFAA program or not using Equation (8).

D Appendix: Other alternative measures of disaster intensity

As a robustness for wildfires and floods, we use the reported number of evacuated persons (per provincial population, $evacuated^d_{i,t}$) as an alternative approximation of the disaster intensity. For summer or winter storms that do not typically generate evacuations, we can use the reported number of persons affected by utility disruptions (per provincial population, $affected^d_{i,t}$) as an alternative approximation of the disaster intensity. Statistics are displayed in Table 2. For wildfires and floods, the combination of parameters $\{\alpha_h^{E,d}, \beta_h^{E,d}\}$ across horizons in Equation (9) allows for the computation of marginal impacts depending on the number of evacuations. For summer and winter storms, the equivalent is the combination of parameters $\{\alpha_h^{A,d}, \beta_h^{A,d}\}$ across horizons for the number of affected persons:

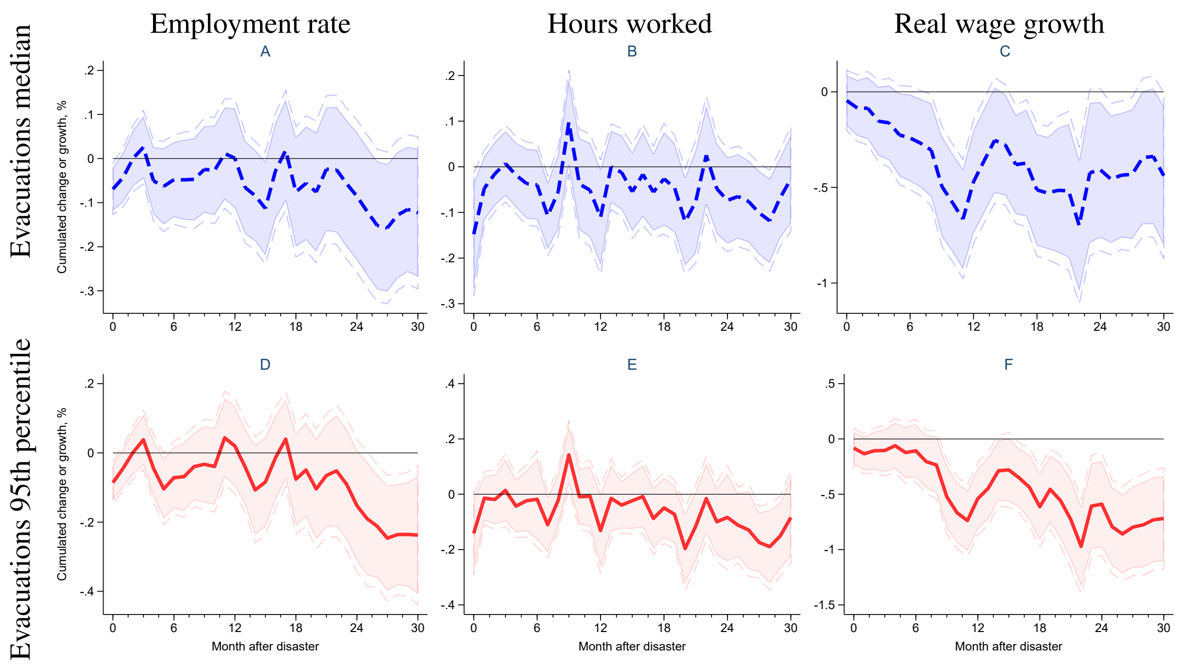
$$\begin{aligned}\Delta Y_{i,t+h:t-1} \;=\;& \sum_{d=1}^{2}\left\{\alpha_h^{E,d}\mathbb{1}(disaster)^d_{i,t} + \beta_h^{E,d} evacuated^d_{i,t} + \sum_{p=-12,\, p\neq 0}^{h} \alpha_h^{d,p}\mathbb{1}(disaster)^d_{i,t+p}\right\} \\ &+ \sum_{d=3}^{4}\left\{\alpha_h^{A,d}\mathbb{1}(disaster)^d_{i,t} + \beta_h^{A,d} affected^d_{i,t} + \sum_{p=-12,\, p\neq 0}^{h} \alpha_h^{d,p}\mathbb{1}(disaster)^d_{i,t+p}\right\} \\ &+ \sum_{\tau=1}^{3}\psi_h^{\tau}\Delta Y_{i,t-\tau:t-\tau-1} + \sum_{\tau=1}^{3}\phi_h^{\tau} GDP_{i,t-\tau} + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h}. \qquad (9)\end{aligned}$$

Figure D.1: Impacts of wildfires depending on the share of evacuated persons



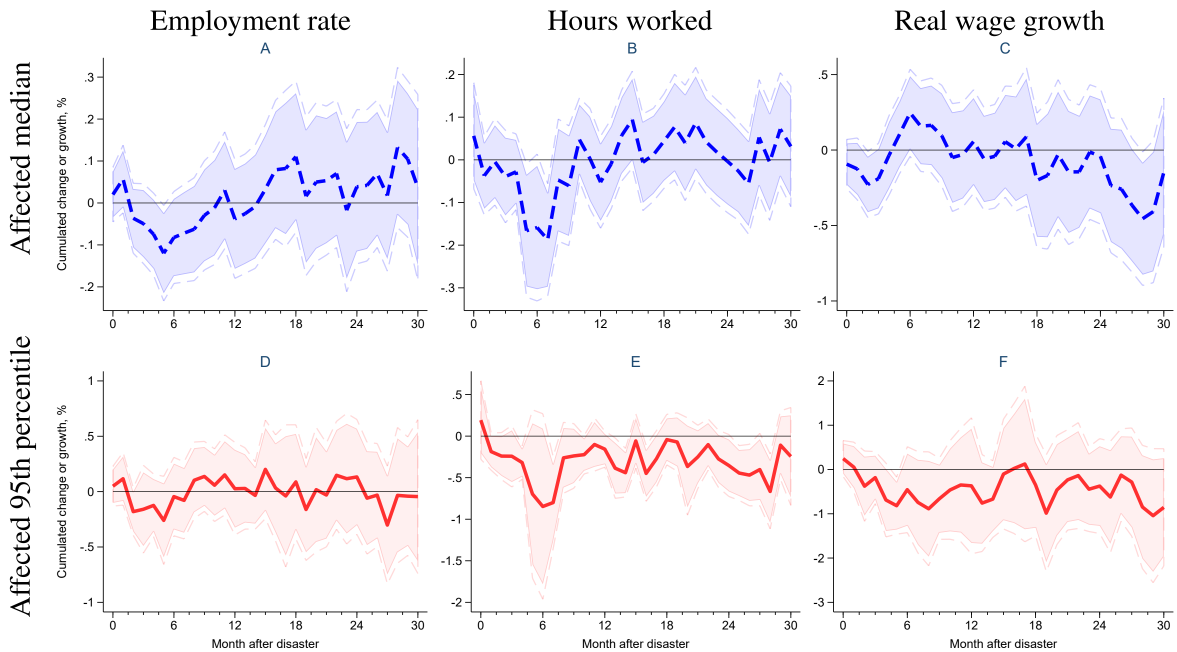
Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with the share of evacuations at the median (Panels A to E) or at the 95th percentile of the distribution (Panels F to J) based on Equation (9).

Figure D.2: Impacts of floods depending on the share of evacuated persons



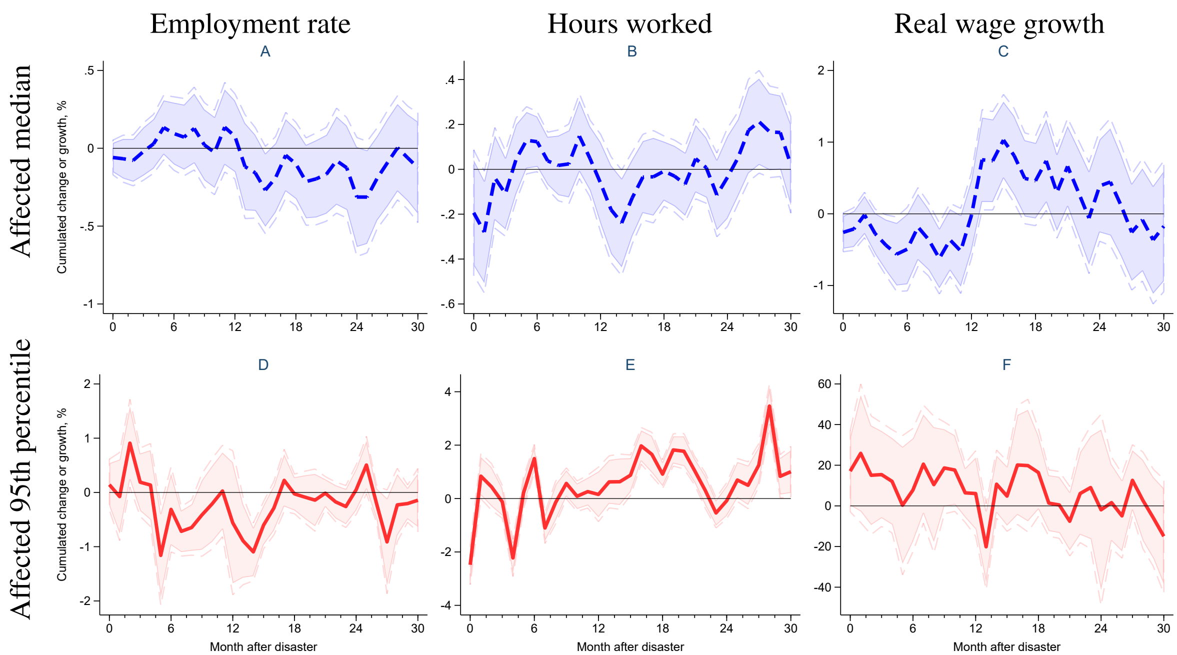
Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with the share of evacuations at the median (Panels A to E) or at the 95th percentile of the distribution (Panels F to J) based on Equation (9).

Figure D.3: Impacts of storms depending on the share of affected persons



Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with the share of affected persons at the median (Panels A to E) or at the 95th percentile of the distribution (Panels F to J) based on Equation (9). Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure D.4: Impacts of winter storms depending on the share of affected persons



Notes: Impact on employment (percentage point, left panels), hours worked (number of worked hours, middle panels) and real wage growth (percentage, right panels) for 0 to 30 months ahead with the 90 and 95% confidence intervals. Responses from the model with the share of affected persons at the median (Panels A to E) or at the 95th percentile of the distribution (Panels F to J) based on Equation (9).

E Appendix: Impacts of the top three largest disasters

Absent adaptation to natural disasters and as climate change intensifies, one may expect that the severity of future disasters could resemble that of the largest in our historical dataset. Hence, we use the shocks generated by the three most severe disasters, the 2016 Fort McMurray wildfire, the 2013 Alberta floods, and the 1998 ice storm, to gauge the impacts of extreme disasters in the future.

We estimate a variant of Equation (1) with three dummy variables for each of the three largest disasters. The coefficients of interest are now $\alpha_h^{d1}, \alpha_h^{d2}, \alpha_h^{d3}$. The new disaster dummy variables span two months for the Fort McMurray wildfire and the Alberta floods, or a single month over two provinces for the 1998 ice storm.[26]

$$\begin{aligned}
\Delta Y_{i,t+h:t-1} \quad = \quad & \alpha_h^{d1}\mathbb{1}(McMurray2016)_{i,t} + \alpha_h^{d2}\mathbb{1}(Calgary2013)_{i,t} + \alpha_h^{d3}\mathbb{1}(IceStorm1998)_{i,t} \\
& + \sum_{o\neq\{d1,d2,d3\}} \sum_{\substack{\tau=-12 \\ \tau\neq 0}}^{h} \alpha_h^o \mathbb{1}(disaster)_{i,t-\tau}^o \\
& + \sum_{\tau=1}^{3} \psi_h^\tau \Delta Y_{i,t-\tau:t-\tau-1} + \sum_{\tau=1}^{3} \phi_h^\tau GDP_{i,t-\tau} + \sum_{\tau=1}^{3} \rho_h^\tau logWTI_{i,t-\tau} \\
& + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h}.
\end{aligned} \tag{10}$$

Since the new dummy variables indicate individual events, the local projection estimation is likely less robust if other events occur in the affected provinces in the months before or after the disasters of interest. Similar to our baseline specification, we control for other individual disaster events with dummy variables $\mathbb{1}(disaster)^o$ such that $o\neq \{d1, d2, d3\}$ happening 12 months before and up to the month of interest $\tau=-12,\ldots,h,\ \tau\neq 0$ around the top three disasters.[27] We also add a control for crude oil prices since the 2016 Fort McMurray wildfire occurred in an oil-producing region just prior to a turning point in oil prices after the 2015 oil shock.[28]

Looking further in the tail of the disaster size distribution, we investigate the impact of the three largest disasters in our database: the 2016 Fort McMurray wildfire, the 2013 Alberta floods, and the 1998 ice storm. Figure E.1 shows the results of the estimation of Equation

[26] We could also add New Brunswick as an additional province affected by the ice storm, but New Brunswick received only 1% of the insurance cost, and maps of the affected area mainly cover southeast Ontario and southern Quebec, where most of the fatalities, power cuts and damages occurred. Including New Brunswick slightly increases uncertainty surrounding initial coefficient estimates.

[27] In particular, several disasters are recorded for Alberta the month before or after the 2016 Fort McMurray wildfire. The month before, there was a smaller wildfire with no reported dollar cost, such that it is unlikely to drive the effect. The month after, several storms and thunderstorms are recorded, but they occurred across the Prairies, such that we control for this disaster happening across several provinces while the Fort McMurray wildfire was specific to Alberta.

[28] More specifically, we use the Western Texas Intermediate prices. Adding this control does not significantly change our baseline results. Our results also remain robust if we control for up to 12 lags of dependent variables of the monthly GDP growth and of the oil price growth.

(10). Note that our identification approach for the largest disasters may be less robust since we can no longer rely on a large number of disaster events.[29]

Turning first to the 2016 Fort McMurray wildfire, we find significant impacts on each of the three labour measures. Despite its remoteness, the town of Fort McMurray is the epicentre of oil and gas extraction in Canada. The 2016 wildfire burned most of the town and had an immediate negative effect on employment that was strong enough to lead to a contraction of national GDP.[30] At its peak, the reduction in employment was of about 100 basis points. This likely explains the subsequent increase in hours worked about a year after the event—labour shortages related to displaced employees who lost their homes could result in longer hours for those remaining. The persistent negative impact on wages may also be the result of a change in the composition of employment, with the population of Fort McMurray still about 10% lower one year after the wildfire.

Second, we turn to the 2013 Alberta floods. Heavy rainfall mixed with melting snow coming down from the Rocky Mountains in June 2013 led to large-scale flooding, most importantly in southern Alberta. Among some of the hardest hit locations was Calgary, Alberta's largest city. Approximately 75,000 residents living along the Bow and Elbow Rivers were evacuated.[31] Large-scale flooding in the downtown areas left workers unable to travel to offices or retail locations, likely driving the immediate decline in hours worked (Figure E.1-E). However, even as waters began to recede four days later, the cost of damages was quickly estimated in the billions of dollars. Over the medium term, it led to a significant reduction in the employment rate, hours worked, and wage growth (Figure E.1-D to -F).

Finally, we investigate the impact of the 1998 ice storm. In January 1998, a series of ice storms moved across eastern Ontario and southern Quebec and together produce widespread outages and destruction. These events were significant enough to lead to the almost complete shutdown of cities like Ottawa and Montreal. In addition, the scale of power outages left some households without power for weeks. On impact, we note an immediate increase in hours worked, which likely reflects a need to clear roads and address power outages (Figure E.1-H). The scale of devastation, particularly to transmission towers and lines, combined with the frigid winter temperatures likely drove labour demand, as shown in the increase of almost 100 basis points of the employment rate within the first four months following the event (Figure E.1-G). Interestingly, this positive effect persisted several years after the event. The nature and extent of the damage could partially explain the estimated long-term effect on employment, since much of the power infrastructure, which spans vast distances, had to be rebuilt or upgraded.[32]

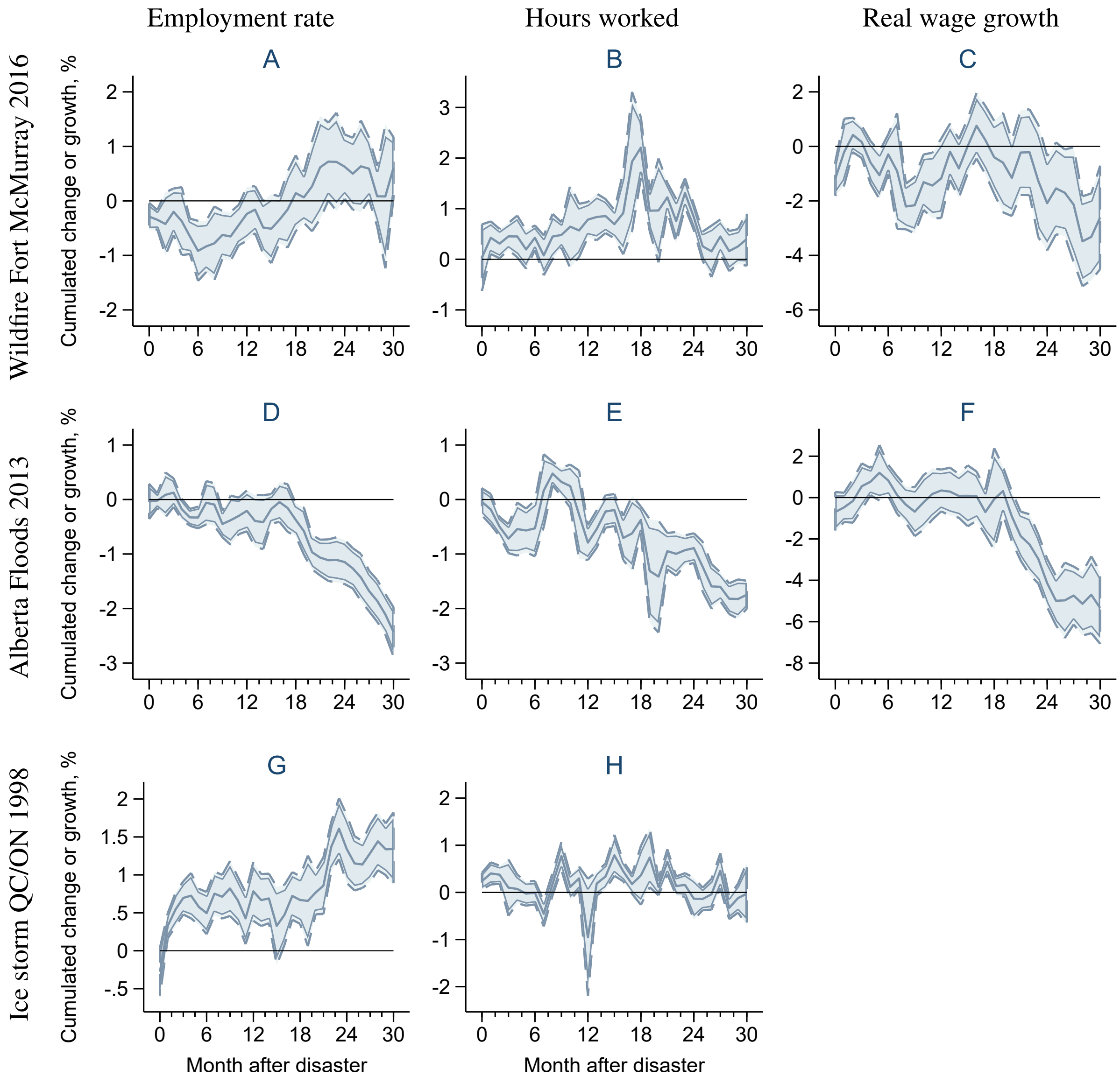
[29]Despite their notable impacts on the labour market, we confirm that these largest disasters are not solely driving the main results of the paper. In Appendix F we repeat our main specifications by leaving one disaster out at a time and find that a single observation event does not generally drive our baseline results.

[30]The interruption in oil extraction operations eventually lead to a 0.4% reduction in national GDP. Data source is Statistics Canada and National Gross Domestic Product by Income and by Expenditure Accounts https://www150.statcan.gc.ca/n1/pub/11-627-m/11-627-m2017007-eng.htm. Accessed September 22, 2023.

[31]The Calgary Herald published a timeline of the floods: https://calgaryherald.com/news/local-news/timeline-how-the-great-flood-of-2013-evolved. Accessed June 5, 2024.

[32]See Hydro-Quebec's website discussing changes made to power lines in the aftermath of 1998 ice storm for more information: https://www.hydroquebec.com/ice-storm-1998/after-the-storm.html. Accessed June 5,

Figure E.1: Impacts of Canada's top three natural disasters on the labour market



Notes: Impact on employment (percentage point, left panels), hours worked (number of hours, middle panels) and real wage growth (percentage, right panels) of the largest natural disasters in Canada for 0 to 30 months ahead with the 90 and 95% confidence intervals using Equation (10). The effects of the ice storm on real wages could not be estimated because the data start in 2001. The 2016 Fort McMurray wildfire had a cost of $4.4 billion, the 2013 Alberta floods a cost of $2.0 billion and the 1998 ice storm a cost of $2.6 billion (Insurance Bureau of Canada, 2021, in 2021 dollar terms).

2024.

F Appendix: Leave-one-out analysis

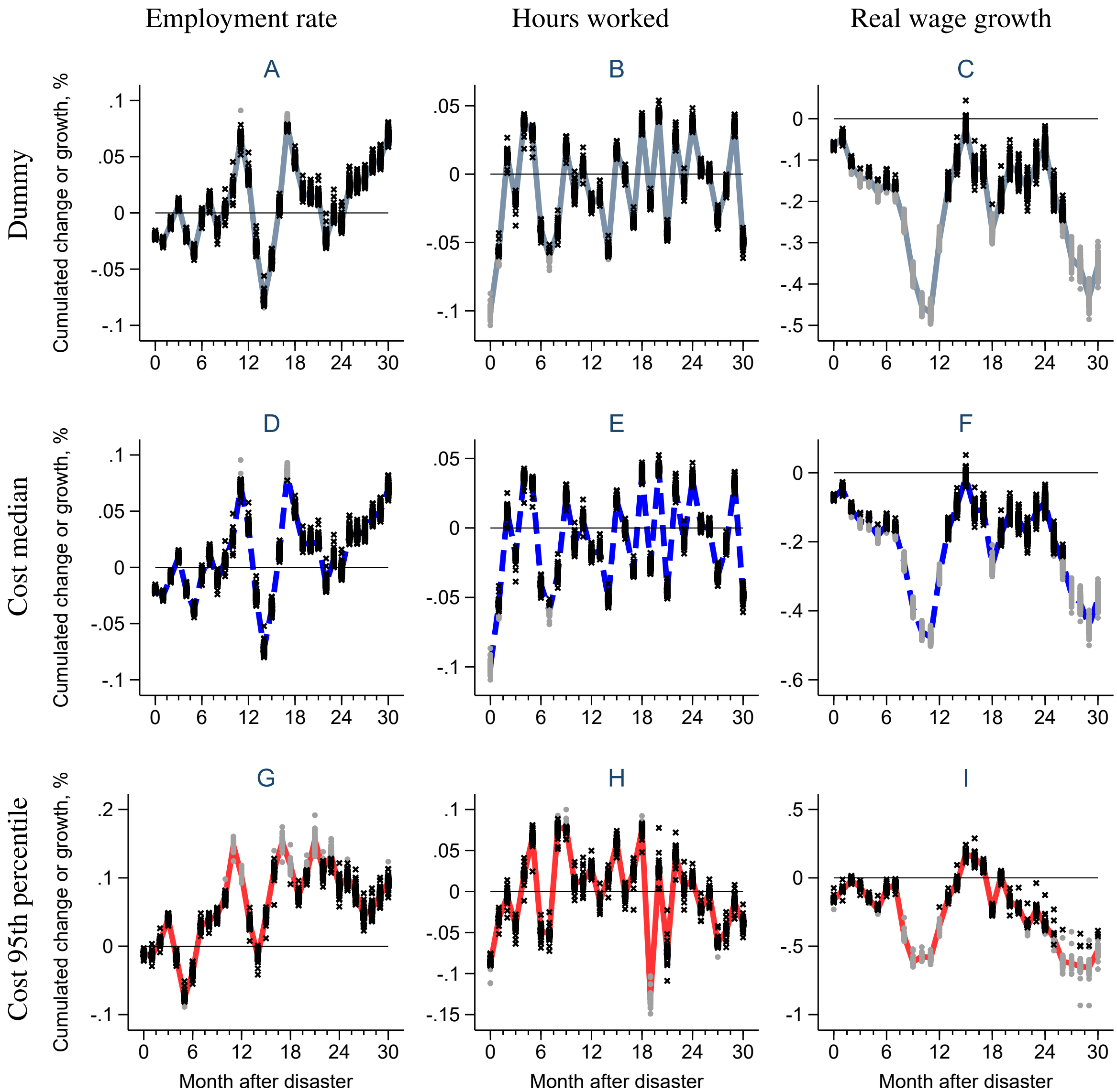
We test whether our results are driven by just one large outlier. We re-run the specification in Equation (5) by excluding one disaster $d\prime$ at a time. To exclude a disaster, we keep it in the sample but include it via a separate dummy $\mathbb{1}(disaster)^{d'}_{i,t}$ and cost variable $cost^{d'}_{i,t}$ that removes the effect of this disaster on the main parameters of interest $\{\alpha_h^{d\backslash d'}, \beta_h^{d\backslash d'}\}$:

$$\begin{aligned}
\Delta Y_{i,t+h:t-1} \;&=\; \sum_{d=1}^{4}\left\{\alpha_h^{d\backslash d'}\mathbb{1}(disaster)^{d\backslash d'}_{i,t} + \beta_h^{d\backslash d'} cost^{d\backslash d'}_{i,t} + \sum_{p=-12,\, p\neq 0}^{h} \alpha_h^{d,p}\mathbb{1}(disaster)^{d}_{i,t+p}\right\} \\
&\quad + \alpha_h^{d'}\mathbb{1}(disaster)^{d'}_{i,t} + \beta_h^{d'} cost^{d'}_{i,t} \\
&\quad + \sum_{\tau=1}^{3}\psi_h^{\tau}\Delta Y_{i,t-\tau:t-\tau-1} + \sum_{\tau=1}^{3}\phi_h^{\tau} GDP_{i,t-\tau} + \eta_i + \eta_y + \eta_m + \eta_{i,m} + \epsilon_{i,t+h} \qquad (11)
\end{aligned}$$

In the figures, each dot or cross corresponds to an estimation with a different d'. Each grey circle corresponds to a significant result, while each black cross corresponds to a non-significant estimate. So the estimation is robust to any outlier if, for a given time horizon, there are no black crosses: the result is not driven by a single event.

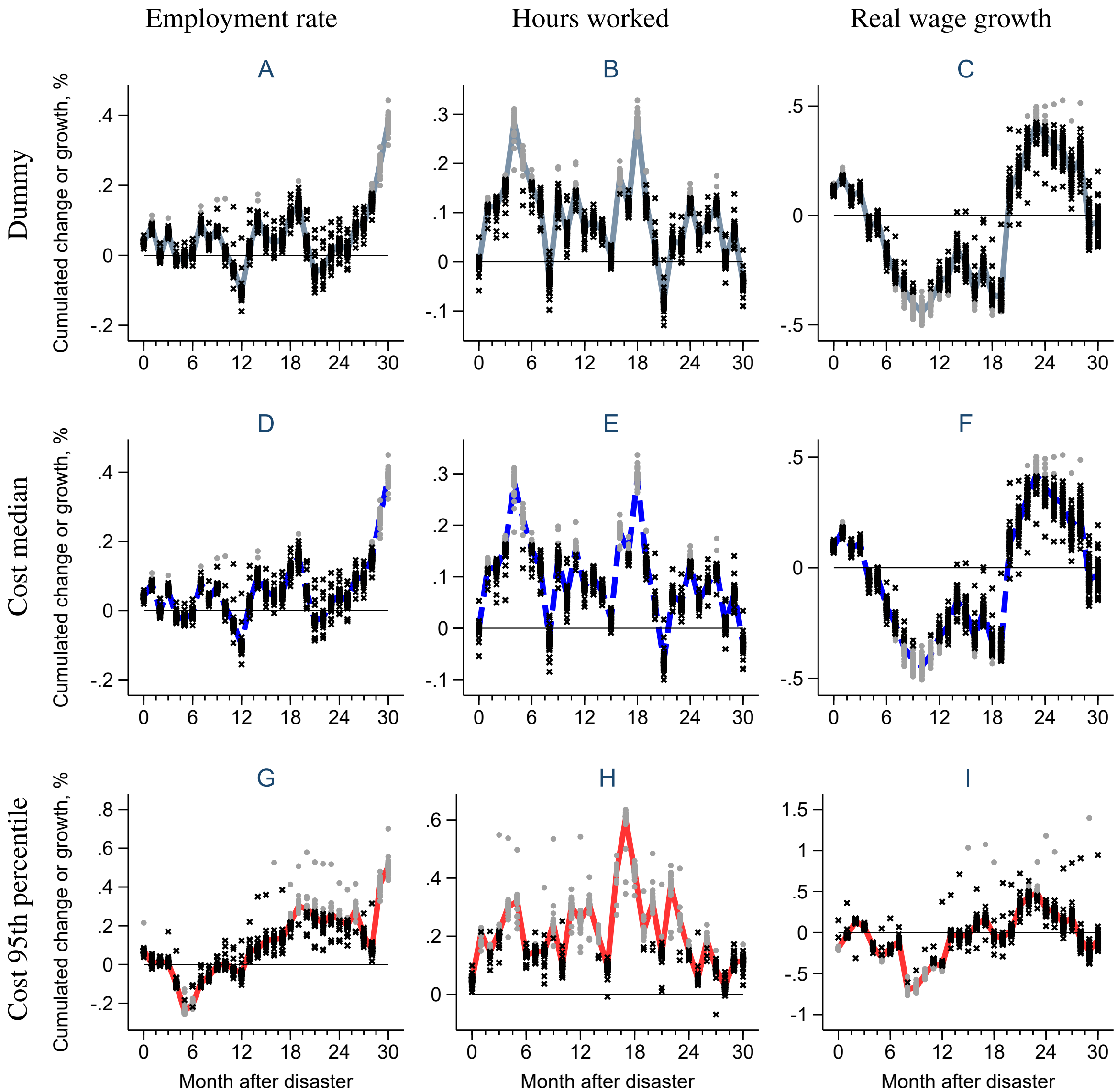
Our main results at the 5% significance threshold do not appear to be driven by a specific outlier, except for the response of the unemployment rate to wildfires in the 95th percentile of the cost distribution. In the latter case, significance across all combinations excluding one disaster at a time is restored if one estimates separately the disaster dummy parameter $\alpha_h^{d\backslash d'}$ for disasters with or without costs, as wildfires without reported costs tend to have a somewhat smaller effect on employment.

Figure F.1: Impacts excluding one disaster at a time



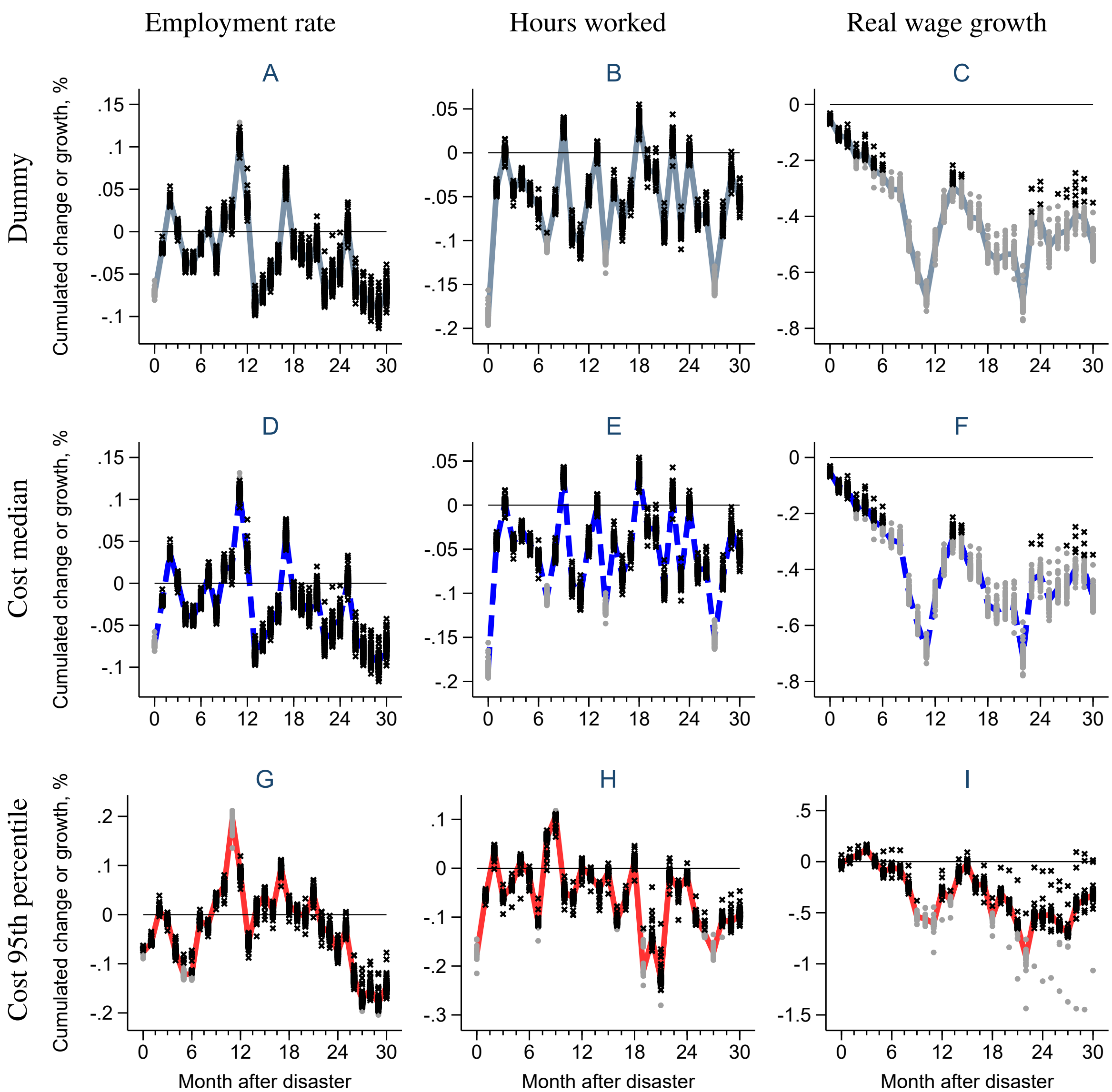
Notes: Results from Equation (11) that exclude one disaster at a time. Each panel is the marginal effect for a disaster at the median or at the 95th percentile of the cost distribution. A grey dot (black cross) represents the (in)significant estimate at the 5% confidence threshold obtained by excluding one disaster. The line is the mean across estimates. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure F.2: Impacts of wildfires: excluding one disaster at a time



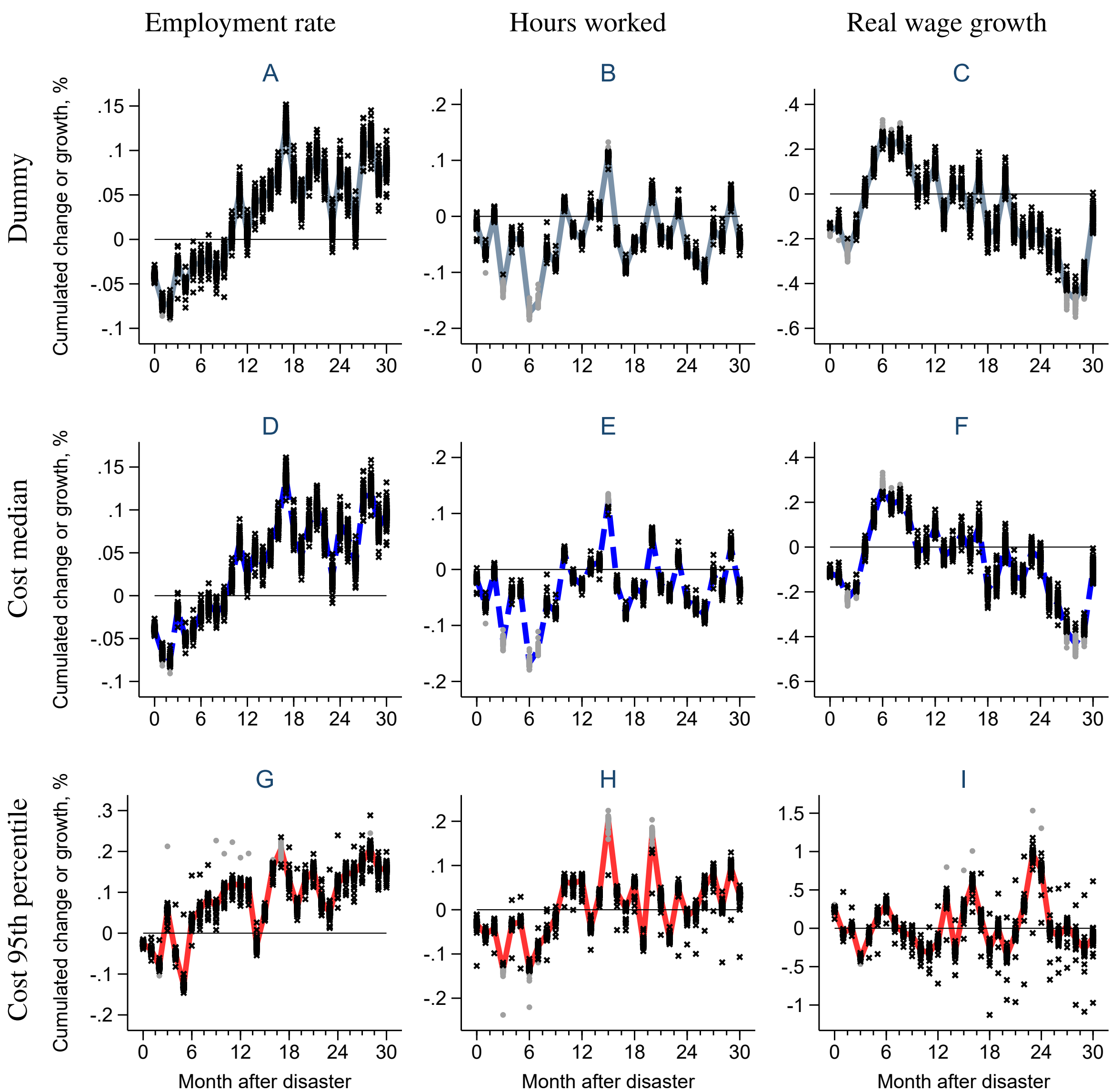
Notes: Results from Equation (11) that exclude one disaster at a time. Each panel is the marginal effect for a disaster at the median or at the 95th percentile of the cost distribution. A grey dot (black cross) represents the (in)significant estimate at the 5% confidence threshold obtained by excluding one disaster. The line is the mean across estimates. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure F.3: Impacts of floods: excluding one disaster at a time



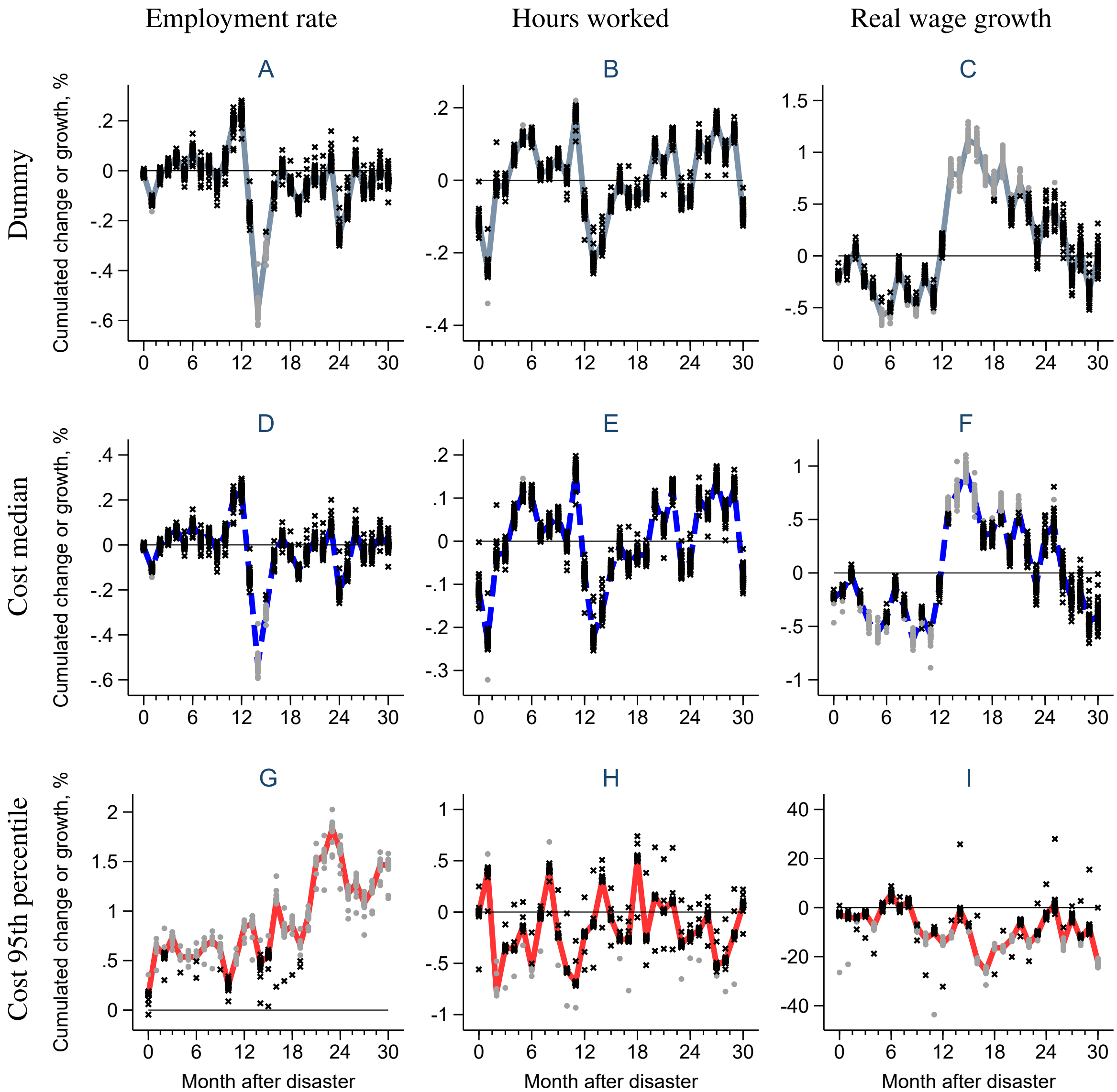
Notes: Results from Equation (11) that exclude one disaster at a time. Each panel is the marginal effect for a disaster at the median or at the 95th percentile of the cost distribution. A grey dot (black cross) represents the (in)significant estimate at the 5% confidence threshold obtained by excluding one disaster. The line is the mean across estimates. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure F.4: Impacts of storms: excluding one disaster at a time



Notes: Results from Equation (11) that exclude one disaster at a time. Each panel is the marginal effect for a disaster at the median or at the 95th percentile of the cost distribution. A grey dot (black cross) represents the (in)significant estimate at the 5% confidence threshold obtained by excluding one disaster. The line is the mean across estimates. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

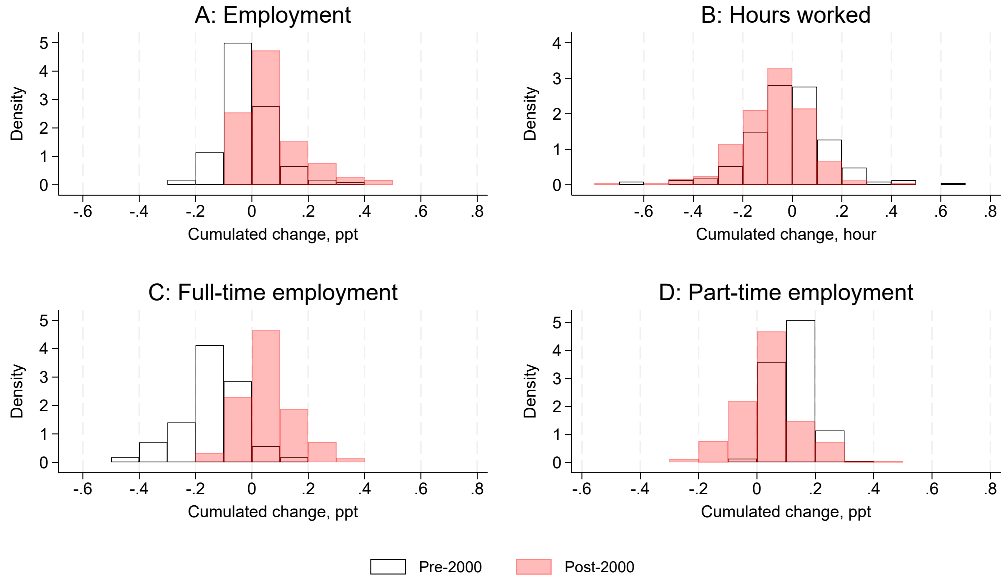
Figure F.5: Impacts of winter storms: excluding one disaster at a time



Notes: Results from Equation (11) that exclude one disaster at a time. Each panel is the marginal effect for a disaster at the median or at the 95th percentile of the cost distribution. A grey dot (black cross) represents the (in)significant estimate at the 5% confidence threshold obtained by excluding one disaster. The line is the mean across estimates. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

G Appendix: Simulated impacts over time using a binary disaster dummy

Figure G.1: Simulated impacts pre- and post-2000 using a binary disaster dummy

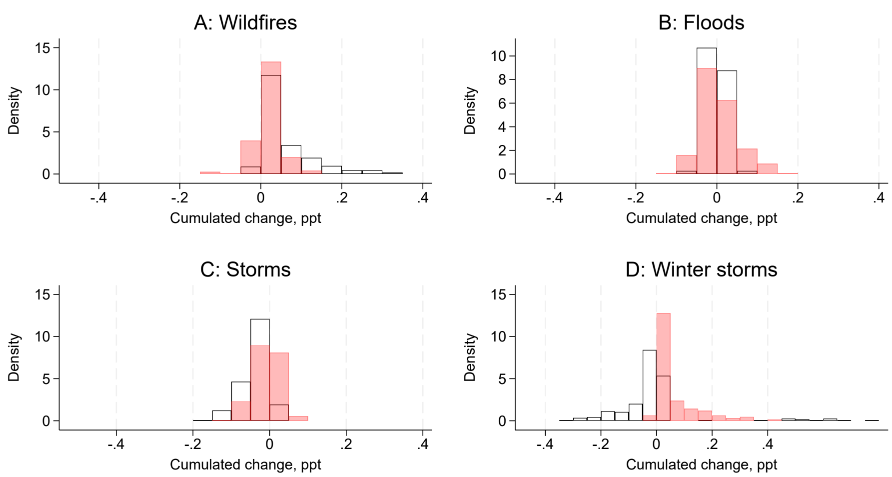


Notes: Simulated impacts of all types of natural disasters before and after 2000. The effects of each disaster are fitted for 0 to 12 months, based on Equation (1), and then aggregated at the Canada-wide level.

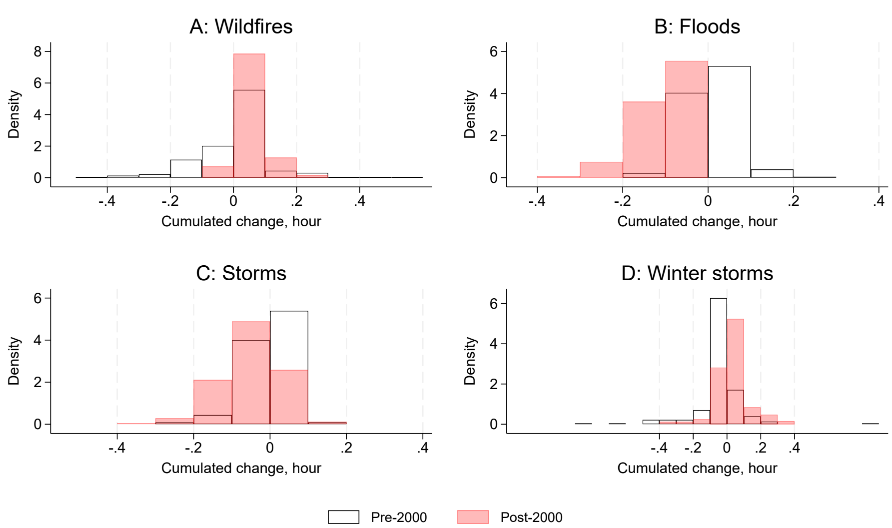
H Appendix: Disaster effects over time by disaster types

Figure H.1: Impact by disaster types pre- and post-2000

(i) Employment

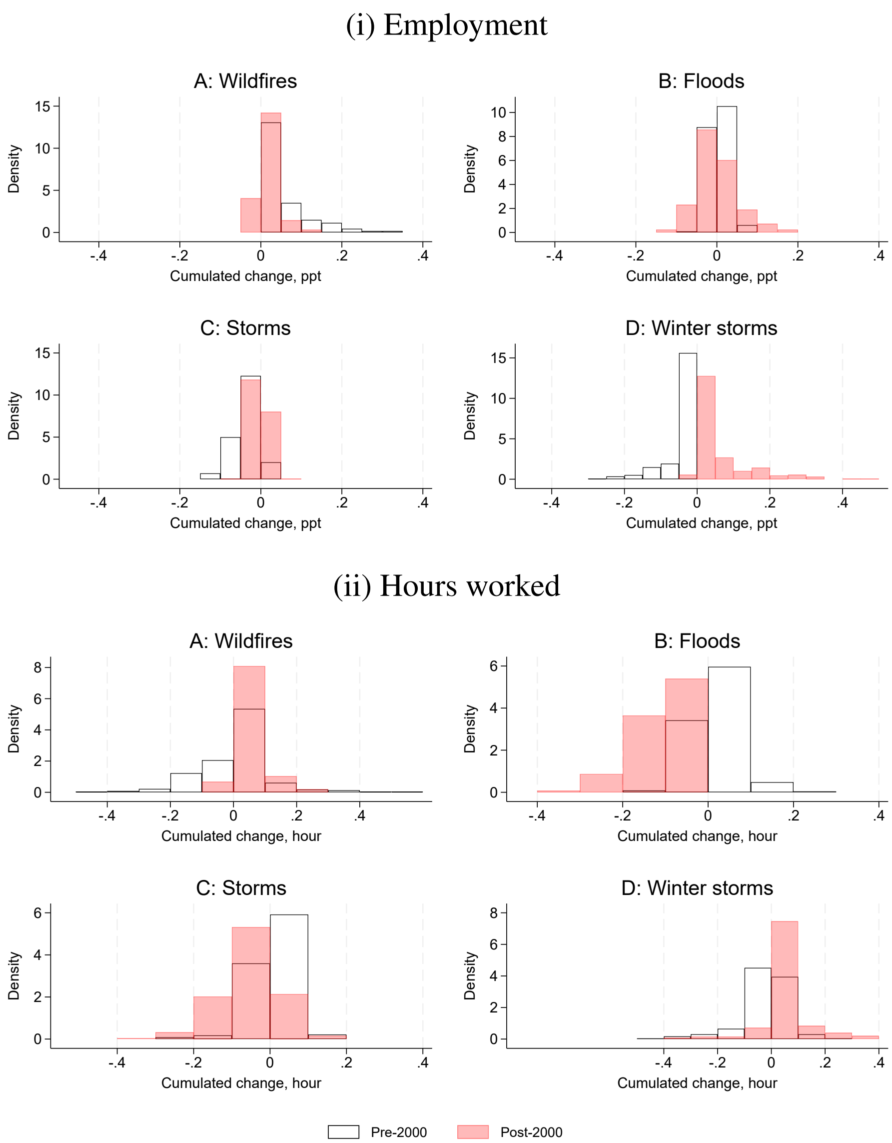


(ii) Hours worked



Notes: Simulated impacts of natural disasters on employment and hours worked before and after 2000. The effects of each disaster are simulated for 0 to 12 months, based on Equation (5), and then aggregated at the Canada-wide level. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.

Figure H.2: Simulated impacts by disaster type pre- and post-2000 using a binary disaster dummy



Notes: Simulated impacts of natural disasters on employment and hours worked before and after 2000. The effects of each disaster are simulated for 0 to 12 months, based on Equation (1), and then aggregated at the Canada-wide level. Storms include thunderstorms, hurricanes and tornadoes but exclude winter storms, which are left as a separate category.