

## Projecting the effect of climate change-induced increases in extreme rainfall on residential property damages:

A case study from New Zealand

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Link to working paper



#### Motivation

- Residential property damages as a result of weather-related hazards are covered by the Public Insurer of New Zealand.
- The effect of climate change is likely to translate into higher property damages and thus an additional liability for the Public Insurer.

## There is a positive correlation between extreme rainfall events and residential property damage



Note: Percent change times series: extreme events, number and value of insurance claims as a result of residential property damages in New Zealand Source: The authors

## 1) What are the Public Insurer's expected future liabilities, given future climate projections?

2) How much more will the Public Insurer have to pay in the future as consequence of anthropogenic-induced climate change?

#### Paper in two slide – setup

- Estimate the relationship (i.e. damage function) between <u>extreme precipitation</u> events and insurance pay-outs.
- 2. Apply the estimated <u>regression coefficients</u> to future climate change scenarios to project the value of insurance claims in the future.

3. Calculate <u>climate change signal</u> i.e. percent changes between past and projected damages.

#### Paper in two slide - results

- Liabilities from property damage as result of climate change vary -increase or decrease over time and space
  - Climate change signal ranges between an increase of 7% and 8% higher in the period 2020 to 2040, and an increase of 9% and 25% higher in the period 2080 to 2100, depending on the greenhouse gases emissions (RCPs) scenario
  - Northernmost areas of NZ will experience less damages, and southernmost areas will experience the highest levels of damages for RCPs 4.5 and 8.5 in the period <u>2080 to 2100</u>
- Observed property damages are heavily driven by exposure
  - Grids with damages are closer to the shoreline and waterways (rivers); are within flood prone areas and lower elevations; have higher economic potential and have higher <u>number</u> and <u>value</u> of residential assets than grids without damages.

### Related literature – Projecting damages

#### Bouwer (2013)

- Provides a classification of studies that project future losses from weather extremes.
- Studies differ in their approach (IAMs, CGEs, risk models) type of hazard, spatial scope, changes in hazard, and climate scenarios, as well as how they consider future changes in exposure and vulnerability.
- Pinto et al (2007), Leckebush et al (2007), and Klawa and Ulbrich (2002)
  - Model the empirical relationship between weather-related insurance pay-outs using risk models.
  - Project future losses using GCMs and find increases in losses as s result of climate change.

### Public Insurance cover scheme (1)

- Insurance cover:
  - Building, land, and contents damage from rainfall-induced landslips
  - Land damage from floods and storms
- Insurance cover caps:
  - Building cap: 150k NZ\$
  - Contents cap: 20k NZ\$
  - Land cap: value of the land
  - Private insurer covers any remaining value above the cap

#### Insurance cover scheme (2)



Source: EQCover Guide, EQC Act 1993

### Empirical strategy (1): Estimate damage function

1. Estimate the relationship (i.e. damage function) between <u>extreme</u> <u>precipitation</u> events and insurance pay-outs.

 $Y_{it} = \beta_1 \ Hazard_{it}$ +  $\beta_2 \ Exposure_i$ +  $\beta_3 \ Vulnerability_i$ +  $\theta_t + \varepsilon_{it}$ 

Y<sub>it</sub> = Total pay-outs (NZ\$) in grid *i* and time t

Hazard<sub>it</sub> = Count of the number of extreme precipitation events in grid *i* and time *t*, based on the 95<sup>th</sup>, 98<sup>th</sup> and 99<sup>th</sup> percentile of <u>observed</u> daily precipitation from a time series between 2000 and 2018. The percentile thresholds are <u>defined separately</u> for each grid and only <u>wet days</u> are considered for the calculation. To account for <u>antecedent</u> conditions, we calculate the same percentile thresholds for up to five days of accumulated rain.

## Empirical strategy (1): Estimate damage function

- *Exposure<sub>i</sub>* = Total number and value of buildings, appurtenant structures, and contents, and land area exposed
  - Share of properties located in: coastal and riverine flood prone areas, and with landslip susceptibility;
  - Share of properties located in soils with poor drainage, low permeability and high water availability;
  - Average slope, elevation (above mean sea level), distance to water bodies (rivers and lakes), floor height (above ground);
  - Share of properties located in areas with economic potential.
- Vulnerability<sub>i</sub> = Share of buildings with: vulnerable materials; in deficient condition.
- $\theta_t$  = time fixed effects
- $\mathcal{E}_{it}$  = disturbances
- Robust standard errors and fixed-effects at grid level *i*

## Empirical strategy (2): Apply regression coefficients

- 2. Apply the estimated <u>regression coefficients</u> to future climate change scenarios to project the value of future insurance claims
  - We use a suite of six Coupled Model Intercomparison Project (CMIP-5) climate models.
  - The climate models reflect the past climate (1971-2005) and project future climate under different green house gasses scenarios (RCPs 2.5, 4.5, 6.0, 8.5).
  - We count the number of future extreme rainfall events as the number of times modelled future rainfall exceeds the percentile thresholds (95<sup>th</sup>, 98<sup>th</sup>, 99<sup>th</sup>) from the model past data from the same simulation

## Empirical strategy (2): Apply regression coefficients

Climate Models	Climate Pas (Historic)	t	Climate Projections (RCPs)			
Model names (Rank) Institute (Country)	Historical	RCP2.6	RCP4.5	RCP6.0	RCP8.5	
HadGEM2-ES (2) MOHC (UK)	1971–2005	2006–2120	2006–2120	2006–2099	2006–2120	
CESM1-CAM5 (1) NSF-DOE-NCAR (USA)	1971–2005	2006–2120	2006–2120	2006–2120	2006–2100	
NorESM1-M (9) NCC (Norway)	1971–2005	2006–2100	2006–2100	2006–2100	2006–2100	
GFDL-CM3 (10) NOAA-GFDL (USA)	1971–2005	2006–2100	2006–2120	2006–2100	2006–2100	
GISS-E2-R (14) NASA-GISS (USA)	1971–2005	2006–2120	2006–2120	2006–2100	2006–2120	
BCC-CSM1.1 (17) BCC (China)	1971–2005	2006–2120	2006–2120	2006–2099	2006–2120	

Source: Tait et al., (2016)

### Empirical strategy (3)

- 3. Calculate <u>climate change signal</u> i.e. percent changes between past and projected damages.
  - To quantify the expected impact of climate change on damages, we compare the predicted damages using the past model of the climate for the years 1986 to 2005, with the damages based on future climate projections (RCPs) for each of the periods 2020-2040, 2040-2060, 2060-2080, 2080-2100.

$$CC \ signal_{pd} = 100 * \frac{\sum_{i}^{n} (CFuture_{ipd} - CPast_{ipd})}{\sum_{i}^{n} (CPast_{ipd})}$$

- d = days, from 1 up to 5 days of accumulated precipitation
- p = percentile threshold values
- i = grids



## Damage function

## Historical relationship between extreme precipitation events and damage

	(1)	(2)	(3)	(4)	
Model type	Logit	Poisson	OLS	OLS	
Hodel type	(Probability)	(Frequency)	(Intensity)	(Intensity)	
				Value of claims	
<b>D</b>	Indicator for at	Number of claims	Value of claims in	relative to	
Dependent variable	least one claim in	in grid/cell	grid/cell	exposed assets in	
	grid/cell	υ,	υ,	grid/cell	
	Odds Ratio (OR)	Incidence Rate	OLS	OLS	
Coefficient type	()	Ratio (IRR)			
arin 1	1.213***	1.241***	319.0***	0.303***	
95th percentile one day	(0.0141)	(0.0237)	(72.46)	(0.0600)	
	1.404***	1.411***	538.1***	1.314	
98th percentile one day	(0.0238)	(0.0492)	(89.42)	(0.716)	
00th	1.597***	1.569***	887.9***	2.502	
99th percentile one day	(0.0364)	(0.0805)	(163.0)	(1.825)	
	1.157***	1.170***	250.5***	0.366**	
95th percentile two days	(0.00915)	(0.0138)	(45.32)	(0.132)	
08th meneoutile true days	1.295***	1.275***	441.4***	1.253	
98th percentile two days	(0.0145)	(0.0368)	(70.27)	(0.800)	
00th noncentile two days	1.463***	1.376***	634.1***	1.803	
99th percentile two days	(0.0235)	(0.0500)	(90.74)	(1.150)	
Of the second tile three down	1.128***	1.127***	187.6***	0.484	
95th percentile three days	(0.00690)	(0.0126)	(32.72)	(0.290)	
09th noncentile three days	1.238***	1.221***	355.4***	1.000	
98th percentile three days	(0.0109)	(0.0248)	(52.28)	(0.630)	
00th perceptile three days	1.359***	1.260***	486.9***	1.454	
99th percentile tillee days	(0.0166)	(0.0322)	(69.25)	(0.890)	
95th percentile four days	1.107***	1.105***	153.7***	0.359	
soth percentile four days	(0.00551)	(0.0104)	(24.15)	(0.197)	
08th perceptile four days	1.192***	1.172***	261.7***	0.836	
soth percentile four days	(0.00867)	(0.0198)	(39.57)	(0.545)	
00th perceptile four days	1.298***	1.255***	432.0***	1.266	
sour percentile four days	(0.0132)	(0.0231)	(63.26)	(0.738)	
05th percentile five days	1.093***	1.090***	132.4***	0.284	
sour percentile live days	(0.00467)	(0.00988)	(21.54)	(0.147)	
98th percentile five days	1.175***	1.152***	237.4***	0.651	
your percentine tive unyo	(0.00741)	(0.0144)	(37.76)	(0.379)	
99th percentile five days	1.250***	1.239***	383.2***	1.134	
, , in percentite any -	(0.0108)	(0.0167)	(57.04)	(0.679)	
Year fixed-effects	Yes	Yes	Yes	Yes	
Grid-cell fixed-effects	Yes	Yes	Yes	Yes	
N	14,238	14,238	112,158	112,158	

Note: This table presents the coefficients on extreme weather events from a series of regressions of insurance claims on extreme events. Each coefficient in the table comes from a separate regression.

#### Magnitude of the relationship

- Column (3) of Table 3 presents results from a series of OLS regressions of the value of total payouts, adjusted for inflation to 2017 NZ\$ values, on extreme weather counts.
- Using our first definition of extreme event, rainfall above the 95th percentile for one day of accumulated precipitation, we estimate that one additional extreme event in a grid cell and year is associated with a NZ\$ 319 increase in pay-outs.
- As we vary our definition of extreme event in the subsequent rows of the table, the estimated coefficients range from NZ\$ 132.4 to NZ\$ 887.9; all are statistically significant at the 0.01 level.



## Projections

#### Projected future liabilities with all climate models for the changing hazard (in NZ\$ millions)

	One day of accumulated precipitation, 99th percentile						
	Climate models	GFFL CM3(10)	GISS-E2 R(14)	NorESM- M(9)	HadGEM 2ES(2)	CESM1 CAM5(1)	BCCCSM1.1(17)
		NOAA-USA	NASA-USA	NCC-Norway	MOHC-UK	NSF-USA	BCC-CHINA
2020-2040	RCP 2.6	1,181.9	1,330.5	1,342.4	1,244.7	1,191.6	1,191.6
	RCP 4.5	1,198.3	1,334.4	1,219	1,193.6	1,230.2	1,230.2
	RCP 6.0	1,215.5	1,196.8	1,353.9		1,213	1,213
	RCP 8.5	1,099.9	1,257.2	1,347.2	1,222.3	1,234.2	1,234.2
2040-2060	RCP 2.6	1,169.7	1,182.6	1,343.2	1,235.2	1,306.8	1,306.8
	RCP 4.5	1,223	1,367.4	1,397	1,203.6	1,213.5	1,213.5
	RCP 6.0	1,211.8	1,304.5	1,292.3		1,292.1	1,292.1
	RCP 8.5	1,245.5	1,379.8	1,321.7	1,276.6	1,299.8	1,299.8
2060-2080	RCP 2.6	1,285.3	1,230.5	1,365.9	1,255.4	1,361.1	1,361.1
	RCP 4.5	1,221	1,252.7	1,340.2	1,308	1,393	1,393
	RCP 6.0	1,240.5	1,355.4	1,432.7		1,354.9	1,354.9
	RCP 8.5	1,359.1	1,420.2	1,485.8	1,292.3	1,467.6	1,467.6
2080-2100	RCP 2.6	1,223.3	1,219.5	1,291.8	1,144.7	1,337.9	1,337.9
	RCP 4.5	1,279.1	1,306	1,397	1,144.2	1,345.7	1,345.7
	RCP 6.0	1,268.9	1,342.2	1,299.8		1,443.1	1,443.1
	RCP 8.5	1,359.1	1,454.1	1,473.1	1,451.4	1,463.8	1,463.8

Note: Projected losses for 20-year aggregates for the 99th percentile value (p=99) and one day of accumulated precipitation (d=1), all Representative Concentration Pathways and all climate models. These results do not consider future changes in exposure or vulnerability. Results for the UK climate model and RCP 6.0 were dubious and thus not included in the table. The projected liability figures were inflated by a correction factor of 2.50. The need for an adjustment rises as a result of the claims omitted from the regression analysis. The factor is calculated such that we add the value of the claims included and the value of the claims omitted and the value of the claims omitted and divide that over the value of the claims omitted.

## Magnitude of the projections across models and RCPs

- Differences across models are not very large, though some models do have a flatter profile across time than others (e.g., the NOAA -USA model).
- We also observe, as can be expected, the differences between the RCP scenarios are more pronounced later in the century than they are in the near future (2020-2040).



## Climate change signal

## Increase in liabilities for the Public Insurer due to climate change: average of all climate models



Note: These results are calculated for the average one day of accumulated precipitation and 99th percentile. The table averages results across six climate models, for each RCP and time horizon.

# Spatial distribution of climate change signal at grid level. RCP 4.5 for the time period 2080-2100



# Spatial distribution of climate change signal at grid level. RCP 8.5 for the time period 2080-2100



### Conclusion

- Climate change will increase future liabilities of the Public Insurer of New Zealand.
- Our results are consistent with findings in previous literature showing that projections from weatherrelated risk will increase as result of climate change.
- Our projections do not consider future changes in exposure and vulnerability. Thus, changes in future damages are driven exclusively by changes in the hazard, due to climate change, given current conditions.

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