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

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Abstract

We quantify the distributional impacts of climate change physical risks on employment, using narrative evidences of monthly natural disasters collected across 10 Canadian provinces over 40 years. We use a novel panel quantile local projection approach, which takes into account that natural disasters are tail events, localized in space and time, and hard to predicted in a given month-province. We find that the odds of a high provincial employment rate decreases on impact, but the effect tends to become positive as the economy recovers from a disaster. We also find substantial heterogeneity across different sectors, employment status and disaster types.

Keywords: Natural disasters, climate change, employment, panel quantile local projection.

JEL Codes: E24, O13, Q54

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1 Introduction

The frequency and severity of natural disasters is rising (Imada et al., 2018; Walsh et al., 2018; Knutson et al., 2018) as a result of anthropogenic climate change (Intergovernmental Panel on Climate Change (IPCC), 2007, 2013). Natural disasters are locally disruptive events that can be destructive on capital, lives, and/or individuals ability to generate income. These effects can potentially propagate to the wider economy or financial system, even if partly covered by insurances.[1] Households can be impacted, either directly through improper insurance coverage or indirectly through an income channel. For instance, Ho et al. (forthcoming) show that the 2016 Fort McMurray wildfires, the most costly natural disaster in Canada, led to a significant rise in mortgage arrears in those areas where damages were most severe. The disruptions to the production chains, the destruction of productive capital or temporary changes in the composition of the labor force could lead to income shortfalls for households that, combined with the physical destruction of properties not well insured, could lead to households' defaults and losses to the financial system.[2]

In this paper, we quantify the effect of natural disasters on employment to shed light on the the income effect through which physical risk can affect households. We compile narrative shocks for natural disasters using the Canadian Disaster Database (CDD) maintained by Public Safety Canada, similar in spirit to narrative shocks for monetary and fiscal policies of e.g. Romer and Romer (2004, 2010) or Ramey and Zubairy (2018). We then use our monthly panel of natural disaster shocks across 10 Canadian provinces over 1980-2019 to project the impact on the labor market across different disaster types and industries in a local projection framework, inspired by Jordá (2005). In particular, we evaluate overall risks posed by such natural disasters by gauging implications across quantiles of employments, not limited to possible changes in the mean.

Our novel approach combined with the province-month panel data provides us several advan-

[1] Canadian insurances covered 2.1 billion of climate-related losses in 2021. 2020 and 2021 in Canada rank respectively as the fourth and sixth years of largest insured losses since 1983. See Insurance Bureau of Canada: http://www.ibc.ca/ns/resources/media-centre/media-releases/severe-weather-in-2021-caused-2-1-billion-in-insured-damage.

[2] Independent banks, for instance, are less resilient than bank holding companies given their more limited geographical diversification (Raykov and Silva-Buston, 2020).

tages for gauging the economic implications of natural disasters. First, the use of disaster-level data allows us to draw causal inference, as provincial macroeconomic conditions over the recent years are unlikely to cause the frequency or the location of extreme weather events. Mitigating actions by local authorities may reduce the odds of some events, like floods (new dam) or wildfires (construction zoning), but it is unlikely over the data frequency we consider. Hence, these natural disasters can be treated as exogenous shocks in a given month and location.

Second, the detailed data enables us to quantify the costs clearly. It is due to the fact that most of the natural disasters are localized in terms of space and time. For instance, extreme weather events last on average 7 days in our sample. Hence, estimating the impact at a lower frequency that monthly would water down the effect of smaller disasters. Also, most disasters affect only one province. Thus, our province-level data allows us to pin down the area that are most affected by a certain disaster and examine the resulting changes in the local economy.[3]

Finally, with our empirical framework, we can move away from mean effects and see if disasters can change the odds of a higher or lower employment. We combine the quantile estimator of Koenker and Bassett (1978) with the local projection of Jordá (2005) to estimate quantile local projections (Loria et al., 2019; Han et al., 2019), that we extend to a panel dimension to capture provincial effects. With this, we can focus on tail elasticities, because disasters are extreme tail events that can have non-linear effects. For instance, natural disasters may interact with pre-existing vulnerabilities such that it could make unemployment more likely to increase, without necessarily changing the mean forecast of unemployment. If so, a mean model would fail to capture those tail effects. Eventually, quarterly, country-wide, and mean estimators would miss the significant effect of natural disasters on employment.

Our findings are as follows. Overall, for a disaster with a cost as high as 20 percent of monthly provincial GDP (the most severe disaster in the period under study), we find an increase of the unemployment rate, by up to 120 basis points in the 95-th percentile of the distribution of unemployment, on impact, before the effect dissipates. We decompose the effect across disasters,

[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.

industries, employment status and time horizon. The decomposition highlights the heterogeneous impacts of disasters.

The higher odds of observing a high provincial unemployment rate on impact is largely driven by employment in the retail sector, mostly following storms and wildfires. However, this is offset by the higher odds of seeing more employment within three months from a disaster, for both the retail and the manufacturing sectors, mainly in the case of storms. Theses subsequent positive responses following the initial destruction is consistent with the evidence supporting the "build back better" hypothesis, documented in Tran and Wilson (2021), as well as the short-lived impacts on workers incomes (Deryugina et al., 2018).

Looking at the composition of employment, we find that the positive impact of disasters on employment is mostly concentrated in part-time workers. Part-time employment increases for the construction sector both on impact and within three months, mostly driven by floods and to a lesser extent by other disaster types. This likely reflects the need for temporary workers to rebuild after the destruction brought by the disasters. This is consistent with findings from Groen et al. (2016) who also document an increase in labour demand in the construction sector in the aftermath of a disaster. Conversely, floods tend to be associated, on impact, with lower part-time employment in the manufacturing sector and lower odds of full-time employment in the retail sector, possibly because of flooded factories and retail stores. Storms are more associated with higher odds of full-time employment for the manufacturing sector with a more persistent effect, while wildfires are associated with higher part-time employment particularly for the manufacturing sector.

Our paper relates to several contemporaneous papers that are part of a growing body of literature focused on transition and physical risks associated with climate change. For instance, Kim et al. (2021) use a smoothed-transition vector autoregressive (VAR) models and find that extreme weather causes persistent damages to economic growth in the U.S., and such negative impacts are more notable in the recent periods. Gallic and Vermandel (2020) use a general equilibrium model with a weather-dependent agricultural sector to assess the contribution of weather shocks on the volatility of output and the implied welfare costs. Kiley (2021) uses a panel quantile regression

on 125 countries and finds that climate change, measured by temperature anomalies, makes contractions in per capita GDP more likely and severe. Instead of focusing on the macroeconomic costs associated with temperature shocks, similarly to us, Tran and Wilson (2021) use natural disaster shocks to quantify macroeconomic impacts. They use U.S. county level data in a panel local projection framework, with frequencies ranging from monthly to yearly depending on the data available. They find that such shocks lead to a decline in the average income per capita but it can generate a medium- to longer- run boost in the local economy. Our study complements this literature using the province-month panel data of Canada. More specifically, we extend the study of the economic impacts of natural disasters by gauging their overall distributional impacts on the labor market across quantiles while incorporating heterogeneous transmissions across sectors and employment status.

Our findings have important policy implications. First, natural disasters can be associated with negative employment shocks in the short run. Thus, when assessing the overall cost of natural disasters or running climate-related stress-tests, policy-makers should not focus only on the insurance costs but also add the cost in terms of lost jobs and distorted income flows. Second, when combined with the destruction of physical assets, the lost income and jobs (as well as the job recovery afterwards) should be jointly considered when assessing households vulnerabilities: a loss of income is one of the main source of households defaults that can generate losses for the financial system. Third, local policy makers need to take into account the heterogeneity across disaster types and sector/employment status when designing the size of a disaster relief funding. It could be that the positive effect on employment after certain disasters for some industries is the outcome of an endogenous rebound of the local economy, or the reflection of delayed relief funds that may over-compensate for the losses. Fourth, there is a distributional aspect of climate disasters: households are not equally exposed to disaster risks based on their location, but also based on the industry their job belongs to. For instance, households living in areas prone to wildfires or storms and working in retail industries are more likely to lose their job, and part-time workers in the construction and manufacturing industries are most likely to benefit, especially from the

recovery phase after a disaster.

The rest of the paper is organized as the follows. Section 2 describes the weather disaster and the province-level data sets in detail. Section 3 presents the baseline panel quantile local projection model. Section 4 shows results for provincial (un)employment, further disaggregated by industries as well as full- and part-time employment status. Finally, section 5 concludes.

2 Data

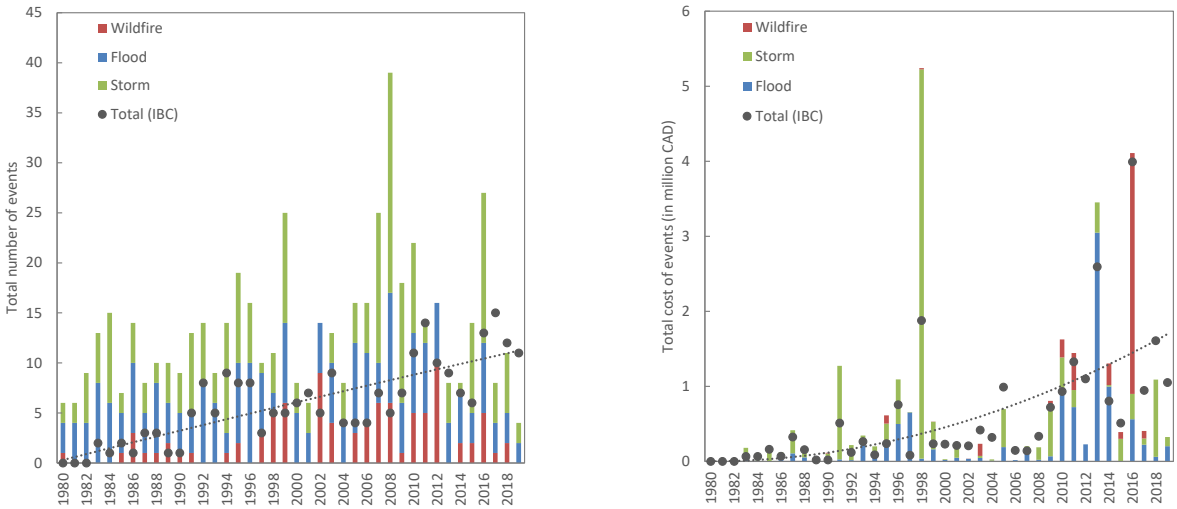
We leverage data on 513 disaster events from the Canadian Disaster Database (CDD) compiled by Public Safety Canada. These events regroup disasters that meet criteria outlined by the Ministers Responsible For Emergency Management (2017), and affected a community "in a way that exceeds or overwhelms that community's ability to cope" and led to one of the following: 10 or more people killed; 100 or more people injured, evacuated or left homeless; an appeal for national or international assistance; historical significance; or significant damage or interruption affecting the community's ability to recover on its own.

We reclassify certain events into three broader types: storms, floods, and wildfires[4]. Figure 1a shows the annual frequency and Figure 1b highlights the annual cost of damages of different disasters from our data set from 1980 to April 2019. We see that during this 40-year period, the number of occurrences of all three disasters tend to increase as well as the severity reflected in increasing costs: this shows that these disasters do reflect the underlying trend of climate change. We also plot another estimates on the number and cost of disasters from the Insurance Bureau of Canada (IBC) in Figure 1, and a similar increasing trend is observed over our sample period in both cases. One important feature of climate change is that it is not limited to the temperature rise. Rather, rising temperatures also increase the sea level and further affects the frequency and the severity of the extreme weather events, see Intergovernmental Panel on Climate Change (IPCC) (2007, 2013).

[4]The former includes everything from winter storms, thunderstorms, hurricanes, and tornadoes; floods regroups storm surges and other flooding events; and finally wildfires only includes these types of events.

Figure 1: Annual number and cost of disasters events in Canada since 1980

(a) Number of disasters **(b) Cost of disaster**

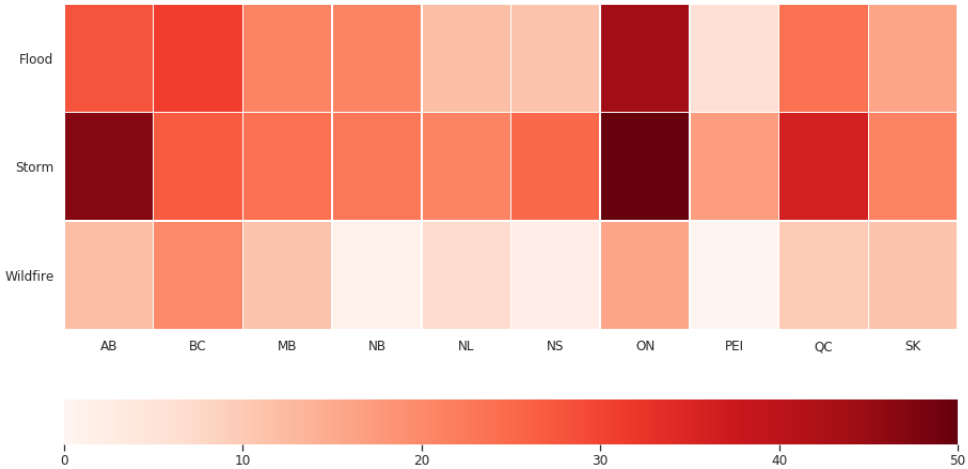


Notes: Number of disasters refers to total number of events reported in the Canadian Disaster Database (CDD) since 1980, as defined by the Ministers Responsible For Emergency Management (2017). Cost of disasters refers to total cost from insurances and federal assistance programs across all events for which a cost estimate is available. Storms include everything from winter storms, thunderstorms, hurricanes, and tornadoes; floods regroup storm surges and other flooding events. We include data from the Insurance Bureau of Canada (2021) (IBC) represented by dots for comparison. Compared to the IBC data, the CDD data includes federal government emergency funding. Note that the CDD data ends in April 2019 and thus the datapoint for 2019 is not complete compared to the IBC dataset.

Figure 2 highlights the uneven distribution of disaster events across provinces, with Ontario and Alberta particularly exposed to the three types of disasters. The seasonality of the different types of disasters can be seen in Table 1. Extreme flood and storm events occur all year round, while wildfires are constrained to the spring and summer months. In terms of costs, damages associated with spring flooding and winter storms tend to be highest. On the other hand, despite a more constrained season, wildfires can be devastating and lead to large costs. For instance, the Fort McMurray wildfire of May 2016 in Alberta is the costliest disaster in our sample with a total insurance cost of about 4 billions as reported by the Insurance Bureau of Canada (2021), followed by the January 1998 ice storm in Eastern Canada at 2 billions (both numbers in 2020 dollar terms).

Using the CDD data, we construct two monthly provincial panels spanning from 1980 to 2019. The first panel identifies extreme weather events across provinces using a binary indicator variables

Figure 2: Heatmap of all disaster events by types across provinces, 1980-2019



Notes: Total number of disasters across Canadian provinces reported in the Canadian Disaster Database (CDD) since 1980, as defined by the Ministers Responsible For Emergency Management (2017). A darker color reflects a higher number of disasters in a given province. Storms include everything from winter storms, thunderstorms, hurricanes, and tornadoes; floods regroup storm surges and other flooding events.

Table 1: Monthly average cost and count of extreme floods, storms, and wildfires, 1980-2019

	Floods		Storms		Wildfires	
	Mean $	*N*	Mean $	*N*	Mean $	*N*
January	3	17	620	17	-	1
February	4	11	50	14	-	-
March	17	18	20	13	-	1
April	75	43	48	10	5	4
May	43	20	88	15	543	25
June	250	29	38	22	4	23
July	116	23	73	42	157	23
August	39	11	66	32	2	7
September	45	5	127	18	-	2
October	12	7	8	11	-	1
November	30	9	58	10	-	-
December	15	9	211	20	-	-
Total	50	202	117	224	134	87

Note: Mean costs are in millions of CAD and calculated only for events for which data on cost is available. *N* represents the total number of events in our dataset.

in the month a disaster occurred. If there were multiple disasters in a province in a given month, we sum up all occurrences. We construct an index capturing total number of all three disasters as well as indexes separated by disaster types. Figure 9 shows the monthly indexes of the total number of disasters for 10 provinces.

Our second panel focuses on those 301 events for which costs of damages are available. Disaster costs comprise of the insurance payouts[5], costs associated to damages incurred by municipalities and provinces, as well as financial assistance provided through provincial and federal Disaster Financial Assistance Arrangements (DFAA) and NGOs. This provides us one way of gauging the severity of disasters, differently from the first panel. One caveat of the cost estimates is that the CDD data does not provide a breakdown of cost by province, but only aggregate cost for entire affected region. Hence, we evenly split the estimated cost across all affected provinces when a disaster hits multiple provinces. To standardize the impact, we normalize these cost by monthly provincial GDP. We use quarterly provincial GDP spliced at the monthly frequency using the monthly variation of the country-level GDP available from 1997 onwards and using the monthly variation of the country-level industrial production index available before 1997.[6] Figure 10 shows the monthly indexes of the relative cost of disasters for 10 provinces, as used in our econometrics analysis.

We want to relate our natural disaster shock series to provincial employment data.[7] We consider the unemployment rate, the employment rate, the full-time employment rate, the part-time employment rate, by industry and by province. Although we have employment data for all NAICS sectors at the 2 digits level, we focus on the construction sector (NAICS 23), the manufacturing sector (NAICS 31-33) and the retail trade sector (NAICS 44-45).

[5]We supplement 4 disasters from the CDD with cost information sourced from the IBC.

[6]Quarterly provincial GDP from The Conference Board of Canada; monthly Canada-wide GDP from Table 36-10-0434-02 of Statistics Canada; monthly Canada-wide industrial production index CANPROINDMISMEI from the FRED database of the Federal Reserve Bank of St. Louis; monthly provincial consumer price index from Table 18-10-0004-01 of Statistics Canada. All data are seasonally adjusted using the X12 seasonal adjustment procedure.

[7]Table 14-10-0287-03 from Statistics Canada.

3 Methodology

Our empirical strategy is driven by the fact that natural disasters are tail events, possibly locally severe events, and difficult to predict. Thus, we build on the local projection model by Jordá (2005). This framework has been extended to gauge the impacts of exogenous shocks in a panel setting (see Tran and Wilson (2021), for example). Others combined the local projection framework with quantile estimator of Koenker and Bassett (1978) and estimated distributional impacts of shocks (Loria et al., 2019; Han et al., 2019). We hence build on the two lines of literature and estimate the panel quantile local projection model, as following:

$$Q_{Y_{c,t+h}|\tau} = \sum_{c=1}^{10} \mu_{c,h,\tau} + \sum_{m=1}^{12} \phi_{m,\tau} + \sum_{l=1}^{L} \beta_{l,h,\tau} Y_{c,t-l} + \gamma_{h,\tau} gdp_{c,t-1} + \alpha_{h,\tau} \mathbb{1}(disaster)_t. \quad (1)$$

Here, c denotes a province and we use $C = 10$ Canadian provinces.[8] Quantiles are indexed by τ; Y_c is a province-level monthly variable of interest, capturing the labor market dynamics, with a specific observation y_c. The corresponding density and inverse cumulated density function are denoted as $f_{Y_c|\cdot}$ and $F^{-1}_{Y_c|\cdot}$, respectively. $Q_\tau \equiv F^{-1}(\tau)$ then represents the quantile operator of order τ. Finally, $Q_{Y_{c,t+h}|\tau}$ denotes the conditional quantile of $Y_{c,t+h}$ for horizon h.

We assume a province dummy ($\mu_{c,h,\tau}$) and a month dummy ($\phi_{m,\tau}$) are part of the distribution of Y_c, to control for any province-specific effects or any remaining seasonality in the labor market. We also include $L = 3$ lags of the variable of interest to capture a potential dependence structure of Y_c. Finally, we add the spliced monthly provincial GDP growth, as overall provincial economic conditions likely affect the distribution of labor market indicators.

We run a different estimation for different horizon $h \in [0, 1, ..., 4]$ and for quantiles $\tau \in [.05, .10, ..., .95]$. In doing so, we use different extreme weather shock series, noted as $\mathbb{1}(disaster)$, as discussed in Section 2. It can be an index counting the number of total disasters or a subset of disasters. Or it can be a series capturing the relative cost of disasters. Our baseline approach uses

[8] We exclude Northern territories, Yukon, and Nunavut from our analysis, as too few disasters that meet the criterion of the CDD are observed in those provinces.

the latter shock series weighted by the cost estimates relative to monthly provincial GDP.

We define a quantile-specific residual $\eta_{c,t+h,\tau} \equiv y_{c,t+h} - Q_{Y_{c,t+h}|\tau}$ such that $Q_\tau\left(\eta_{c,t+h,\tau}\right) = 0$. Then, Equation (1) can be rewritten as:

$$Y_{c,t+h} = \sum_{c=1}^{10} \mu_{c,h,\tau} + \sum_{m=1}^{12} \phi_{m,\tau} + \sum_{l=1}^{L} \beta_{l,h,\tau} Y_{c,t-l} + \gamma_{h,\tau} gdp_{c,t-1} + \alpha_{h,\tau} \mathbb{1}(disaster)_t + \eta_{c,t+h,\tau}. \quad (2)$$

From Equation (2), we can see that the disaster dummy acts as an external instrument for the identification of the disaster shock α_τ that is homogeneous across provinces but heterogeneous across the distribution of the variable of interest. The remaining shocks that are not identified are left in the province and quantile-specific residual term $\eta_{c,t+h,\tau}$.

The parameters $\{\mu_{c,\tau}, \phi_{m,\tau}, \beta_{l,\tau}, \gamma_{tau}, \alpha_\tau\}$ are estimated separately for each quantile τ using the linear quantile regression method of Koenker and Bassett (1978) with the check function $\rho_\tau = u(\tau - \mathbb{1}(u < 0))$:

$$\{\mu_{c,h,\tau}, \phi_{m,h,\tau}, \beta_{l,h,\tau}, \gamma_{h,\tau}, \alpha_{h,\tau}\} = \underset{\{\mu_{c,h,\tau}, \phi_{m,\tau}, \beta_{l,h,\tau}, \alpha_{h,\tau}\}}{\operatorname{argmin}} \sum_t \rho_\tau \left(y_{c,t+h} - \sum_{c=1}^{10} \mu_{c,h,\tau} - \sum_{m=1}^{12} \phi_{m,\tau} - \sum_{l=1}^{L} \beta_{l,h,\tau} Y_{c,t-l} - \gamma_{h,\tau} gdp_{c,t-1} - \alpha_{h,\tau} \mathbb{1}\left(disaster\right)_t \right).$$

If the parameters are all identical across quantiles τ, then one can drop the quantile specific subscript τ. If so, the assumption of a location shift without shape shifts with the ordinary least square would be enough and more efficient.

Note that the estimations for each quantiles are performed independently, as it is standard in the literature, even though it uses the same data. Thus, if we wanted to simulate the conditional distribution of $Y_{c,t+h}$, quantile predictions might cross, which directly contradicts the monotonicity of quantiles of $Y_{c,t+h}$ with respect to τ.[9] However, we are not focusing on quantile predictions of $Y_{c,t+h}$. We are solely interested in the set of parameters $\alpha_{h,\tau}$ that govern the impact of disasters, from which we cannot infer that quantile crossings would occur. Crossings may not occur if

[9]This quantile crossing is a well-known consequence of the linear form of the conditional quantiles in Koenker's estimator.

the marginal impact is relatively small. If we were interested in the quantile predictions of the employment related distributions, we could follow Chernozhukov et al. (2010) to effectively solve the quantile crossing problem, by sorting conditional quantile predictions, but, in this setup, the model parameters would remain unchanged.[10] Thus we prefer to report the marginal effects as is and focus on their possible significance across some parts of the distribution of employment data.

4 Results

This section presents our findings from estimating the baseline model where the relative cost of disasters to monthly provincial GDP is used as a measure of disaster shocks. Table 2 synthesizes the impact of natural disasters across all measures of labor market indicators under study. The table shows the changes in the overall distribution on impact and 3 months later, further broken down by disaster types.

In sum, natural disasters tend to have a negative effect on total employment on impact, particularly that of the retail sector. Looking into sectoral impacts, construction employment experiences a positive effect in three months following disasters. Together, these results support findings that show natural disasters are destructive in the short run, creating transitory disruptions in the labor market, but are often followed by rebuilding efforts that boost labour demand (Deryugina et al., 2018; Groen et al., 2016; Tran and Wilson, 2021).

We also find a substantial heterogeneity across different types of disasters and employment status. For instance, the observed rebound effects for overall employment appears strongest for storms. In the case of wildfires and floods, such effects are rather muted and concentrated to specific sectors. Also, the distributional impacts on part-time employment appear to be stronger compared to full-time employment.

[10] Several other solutions to the crossing problem have been proposed, but they are usually more data-intensive, namely by He (1997) and Bondell et al. (2010), who impose a set of restrictions on the quantile process to preserve monotonicity, and Schmidt and Zhu (2016), who model the spacings between adjacent quantiles as positive functions.

Table 2: Summary of the Quantile Responses of Labor

Disaster type	Combined		Floods		Storms		Wildfires	
	impact	3 mths	impact	3 mths	impact	3 mths	impact	3 mths
Unemployment rate								
total	·· →	···	···	···	···	· ← ·	···	→ ··
construction	···	···	···	···	···	· ← ·	···	···
retail	← · →	←← ·	← ··	← ··	···	← ··	→→ ·	···
manufacturing	···	···	···	···	← ··	← ··	···	···
Employment rate								
total	← ··	···	···	···	← ··	→→ ·	···	···
construction	···	···	···	···	···	· →→	···	···
retail	← · →	·· →	· →→	···	← ··	· →→	· ←←	···
manufacturing	···	·· →	···	···	·· →	·· →	···	···
Full-time emp. rate								
total	···	···	→→ ·	→ ··	···	···	← ··	·· ←
construction	···	···	···	···	···	···	···	···
retail	···	···	→→ ·	···	···	···	···	···
manufacturing	···	·· →	···	···	···	·· →	· ← ·	← ··
Part-time emp. rate								
total	· ← ·	···	···	← ··	·· ←	·· →	·· →	···
construction	→ ··	· →→	→→ ·	· →→	···	· →→	···	→ · →
retail	···	···	···	···	···	···	···	···
manufacturing	← · →	·· →	← · →	·· →	···	···	→→→	→ ··

Notes: This table summarizes estimation results from the baseline model. The three symbols in each cell denote changes in 5 to 35, 40 to 60, and 65 to 95 percentiles, respectively. "←" ("→") implies that the respective part of the distribution moves to the left (right). "·" shows no significant changes in the corresponding part of the distribution.

4.1 Effects of Disasters on Overall (Un)Employment

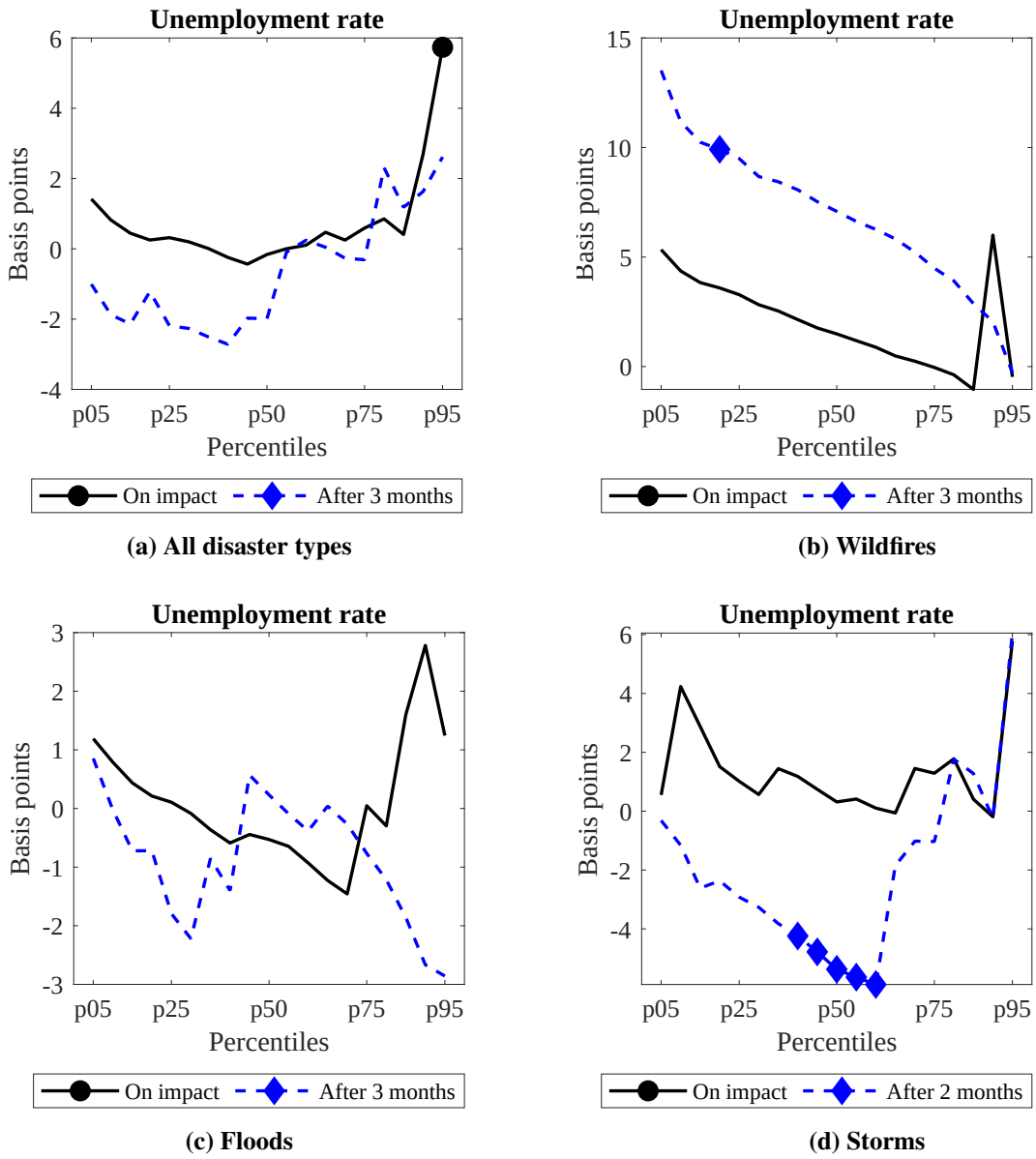
Across all sectors and all natural disaster types, the odds of a higher provincial unemployment rate increases on impact after a natural disaster (Figure 3a), but this effect is short-lived. A natural disaster with a reported cost equivalent to 1 percent of monthly provincial GDP is associated with a 6 basis points increase in the unemployment rate in the upper percentiles of its distribution. For a disaster with a cost as high as 20 percent of monthly provincial GDP (the most severe disaster in the period under study), it implies an increase of the unemployment rate by up to 120 basis points

in the 95-th percentile on impact. Not surprisingly, the inverse result holds true when considering the impact on employment, further confirming our result. However, the overall response of total unemployment and employment hides some heterogeneity across disaster types and across sectors.

Across disaster types, we also observe a tendency towards higher odds of high unemployment on impact, but it is not significant. There are more nuances in the effect within three months. For wildfires (Figure 3b), the effect tends to become stronger within the first three months, likely in part because wildfires tend to last anywhere from a few days to a few months. For storms (Figure 3d), the effect tends to go in the opposite direction within the first three months, with lower median unemployment and a peak effect after 2 months. This rebound effect in the labor market is also observed for the distributional impacts on employment, particularly in the case of storms.

Figure 4 displays the response of employment rates split across sectors. As expected, we observe a lower employment rate in the lower percentiles across industries (as such, it mirrors the higher unemployment rate in the higher percentiles in Figure 3a). Changes in employment rate on impact is largely driven by the retail sector. The lower employment in the lower percentiles of the distribution is largely due to the responses to storms and is even more broad-based for wildfires. The retail sector also faces a higher employment in the upper percentiles of the distribution coming from floods. Within the first three months after the start of the disaster, the odds of a higher employment rate increase for both the retail and the manufacturing sectors, and this is driven by storms. More generally, the employment rate after a storm that destroys 1 percent of monthly provincial GDP moves the upper half of the distribution of employment by about 20 basis points within three months for the retail, manufacturing and construction sectors (Figure 5).

Figure 3: Impact of a natural disaster on the provincial unemployment rate



(a) All disaster types

(b) Wildfires

(c) Floods

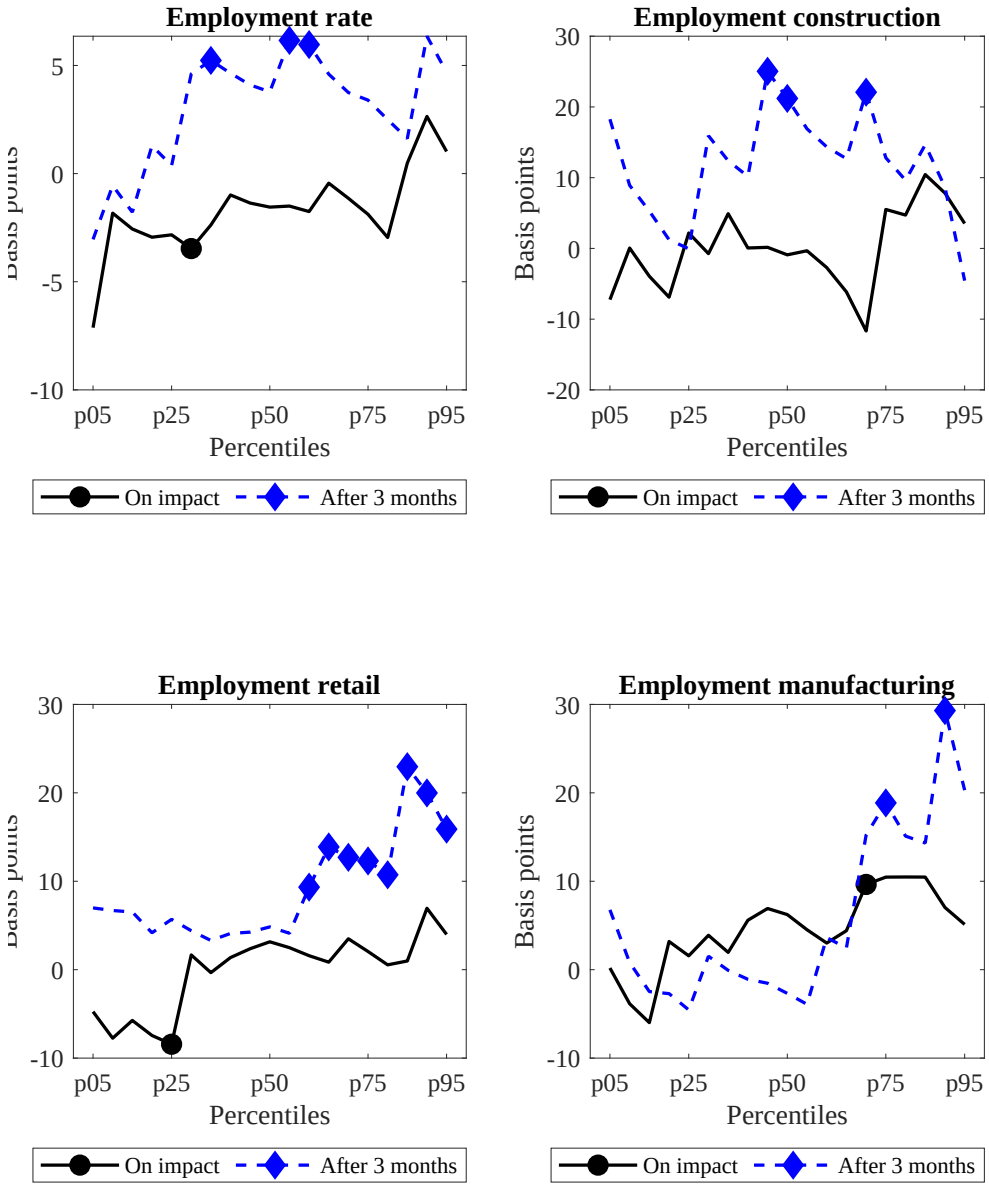
(d) Storms

Notes: Impact of a natural disaster of 1 percent of monthly provincial GDP on the provincial unemployment rate either on impact or the cumulative effect over 3 months. Solid symbols correspond to significant estimates at the 10 percent confidence interval.

Figure 4: Impact of a natural disaster on provincial employment across sectors

Notes: Impact of a natural disaster of 1 percent of monthly provincial GDP on the provincial employment rate either on impact or the cumulative effect over 3 months. Solid symbols correspond to significant estimates at the 10 percent confidence interval.

Figure 5: Impact of a storm on provincial employment across sectors



Notes: Impact of a natural disaster of 1 percent of monthly provincial GDP on the provincial employment rate either on impact or the cumulative effect over 3 months. Solid symbols correspond to significant estimates at the 10 percent confidence interval.

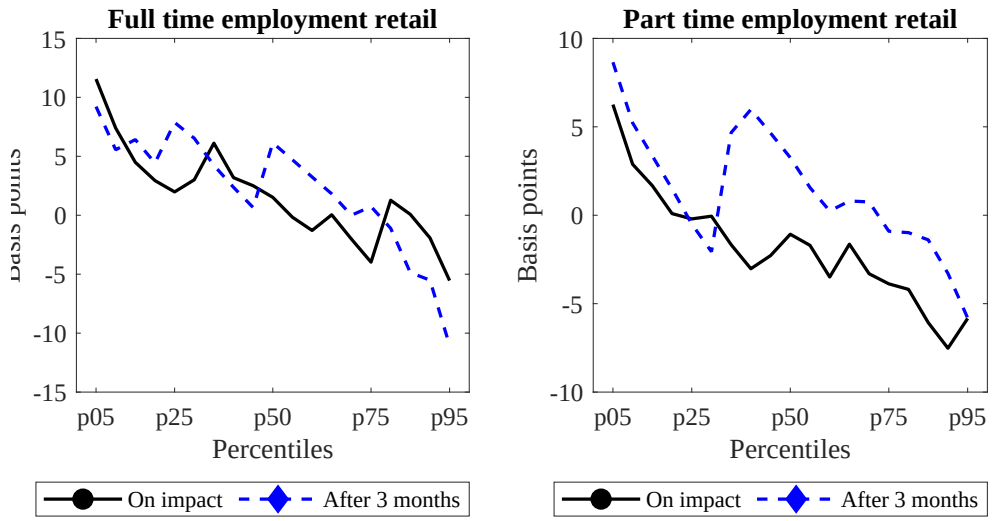
4.2 Effect of Disasters on the Composition of Employment

With our detailed provincial labour data, we can further examine the effects of natural disaster shocks by employment status at the aggregate and sector levels. This provides an important piece of information to understand who are more affected by physical risks posed by natural disasters.

In general, we find that part-time employment shows more significant and broad-based responses to a natural disaster than full-time. This implies that the responses at the aggregate level presented earlier are likely driven by this group of workers. Relatively high flexibility associated with part-time workers in addition to the short duration of disaster on average could be the factors underlying this result. Jobs and firms may quickly switch to labor sources with lower adjustment costs.

Further differentiating sectors, we see that both full- and part-time employment in the retail sectors do not respond significantly when combining disasters (Figure 6). We only observe lower odds of low full-time employment for the retail sector on impact following a flood.

Figure 6: Impact of a natural disaster on full- and part-time employment in the retail sector

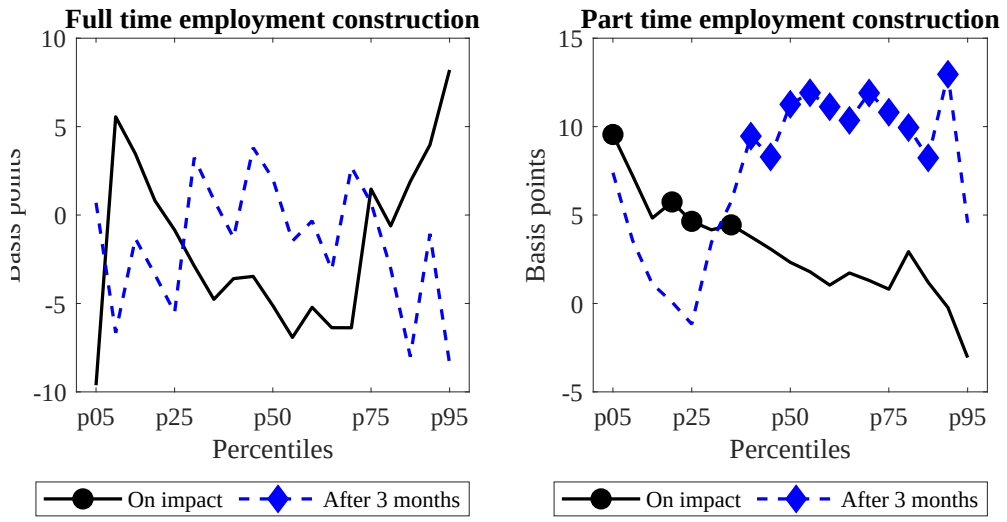


Notes: Impact of a natural disaster of 1 percent of monthly provincial GDP on the provincial full or part-time employment rate either on impact or the cumulative effect over 3 months. Solid symbols correspond to significant estimates at the 10 percent confidence interval.

For the construction sector, when disasters are combined, we observe a persistent increase in part-time employment (Figure 7). On impact, there are lower odds of low part-time employment, and within 3 months, there are higher odds of higher part-time employment. This suggests that the construction sector mostly relies on temporary workers to absorb the temporary additional work that follows from the destruction of a disaster. This pattern is mostly driven by floods and to a lesser extent by other disaster types.

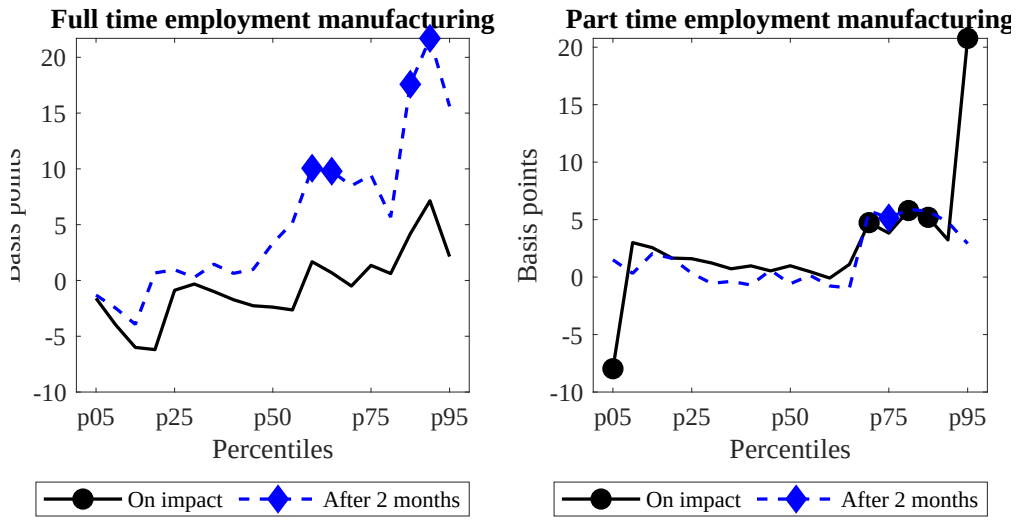
For the manufacturing sector, we see responses differ to a great extent depending on the types of disasters. This heterogeneity explains the overall muted responses of total full- and part-time employment in Figure 8. On impact, the lowest percentile of the part-time employment in manufacturing shifts significantly to the left, mainly driven by the responses to floods. This implies that in response to a flood, we see that part-time employment is more likely to respond negatively. In contrast, wildfires tend to move the overall part-time distribution to the right. Finally, in the case of storms, the chance of observing high full-time employment is more likely, peaking in 2 months from the impact, while part-time employment does not significantly respond. Thus the apparent re-balancing of employment from initially part-term to full-time employment observed on Figure 8 is driven by the heterogeneity across disaster types.

Figure 7: Impact of a natural disaster on part-time employment in the construction sector



Notes: Impact of a natural disaster of 1 percent of monthly provincial GDP on the provincial full or part-time employment rate either on impact or the cumulative effect over 3 months. Solid symbols correspond to significant estimates at the 10 percent confidence interval.

Figure 8: Impact of a natural disaster on part-time employment in the manufacturing sector



Notes: Impact of a natural disaster of 1 percent of monthly provincial GDP on the provincial full or part-time employment rate either on impact or the cumulative effect over 3 months. Solid symbols correspond to significant estimates at the 10 percent confidence interval.

5 Conclusion

This paper examines the cost in terms of employment that results from natural disasters, such as floods, storms, and wildfire. We use a combination of detailed disaster-level data and monthly employment data for 10 Canadian provinces over the period of 1980 to 2019. It is crucial to use provincial data on a monthly basis; most natural disasters affect confined area rather than an entire country and last on average 7 days only. Therefore, their impacts would be difficult to capture if one were to use aggregate level data at a lower frequency. On the methodological side, we extend the local projection framework first introduced by Jordá (2005) and adjusted for quantile regression. Our approach, a panel quantile local projection model, enables us to move away from linear average effects when looking at the potentially non-linear impact of extreme weather events across different regions.

We find that the probability of observing a high provincial unemployment rate increases on impact, but the effect on employment tends to become positive in the aftermath of disasters as the economy recovers. However this hides large heterogeneous effects when the data is further disaggregated by sectors, disaster type and employment status. The positive impact on employment is strongest after storms and the effect persists for a few months. When looking more at the composition of employment, we find that the construction sector experiences an increase in part-time workers to contribute to the rebuilding efforts in the aftermath of disasters. But part-time employment also decreases on impact especially after floods in the manufacturing sectors, likely because factories get flooded, before recovering in the subsequent months.

Our findings have two main policy implications. First, when assessing the overall cost of natural disasters, the employment channel should not be overlooked, on top of the insurance costs. This implies, for instance, that climate-related stress-tests should include an unemployment channel amplifying households vulnerabilities: income losses are one of the main drivers of households defaults, potentially generating more losses for the financial system. Second, local policy makers need to take into account the heterogeneity across disaster types and sector/employment status when designing a disaster relief funding. The positive rebound of the local economy after some

disasters might reflect delayed relief funds that over-compensate for the losses. Relief funds may also target different groups to address the distributional impact: those living in areas prone to wildfires or storms and working in retail industries are more likely to lose their job, but part-time workers in the construction and manufacturing industries are most likely to benefit, especially from the recovery phase after a disaster.

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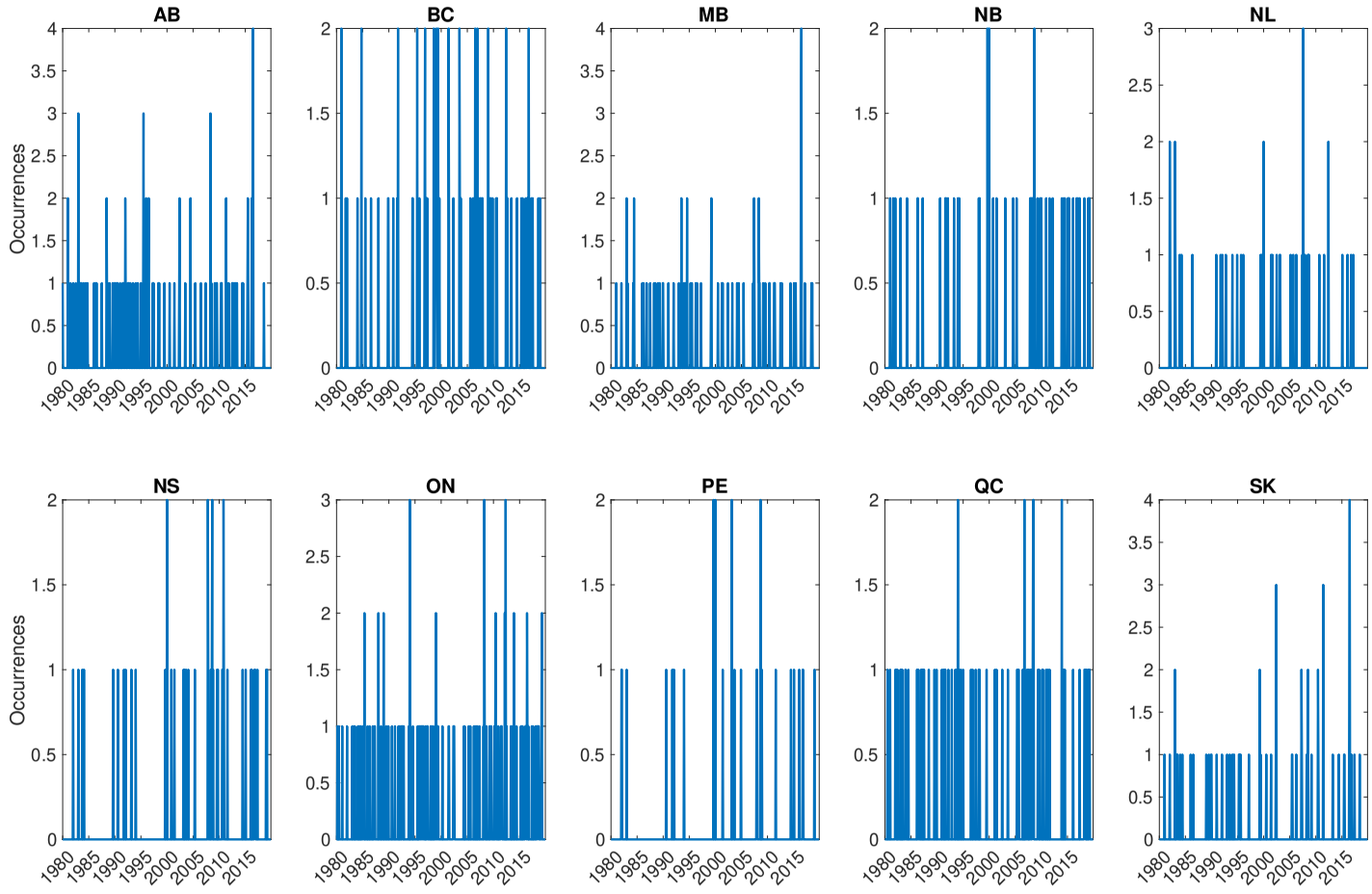

Figure 9: Number of Natural Disasters in Each Province: 1980-2019

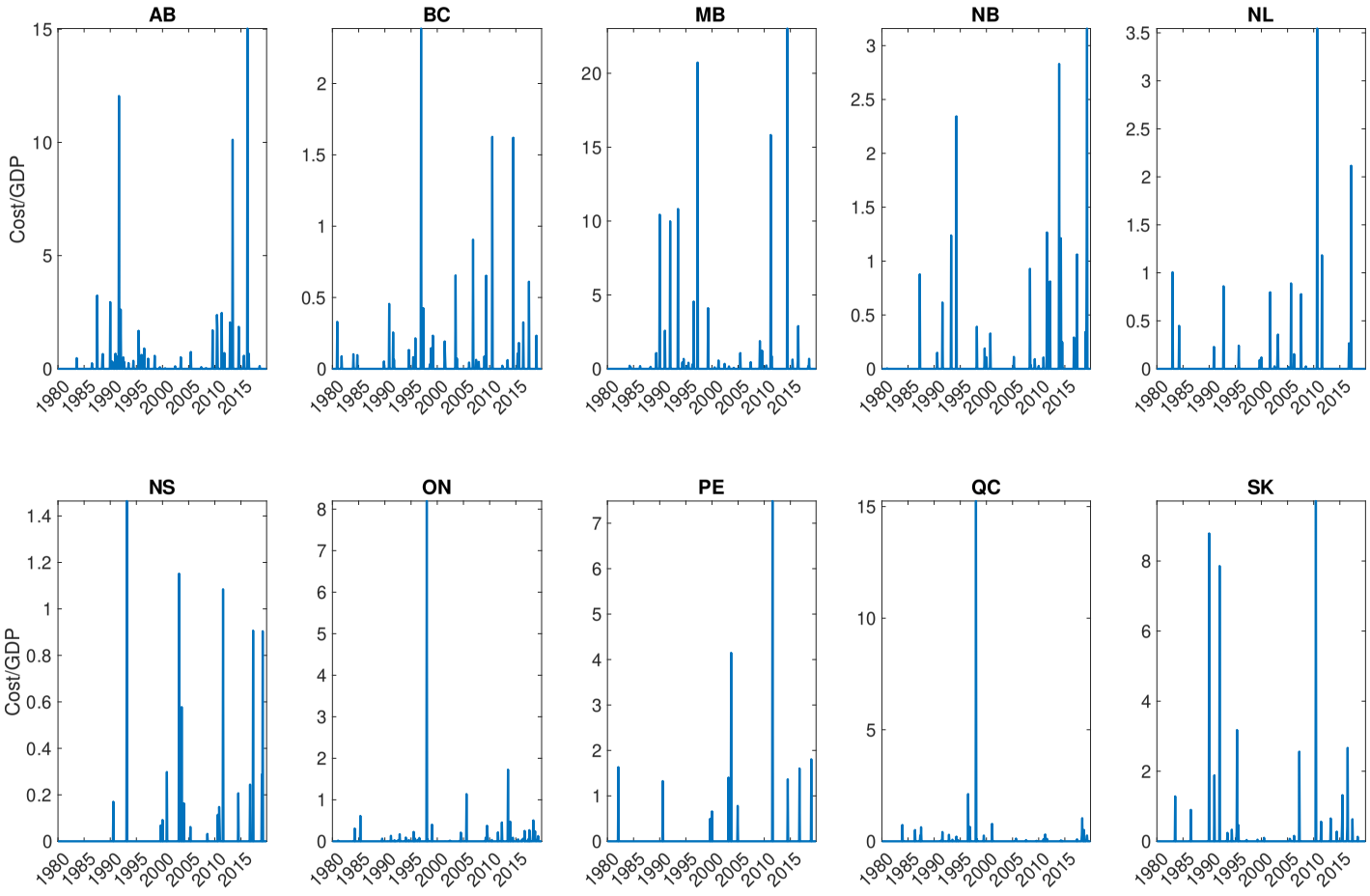

Figure 10: Relative Cost of Natural Disasters in Each Province: 1980-2019