THE INFLATIONARY COSTS OF EXTREME WEATHER IN DEVELOPING COUNTRIES

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INTRODUCTION

- Extreme weather → US$3 trillion of damages globally since 1980
- Academic literature focused mostly on long-term impact
- However, driving factor is the short-term adjustment process
- Ex: shortages of goods and services → prices↑
- Being able to predict prices will help policy makers choose the right fiscal & monetary policies in the aftermath

INTRODUCTION

- Previous literature: Cavallo & Cavallo (2014) examine 2010 Chile and 2011 Japan earthquakes → no price effect

- They argue this may be due to price stickiness (no price gauging)

- But: they estimate the effect on national prices of one large international supermarket

INTRODUCTION

This paper:

a. Estimates the impact of extreme weather on inflation in the Caribbean

b. Calculates expected welfare effects using case study of Jamaica

INTRODUCTION

INTRODUCTION

- Arguably Caribbean is a good case study b/c:

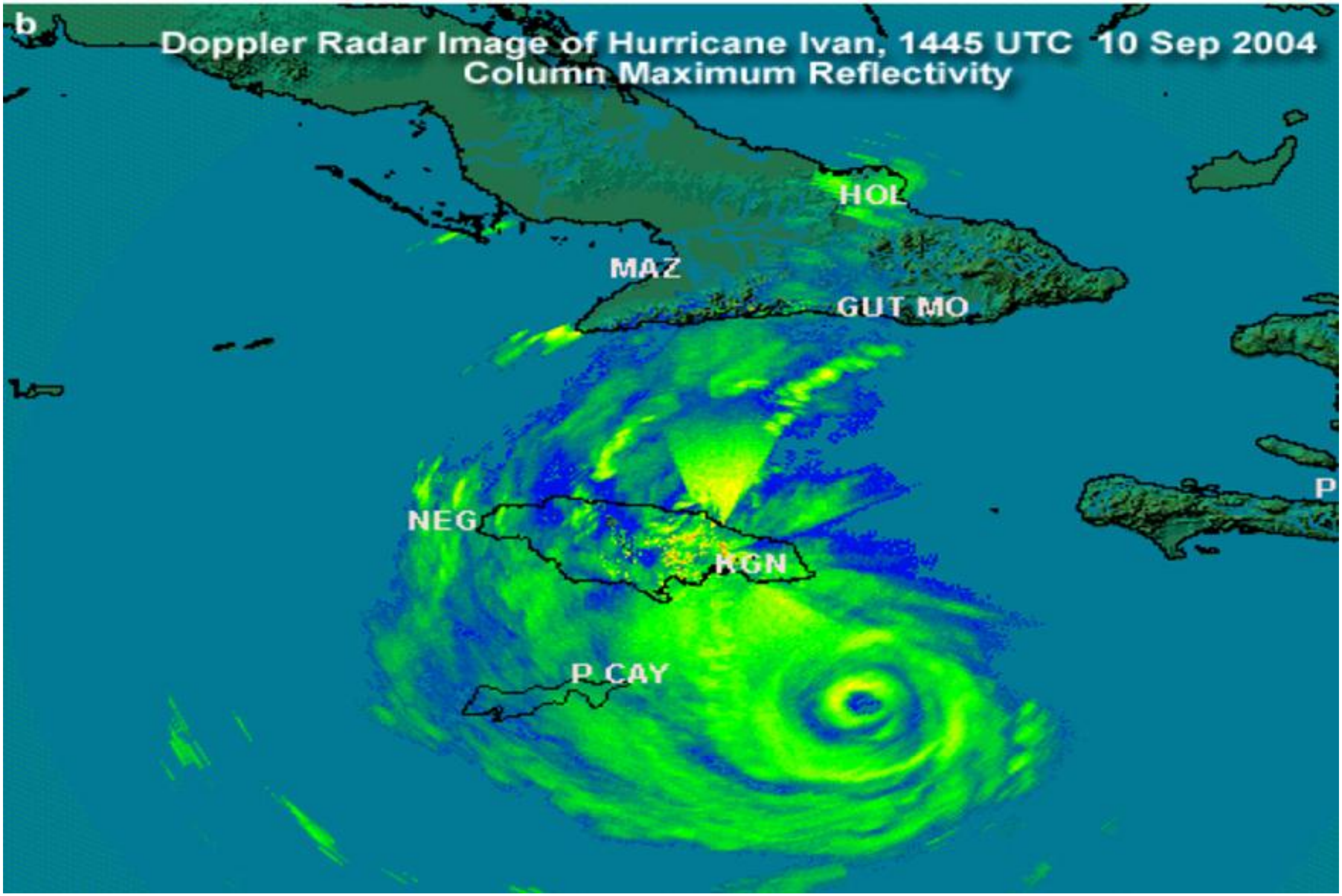
  a. many hurricanes and floods per year (ex: Grenada 2004, St. Vincent & Grenadines 2013)

  b. small, non-diversified, import dependent economies

  c. potential costs of extreme weather estimated to be around 9 per cent of annual GDP by 2050

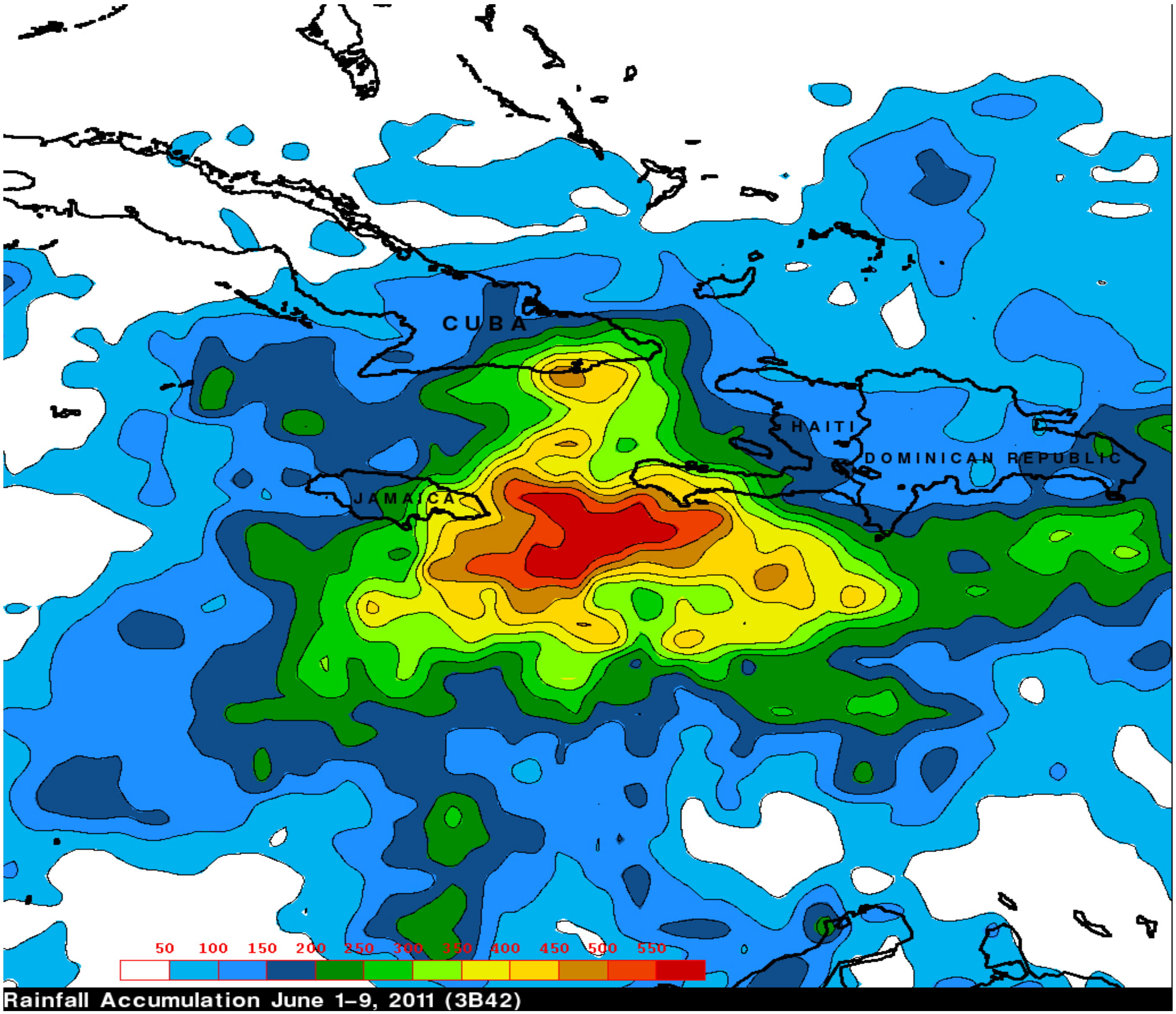
NATURAL DISASTER MODELING

Hurricane



NATURAL DISASTER MODELING

Excess Rainfall (Floods)



NATURAL DISASTER MODELING

- Modeling approach:
  a. Take physical characteristics of the event into account
  b. Model these at the ‘local’ level
  c. Take account of local exposure
  d. Assume a damage function

NATURAL DISASTER MODELING

- Hurricane Damage Function:

$$H_{j,t} = \sum_{i=1}^{I} w_{i,t-1} \sum_{k=1}^{K} \left(W_{j,i,k,t}^{max}\right)^3 \mathbb{1}_{\{W_{j,i,k,t}^{max} \geq W*\}},$$

j:island

t:time (short-term)

w: exposure weights at point *i;*

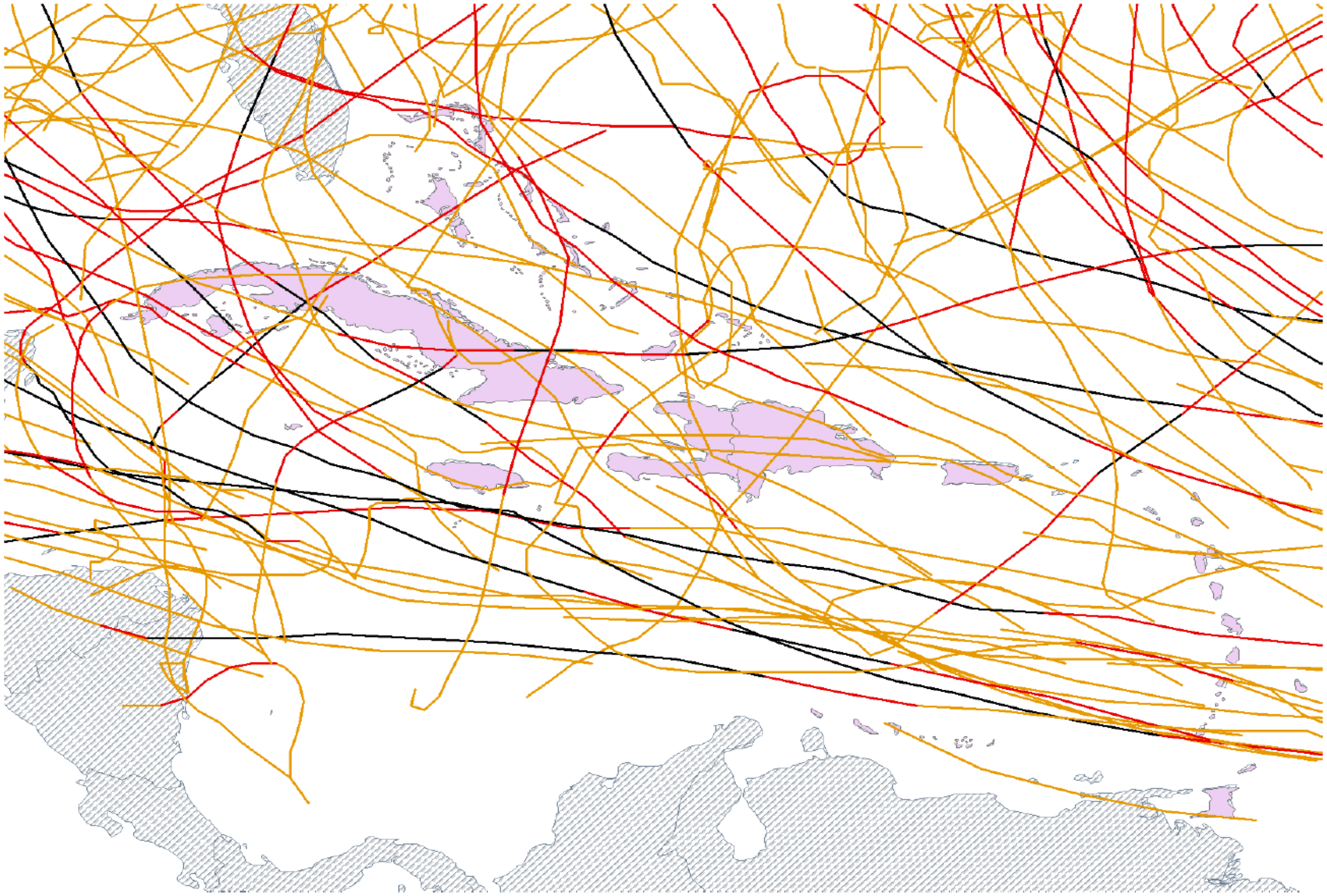
W^{max}: maximum wind at *i*

W:* Threshold below which no damage

Note: cubic function

DATA (hurricane tracks - HURDAT)

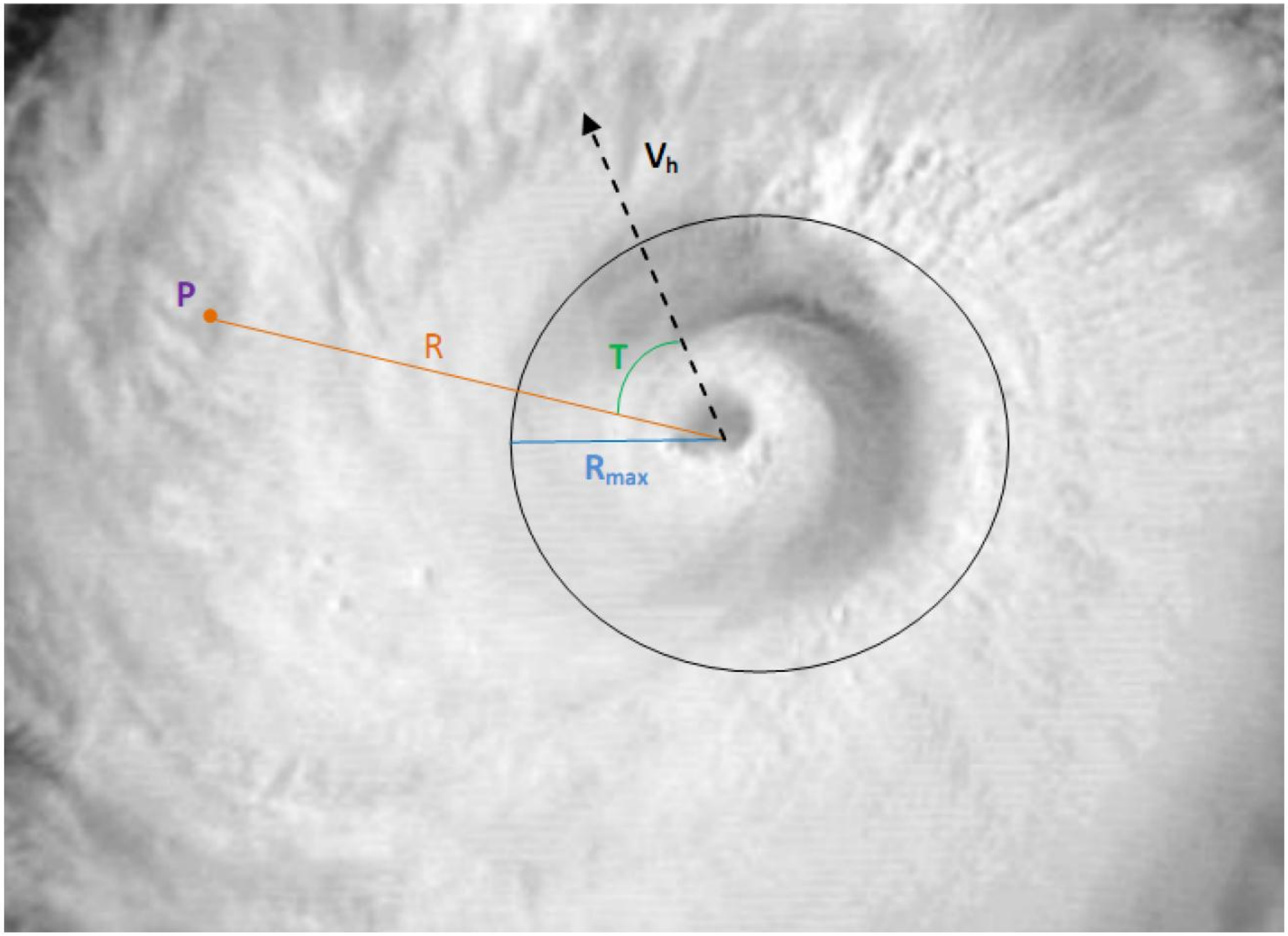
Figure 2: Tropical Cyclones in the Caribbean Region 2000-2012



Notes: Orange, red and black, portions of the tracks indicates tropical storm, hurricane Saffir-Simpson Scale 1 (119-153 km/hr), and at least hurricane Saffir-Simpson Scale 3 (178 km/hr+) strength storms.

DATA (wind field model)

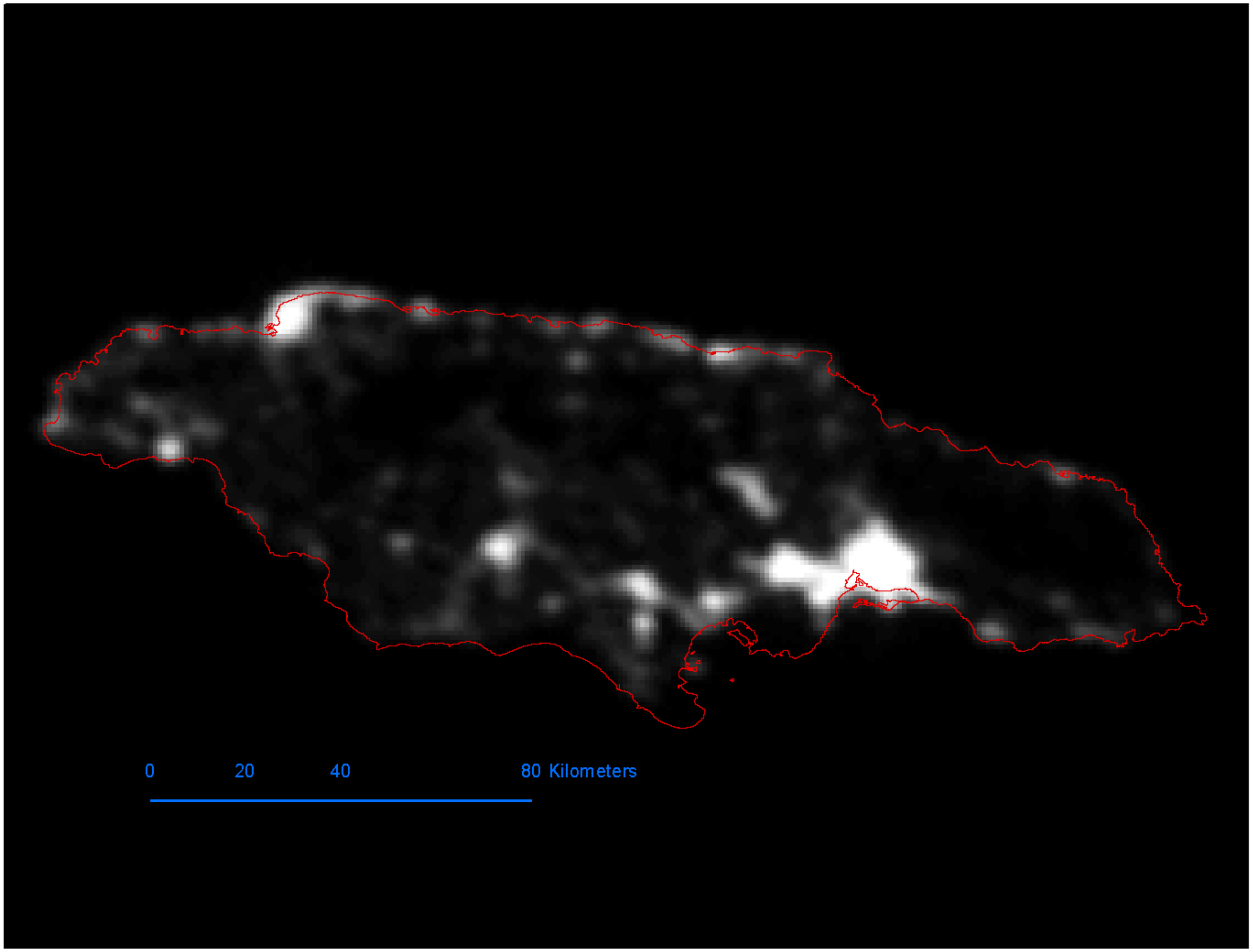
Figure 1: Hurricane Wind Field Model



Notes: (1) Sample diagram of input parameters into typhoon wind field model; (2) P: point of interest, R: distance from storm eye to point of interest, R_{max}: radius of maximum wind speed, T: angle of point relative to direction of storm; V_h: forward speed of storm.

DATA (weights *w*)

Exposure: Nightlight Intensity – Jamaica (2012)



NATURAL DISASTER MODELING

- To identify floods we use an intensity duration model:

$$Intensity = \alpha Duration^{\beta}$$

- Intensity: rainfall intensity
- Duration: rainfall duration
- α and β: estimated from Trinidad data on known flood events

NATURAL DISASTER MODELING

- Flood damage function:

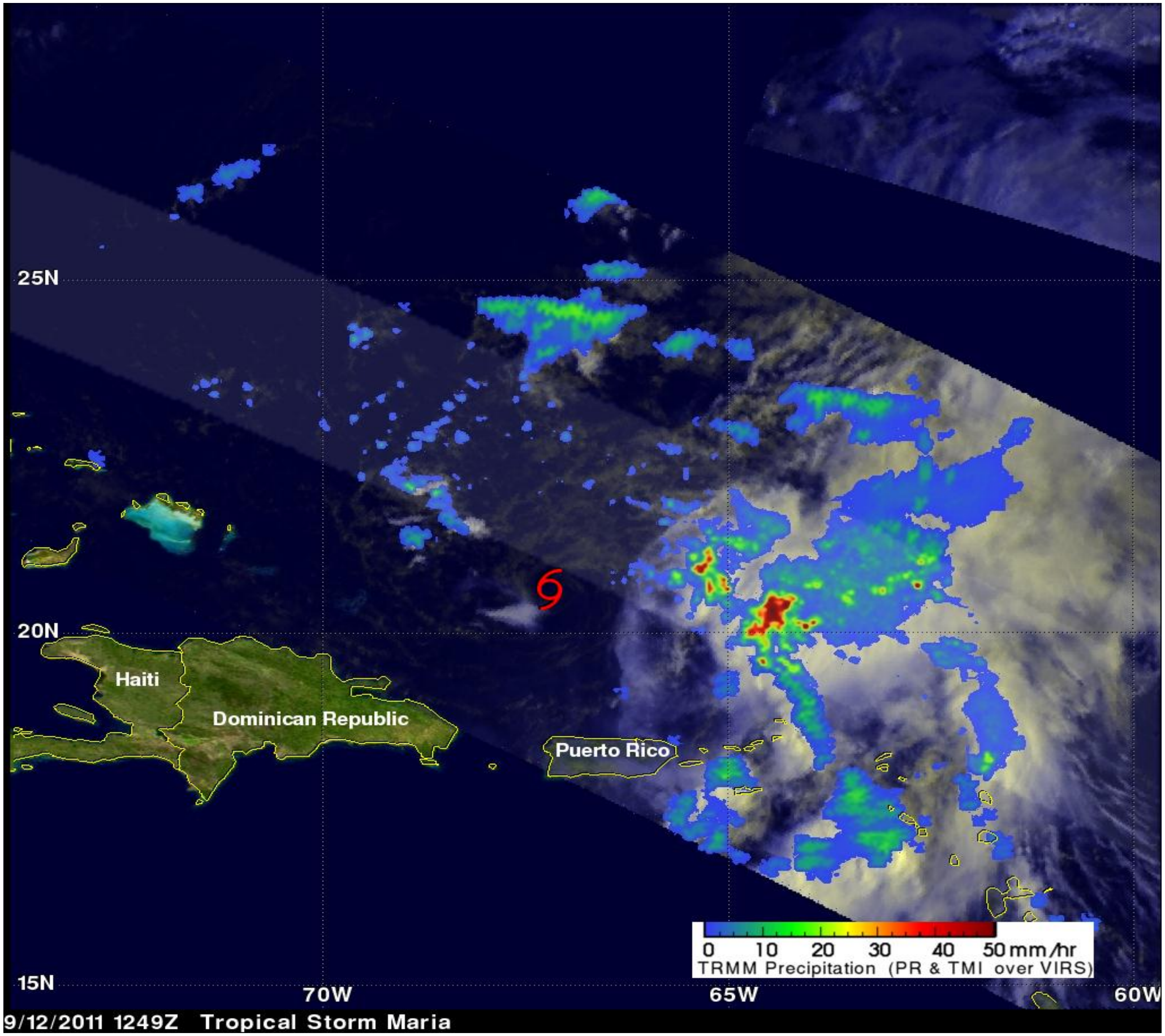
$$F_{j,t} = \sum_{i=1}^{I} w_{i,j,t-1} \sum_{d=1}^{t} r_{i,j,d} \mathbb{1}_{\{\sum_{d-3}^{d} r_{i,j,d} \geq r^*\}}$$

w: exposure weights at point *i* at time *t-1*

r: measure of rainfall

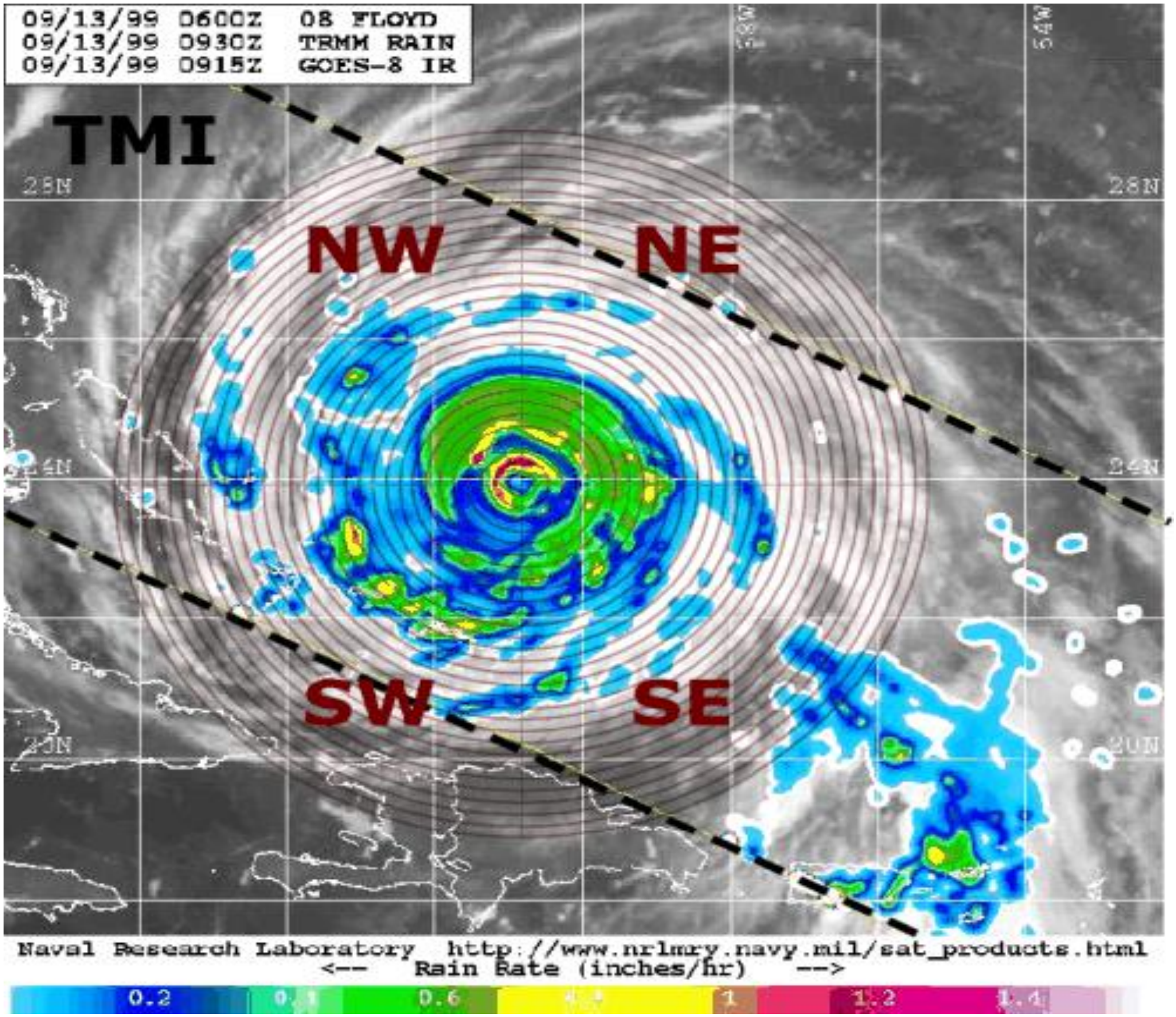
*r**: threshold above which rainfall becomes `excessive’

DATA (Rainfall - TRMM)



DATA

Problem: Correlation between *H* and *F* during tropical storms



DATA

- Monthly price data:

  Nearly balanced panel for 15 island economies over the 2000-2012 period for overall, food, housing, and other categories

	Avg	Max	Min	St.dev.
Inflation				
All	0.37	12.23	-10.64	0.91
Food	0.50	16.79	-13.02	1.36
Housing & Utilities	0.35	46.47	-47.35	2.20
Other	0.41	-11.38	11.63	0.98

- A total of 2,340 island-months of data
- Non-zero obs.: 142 for Hurricane and 683 for Floods

ECONOMETRIC ESTIMATION

- Specification:

$$INFL_{j,t} = \alpha + \sum_{s=0}^{S} \beta_{t-s} H_{j,t-s} + \sum_{s=0}^{S} \theta_{t-s} F_{j,t-s} + \mu_j + \lambda_t + \nu_{j,t},$$

- Estimation: Panel FE model with serially and cross-sectionally correlated errors, as well as year and month dummies

- Note: arguably *H* and *F* are exogenous

ECONOMETRIC RESULTS

INFL :	(1) ALL	(2) ALL	(3) ALL
H_t	1.311**	1.336**	1.325**
	(0.233)	(0.244)	(0.248)
H_{t-1}		1.058**	1.060**
		(0.264)	(0.267)
H_{t-2}			0.0618
			(0.253)
F_t	0.119*	0.123*	0.122*
	(0.0574)	(0.0590)	(0.0599)
F_{t-1}		0.0316	0.0295
		(0.0672)	(0.0686)
F_{t-2}			-0.0454
			(0.0624)

Avg. (max) economic impact:

H: 1st month - 0.08 (1.5); 2nd month: 0.06 (1.2)

F: 1st month - 0.07 (0.514)

ECONOMETRIC RESULTS

By commodity group:

i. Hurricanes affected all categories, largest impact for Food

ii. Floods only affected Food and Other Goods

EXPECTED WELFARE EFFECT

- To know potential welfare effects we need to measure:
  a. Effect on welfare of Δp's changing due to extreme weather events
  b. Probabilities associated events
- To calculate welfare effect we use the concept of compensating variation:

$$\Delta C = C(u^{t-1}, p^{t}) - C(u^{t-1}, p^{t-1})$$

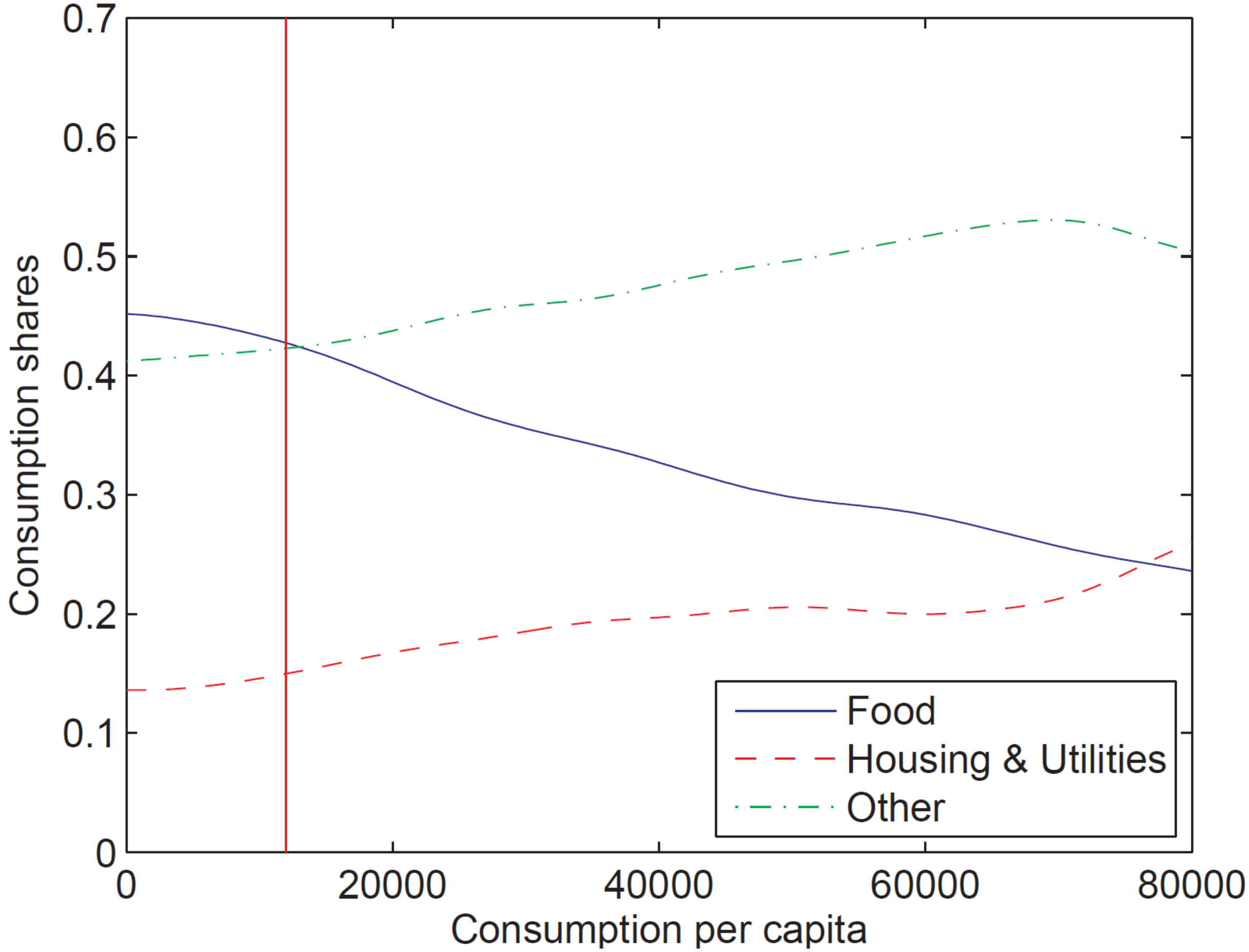
$$\Delta \ln(C) \approx \sum_{i=1}^{n} s_i \Delta \ln(p_i) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} s_i \varepsilon_{ij} \Delta \ln(p_i) \Delta \ln(p_j)$$

EXPECTED WELFARE EFFECT

- Used Jamaica as a case study – Jamaica 2012 SLC (6,000 households)
- Jamaica: monthly CPI by good group (12) & region (3)
- Aggregated groups into food, housing, and other
- Used Δp’s and Δ’s to estimate price elasticities with an AIDS model

EXPECTED WELFARE EFFECT

Figure 4: Budget Share of different goods, as a function of consumption per capita



EXPECTED WELFARE EFFECT

Table 4: Price Elasticities

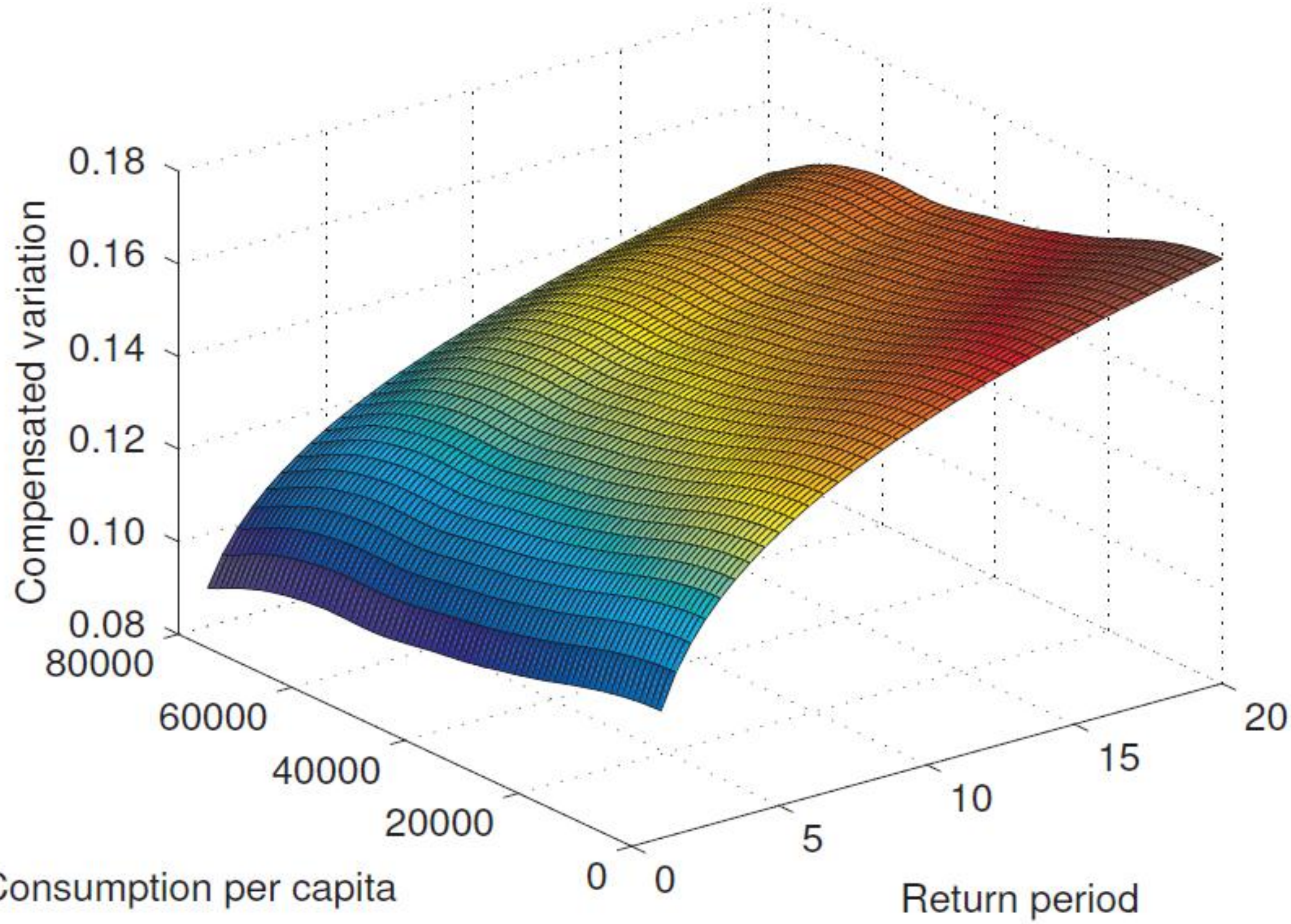
	Food	Housing & Utilies	Other
Food	-0.915**	0.503**	0.412
	(0.182)	(0.097)	(0.206)
Housing & Utilities	0.971**	-2.004**	1.033**
	(0.188)	(0.198)	(0.243)
Other	0.313	0.0406**	-0.719**
	(0.157)	(0.096)	(0.212)

EXPECTED WELFARE EFFECT

- These estimates with the *s*’s allow us to calculate out welfare loses due events
- To get ‘expected’ losses need to calculate out probabilities of events
- Two aspects:
  a. Hurricanes and Floods are extreme events
  b. They are not independent
- Used Bivariate POT models: (extreme value) Gumbel model
  → probability distribution of inflation effect (CV) of events
- But: infinite combinations of *H* and *F*…

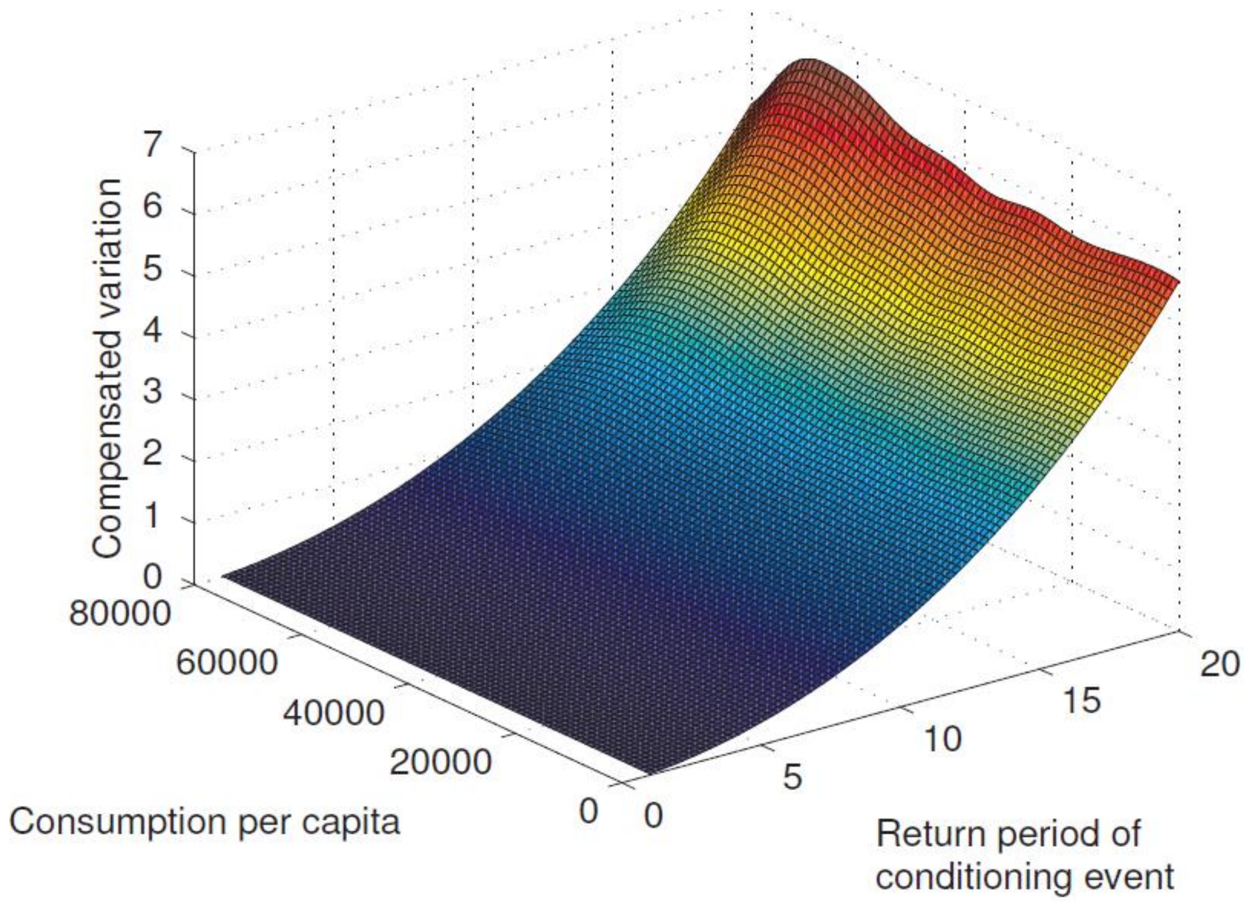
EXPECTED WELFARE EFFECT

Conditional (5 year Hurricane) Flood Events



EXPECTED WELFARE EFFECT

Conditional (5 year Flood) Hurricane Events



CONCLUSION

- Extreme Weather Events can have significant, albeit short-lived effects on prices

- Depending on the ‘rarity’ of the events, these can then translate into substantial welfare losses

- Welfare losses larger for the rich due to their greater spending on housing related goods and the greater price elasticity of housing related goods