The Long-Term Effects of Unexpected Interruptions in Compulsory Schooling

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Motivation

- Reported losses from natural disasters are projected to increase from \$195 billion a year to \$234 billion a year by 2040 (Reuters, 2020)
- Studying the economic effects of natural disasters has become a central research question in several fields of economics

Motivation

- Extensive literature looking at the impacts of natural disasters on economic growth

  (e.g. Cavallo & Noy, 2010; Strobl, 2011; Cavallo et al., 2013; Dell et al., 2014)

  - agreement on the negative short-term effects
  - little empirical consensus on the long-term effects

- Majority of studies relates the path of GDP growth to physical capital construction and potential technological upgrading

- Little causal evidence on the long-term effects on human capital formation, which is also an important determinant of economic growth

Research question

What are the long-run effects of natural disasters (tropical storms) on education?

- We quantify the long-run effects of unexpected interruptions in regular schooling in rural and urban India on
  1. educational attainments / delays
  2. the type of activity performed by individuals in young adulthood

- Identification:
  - measure of childhood exposure to storms
  - constructed from exogenous variations in wind exposure across birth-year cohorts and districts during compulsory schooling

- Exogenous shocks: tropical storms

  Exogeneity

Preview of results

Tropical storms cause:

- schooling delays
  - an increase by up to 18 percentage points in the probability to either repeat a year or drop out
  - a decrease of up to 8 percentage points in the probability of completing post-secondary education
  - → for super storms, these estimates translate into a lifelong fall in returns of 2.1%-3.3%
- a decrease of up to 16 percentage points in the probability of accessing regular salaried jobs

Investigation of the channels suggests:

- educational delays result not only from infrastructure damages but also from sharp declines in income

Data

- Twofold data requirement:
  - current outcomes – educational attainment and labor market outcomes in young adulthood
  - past outcomes – whether individuals observed today were exposed to storms during childhood
- We combine two sources of data:
  1. Indian Periodic Labour Force Survey (PLFS), 2018 release
  2. Historical storms best tracks data from the NOAA

PLFS

- Individual- and household-level representative survey of the population
- District of residence and age:
  - childhood exposure to storms varies by birth-year cohort and district
  - assumption: individuals completed compulsory schooling in the district where they currently live

    → low rate of out-of-district migration (official stats.; Topalova, 2010)
- Labor market outcomes:
  - Hours worked and earnings
  - Principal activity
    - formal work w. empl. contract (22%)
    - casual work w. periodic contract only (12%)
    - self-empl. (15%)
    - unpaid family business (9%)
    - performing domestic duties (41%)

PLFS: education

- # of years individual i spent at school (N_i)
- Level of educational attainment of i

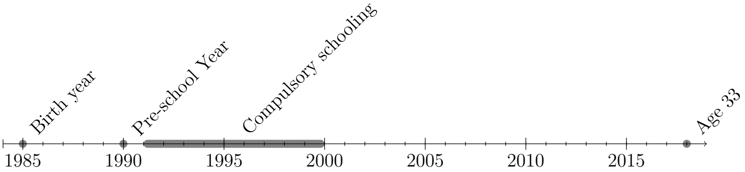
  $\rightarrow$ infer # of years typically needed to reach the educ. level reported by i (N_{Educ_i})

	Duration (1)	Cumulated Years of Education (2)
Lower education:		
Primary	5	5
Middle	3	8
Secondary	2	10
Higher secondary	2	12
Higher education:		
Path 1:		
Diploma/certificate course	1	13
Path 2:		
Graduate	3	15
Path 3:		
Diploma/certificate course	1	13
Graduate	3	16
Path 4:		
Graduate	3	15
Postgraduate and above	2	17
Path 5:		
Diploma/certificate course	1	13
Graduate	3	16
Postgraduate and above	2	18

$\Rightarrow$ We define educational delay as $N_i - N_{Educ_i}$

PLFS: sample

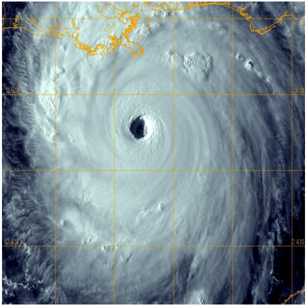
- Our focus: 81,542 individuals aged 23 to 33
- Young adulthood: 23 years old in 2018 ($\sim$ master degree)
  $\rightarrow$ youngest cohort born in 1995 and completes compulsory schooling in 2010
- Oldest cohort: 33 years old in 2018, due to reliability of satellite data
  $\rightarrow$ oldest cohort born in 1985 and completes compulsory schooling in 2000



- Thus, we focus on storms that took place between 1990 and 2010

Childhood exposure to storms

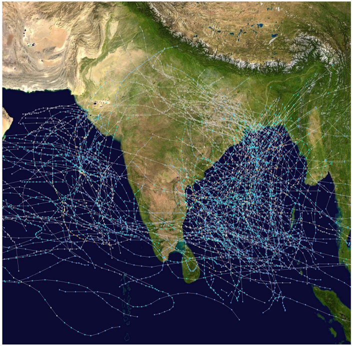
- Accounts for the intensity of winds to which children of a given cohort and district were exposed during compulsory schooling
- Focus on winds (not flood or surges), because
  - exogenous nature
  - position and wind speed of the eye of a storm can be used to obtain wind speed in all the areas around the eye of a storm



- Constructed in three steps

District wind speed

1. For each storm h, we compute wind speed (w_{dh}) in each district d using storms' best tracks (NOAA)
   → contains coordinates, date, windspeed of the eye at 6 hours intervals



Source: National Hurricane Center (NOAA).

Index of yearly district exposure x_{dt}

2. Convert winds into an index of yearly district exposure using the following damage function

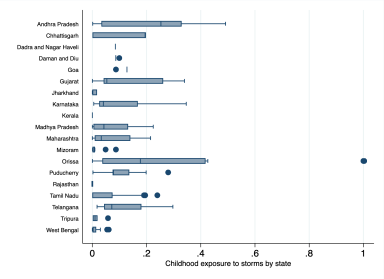
$$x_{dt} = \sum_{h \in H_t} \frac{(w_{dh} - 50)^2}{(w^{max} - 50)^2} \qquad \text{if} \qquad w_{dh} > 50$$

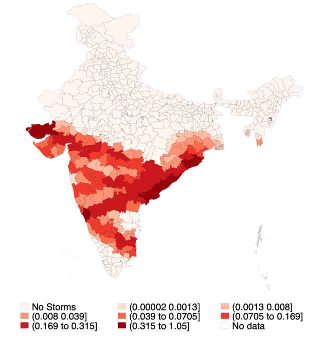
- w: wind speed
- w^{max}: maximum wind speed in the sample
- 50: windspeed threshold in knots
- square accounts for the force exerted by winds on built structures

Birth-year cohort b and district d exposure index

3. Sum district exposure index over the period of time during which a birth-year cohort was attending compulsory school

$$C_{bd} = \sum_{t=b+5}^{t=b+15} x_{dt}$$





Identification

$$Y_i = \alpha_0 + \alpha_1 C_{bd} + \mathbf{X_i'}\boldsymbol{\beta} + \delta_d + \delta_b + \epsilon_i$$

- where:
  - $i = (b, d)$: individual in birth-year cohort b and district d
  - Y_i: education delay / labor market outcomes
  - C_{bd}: childhood exposure to tropical storms
  - $\mathbf{X_i'}$: vector of individual characteristics (gender, first-born, Hindu)
  - δ_d : district fixed effects
  - δ_b : birth-year cohort fixed effects
- Identification is achieved using two sources of data variation:
  1. educational delays of cohorts with different exposures within districts
  2. same birth-year cohort across districts with different exposures
- Two-way clustering: state level and district-birth year level

Main results – educational delay

	Educational delay			
	(1)	(2)	(3)	(4)
Panel A:				
# of years				
Childhood exposure	0.31^{***}	0.27^{**}	0.20	0.29^{***}
	(0.079)	(0.13)	(0.15)	(0.097)
Panel B:				
yes=1, no=0				
Childhood exposure	0.18^{***}	0.20^{***}	0.20^{**}	0.19^{***}
	(0.052)	(0.067)	(0.082)	(0.065)
Individual controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes
State trends	No	Yes	No	No
State-(birth)-year FE	No	No	Yes	No
State-period FE	No	No	No	Yes
Observations	77,737	77,737	77,737	77,737

A super storm would:

- delay a child by 0.31 years on average, or $\sim$ 13 weeks (3 months)
- cause an 18 percentage points increase in the probability of accumulating a delay

→ this estimate implies that the share of kids with a delay would ↑ by 69% if states with zero exposure were hit by a super storm

Main results – educational attainment (ordered logit)

	Logit estimates	No formal schooling	Primary school	Middle school	Secondary education	Above-secondary education
	(1)	(2)	(3)	(4)	(5)	(6)
Childhood exposure	-0.48***	0.048***	0.028***	0.031***	-0.026***	-0.081***
	(0.130)	(0.012)	(0.008)	(0.009)	(0.007)	(0.022)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,737	77,737	77,737	77,737	77,737	77,737

- A super storm increases by 4.8 percentage points the probability of no formal education
- A super storm decreases by 8.1 percentage points the probability of going above secondary education
- Suggest a deskilling of the regions affected by storms in the long run

Figures A Figures B

Main results – type of activity

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
Childhood exposure	-0.16**	-0.059	-0.12***	0.046	0.18**
	(0.069)	(0.049)	(0.020)	(0.045)	(0.073)
Individual controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes	Yes
State trends	Yes	Yes	Yes	Yes	Yes
Observations	77,737	77,737	77,737	77,737	77,737

⇒ A super storm decreases by 16 percentage points the probability of being a regular salaried worker

▸ Wages and Hours Worked

Robustness and heterogeneity analysis

- Robustness tests:
  1. Placebo 1: randomization of the childhood exposure measure over our sample
  2. Placebo 2: assign childhood exposure to older cohorts ▸ Placebo
  3. Control for predicted educational attainments and level of parental education ▸ Parent
  4. Drop extreme values and Orissa (because of super storm) ▸ Extremes
  5. Alternative specification of the storm index (changes in threshold and coefficient of wind on structures) ▸ Alternatives
- Heterogeneity analysis:
  1. Male/female
  2. Rural/urban

  ▸ Education ▸ Activity

Channels

- Childhood exposure to storms has detrimental long-term consequences both in terms of educational attainments and labor market prospects

- Worrisome as deskilling of the population can hinder economic growth
  - e.g. our results imply a lifelong fall in returns of 2.1%-3.3% for super storms and 0.13%-0.21% for average storms

- In order to formulate policy recommendations, it is important to understand the channels through which storms affect education

  1. Households experience a **negative income shock** (e.g. kids may have to work, could be removed from schools)

  2. School **facilities** are **damaged**

  3. Psychological stress – hard to identify and disentangle from (1) & (2)

- Next: evaluate whether (1) & (2) are at play and how they are mirrored in kids scholastic outcomes in primary and middle school

Income channel

- Consumer Pyramids dx:
  - **panel of ~200,000 households**
  - detailed information on **monthly income** for the period **2014-2019**

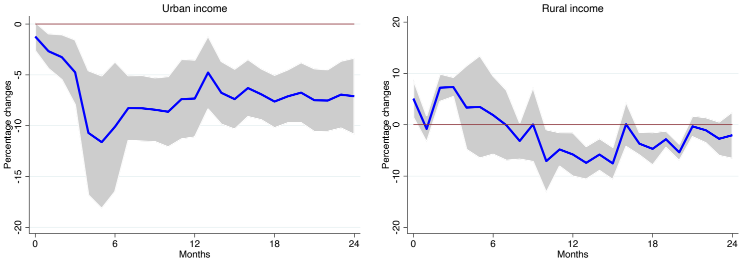
- We uncover the short-term dynamic income effects of storms using local projections over 24 months

▸ Local projections (Jorda) ▸ Local projections

- Unit of observation: **month-district** level, so we reconstruct the measure of storm exposure using monthly wind exposures

→ Storms act as a negative income shock, particularly so for urban areas which do not seem to have recovered after 24 months

Income channel



- **Urban:** average exposure causes a fall in household income
  - peaks at 5 months, slight recovery up to a year and then stabilizes at levels 8% below the no-disaster counterfactual
    - → consistent with a ↓ in hours of work or loss of job of a household member (mirrored in a ↓ of monthly wages)
- **Rural:**
  - sharp increase peaking at 3 months, then a gradual fall
    - → immediate help + destruction of agricultural land may be felt in the next growing season
  - at 10 months income is 8% lower, then slowly recovers to pre-disaster level
    - → ↓ in wages compensated by an ↑ in rural business profits

▸ Income by source

School infrastructure channel

- DISE data from the Ministry of Education in India:
  - virtually all schools with formal education up to middle school
  - physical infrastructure, teachers, enrollment, examination results at the school level with exact location information
- We aggregate the school information at the pincode level and re-construct our measure of storm using pincode(-year) wind exposures
- Focus: **2010-2018**

Damages to school facilities

	Avg. # of classrooms in good conditions	# of schools with electricity	# of schools with unreliable electricity
	(1)	(2)	(3)
Storm exposure	-0.29*	-5.28**	1.40*
	(0.17)	(2.43)	(0.82)
Pincode FE	yes	yes	yes
District-year FE	yes	yes	yes
Observations	153794	153789	153789

- Storms damage facilities: avg. # of classrooms in good conditions declines and the # of schools with electricity falls

School destruction

	Net entry		# of buildings under construction	
	(1)	(2)	(3)	(4)
Storm exposure	-5.03**	-1.29***	-2.29***	-1.69***
	(2.24)	(0.23)	(0.62)	(0.39)
Storm exposure$_{(t-1)}$		-1.12***		-1.16
		(0.20)		(1.22)
Storm exposure$_{(t-2)}$		0.49		0.79
		(0.71)		(1.27)
Storm exposure$_{(t-3)}$		1.65*		2.53***
		(0.97)		(0.84)
Pincode FE	yes	yes	yes	yes
District-year FE	yes	yes	yes	yes
Observations	136780	72168	153785	91074
R^2	0.54	0.71	0.80	0.88

- Storms destroy schools and reconstruction takes place after three years

Scholastic outcomes

- Both the drop in household income and damages to school facilities can affect academic outcomes
  - school closures
  - kids may drop out and work to financially provide for the household
  - they may be involved in reconstruction activities and have less time to concentrate on their homework
- Using the DISE data, we evaluate whether both channels are mirrored in scholastic outcomes – school attendance and academic performance
- Interestingly, responses are strikingly different depending on whether kids attend primary or middle school at the time of the disaster
  - primary school kids only respond by dropping out
  - middle school kids only tend to perform worse

School attendance

	Avg. # of kids in primary school					Avg. # of kids in middle school		
	C1	C2	C3	C4	C5	C6	C7	C8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm exposure	-2.21	-2.86	-2.46*	-2.66***	-2.73**	-0.62	-1.02	-1.98
	(2.03)	(2.10)	(1.42)	(0.97)	(1.11)	(1.85)	(1.82)	(2.36)
Pincode FE	yes	yes	yes	yes	yes	yes	yes	yes
Distict-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	143579	143579	143579	143579	143579	143579	143579	143579

- Storms reduce the average number kids attending primary school levels C3-C5 (ages 8-11)
  - → consistent with a story where the income shock causes parents to remove their kids from school
  - → kids below the age of 8 are too young to work or lack the physical strength to work in reconstruction activities
  - → in middle school, the share of kids from wealthier households is higher

Examination results

	Appeared		Passed		Grade > 60%	
	C5	C8	C5	C8	C5	C8
	(1)	(2)	(3)	(4)	(5)	(6)
Storm exposure	16.1	-3.05***	15.9	-3.05***	15.0*	-2.72***
	(10.0)	(1.00)	(9.96)	(0.92)	(8.21)	(0.88)
Pincode FE	yes	yes	yes	yes	yes	yes
District-year FE	yes	yes	yes	yes	yes	yes
Observations	126760	65195	126758	65195	126737	65195

- No impact for kids in primary school
- Worsening of academic performances at the end of middle school

Conclusion

- Our findings suggest that the estimated long-term educational delays result not only from infrastructure damages but also from sharp declines in income
- The negative income effects translate in a drop of school attendance for kids at the primary level and a deterioration of academic performances
- Highlights the need for better social safety nets and expanding post-disaster policies beyond reconstruction activities
- Policies should couple financial transfers with educational policies, e.g. cash transfers conditional on school attendance and stronger school support

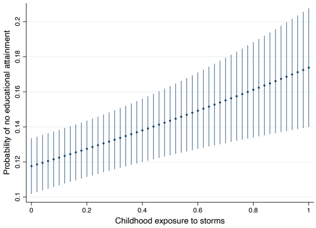
Thank you for your attention

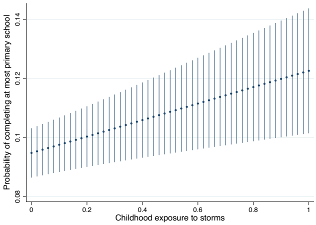
Exogeneity of storms and storms in India

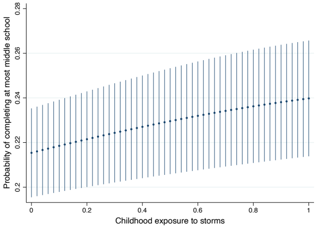
1. Storms are unpredictable:
   - Frequency of occurrence of Storms is stationary [e.g. Elsner and Bossak (2001), Pielke et al. (2005)].
   - Storms are erratic phenomena.
2. Do we observe violent storms in India?
   - 7,516 km of coastline make it the most affected country in the world.
   - Exposed to 10% of the world's cyclones.
   - In India, every year, over 370 million people are affected by cyclones.

▸ return

No formal schooling, primary and middle school

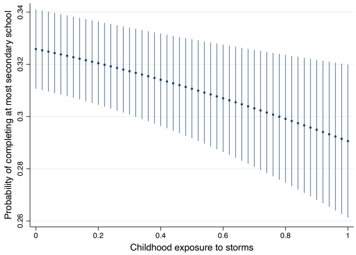


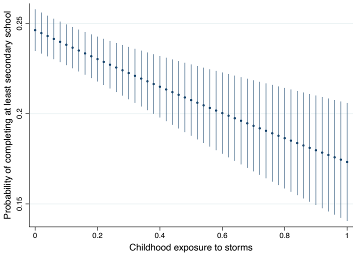




Logit

Secondary and above-secondary education





▸ Logit

Main results – wages and hours worked

	Log hourly wages	Hours of work
	(1)	(2)
Childhood exposure	-0.021	5.72
	(0.19)	(4.55)
Individual controls	Yes	Yes
District FE	Yes	Yes
Birth-year FE	Yes	Yes
State trends	Yes	Yes
Observations	31,534	31,534

▸ Type of Activity

Robustness – falsification, education

	Placebo Share of estimations with statistical significance at: 1%	5%	10 %	Older cohort assignment + 10 years
	(1)	(2)	(3)	(4)
Panel A:				
Educ. delay: # of years				
Childhood exposure	0.026	0.079	0.128	-0.040
				(0.12)
Panel B:				
Educ. delay: yes=1, no=0				
Childhood exposure	0.024	0.079	0.132	-0.038
				(0.064)
Panel C:				
Educ. attainment				
Childhood exposure	0.012	0.060	0.108	-0.370
				(0.410)
Individual controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes
Observations	77,737	77,737	77,737	67,765

Return

Robustness – education controls, education

	Baseline	Predicted educ. attainment	Sub-sample	Parental education
	(1)	(2)	(3)	(4)
Panel A:				
Educ. delay: # of years				
Childhood exposure	0.31***	0.31***	0.36**	0.36**
	(0.079)	(0.079)	(0.15)	(0.15)
Panel B:				
Educ. delay: yes=1, no=0				
Childhood exposure	0.18***	0.18***	0.21***	0.21***
	(0.052)	(0.051)	(0.075)	(0.075)
Individual controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes
Predicted educ. attainment	No	Yes	No	No
Parental education	No	No	No	Yes
Observations	77,737	77,737	32,581	32,581

Return

Robustness – extreme values, education

	Baseline	Excluding Orissa	Interaction: Orissa × C_{bd}	Excluding extreme winds
	(1)	(2)	(3)	(4)
Panel A:				
Educ. delay: # of years				
Childhood exposure (C_{bd})	0.31***	0.30***	0.30***	0.20***
	(0.079)	(0.10)	(0.10)	(0.067)
Orissa × C_{bd}			0.016	
			(0.10)	
Panel B:				
Educ. delay: yes=1, no=0				
Childhood exposure (C_{bd})	0.18***	0.16**	0.16**	0.10**
	(0.052)	(0.061)	(0.061)	(0.040)
Orissa × C_{bd}			0.055	
			(0.061)	
Panel C:				
Educ. attainment				
Childhood exposure (C_{bd})	-0.48***	-0.53***	-0.55***	-0.32***
	(0.13)	(0.18)	(0.19)	(0.10)
Orissa × C_{bd}			0.23	
			(0.19)	
Individual controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes
Observations	77,737	75,192	77,737	77,737

Return

Robustness – alternative measures, education

	Baseline	50, cubic	64, square	64, cubic	All winds	HURRECON
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:						
Educ. delay: # of years						
Childhood exposure	0.31***	0.47***	0.42***	0.50***	0.0033	0.33***
	(0.079)	(0.12)	(0.094)	(0.17)	(0.0079)	(0.090)
Panel B:						
Educ. delay: yes=1, no=0						
Childhood exposure	0.18***	0.28***	0.25***	0.31***	0.0006	0.21***
	(0.052)	(0.052)	(0.049)	(0.070)	(0.0042)	(0.054)
Panel C:						
Educ. attainment						
Childhood exposure	-0.48***	-0.60***	-0.58***	-0.54***	0.006	-0.60***
	(0.13)	(0.20)	(0.15)	(0.21)	(0.013)	(0.15)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,737	77,737	77,737	77,737	77,737	77,737

Return

Education

	Educational delay		Category of schooling completed: yes=1, no=0				
	# of years	yes=1, no=0	No educ.	Primary	Middle	Secondary	Above
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:							
Male							
Childhood exposure	0.41***	0.23***	0.028**	0.025**	0.038**	-0.014**	-0.077**
	(0.13)	(0.061)	(0.011)	(0.010)	(0.015)	(0.0056)	(0.031)
Observations	39,272	39,272	39,272	39,272	39,272	39,272	39,272
Panel B:							
Female							
Childhood exposure	0.25**	0.14***	0.078***	0.031***	0.025***	-0.040***	-0.095***
	(0.12)	(0.049)	(0.028)	(0.012)	(0.0095)	(0.015)	(0.034)
Observations	38,465	38,465	38,465	38,465	38,465	38,465	38465
Panel C:							
Rural							
Childhood exposure	0.27**	0.19***	0.054**	0.038**	0.059**	0.0030**	-0.15**
	(0.10)	(0.060)	(0.024)	(0.016)	(0.025)	(0.0014)	(0.066)
Observations	42,281	42,281	35,456	35,456	35,456	35,456	35456
Panel D:							
Urban							
Childhood exposure	0.33***	0.10**	0.051**	0.025**	0.020**	-0.045**	-0.052**
	(0.12)	(0.046)	(0.022)	(0.011)	(0.0086)	(0.019)	(0.023)
Observations	35,454	35,454	42,281	42,281	42,281	42,281	42,281
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Return

Activity

	Regular work	Casual labor	Self-employed	Unpaid family work	Domestic duties
	(1)	(2)	(3)	(4)	(5)
Panel A:					
Male					
Childhood exposure	-0.29**	-0.025	0.0036	0.094	0.025*
	(0.14)	(0.082)	(0.056)	(0.068)	(0.013)
Observations	39,272	39,272	39,272	39,272	39,272
Panel B:					
Female					
Childhood exposure	-0.079***	-0.071	-0.20***	0.019	0.29**
	(0.028)	(0.083)	(0.044)	(0.036)	(0.12)
Observations	38,465	38,465	38,465	38,465	38,465
Panel C:					
Rural					
Childhood exposure	-0.098*	-0.062	-0.18***	0.093	0.16**
	(0.054)	(0.058)	(0.019)	(0.065)	(0.074)
Observations	42,281	42,281	42,281	42,281	42,281
Panel D:					
Urban					
Childhood exposure	-0.36***	-0.026	0.028	-0.045*	0.24***
	(0.093)	(0.033)	(0.038)	(0.024)	(0.043)
Observations	35,454	35,454	35,454	35,454	35,454
Individual controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Educ.-Birth year FE	Yes	Yes	Yes	Yes	Yes

Return

Why Local Projections? (Jorda, 2005)

- We want to produce Impulse Response Functions (IRFs) for the impact of a hurricane. Local projections allow us to do it without specifying and estimating the underlying multivariate dynamic system.
- The **central idea** consists in estimating local projections **at each period of interest** rather than **extrapolating** into increasingly distant horizons from a given model (as in a VAR).
- Advantages of Local Projections:
  1. Estimated by **simple regression techniques**
  2. More robust to **misspecification**
  3. Joint or point-wise analytic **inference is simple**
  4. Easily accommodate experimentation with highly nonlinear and flexible specifications (impractical in a multivariate context)

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Panel Local Projection

- k-step ahead panel predictive regressions:

$$\Delta X_{d,t+k} = \alpha^{k} + \gamma_1^{k} S_{dt} + \sum_{p} \beta_p \Delta X_{d,t-p} + \delta_{dt} + \eta_h \ + \epsilon_{d,t+k}$$

- $\Delta X_{c,t+k} \equiv \log X_{c,t+k} - \log X_{c,t-1}$
- X: household monthly income
- S_{dt}: index of exposure to storms
- Object of interest: γ_1^{k} , the average response of X at horizon k to a disaster shock at time t
- $\sum_p \Delta X_{d,t-p}$ lag of the dependent variable
- δ_{dt} and η_h are district-time and household fixed effects

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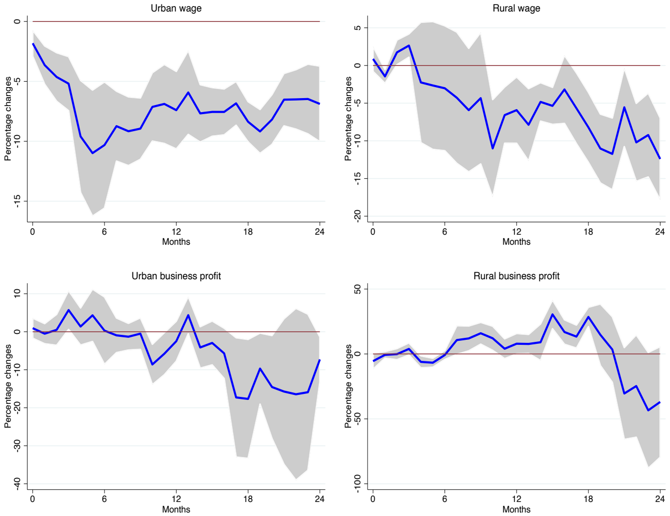
Income channel, by source



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