Assessing the safety effectiveness of citywide speed limit reduction: A causal inference approach integrating propensity score matching and spatial difference-in-differences

Presented by Guocong Zhai

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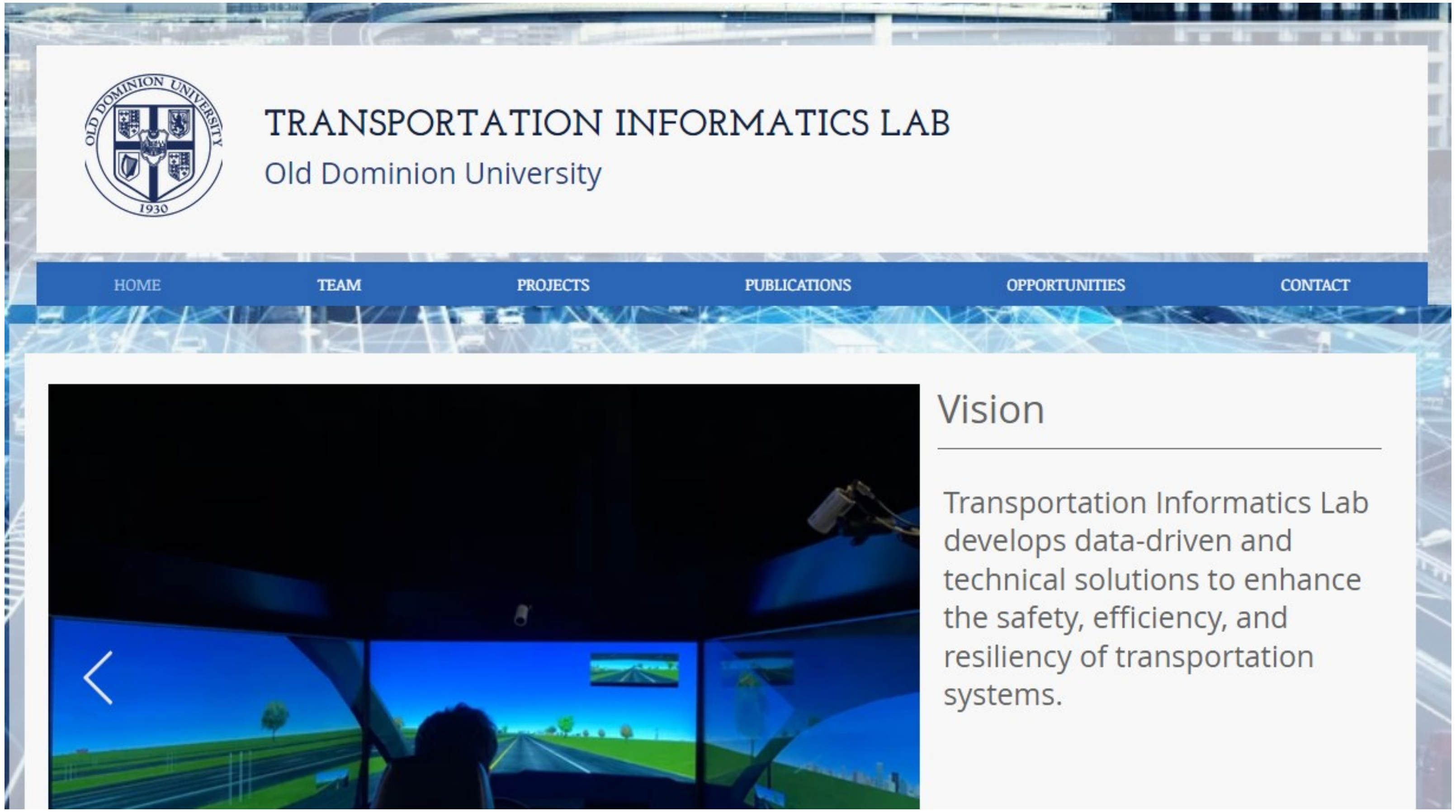
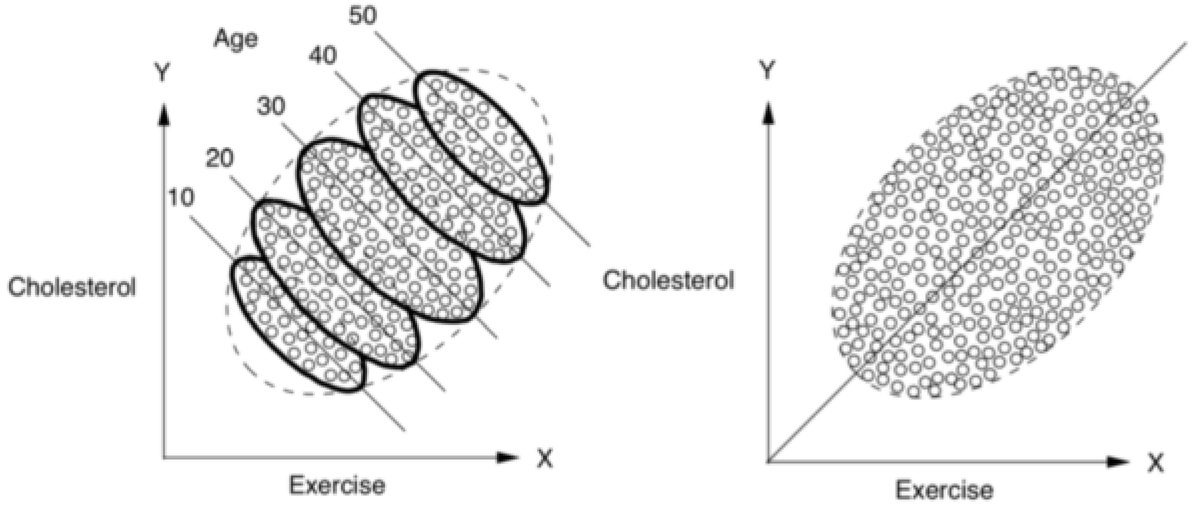


Motivation Examples

- Simpson's Paradox



Exercise is helpful in every age group but harmful for a typical person. **IS EXERCISE HELPFUL OR NOT?**

Motivation Examples

- Simpson's Paradox

	All		Men		Women	
	Applicants	Admitted	Applicants	Admitted	Applicants	Admitted
Total	12,763	41%	8,442	**44%**	4,321	35%

Department	All		Men		Women	
	Applicants	Admitted	Applicants	Admitted	Applicants	Admitted
A	933	64%	***825***	62%	108	**82%**
B	585	63%	***560***	63%	25	**68%**
C	918	35%	325	**37%**	***593***	34%
D	792	34%	417	33%	375	**35%**
E	584	25%	191	**28%**	***393***	24%
F	714	6%	373	6%	341	**7%**
Total	4526	39%	2691	45%	1835	30%

https://en.wikipedia.org/wiki/Simpson%27s_paradox

Motivation Examples

- Simpson's Paradox

Simpson's paradox in Covid-19 case fatality rates: a mediation analysis of age-related causal effects

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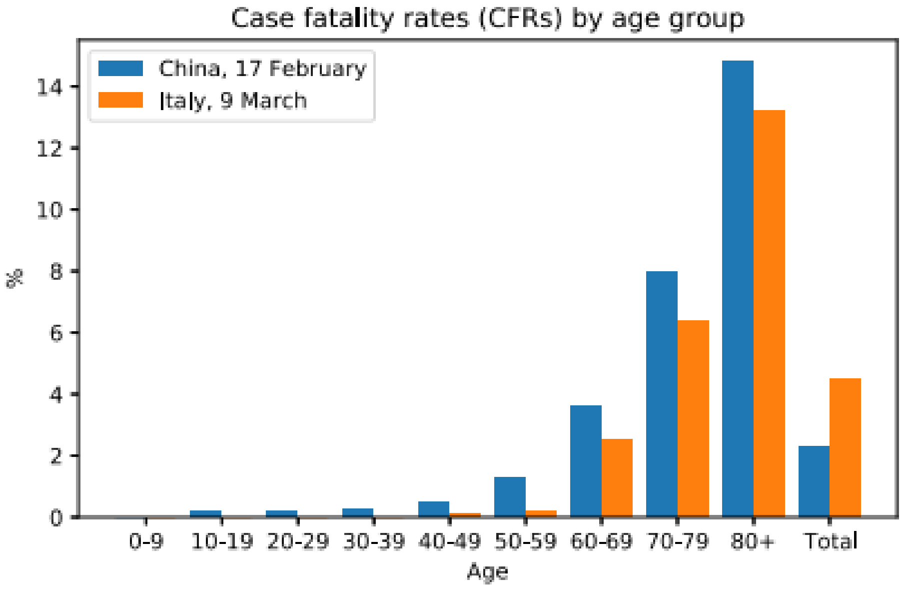
Abstract

We point out an instantiation of Simpson's paradox in Covid-19 case fatality rates (CFRs): comparing data of 44,672 cases from China with early reports from Italy (9th March), we find that CFRs are lower in Italy for every age group, but higher overall. This phenomenon is explained by a stark difference in case demographic between the two countries. Using this as a motivating example, we introduce basic concepts from mediation analysis and show how these can be used to quantify different direct and indirect effects when assuming a coarse-grained causal graph involving country, age, and mortality. As a case study, we then investigate total, direct, and indirect (age-mediated) causal effects between different countries and at different points in time. This allows us to separate age-related effects from others unrelated to age, and thus facilitates a more transparent comparison of CFRs across countries throughout the evolution of the Covid-19 pandemic.



Motivation Examples

- Simpson's Paradox

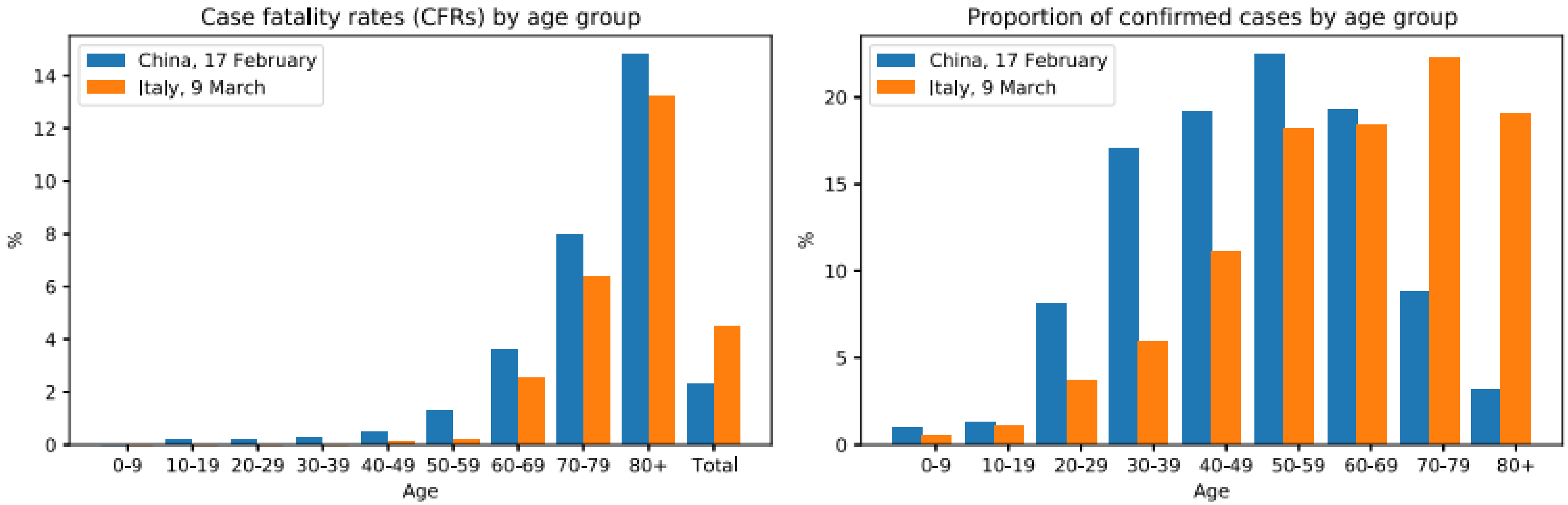
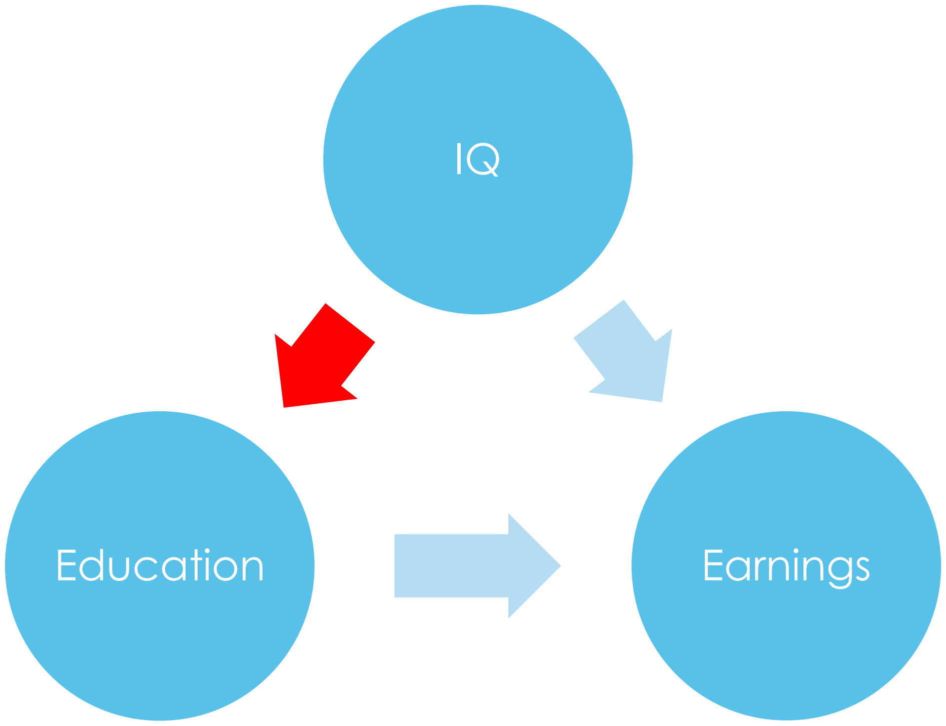


Fig. 1. (Left) COVID-19 CFRs in Italy and China by age group and in aggregated form ("Total"), i.e., including all *confirmed* cases and fatalities up to the time of reporting (see legend). (Right) Proportion of cases within each age group.

Motivation Examples

- Simpson's Paradox




````
```{r}

N <- 1000

# generate data

IQ <- rnorm(N,mean = 110,sd=30)
edu <- .6*IQ+ rnorm(N)
earnings <- 0.3*IQ+0.4*edu+rnorm(N)

```

For which could we get an unbaised estimation?

```{r}
summary(lm(earnings~edu))
summary(lm(earnings~IQ))
summary(lm(earnings~edu+IQ))
```
````

Motivation Examples

```
Call:
lm(formula = earnings ~ edu)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.1048 -0.7725 -0.0018  0.7938  3.5569 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.003564   0.139084  -0.026     0.98    
edu          0.899652   0.002025 444.267   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.156 on 998 degrees of freedom
Multiple R-squared:  0.995,	Adjusted R-squared:  0.995 
F-statistic: 1.974e+05 on 1 and 998 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = earnings ~ IQ)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.7717 -0.7218 -0.0079  0.7106  3.6291 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.183965   0.132054  -1.393    0.164    
IQ           0.541396   0.001154 469.245   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.095 on 998 degrees of freedom
Multiple R-squared:  0.9955,	Adjusted R-squared:  0.9955 
F-statistic: 2.202e+05 on 1 and 998 DF,  p-value: < 2.2e-16
```

```
Call:
lm(formula = earnings ~ edu + IQ)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.3038 -0.7141  0.0036  0.6659  3.2493 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -0.15283    0.12448  -1.228     0.22    
edu          0.37186    0.03304  11.253   <2e-16 ***
IQ           0.31801    0.01988  15.997   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.032 on 997 degrees of freedom
Multiple R-squared:  0.996,	Adjusted R-squared:  0.996 
F-statistic: 1.24e+05 on 2 and 997 DF,  p-value: < 2.2e-16
```

````
```{r}

N <- 1000

# generate data

IQ <- rnorm(N,mean = 110,sd=30)
edu <- .6*IQ+ rnorm(N)
earnings <- 0.3*IQ+0.4*edu+rnorm(N)
```
````

Motivation Examples

- Spillover
  - Contagion: a lower possibility of contracting a disease for unvaccinated people if others have been vaccinated.
  - Displacement: police enforcement designed to suppress crime in one location might displace criminal activities to nearby locations.
  - Communication: control group imitates neighbors' hygiene practices or learns about the health benefits.
- Time trend
  - Police enforcement might change over time before and after installing the red light camera.

Agenda

- Introduction
  - Background
  - Challenges and solutions
- Data Preparation
- Method
  - PSM (Propensity Score Matching)
  - SDID (Spatial Difference in Differences)
- Results
- Conclusions

ELSEVIER

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Introduction: Background

- Citywide speed limit reduction in New York City
  - The default speed limit was changed from 30 mph to 25 mph.
  - Effective on November 7th, 2014.

- Safety impacts
  - Give road users more time to react to unexpected safety-related events.
  - Reduce impact speeds when crashes occur.

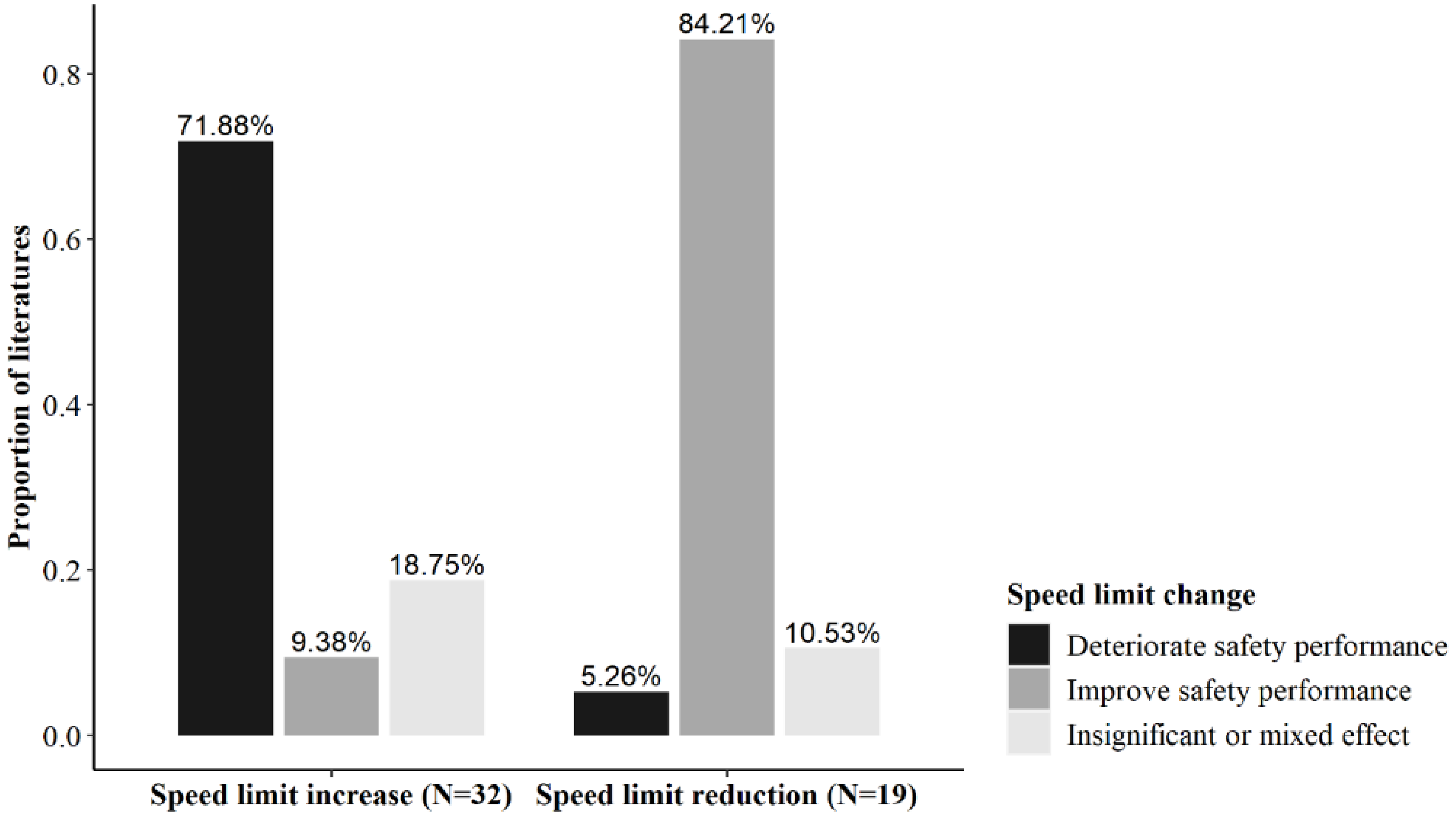
Source: https://www1.nyc.gov/html/dot/html/motorist/vision-zero-safe-driving.shtml

Introduction: Background

- Randomized control trials (RCTs) are the “Gold Standard”.
- Drawbacks of RCTs?:
  - Cost
  - Unethical
- What can we do when an experiment is not possible?
  - Observational studies

Introduction: Background

- Previous observational studies on safety effectiveness of speed limit changes (before 2021)



Introduction: Challenges and Solutions

Time trend: potential enforcement and drivin behavior changes in post-treatment periods.

Spatial spillover effect: speed limit reduction affect neighboring streets.

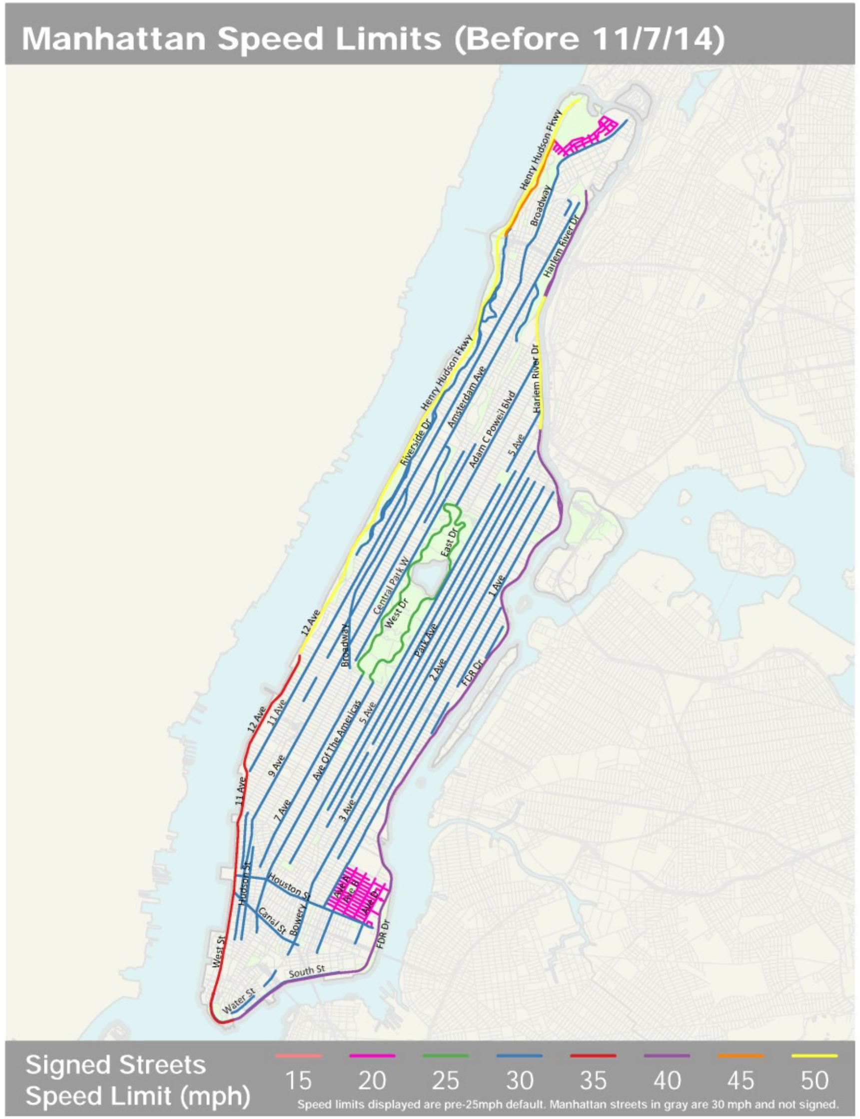
Confounding bias: confounders might affect the treatment indicator and safety outcomes simultaneously.

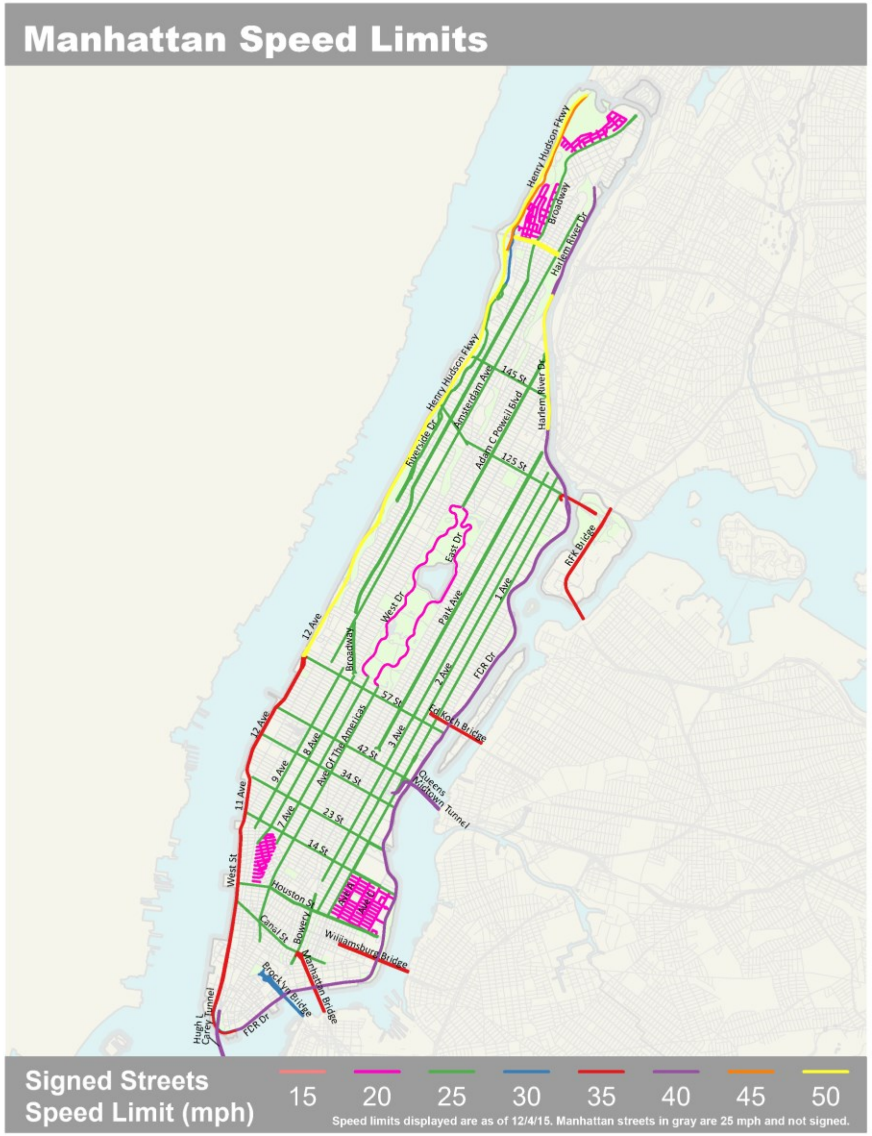
Spatial difference-in-differences (SDID)

Propensity score matching (PSM)

Integrated causal inference approach

Data Preparation: Speed Limit Reduction



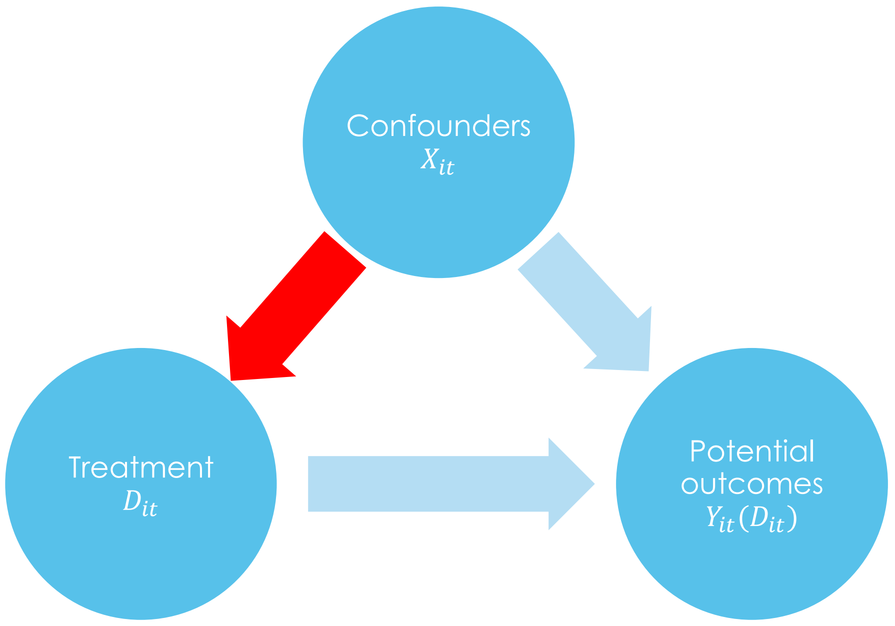


Source: https://www1.nyc.gov/html/dot/downloads/pdf/current-pre-vision-zero-speed-limit-maps.pdf

Variables	Before the speed limit reduction (year: 2013)				After the speed limit reduction (year: 2015)			
	Treatment sites		Control sites		Treatment sites		Control sites	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Fatal crash frequency	0.07	0.30	0.04	0.25	0.06	0.27	0.06	0.33
Injury crash frequency	11.04	17.97	7.17	12.20	9.99	16.02	6.17	11
PDO crash frequency	43.38	80.67	29.65	49.71	46.32	84.37	30.10	54.04
Bronx (no = 0, yes = 1)	0.18	0.38	0.06	0.25	0.18	0.38	0.06	0.25
Brooklyn (no = 0, yes = 1)	0.27	0.45	0.13	0.33	0.27	0.45	0.13	0.33
Manhattan (no = 0, yes = 1)	0.19	0.39	0.22	0.41	0.19	0.39	0.22	0.41
Queens (no = 0, yes = 1)	0.29	0.45	0.34	0.48	0.29	0.45	0.34	0.48
Staten Island (no = 0, yes = 1)	0.07	0.25	0.24	0.43	0.07	0.25	0.24	0.43
Arterial street (no = 0, yes = 1)	0.37	0.48	0.48	0.50	0.37	0.48	0.48	0.50
One-way street (no = 0, yes = 1)	0.51	0.50	0.66	0.48	0.51	0.50	0.66	0.48
Number of intersections	10.60	13.44	8.04	10.89	10.60	13.44	8.04	10.89
Log VMT (vehicle. mile)	7.72	1.48	8.27	1.62	7.67	1.52	8.27	1.62
Number of lanes	2.31	1.13	3.19	1.96	2.31	1.17	3.21	1.97
Number of road segments	3,745		467		3,745		467	

Methods

- Ignorability assumption: $(Y_{it}(0), Y_{it}(1)) \perp D_{it} \mid X_{it}$
- Positivity assumption: $0 < P(D_{it} \mid X_{it}) < 1$
- SUTVA (Stable unit treatment value assumption): Potential outcomes of one site are unrelated to treatment status of other sites



Methods: PSM

- Logistic generalized additive model: identify nonlinear relationships between the treatment indicator and covariates.

- The propensity score $e_i(\mathbf{X}_{i0})$

Smooth function between the p_{th} X_{i0} and D_{i0} at site i

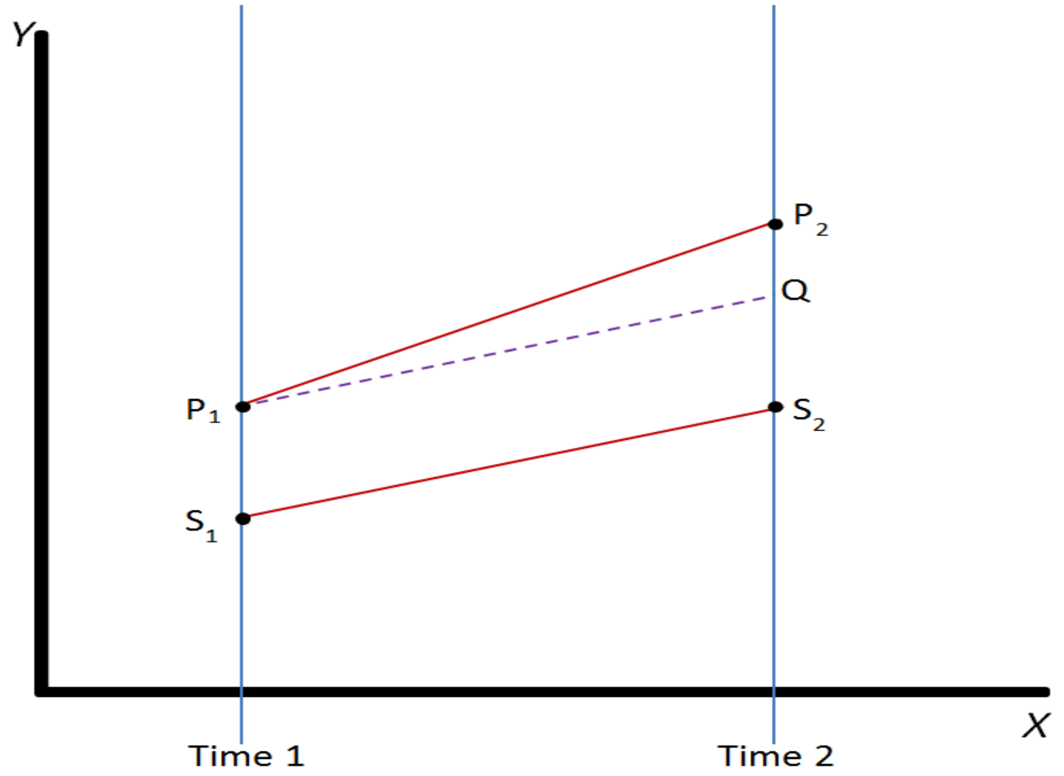
$$E(\log(\frac{e_i(\mathbf{X}_{i0})}{1-e_i(\boxed{\mathbf{X}_{i0}})})) = \beta_0 + \beta_1 X_{1,i0} + \beta_2 X_{2,i0} + \ldots + \beta_{p-1} X_{p-1,i0} + \boxed{f_p(X_{p,i0})}$$

Pre-treatment covariates at site i

- Matching with replacement: repeated use of control sites (much more treatment sites than control sites).

Methods: SDID

- Assume parallel trend of control and treatment sites.
- Use a spatial lag framework to address spatial spillover effect of the treatment.



Source: https://en.wikipedia.org/wiki/Difference_in_differences

Methods: SDID

- Model specification

Observed crash frequency for site i at period t

$$P(Y_{it} = y_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{\;y_{it}}}{y_{it}!}$$

Expectation of y_{it}

Proportion of treated neighboring sites for site i at period t

$$\begin{aligned} \ln(\lambda_{it}) &= \alpha_0 + \alpha_1 \mathbf{X}_{it} + \alpha_2 D_{it} + \alpha_3 T_{it} + \alpha_4 (1 + \rho \mathbf{W}_{s,it}) D_{it} T_{it} + \varepsilon_{it} \\ &= \alpha_0 + \alpha_1 \mathbf{X}_{it} + \alpha_2 D_{it} + \alpha_3 T_{it} + \alpha_4 D_i T_t + \alpha_{4,\rho} \mathbf{W}_{s,it} D_{it} T_{it} + \varepsilon_{it} \end{aligned}$$

Error term, with $\exp(\varepsilon_{it}) \sim Gamma(\frac{1}{\eta}, \frac{1}{\eta})$

Methods: SDID

- Average direct treatment effect for the treated (ADTT)

$$\tau_{ADTT} = \alpha_4$$

- Average spatial spillover effect (average indirect treatment effect, AITT)

$$\tau_{AITT} = \alpha_{4,\rho}\overline{\mathbf{W}_{s,it}D_{it}}$$

$$se(\tau_{AITT}) = \sqrt{Var(\tau_{AITT})} = \sqrt{Var(\alpha_{4,\rho})} \times \boxed{\overline{W_{s,it}D_{it}}}$$

Average spatial weight

- Average treatment effect for the treated

$$\tau_{ATT} = \tau_{ADTT} + \tau_{AITT} = \alpha_4 + \alpha_{4,\rho}\overline{\mathbf{W}_{s,it}D_{it}}$$

Covariance between the two parameters

$$se(\tau_{ATT}) = \sqrt{Var(\tau_{ATT})} = \sqrt{Var(\alpha_4) + \overline{\mathbf{W}_{s,it}D_{it}}^2 Var(\alpha_{4,\rho}) + 2\overline{\mathbf{W}_{s,it}D_{it}}\boxed{Cov(\alpha_4, \alpha_{4,\rho})}}$$

Results

- Modeling results for the integrated causal approach: PSM

		Logistic GAM		Logistic regression	
Variables		Coefficient	Std. Error	Coefficient	Std. Error
Intercept		3.70***	0.20	6.66***	0.36
Borough areas (base: Bronx & Brooklyn)	Manhattan	-0.83***	0.16	-0.86***	0.16
	Queens	-1.14***	0.15	-1.13***	0.14
	Staten Island	-2.69***	0.17	-2.71***	0.17
One-way street		-0.63***	0.12	-0.64***	0.12
Number of intersections		0.05***	0.01	0.05***	0.01
Number of lanes		-0.21***	0.04	-0.25***	0.04
Arterial street		-0.24*	0.12	-0.23*	0.11
Log (VMT)		-	-	-0.37***	0.05
Approximate significance of smooth terms					
		Effective degree of freedom	Chi. squared		
Smooth function of Log (VMT)		6.18	80.66***	-	-
AIC		2444		2463	

Statistical significance levels: *0.01 ≤ p-value < 0.05; **0.001 ≤ p-value < 0.01; *** p-value < 0.001

Results

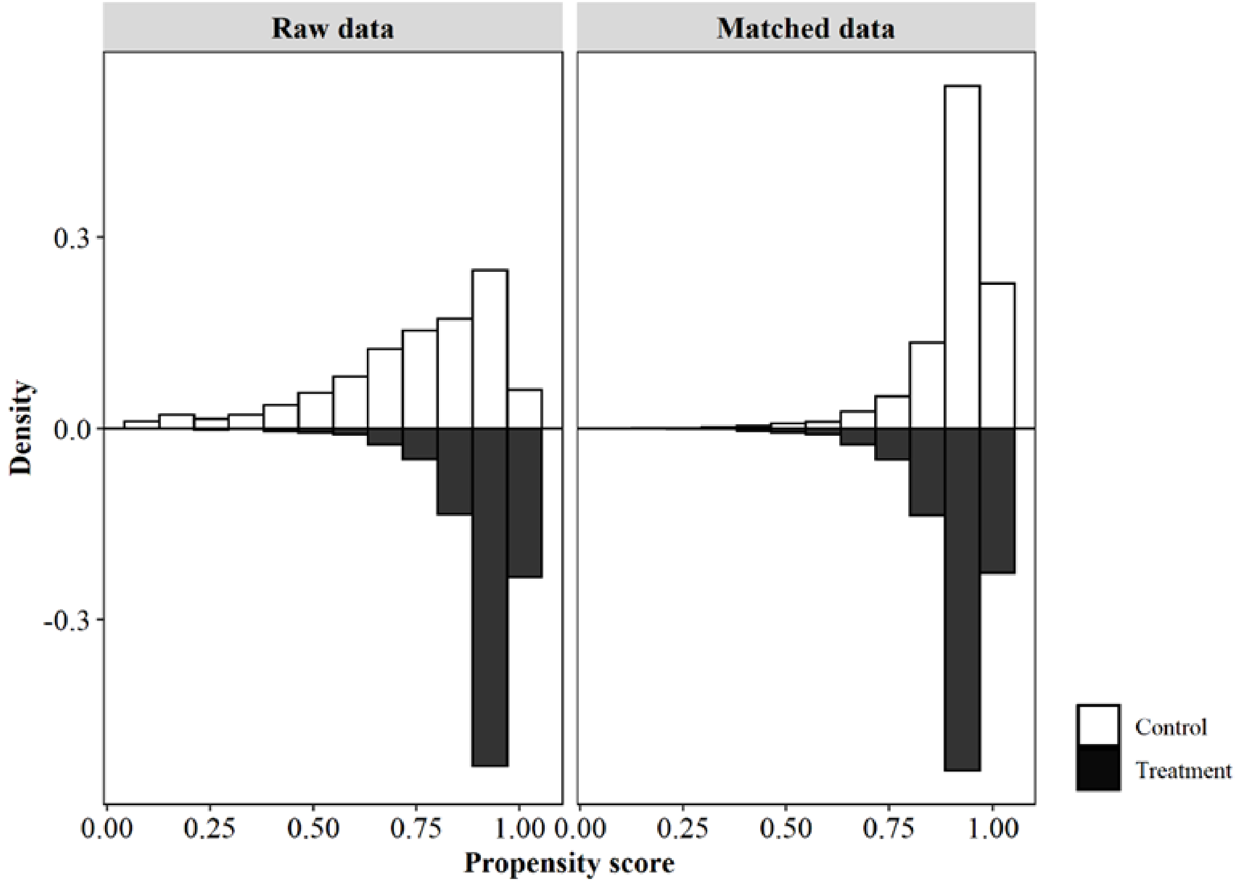
- Modeling results for the integrated causal approach: Balance statistics

Covariates	Raw data			Matched data		
	Mean of treatment sites	Mean of control sites	ASMD	Mean of treatment sites	Mean of control sites	ASMD
Manhattan	0.19	0.22	**0.08**	0.19	0.20	**0.02**
Queens	0.29	0.34	**0.11**	0.29	0.34	**<0.10**
Staten Island	0.07	0.24	**0.71**	0.07	0.05	**0.07**
One-way street	0.51	0.66	**0.29**	0.51	0.49	**0.04**
Arterial street	0.40	0.55	**0.31**	0.40	0.40	**0.01**
Number of intersections	10.52	8.05	**0.18**	10.17	10.41	**0.02**
Number of lanes	2.31	3.19	**0.78**	2.31	2.25	**0.05**
Log (VMT)	7.66	8.27	**0.38**	7.68	7.59	**0.06**

$$ASMD = \frac{\left|\mu_{w_{i0}\mathbf{X}_{i0}|D_{i0}=1} - \mu_{w_{i0}\mathbf{X}_{i0}|D_{i0}=0}\right|}{s_{w_{i0}X_{i0}|D_{i0}=1}} = \frac{\left|\frac{1}{n_1}\sum_{D_{i0}=1} w_{i0}X_{i0} - \frac{1}{n_0}\sum_{D_{i0}=0} w_{i0}X_{i0}\right|}{\sqrt{\frac{\sum_{i\in\{i:D_{i0}=1\}}(w_{i0}X_{i0} - \mu_{w_{i0}\mathbf{X}_{i0}|D_{i0}=1})^2}{n_1 - 1}}}$$

Results

- Modeling results for the integrated causal approach: Propensity score distributions



Results

- Modeling results for our integrated causal approach

		Fatal crashes		Injury crashes		PDO crashes	
		Coeff.	Std. Err	Coeff.	Std. Err	Coeff.	Std. Err
Intercept		-9.39^{***}	0.64	-2.46^{***}	0.09	-1.07^{***}	0.09
Borough areas (base: Brooklyn & Bronx)	Manhattan	-0.33^{*}	0.13	-	-	0.55^{***}	0.03
	Queens	-0.40^{***}	0.12	-0.46^{***}	0.03	-0.29^{***}	0.03
	Staten Island	-1.50^{***}	0.33	-1.18^{***}	0.05	-0.83^{***}	0.05
One-way street		-	-	$-0.04'$	0.02	0.07^{**}	0.02
Arterial street		-	-	-	-	0.08^{***}	0.02
Number of intersections		0.02^{***}	<0.01	0.03^{***}	<0.01	0.03^{***}	<0.01
Log (VMT)		0.58^{***}	0.05	0.54^{***}	0.01	0.50^{***}	0.01
T_{it}		0.79	0.58	-0.14	0.07	0.06	0.08
D_{it}		1.84^{***}	0.49	0.06	0.05	0.08	0.06
$D_{it}T_{it}$		-0.01	0.73	0.24	0.14	0.22	0.14
$W_{s,it}D_{it}T_{it}$		-1.10^{*}	0.52	-0.19	0.12	-0.19	0.12
η		1.81^{*}	0.78	1.32^{***}	0.03	1.00^{***}	0.02
AIC		3232.25		46841.11		69132.50	
Pseudo R-Squared		0.16		0.52		0.51	

Statistical significance levels: ‘0.05 ≤ p-value < 0.10; *0.01 ≤ p-value < 0.05; **0.001 ≤ p-value < 0.01; *** p-value < 0.001

Results

- Safety effectiveness of the speed limit reduction

Safety effectiveness	Causal approach	τ_{ADTT}		τ_{AITT}		τ_{ATT}	
		Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Fatal crash frequency	CG	-		-		-0.60	-
	PSM	-		-		-0.63^{*}	0.31
	DID	-		-		-0.60^{*}	0.33
	SDID	0.30	0.60	-0.68^{*}	0.33	-0.50^{***}	0.12
	PSM + DID	-		-		-1.06^{*}	0.47
	PSM + SDID	-0.01	0.73	-0.96^{*}	0.39	**-0.97^{*}**	**0.48**
Injury crash frequency	CG	-		-		0.05	-
	PSM	-		-		0.18^{***}	0.06
	DID	-		-		0.11	0.07
	SDID	0.16	0.14	-0.04	0.07	0.11	0.07
	PSM + DID	-		-		0.06	0.08
	PSM + SDID	0.24	0.14	-0.17	0.09	**0.07**	**0.10**
PDO crash frequency	CG	-		-		0.05	-
	PSM	-		-		0.22^{***}	0.06
	DID	-		-		0.11	0.07
	SDID	0.18	0.14	-0.05	0.07	0.12	0.08
	PSM + DID	-		-		0.04	0.08
	PSM + SDID	0.22	0.14	-0.17	0.09	**0.05**	**0.08**

Statistical significance levels: $^{*}0.01 \le$ p-value < 0.05; $^{**}0.001 \le$ p-value < 0.01; *** p-value < 0.001

Conclusions

- Speed limit reduction is estimated to decrease the fatal crash frequency by 62.09% ($\exp^{-0.97}-1$), likely due to the reduced impact speed of collisions.

- Spatial spillover effect of speed limit reduction is found to be significant.

- Insignificant impacts on injury and PDO crashes, likely due to less awareness in a low-speed environment.

Thank you!

Questions?

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