The commuting costs of high intensity rains

Evidence from Rio de Janeiro

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Motivation

- High intensity rains (HIRs) are a recurrent problem for developing country cities
  - Seasonal occurrence frequency
  - HIRs + poor infrastructure ⇒ traffic disruption + floods + landslides
  - 40.6% of cities over 10 million inhabitants are in the tropic
- Extreme rainfall should increase in eastern South America due to climate change (Gutiérrez et al. 2021)
- Losses mainly incurred by the housing sector, followed by the transportation sector (World Bank 2014)
- **This paper:** Impact of HIRs on buses speed + public transportation demand
  - Novel GPS database covering the universe of buses in Rio
  - Contribution literature
    - ⋆ Transportation + rainfall ⇒ high frequency data
    - ⋆ High frequency data ⇒ public transportation.
    - ⋆ Direct policy relevance

Data

- Buses speed
  - GPS observations (15-minute intervals) for all buses in Rio between 2017-2018
  - Rush-hour only (4-10 am/pm)
  - Data mapped onto an one-square-kilometer grid
- Rains
  - 33 pluviometric/telemetric stations spread throughout the city stations
- Supply and Demand
  - Subway system hourly passengers transported
  - Train system daily passengers transported
  - Bus system fleet size and passengers transported descriptive statistics

Measuring HIRs

- I measure HIRs by using *Sistema Alerta Rio* (Rio Alert System, SAR) definition
  - **Stage of Attention (SA)**: At least 15mm/15min or 20mm/30min or 25mm/1h
  - **Stage of Crisis (SC)**: At least 40mm/30min or 55mm/1h in two or more stations
- SAR was created specifically to measure rainfall intensity and dispersion
- I use river level data to validate their definition link

HIRs-Derived Buses Speed Loss

$$Speed_{ilt} = \beta^A SA_t + \beta^C SC_t + f(Time_t) + Line_l + Gridcell_i + \epsilon_{ilt}$$

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	Speed
Stage of Attention	-0.173***
	(0.030)
Stage of Crisis	-1.222***
	(0.129)
Mean Speed	16.746
Observations	76,338,604

Notes: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Robust standard errors in parentheses clustered at cell level. The dependent variable is Speed in km/h and Winsorized at 0.5%.

- Speed loss between 1.03% (SA) and 7.30% (SC)
- Local effects as high as 41.92% link
- Control for interventions link

Supply and Demand Considerations

$$Reaction_{itl} = \beta^A SA_t + \beta^C SC_t + f(Time_t) + Line_l + Station_i + \epsilon_{tl}$$

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	Buses		Subway	Train
	Fleet Size	Passengers Transported	Passengers Transported	Passengers Transported
Stage of Attention	-0.037***	-91.867***	-19.547***	-141.843***
	(0.007)	(5.907)	(3.750)	(18.803)
Stage of Crisis	0.060***	45.874***	30.716***	199.944***
	(0.017)	(11.699)	(9.643)	(44.671)
Dep. Var. Mean	9.98	4084.66	763.41	4286.68
Station FE	No	No	Yes	Yes

*p < 0.10, **p < 0.05, ***p < 0.01. Robust standard errors in parentheses clustered at station level where applicable, otherwise at line level. Subway demand is measured at 1-hour intervals while the other variables at 1-day intervals.

- Evidence of substitution effect only in SC occurrences

Back-of-the-Envelope Welfare Cost

$$\Delta Cost_l^r = d_l \times \left(\frac{1}{s_l^{b,r}(1)} - \frac{1}{s_l^{b,r}(0)} \right) \times \sum_{i \in \mathcal{I}(l)} v_i \times Wages_{il} \times Commuters_{il}$$

- Data limitations.
- **Upper Bound:** the entire sample → inelastic demand
- **Lower Bound:** Census tracts without train or subway stations map

- Yearly wage opportunity cost of HIRs: \$57.43 - \$97.82 million dollars link
  - Equivalent to 0.82% - 2.18% (Machado and Vianna 2017; Vianna and Young 2015) or 1.01% - 1.72% (*O custo dos deslocamentos: RJ* 2015) of the total traffic-derived wage opportunity cost
  - Expected to increase by 25% by the end of the century (Gutiérrez et al. 2021)

Conclusion

- HIRs do disrupt buses speed to a significant extent
  - The generalized effect can be as high as 7.3%
  - The localized effect can be as high as 41.92%
- Substitution effect between bus and rail systems during highly disruptive HIRs (SC occurrences)
- Mildly disruptive HIRs (SA occurrences) cause a reduction in demand for the public transportation system
  - Likely due to less non-essential trips
- HIRs welfare cost can grow up to $122.27 million dollars by the end of the century

Thank you

Related literature

- Transportation + precipitation literature
  - Smith et al. (2020) and Hofmann and O'Mahony (2005).
  - **Contribution:** I contribute by isolating the impact of HIRs on buses + rail system substitution effect discussion

- High-frequency big data in urban transportation literature
  - Kreindler and Miyauchi (2021), Akbar et al. (2018), Gu et al. (2021), and Sun et al. (2020) .
  - **Contribution:** I contribute by using high frequency (15 minute observations) buses GPS data to infer supply side considerations of HIRs.

- Public system weather assessment literature
  - Guo, Wilson, and Rahbee (2007), Zhou et al. (2017), and Hofmann and O'Mahony (2005)
  - **Contribution:** First, I identify supply-side effects on the bus system front. Second, I find evidence for both increase and decrease in both the rail system and buses demand depending on the intensity of the HIR (rush-hour).

Descriptive Statistics

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	Bus Speed	Fleet Size	Bus Demand	Subway Demand	Train Demand
Mean	16.746	9.976	4084.657	763.409	4286.681
Std. Dev.	18.763	8.180	4124.524	1134.640	4589.092
Min.	0	1	81	0	330
Max.	72.970	30	14592	8234.000	18083.000
Obs.	7.63e+07	3.55e+5	3.55e+5	6.28e+05	2.50e+4
Pct. of SA Obs.	2.786	11.31	11.31	2.645	12.420
Pct. of SC Obs.	0.431	1.78	1.78	0.328	2.071
No. of Lines	492	409	409	3	5

Notes: All data is winsorized at 0.5%. Buses speed is measured at each 15-minute interval, subway demand at 1-hour intervals and the other variables at 1-day intervals.

River Level Results

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	15 minutes	01 hour	01 day
Stage of Attention (1)	0.128***		
	(0.042)		
Stage of Crisis (1)	0.593***		
	(0.150)		
Stage of Attention (2)		0.098***	
		(0.031)	
Stage of Crisis (2)		0.499***	
		(0.123)	
Stage of Attention (3)			0.045**
			(0.017)
Stage of Crisis (3)			0.269***
			(0.071)
Observations	71151	71151	71151

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors in parentheses clustered at day level. Dependent variable: River Level in meters.

HIRs-Derived Buses Speed Loss per PA

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	PA 1	PA 2	PA 3	PA 4	PA 5
Stage of Attention	-0.651*	-0.098*	-0.836***	-0.454***	-0.957***
	(0.322)	(0.057)	(0.126)	(0.116)	(0.212)
Stage of Crisis	-6.396***	-2.343***	.	-5.139***	-0.343
	(1.821)	(0.398)	(.)	(1.107)	(0.322)
p-value (SA=SC)	0.003	0.000	0.000	0.000	0.079
Dependent Variable Mean	15.252	15.554	16.642	17.474	18.902
Observations	9034209	18855940	23637003	10570364	14241021

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors in parentheses clustered at cell level. The dependent variable is Speed in km/h and Winsorized at 0.5%.

Notes: The table shows the impact of high intensity rains (HIR) on the bus system during 2017/01 - 2018/08 by Planning Area (PA). All regressions are using the FE-4 specification. State of Attention and State of Crises are locally defined, applying the definition shown in Table 2 to each PA. The time window considered for these events is of 01 hour from the triggering of an operational stage.

Buses Distribution

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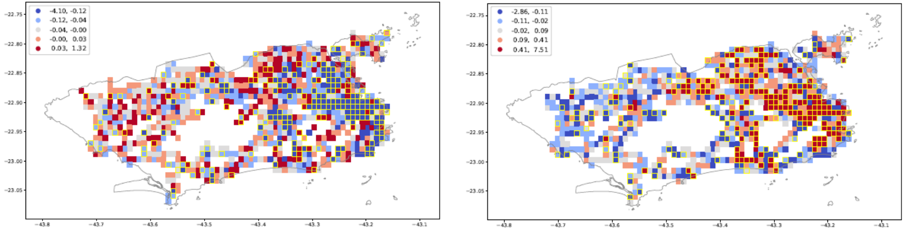
Figure 3: HIRs Impact on Buses Density per Grid Cell

Panel A: Density changes during Stage of Attention

Panel B: Density changes during Stage of Crisis



Notes: The figure shows the HIRs induced buses density changes, with Panels A and B contemplating Stage of Attention and Stage of Crisis occurrences, respectively. Density here is defined as the number of buses observed in a grid cell at each 15 minutes interval. In each cell is reported the coefficient derived from estimating equation (4) at cell level, removing cell fixed effects and using robust standard errors. Yellow outlines represents cells which have statistically significant coefficients at 0.5%. HIRs are defined using SAR definition (see Table 2). The data is respective to the period between 2017/01 - 2018/02

Rail System - Line Effects

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	Whole System	Line 1	Line 2	Line 3	Line 4
Panel A: Subway System Demand					
morning Stage of Attention	-77.602***	-75.650***	-88.436***	-46.841	
	(14.615)	(18.194)	(28.523)	(33.145)	
morning Stage of Crisis	19.286	-5.315	28.039**	95.544**	
	(13.215)	(23.201)	(10.441)	(24.766)	
non-morning of Attention	-3.452	-5.436	-4.919**	7.768	
	(3.032)	(5.373)	(1.786)	(11.662)	
non-morning Stage of Crisis	33.089***	49.357**	0.366	93.629**	
	(12.221)	(22.724)	(5.858)	(22.504)	
Dependent Variable Mean	1043.319	1361.195	672.821	967.598	
Observations	295235	143503	115772	35960	
Panel B: Train System Demand					
Stage of Attention	-207.094***	-185.217***	-213.152**	-135.450***	-58.635**
	(37.471)	(35.179)	(66.584)	(28.333)	(24.089)
Stage of Crisis	350.234**	227.694***	305.474*	206.177***	86.635
	(127.019)	(61.350)	(136.637)	(53.867)	(56.155)
Dependent Variable Mean	6567.406	6613.302	9870.129	4779.782	3087.313
Observations	7581	9121	2596	5655	6090

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors in parentheses clustered at station level. The dependent variable in Panel A is the number of passengers per hour and station, while in Panel B is the daily number of passengers per station.

Welfare Analysis

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	PA 1	PA 2	PA 3	PA 4	PA 5	RJ
			Panel A: General Terms			
Distance (Km)	4.671	5.989	8.499	9.503	12.818	9.076
Stage of Attention	246	475	249	379	228	814
Stage of Crisis	3	77	0	34	5	112
			Panel B: Upper Bound			
$\Delta Cost^a$(d=1)(thousand R$)	6.254	6.351	48.275	15.609	24.729	32.351
$\Delta Cost^c$(d=1)(thousand R$)	101.300	177.639	.	243.796	8.570	243.954
Total Cost (millions R$)	8.606	99.986	102.162	134.989	72.820	486.987
			Panel C: Lower Bound			
$\Delta Cost^a$(d=1)(thousand R$)	3.664	3.850	21.415	14.186	17.744	20.582
$\Delta Cost^c$(d=1)(thousand R$)	59.358	107.687	.	221.572	6.149	155.206
Total Cost (millions R$)	5.042	60.613	45.320	122.683	52.251	309.826

Notes: The table presents in Panel A both the total number of occurrences of Stage of Attention and Stage of Crisis (as defined in Table 2 and using 01 hour time window) and the distances considered for each PA. In Panels B and C is presented the HIR total welfare cost (both upper and lower bounds), where $TotalCost = \Delta Cost^a \cdot SA + \Delta Cost^c \cdot SC$. There are 18 months in my analysis (01/2017 - 08/2018) and $\Delta Cost^a$ and $\Delta Cost^a$ are as in Table A.4 (where the distance d is equal to 1).

HIRs Distribution

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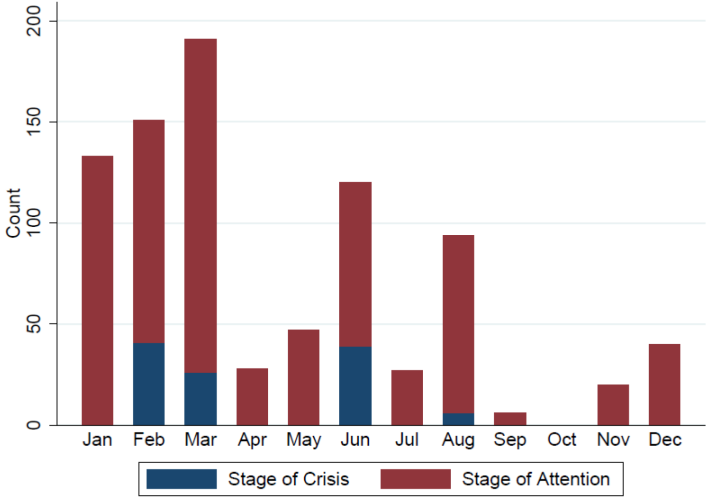

Notes: The figure show the number of occurrences, measured at 15 minutes intervals, of Stage of Attention or Stage of Crisis between 2017/01 - 2018/08 in Rio de Janeiro.

SAR Stations

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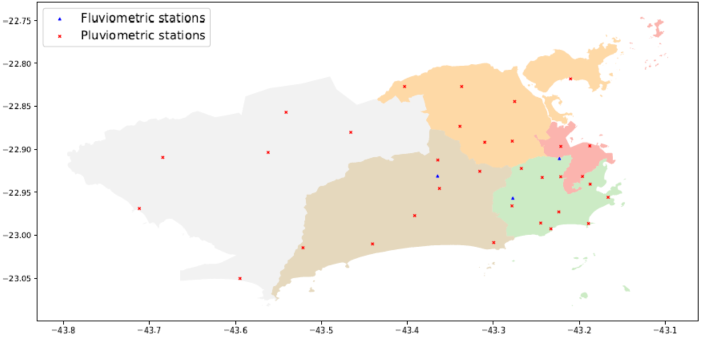

Census Tracts and Rail System Stations

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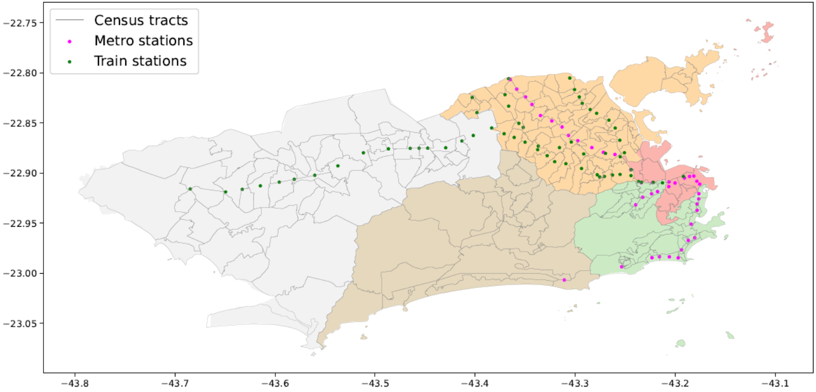

COR Action

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	Reference	COR Action
Stage of Attention	-0.435***	-0.359***
	(0.061)	(0.098)
Stage of Crisis	-1.237***	-1.130***
	(0.127)	(0.153)
COR Action # Any Stage		-0.109
		(0.128)
Observations	6213938	6213938

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Robust standard errors in parentheses clustered at cell level. The dependent variable is speed in km/h and Winsorized at 0.5%.

Bibliography I

- Akbar, Prottoy A. et al. (2018). *Mobility and Congestion in Urban India*. DOI: 10.3386/w25218.
- Gu, Yizhen et al. (2021). "Subways and Road Congestion". In: *American Economic Journal: Applied Economics* 13.2, pp. 83–115. ISSN: 1945-7782. DOI: 10.1257/app.20190024.
- Guo, Zhan, Nigel Wilson, and Adam Rahbee (2007). "Impact of Weather on Transit Ridership in Chicago, Illinois". In: *Transportation Research Record* 2034, pp. 3–10. DOI: 10.3141/2034-01.
- Gutiérrez, J.M et al. (2021). "Atlas". In: *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK and New York, NY, USA: Cambridge University Press, pp. 1927–2058.
- Hofmann, M. and M. O'Mahony (2005). "The impact of adverse weather conditions on urban bus performance measures". In: *Proceedings. 2005 IEEE Intelligent Transportation Systems, 2005.* Proceedings. 2005 IEEE Intelligent Transportation Systems, 2005. ISSN: 2153-0017, pp. 84–89. DOI: 10.1109/ITSC.2005.1520087.

Bibliography II

Kreindler, Gabriel E. and Yuhei Miyauchi (2021). "Measuring Commuting and Economic Activity Inside Cities with Cell Phone Records". In: *The Review of Economics and Statistics*, pp. 1–48. ISSN: 0034-6535. DOI: 10.1162/rest_a_01085.

Machado, Danielle Carusi and Guilherme Szczerbacki Besserman Vianna (2017). "Uma Análise dos Custos da Mobilidade Urbana no Brasil: Perdas do PIB com Deslocamentos". In: *Revista Brasileira de Estudos Regionais e Urbanos* 11.2. Number: 2, pp. 152–172. ISSN: 2447-7990.

O custo dos deslocamentos: RJ (2015). *O custo dos deslocamentos nas áreas metropolitanas: Rio de Janeiro*. Rio de Janeiro, Brazil: Federação das Indústrias do Estado do Rio de Janeiro (FIRJAN), p. 2.

Smith, Brian L. et al. (2020). *An Investigation into the Impact of Rainfall on Freeway Traffic Flow*. type: article. Engineering Archive. DOI: 10.31224/osf.io/9xnzc.

Sun, Jian et al. (2020). "Quantifying the Impact of Rainfall on Taxi Hailing and Operation". In: *Journal of Advanced Transportation* 2020. Ed. by Guohui Zhang. Publisher: Hindawi, p. 7081628. ISSN: 0197-6729. DOI: 10.1155/2020/7081628.

Bibliography III

- Vianna, Guilherme Szczerbacki Besserman and Carlos Eduardo Frickmann Young (2015). "Em Busca do Tempo Perdido: Uma Estimativa do Produto Perdido em Trânsito no Brasil". In: *Revista de Economia Contemporânea* 19.3, pp. 403–416. ISSN: 1415-9848. DOI: 10.1590/198055271933.
- World Bank (2014). *Coping with Losses: Options for Disaster Risk Financing in Brazil*. Accepted: 2018-02-28T20:04:15Z Journal Abbreviation: Lidando com perdas : opções de proteção financeira contra desastres no Brasil. Washington, DC: World Bank. DOI: 10/Coping-with-losses-options-for-disaster-risk-financing-in-Brazil.
- Zhou, Meng et al. (2017). "Impacts of weather on public transport ridership: Results from mining data from different sources". In: *World Transit Research*.