Testing the Association Between Development Patterns and Truck Crashes: A Case Study in Dallas-Fort Worth, TX

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Restructuring Urban Freight Landscape

- Expanding online shopping sales and package deliveries
  - Delivered packages by USPS from 3.1 billion (2010) to 6.2 (2019)
  - Delivery vehicles, as an integrated component of "convenient" urban lives

- Restructured freight transportation and logistics practices
  - Globalized production and distribution systems
  - Expanding online shopping sales

→ Changes in how goods are produced, distributed, stored, sold, and delivered

  - Restructured freight activity + associated **negative externalities**

- Negative externalities?
  - E.g., pollution, congestion, and **vehicle crashes** ⇐ **Our interest.**

Factors examined in road safety research

- Driver factors
- Vehicle factors
- Working conditions
- Network and road design
- Road safety devices
- Traffic flow and patterns
- Weather conditions
- Built environment characteristics
  - To formulate effective road safety policies at the regional level

Freight demand in urban areas → freight flows → truck crashes

(*restructured demand*) (*unknown*) *Proprietary aspects* (*externalities*)

Prior studies

- **Between development patterns and freight trip generation**
  - Sanchez-Diaz, Holguin-Veras, and Wang (2016)
- **Between development patterns and freight vehicle activity**
  - Giuliano, Kang, and Yuan (2018)
- **Between development patterns and freight vehicle crashes**
  - McDonald, Yuan, and Naumann (2019)
  - Yang, Chen, and Yuan (2021)
  - Not yet rigorously examined
- **Data issues**
  - Proprietary nature of freight activity
  - Lack of detailed data

Research objectives

1. ***Examine if*** the spatial distribution of ***truck crashes*** on city streets is different from ***those of other vehicles***

2. Test if truck crashes have ***a unique association with development patterns***

3. This is ***a case study*** in the North Central Texas Council of Government region in ***Dallas-Fort Worth (DFW), TX***

Research approach

- **Conceptual model**
  - Spatially disaggregate analysis (Noland and Quddus, 2004)

$$Y_i = f(S_i, D_i, V_i)$$

Unit of analysis:
a one square-mile hexagon

  - Y is the **number of vehicle crashes** in zone (i)
  - S is a vector for **transport supply** in zone (i)
  - D is a vector for **transport demand** in zone (i)
  - V is a vector for **vehicle movement levels** (*exposure*) in zone (i)
  - f(•) is a functional form
    - Over-dispersed count data model, negative binomial

Research approach

- **Dep. Variable: N of vehicle crashes on city streets only**
  - Truck crashes (N=19,144)
  - Van crashes (N=29,171)
  - Passenger vehicle crashes (N=303,121)
  - Excluding the crashes on highways

  ] ***Compare among three crash types***

- **Data source**
  - TxDOT Crash Records Information System (CRIS)
  - From 2010 to 2017
  - Crashes with property damage ($1,000+) or with injury or death only
  - Trucks include truck, trailer, semi-trailer, pole trailer, and truck tractor
    - Likely to include non-freight vehicles (utility and service)

Research approach

- **Explanatory variable 1: Transport supply**
  - Intersection density
  - Distance to nearest transport facilities (airport, intermodal terminals, highways)

- **Explanatory variable 2: Transport demand**
  - Population and employment characteristics
  - E.g., population and employment densities, combination of density quartiles
  - E.g., median household income, % below poverty, % non-white, % drive alone for work, % no high school diploma, relative industry diversity index

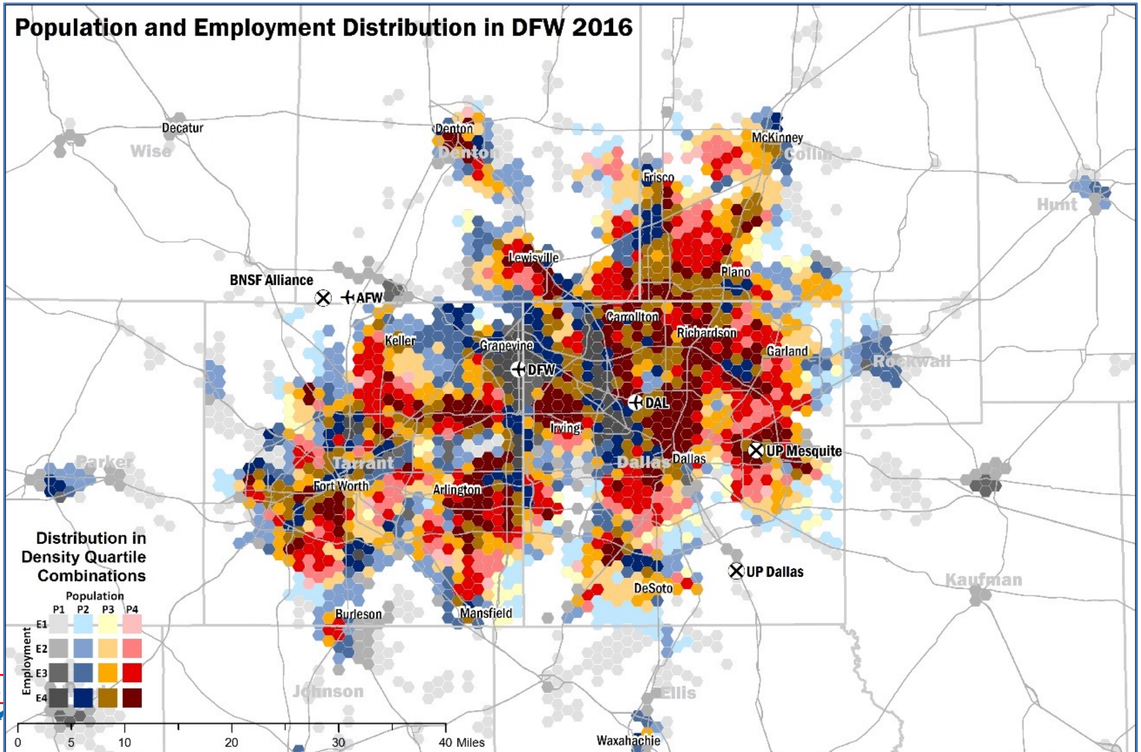
- **Explanatory variable 3: Vehicle movement levels**
  - VMT per network mile per hexagon

Definition of explanatory variables

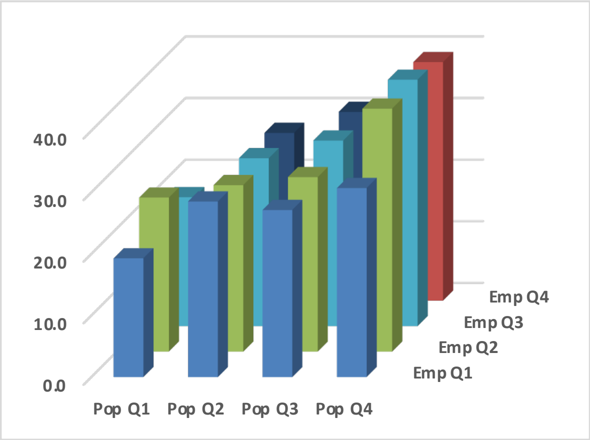
Variables	Definition	Data source
Transport supply		
Miles to the nearest airport	Euclidean miles to the nearest airport from the centroid of a hexagon (in log)	My calculation
Miles to the nearest intermodal terminal	Euclidean miles to the nearest intermodal terminal from the centroid of a hexagon (in log)	My calculation
Miles to the nearest highway exit	Euclidean miles to the nearest highway ramp from the centroid of a hexagon (in log)	My calculation
Intersection density	Number of intersections per sq-mile (in log)	2019 NCTCOG Regional Data Center
Transport demand		
Population	Number of population per sq-mile (in log)	ACS 2013-2017
Employment	Number of employment per sq-mile (in log)	LEHD 2015
Household income	Median household income (in $10,000)	ACS 2013-2017
% non-white	% of non-white population (in %)	ACS 2013-2017
% no high school diploma	% of the population over 25 without a high school diploma (in %)	ACS 2013-2017
% drive alone for commute	% of workers over 16 who drive alone for the commute (in %)	ACS 2013-2017
% below poverty	% of population below the poverty line (excluded due to multicollinearity)	ACS 2013-2017
Relative diversity	The inverse of the sum of absolute differences of two-digit industry sector employment share between a hexagon and the regional average	LEHD 2015
Vehicle movement		
All vehicle VMT per network mile	= ∑ vehicle miles traveled per zone / ∑ network miles per zone (in log)	2013 NCTCOG Regional Travel Model

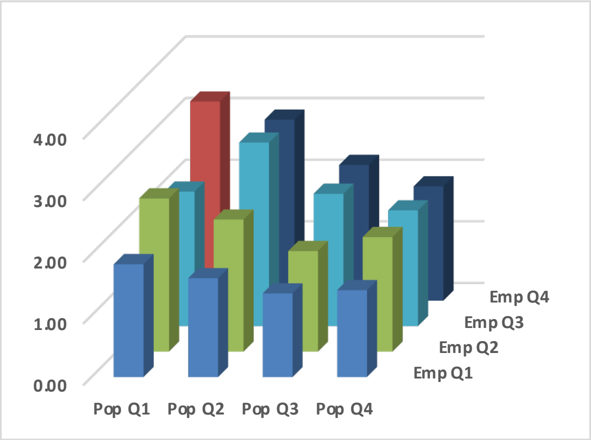
Study area: Dallas-Fort Worth, TX

- 7.10 million population (ACS 2013-2017), 3.37 million employment (LEHD 2015)
- Intensive freight activity via D/FW International Airport, NAFTA corridors (Canada-US-Mexico), three Class I railroads, three Intermodal terminals



Distribution of car crashes by density quartiles





Passenger car crashes per 1,000 residents				
	Pop Q1	Pop Q2	Pop Q3	Pop Q4
Emp Q4	15.0	27.2	30.6	**38.7**
Emp Q3	20.9	27.3	30.1	42.5
Emp Q2	25.0	27.0	28.3	39.4
Emp Q1	19.3	28.5	27.1	30.7

Truck crashes per 1,000 residents				
	Pop Q1	Pop Q2	Pop Q3	Pop Q4
Emp Q4	**3.23**	2.94	2.20	1.86
Emp Q3	2.18	2.98	2.15	1.88
Emp Q2	2.49	2.14	1.63	1.86
Emp Q1	1.83	1.61	1.36	1.41

Estimated negative binomial models

Model 1

$$N_{crash} = \exp(\beta_0 + \beta_1 * VMTPM + \beta_2 * Air + \beta_3 * Intm + \beta_4 * Hwy + \beta_5 * Intsec + \boldsymbol{\beta_6 * Pop + \beta_7 * Emp} + \beta_8 * Inc + \beta_9 * NWh + \beta_{10} * NHSD + \beta_{11} * Drive + \beta_{12} * RDI + \varepsilon)$$

Model 2

$$N_{crash} = \exp(\beta_0 + \beta_1 * VMTPM + \beta_2 * Air + \beta_3 * Intm + \beta_4 * Hwy + \beta_5 * Intsec + \beta_6 * Inc + \beta_7 * NWh + \beta_8 * NHSD + \beta_9 * Drive + \beta_{10} * RDI + \boldsymbol{\beta_{11} * ComQt} + \varepsilon)$$

N is the number of vehicle crashes;
$\boldsymbol{\beta_n}$ are coefficients to be estimated (n=0, 1, …, 12);
VMTPM is VMT per network mile;
Air is miles to the nearest airport;
Intm is miles to the nearest intermodal terminal;
Hwy is miles to the nearest highway ramp;
Intsec is intersection density;
Pop is population density;
Emp is employment density;
Inc is median household income;
NWh is % of non-white population;
NHSD is % of the population over 25 without a high school diploma;
Drive is % of workers over 16 who drive alone for the commute;
RDI is a relative diversity index;
ComQt is a categorical variable for the combined density quartiles;
$\boldsymbol{\varepsilon}$ is an error term.

Estimated negative binomial model 1

Dependent variables	Model 1-1 N of passenger car crashes		Model 1-2 N of truck crashes		Model 1-3 N of van crashes	
Independent variables	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
Vehicle movement						
VMT per link mile (log)	0.197	**	0.197	**	0.271	**
Transport supply						
Miles to airport (log)	-0.070	+	-0.059		-0.023	
Miles to intermodal (log)	-0.048		-0.073	+	-0.059	+
Miles to highway exit (log)	-0.019		-0.026	+	0.008	
Intersection density (log)	0.748	**	0.491	**	0.789	**
Transport demand						
Population (log)	0.306	**	0.022		0.281	**
Employment (log)	0.282	**	0.375	**	0.287	**
Median HH income ($10k)	-0.050	**	-0.037	**	-0.040	**
% Non-white	0.009	**	0.007	**	0.005	**
% No high school diploma	0.007	**	0.021	**	0.012	**
% Drive alone	-0.007	*	-0.002		-0.014	**
Relative diversity index	0.044		0.005		0.058	
Constant	-5.340	**	-5.409	**	-8.077	**
Log Alpha	-0.716	**	-0.703	**	-0.824	**
Log Likelihood	-11,096.3		-5,836.2		-6,307.1	
Log Likelihood, constant-only	-12,574.4		-6,810.4		-7,602.5	
Pseudo-R-squared	0.118		0.143		0.170	
N	2,157		2,157		2,157	

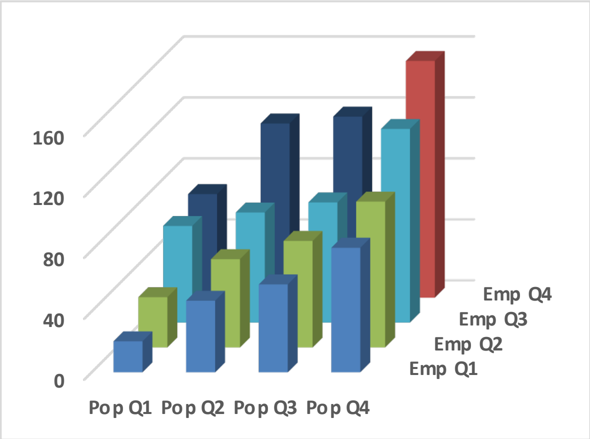
Note: +P < 0.10, *P < 0.05, **P < 0.01

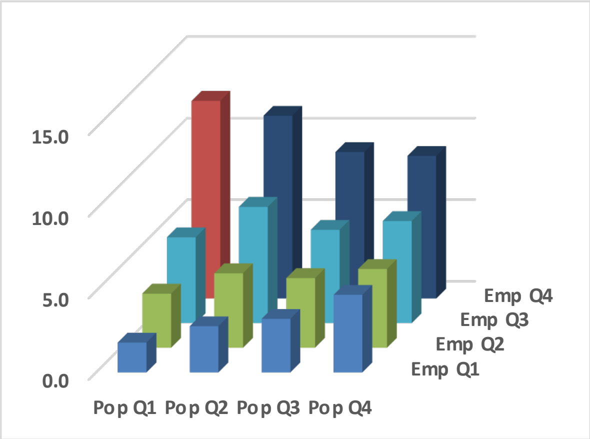
Estimated negative binomial model 2

Dependent variables	Model 1-1 N of passenger car crashes		Model 1-2 N of truck crashes		Model 1-3 N of van crashes	
Independent variables	Coef.	Sig.	Coef.	Sig.	Coef.	Sig.
Vehicle movement						
VMT per link mile (log)	0.206	**	0.212	**	0.296	**
Transport supply						
Miles to airport (log)	-0.059		-0.070		0.009	
Miles to intermodal (log)	-0.056	+	-0.110	**	-0.085	*
Miles to highway exit (log)	-0.037	*	-0.041	**	-0.016	
Intersection density (log)	0.752	**	0.533	**	0.783	**
Transport demand						
Median HH income ($10k)	-0.040	**	-0.045	**	-0.027	**
% Non-white	0.009	**	0.006	**	0.005	**
% No high school diploma	0.010	**	0.018	**	0.014	**
% Drive alone	0.001		-0.004		-0.006	*
Relative diversity index	0.110	+	0.028		0.121	*
Constant	-3.460	**	-3.933	**	-6.532	**
Log Alpha	-0.695	**	-0.669	**	-0.819	**
Log Likelihood	-11,117.0		-5,855.1		-6,297.2	
Log Likelihood, constant-only	-12,574.4		-6,810.4		-7,602.5	
Pseudo-R-squared	0.116		0.140		0.172	
N	2,157		2,157		2,157	

Note: +P < 0.10, *P < 0.05, **P < 0.01

Estimated negative binomial model 2

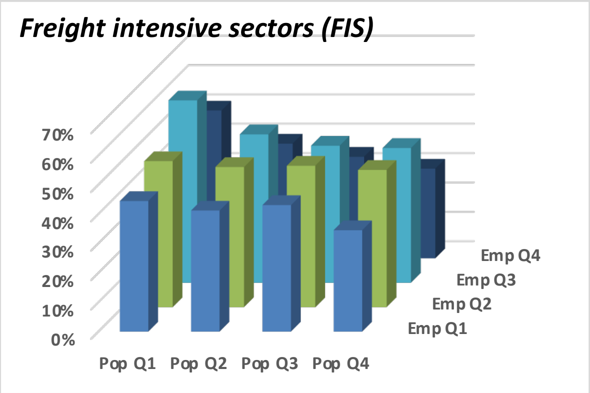




Predictive margins of the combined quartiles (passenger car crashes)					Predictive margins of the combined quartiles (truck crashes)				
	Pop Q1	Pop Q2	Pop Q3	Pop Q4		Pop Q1	Pop Q2	Pop Q3	Pop Q4
Emp Q4	67.9	114.3	118.8	155.3	Emp Q4	12.1	11.2	9.0	8.7
Emp Q3	63.4	72.2	78.8	127.0	Emp Q3	5.3	7.1	5.7	6.3
Emp Q2	33.0	57.9	69.9	95.7	Emp Q2	3.3	4.6	4.3	4.8
Emp Q1	20.3	46.9	57.7	81.7	Emp Q1	1.8	2.8	3.3	4.8

Conclusions and discussion

- **Results are consistent with prior studies**
  - VMT per network mile (+), intersection density (+), household income (-), % non-white (+), % no high school diploma (+)
  - Some variables were not as consistent as expected (Miles to nearest airport, intermodal terminal, highway exit)
- **Zone-level heterogeneity beyond simple density aspects**
  - Percent distribution of employment by sector

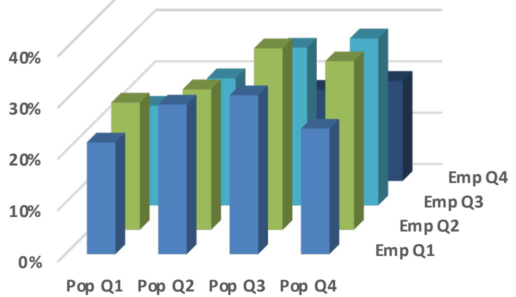


***FIS:** manufacturing, wholesale/retail trade, transportation and warehousing, accommodation and food services*
Holguin-Veras et al. (2011), Sanchez-Diaz et al. (2016)

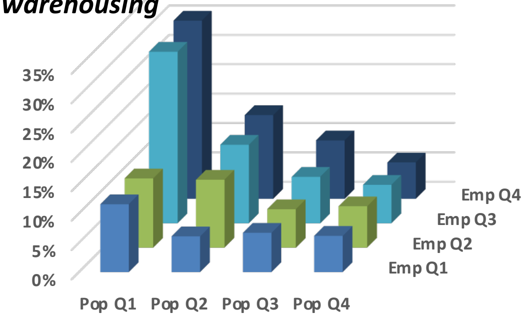
Conclusions and discussion

- Zone-level heterogeneity beyond simple density aspects
  - Percent distribution of employment by sector

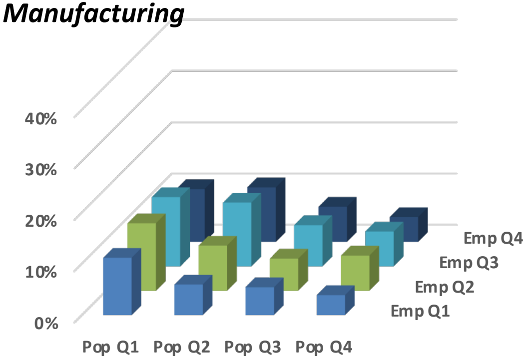
"Population-serving" – retail, accommodation, food services



"Distribution" – wholesale, transportation, warehousing



Manufacturing



Thank you!

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