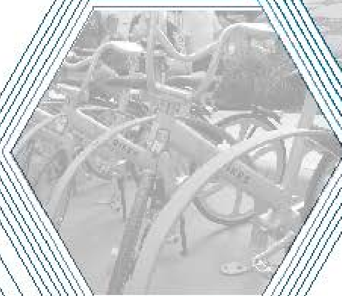

More Freight Vehicle Crashes on City Streets in Residential Areas: Why and to What Extent? A Case Study in Dallas-Fort Worth, TX

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University of Texas at Arlington

FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

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FINAL PROJECT REPORT

by

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Sponsorship
Center for Transportation Equity, Decisions and Dollars

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16. Abstract

Over the last decade, globalized supply chains, restructured logistics and freight transportation practices, and exploding online shopping have influenced how goods are produced, transported, stored, and sold. All these changes have resulted in substantial shifts in the spatial distribution of freight activity, as well as vehicles crashes that involved at least one freight vehicle (freight vehicle crash). As a case study, we examine the correlation between development patterns and freight vehicle crashes on city streets in Dallas-Fort Worth (DFW), TX. The DFW region is one of the largest metro areas, of which population has been growing most extensively over the last decade in the US. We use the "freight landscape" framework and test the extent to which the proxies for freight supply and demand explain the spatial and temporal variation in freight vehicle crashes, controlling for freight activity levels. We examine two models, 2016 cross-section and 2010-2016 time-series, using the crash records from the TXDOT Crash Records Information System. We test six models in terms of two crash severity levels (all crashes and the crashes with a fatality or injury) and three vehicle types (all vehicles, vans, and trucks). The unit of analysis is a one-square-mile urban hexagon (N=2,262). As proxies for freight demand, we use population and freight-intensive-sector employment densities, median household income, and relative industry sector diversity. As proxies for freight supply, we use distance to the nearest airport, intermodal terminal, and highway ramp. Results show that the elasticity between population density and freight vehicle crashes is the largest, followed by freight intensive sector density. Results also suggest that freight-oriented activity alone may not sufficiently increase the likelihood of freight vehicle crashes. Rather, it may be the conflict between freight- and non-freight-oriented traffic or the conflict among various travel purposes originating from residence, service sector, and freight transport sector land uses.

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Over the last decade, globalized supply chains, restructured logistics and freight transportation practices, and exploding online shopping have influenced how goods are produced, transported, stored, and sold. All these changes have resulted in substantial shifts in the spatial distribution of freight activity, as well as vehicles crashes that involved at least one freight vehicle (freight vehicle crash). As a case study, we examine the correlation between development patterns and freight vehicle crashes on city streets in Dallas-Fort Worth (DFW), TX. The DFW region is one of the largest metro areas, of which population has been growing most extensively over the last decade in the U.S. We use the "freight landscape" framework and test the extent to which the proxies for freight supply and demand explain the spatial and temporal variation in freight vehicle crashes, controlling for freight activity levels. We examine two models, 2016 cross-section and 2010-2016 time-series, using the crash records from the TXDOT Crash Records Information System. We test six models in terms of two crash severity levels (all crashes and the crashes with a fatality or injury) and three vehicle types (all vehicles, vans, and trucks). The unit of analysis is a one-square-mile urban hexagon (N=2,262). As proxies for freight demand, we use population and freight-intensive-sector employment densities, median household income, and relative industry sector diversity. As proxies for freight supply, we use distance to the nearest airport, intermodal terminal, and highway ramp. Results show that the elasticity between population density and freight vehicle crashes is the largest, followed by freight intensive sector density. Results also suggest that freight-oriented activity alone may not sufficiently increase the likelihood of freight vehicle crashes. Rather, it may be the conflict between freight- and non-freight-oriented traffic or the conflict among various travel purposes originating from residence, service sector, and freight transport sector land uses.

Keywords

Traffic Safety;
Development Patterns;
Truck-involved Crash;
Negative Binomial Model;
Fixed Effects Panel Model

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1 Introduction

Over the last decade, the spatial distribution of freight activity has changed substantially. At the global level, freight and logistics practices have been restructured in terms of how goods are produced, distributed, and stored through globalized supply chains (Dablanc & Ross, 2012; Golob & Regan, 2001; Hesse & Rodrigue, 2004; McKinnon, 2009). The restructuring has also influenced the spatial distribution of freight activity at the local and regional level. Moreover, significant volumes of online shopping deliveries are made to residential destinations by various types of freight vehicles (Cao, Chen, & Choo, 2013; Comi & Nuzzolo, 2016; Rotem-Mindali & Weltevreden, 2013). The B2C (business-to-customer) sales from online platforms have increased by 15% annually over the past several years (Conwell, 2016). The US Postal Service delivered 5.1 billion packages nationwide in 2016, a substantial increase from the 3.1 billion packages delivered in 2010 (Zaleski, 2017). These systematic and behavioral changes have resulted in a substantial shift in the geography of freight activity as well as its negative externalities, such as pollution, congestion, and vehicle crashes.

Freight transportation generates disproportionately negative externalities in urban areas. Trucks constitute 7% of the urban traffic but generate 17% of congestion costs in terms of delays and fuel consumption (Zaleski, 2017). Truck-involved vehicle crashes tend to be more severe, and are more likely to result in fatalities (Chang & Mannering, 1999; Dong, Richards, Huang, & Jiang, 2015; Zahabi, Strauss, Manaugh, & Miranda-Moreno, 2011). In 2015, the financial cost of vehicle crashes exceeded that of congestion in urban areas (Najaf, Thill, Zhang, & Fields, 2018). Freight activity is also distributed unevenly across the urban fabric. With the changes in freight transportation practices and online shopping behavior, we expect that there will be more freight activity and associated externalities in residential areas, which have not been commonly associated with freight transportation so far. With that perspective in mind, this becomes a transportation crisis worthy of in-depth research.

Transportation planning scholars have rigorously examined the factors that contribute to vehicle crashes and have established robust theoretical frameworks with enough empirical evidence to explain the association between development patterns and vehicle crash patterns. However, only a few studies have tested the potential association between development patterns and freight activity or freight vehicle crashes. In this research, we use the freight landscape framework to examine the association between development patterns and freight vehicle crashes on city streets, controlling for freight activity levels. This research is a case study in the Dallas-Fort Worth metropolitan area in Texas.

This paper is organized as follows: Section 2 reviews the recent literature on traffic safety and vehicle crashes. Section 3 presents the conceptual framework and study area. Section 4 presents data with descriptive statistics. Section 5 shows the results of spatial analysis and econometric models. We conclude in section 6 with conclusions and discussion.

2 Background

Transportation scholars have rigorously examined the factors associated with traffic safety and vehicle crashes. These factors include driver and vehicle characteristics, street network and road design, road-safety devices, traffic flow and patterns, as well as built environment characteristics (Bédard, Guyatt, Stones, & Hirdes, 2002; Clark & Cushing, 2004; Dumbaugh & Rae, 2009; Ewing & Dumbaugh, 2009; Gladhill & Monsere, 2012; Jovanis & Chang, 1986; Najaf et al., 2018; Retting, Ferguson, & McCartt, 2003; Rifaat, Tay, & de Barros, 2011; Yu & Xu, 2017; Zahabi et al., 2011; Zwerling, 2005). Transportation planning scholars have focused on examining the extent to which built environment characteristics influence vehicle crashes. It is to formulate effective transportation and road safety policies at the regional level (Washington et al., 2006; Yu & Xu, 2017). In 2015, the costs originating from vehicle crashes exceeded those from traffic congestion, and vehicle crashes generate the largest negative externalities from transportation infrastructure and the vehicle activity (Najaf et al., 2018). Thus, road safety – and in particular vehicle crashes – merits in-depth research.

Numerous studies have theoretically and empirically examined the association between the built environment, travel behaviors, and vehicle crash patterns in terms of its frequency and severity (Dumbaugh & Rae, 2009; Ewing & Dumbaugh, 2009). The conceptual framework proposed by Ewing and Dumbaugh (2009) explains this mechanism: "The built environment affects the crash frequency and severity through the mediators of traffic volume and traffic speed" (pp. 348). The connection between the built environment (e.g., density, diversity, design, and destination accessibility) and travel patterns, as the mediators (mode, speed, frequency, and distance of travel, as mediators), has been well examined in travel behavior research (Cervero, 1996; Cervero & Kockelman, 1997; Ewing & Cervero, 2001, 2010). People in dense and mixed-use areas with high destination accessibility, compared to those in suburban areas, tend to generate more frequent and shorter trips and are more likely to use alternative modes of travel (e.g., walking and public transit). They are also more likely to generate lower vehicle travel miles (VMT). The fewer people drive, the fewer vehicle crashes are likely to occur. Further, the road design aspects that deter high traffic speed (e.g., narrow rights-of-way, shorter network length, on-street parking, traffic-calming devices, and intersection and signal controls) are associated with fewer and less severe vehicle crashes as well as pedestrian-involved crashes. Central urban areas with high population and employment densities not only generate traffic activities derived from local residents and businesses but also attract externally/regionally oriented traffic from many different parts of the region. This aspect of traffic flows sometimes confound the effect of the built environment on vehicle crashes (Ewing & Dumbaugh, 2009). Overall, the connection across the built environment, development patterns, travel behavior, and traffic safety is theoretically sound and empirically supported (Najaf et al., 2018).

Various quantitative analysis methodologies have been used to examine the association between development patterns and vehicle crash patterns. Binary outcomes (e.g., areas with or without crashes) are examined by logit or probit models (Rifaat & Tay, 2009). Ordered outcomes (e.g., severity scales from fatal, severe, minor, possible, and no injury) by ordered logit models (Clifton, Burnier, & Akar, 2009; Zahabi et al., 2011; Zhu & Srinivasan, 2011). Count outcomes (e.g., number of crashes in a region) by count data models, such as Poisson, negative binomial, and zero-inflated negative binomial models (Dumbaugh & Rae, 2009; Gladhill & Monsere, 2012; Marshall & Garrick, 2011). A few studies used geographically weighted regression (GWR) and geographically weighted negative binomial models to account for the variant effects of the development patterns across locations (Yu & Xu, 2017). A few studies used structural equation models to disentangle the direct and indirect effects of exogenous and mediating variables that influence vehicle crash patterns (Ewing, Hamidi, & Grace, 2016; Najaf et al., 2018). Few examined if the changes in the development patterns have any effect on the distribution of vehicle crashes over time.

There is no established theory behind the connections between development patterns, freight travel patterns, and freight vehicle crashes. The scarcity of research is partly due to the proprietary nature of freight activity. Primarily, commercial shippers (the entity which sends out shipment) and carriers (the entity which transports the shipment from shippers to receivers) fulfill freight shipment, and in most cases, they treat vehicle activity data (e.g., origin, destination, time, vehicle, route, schedule, volume, and purpose) as a trade secret. National and regional-level efforts to collect freight travel data have been made, but they are not sufficient to conduct meaningful intra-metropolitan-level research. The Census Bureau, Bureau of Transportation Statistics, and Federal Highway Administration have published a national-level freight movement dataset (Commodity Flow Survey, CFS; Freight Analysis Framework, FAF). Regional transportation planning agencies have conducted ad-hoc firm-based truck trip surveys for building and verifying regional freight travel models. The CFS and FAF provide freight flow information for 1997, 2002, 2007, and 2012 but lack geographical precision. They are available only at the state or metropolitan level for limited periods. Regional travel models provide intra-metropolitan-level information of freight flows, but they are not actual but modeled, simulated, and rectified counts of vehicle travel. Otherwise, engineering, planning, business, logistics, and operations research scholars have collected primary data through the site/firm surveys or have examined the operation/optimization aspects of the freight activity based on the simulation and modeling framework.

There have been a few attempts to describe and explain intra-metropolitan-level freight activity using publicly available datasets. In Giuliano et al. (2018), the authors proposed the "freight landscape" framework to examine the variation in freight activity (zone-level VMT) using the proxies for freight supply and demand in Los Angeles, CA. As supply variables, they used access to transport infrastructures, such as airport, seaport, intermodal terminals, and highways, and as demand variables, they used land use characteristics, such as population density, household income, employment density, and relative industry mix. The framework has been replicated in San Francisco and Paris (Giuliano, Kang, Yuan, & Hutson, 2015; Sakai, Beziat, Heitz, & Dablanc, 2018). Findings show that the freight landscape framework has significant explanatory power.

We also found several papers that examined factors but not necessarily related to development patterns, associated with the frequency of freight vehicle (trucks) crashes and their fatality/severity. For example, crashes that involved one or multiple trucks tended to result in higher injury severity than the crashes without involvement of truck(s) (Chang & Mannering, 1999; Zahabi et al., 2011). Crash severity is associated more with truck percentage than the size of traffic volume (Dong et al., 2015). Other commonly examined factors include driver characteristics (age, gender, fatigue, illness, emotions, distraction, and familiarity with the surroundings), freight vehicle configurations, road geometry (curve and grade), physical characteristics (lighting, weather, surface conditions), flow characteristics (traffic, peak/off-peak, time of day), driving behavior (alcohol/drug use, speeding, complying with traffic control devises), and location (urban or rural) (Blower, Campbell, & Green, 1993; Gander, Marshall, James, & Quesne, 2006; Golob, Recker, & Leonard, 1987; Khattak, D, Schneider, & Targa, 2003; Uddin & Huynh, 2017; Zhu & Srinivasan, 2011; Zou, Wang, & Zhang, 2017). Still, prior research in freight vehicle crashes is scarce.

3 Research Approach

3.1 Conceptual Framework

Concerning the relationship between development patterns and freight travel patterns, Giuliano et al. (2018) proposed one of the first frameworks to describe the level of freight movement at the sub-metropolitan level using vectors of freight transport supply and demand. The effectiveness of this framework has been empirically tested in multiple metropolitan areas, including the Greater Los Angeles and Greater San Francisco regions in California and the Paris region (Ile-de-France) in France (Giuliano et al., 2018, 2015; Sakai et al., 2018). In this research, we use the framework to examine the relationship between development patterns, using the proxies for freight transport supply and demand, and the spatial distribution of freight vehicle crashes, controlling for freight movement levels. With statistical and spatial analyses, as well as econometric models, we aim to provide empirical evidence regarding the following three research questions. Has the spatial distribution of freight vehicle crashes changed over time? Do development patterns have an association with the spatial distribution of freight vehicle crashes? Do changes in development patterns have an association with changes in the spatial distribution of freight vehicle crashes?

As dependent variables, we use the number of vehicle crashes that involved at least one freight vehicles (truck or van) in a spatial unit. We consider two crash types: all crashes and the crashes that resulted in at least one fatality or injury (severe crashes). As proxies for transport supply, we use access to major transport facilities, such as airports, intermodal terminals, and highways. Controlling for all other factors, the level of transport activity would decrease with respect to the distance from a facility. Hence, we use Euclidean miles to the nearest facility as a transport supply measure. As proxies for transport demand, we use population and employment characteristics (densities, household income, and relative industry sector diversity). We also consider the industry sector composition because the level of freight activity (e.g., freight trip generation and attraction) varies with respect to the industry sector composition (Holguín-Veras et al., 2016). As a proxy for freight movement levels, we use freight vehicle miles traveled (VMT) per network mile.

We estimate both cross-section and time-series models. To estimate the cross-section model, we use count data model. Our dependent variables are counts of traffic failure events, and they are not normally distributed (Gladhill & Monsere, 2012). With a preliminary analysis, we also documented that dependent variables are over-dispersed (the variance is larger than the mean). Thus, we use negative binomial model. To estimate the time-series model, we use fixed effects panel model that controls for entity-level heterogeneity (fixed effects) and excludes all time-invariant variables. We present the general model below.

$$Y_{it} = f(S_{it}, D_{it}, F_{it})$$

Equation (1)

Where:

Y is the number of vehicle crashes in zone *i* in time *t*
S is a vector for freight transport supply in zone *i* in time *t*
D is a vector for freight transport demand in zone *i* in time *t*
F is a vector for freight movement levels in zone *i* in time *t*
f(•) is a functional form: count data model for cross-section models and random-effects panel model for time-series models

3.2 Study Area

This research is a case study in the Dallas Fort Worth, TX metropolitan area, which is one of the largest and rapidly growing US metro areas. To be specific, we use the NCTCOG (North Central Texas Council of Governments, a regional metropolitan planning organization) region, which consists of twelve counties. From 2010 to 2016, Dallas-Fort Worth (DFW)'s population increased from 6.42 million to 6.95 million (8.3%), and employment from 2.88 million to 3.37 million (16.9%). We will present detailed population and employment statistics in the following section. In short, the region has a diverse, dynamic, and polycentric urban structure in terms of its population and industry sector compositions.

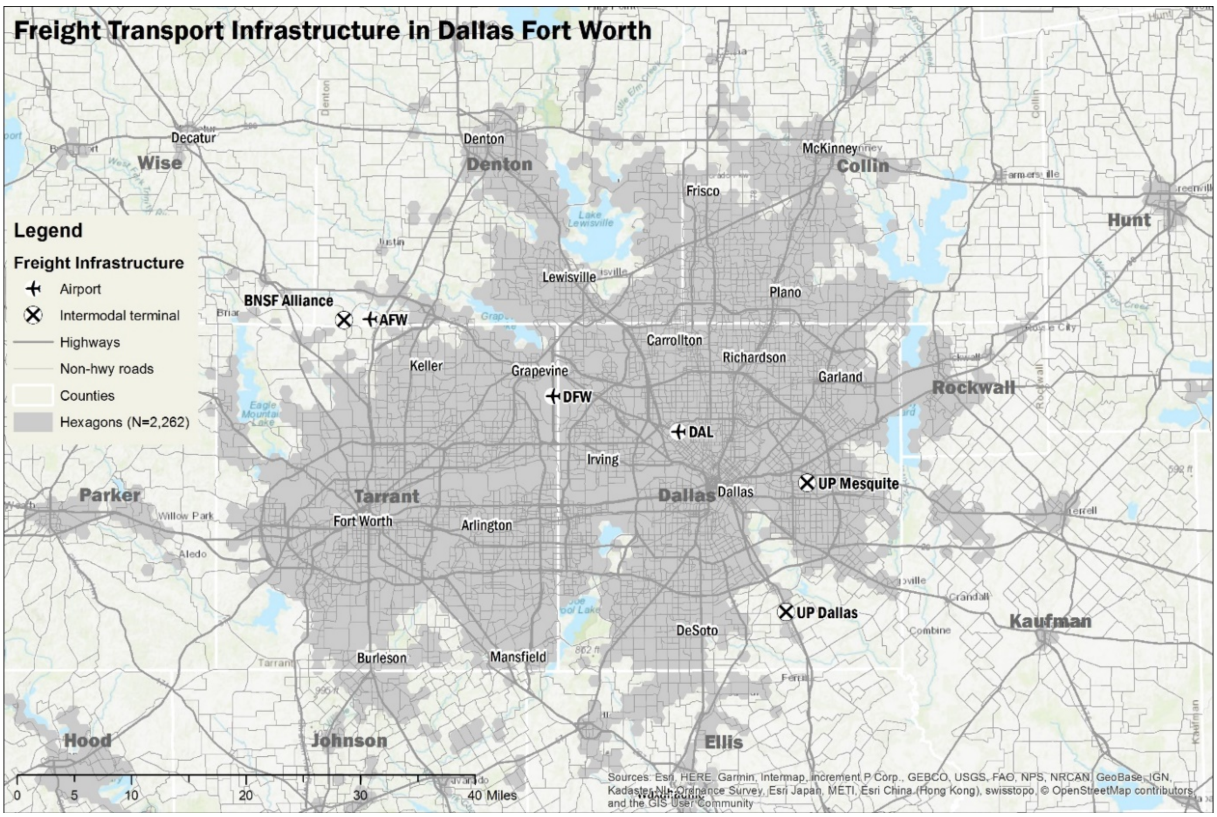


Figure 1 Freight transport infrastructure in the DFW region

In addition to the massive, dynamic consumer markets, the DFW region is involved in intensive freight transportation activity. It is located along the so-called North American Free Trade Agreement (NAFTA) Corridor (Interstate 35E and 35W) that connects international consumer markets in Canada and Mexico. The region houses three Class-I railroad terminals (BNSF Railway, Kansas City Southern Railway, and Union Pacific Railroad) and three truck-to-rail intermodal terminals (BNSF Alliance, UP Mesquite, and UP Dallas) that transport agricultural products from the Midwest to other parts of the US, as well as the import/export shipment between the east and west coasts. The region has three major cargo-service airports: Dallas/Fort Worth International (DFW), Dallas Love Field (DAL), and Fort Worth-Alliance (AFW). These characteristics show that a substantial volume of internally and externally-driven freight movement occurs on a daily basis in this region and make the region an appropriate place to examine how development patterns have been associated with vehicle crash patterns over time. In Figure 1, we present the freight transport infrastructure in the DFW region.

4 Data

4.1 Crash Data

We used the Texas Department of Transportation Crash Records Information System (CRIS) and retrieved all available crash records from 2010 to 2016 in the NCTCOG region. The Texas Department of Transportation (TxDOT) publishes and maintains the database based on crash reports submitted by law enforcement officers in Texas using form CR-3, Texas Peace Officer's Crash Report. The database has a three-level structure of crash, vehicle, and person. Unique identification codes for each of the three levels allow users to associate various attributes across the three levels and conduct comprehensive multi-level analysis.

We used various crash and vehicle attributes to identify accurate locations of all the crashes that involved at least one freight vehicle on city streets. At the crash level, we used latitudes/longitudes and road class attributes to exclude all the crashes on Interstate, US, and State Highways, farm to market roads, county roads, tollways, toll bridges, and other roads. Travels on these types of roads are more likely to be through traffic than traffic originating or ending in the region. Hence, we included the crash records on city streets only for more accurate an estimation of the effect of the development patterns on crash patterns.

At the vehicle level, we used vehicle body style information to distinguish the crashes that involved at least one freight vehicles. We divide freight vehicles into two groups: "truck" as truck, trailer, semi-trailer, pole trailer, and truck tractor and "van" as a van. We define van crashes as the crashes that involved at least one van; and truck crashes as the crashes that involved at least one truck. A very small overlap exists between van and truck crashes, but it is not significant to our analysis. We distinguish vans from all other trucks and trailers. Vans can be used for many purposes, such as freight transportation, utilities, services, and maintenance. However, there is no data to identify their usage. Thus, we include all van-related crash records. Other (non-freight) body styles include passenger cars, sport utility vehicles, pickup trucks, motorcycles, bus, and other special utility vehicles. Again, these vehicles could be used for freight transportation, but there is no information to identify their usage. We thus use three vehicle types: all vehicles, vans, and trucks.

At the vehicle level, we used fatality and injury information to identify the crashes with a fatality or injury. Using the FHWA KABCO injury classification scale, we defined K (killed), A (incapacitating injury), B (non-incapacitating injury), and C (possible injury), as the severe crashes. We use two crash types in terms of severity: all crashes and severe crashes with a fatality or injury. Table 1 presents a summary of the terms.

Table 1 Summary of the terms defined to distinguish vehicle crashes by crash and vehicle type

	All vehicles	Vans	Trucks
All crashes	All vehicle crashes	Van crashes	Truck crashes
Severe crashes	Severe all vehicle crashes	Severe van crashes	Severe truck crashes

4.1.1 Freight Crash Trends in Dallas Fort Worth from 2010 to 2016

In Table 2 and Figure 2, we present the trend of all vehicle crashes in the Dallas Forth Worth region from 2010 to 2016. Over time, the number of vehicle crashes increased substantially from 82 thousand to 137 thousand (66.6% increase). Vehicle crashes on highways (Interstate, US, State) increased very rapidly (100.2%), whereas those on city streets increased by 45.6%. City street crashes comprise approximately 43-50% of all crashes, and the share has decreased slightly over time.

Table 2 Overall crash statistics by road class

Year	All crashes	Highways	City streets	% share	All others
2010	82,004	32,451	40,671	49.6%	8,882
2011	80,180	31,808	39,784	49.6%	8,588
2012	86,127	36,763	40,287	46.8%	9,077
2013	93,218	38,774	45,144	48.4%	9,300
2014	103,561	44,859	48,516	46.8%	10,186
2015	123,265	57,943	53,790	43.6%	11,532
2016	136,656	64,953	59,235	43.3%	12,468
Changes 2010-2016	54,652	32,502	18,564	-	3,586
% change	66.6%	100.2%	45.6%		40.4%

*Highways include Interstate, US, and State Highways as well as toll roads. All others include farm to market, county road, and other roads.

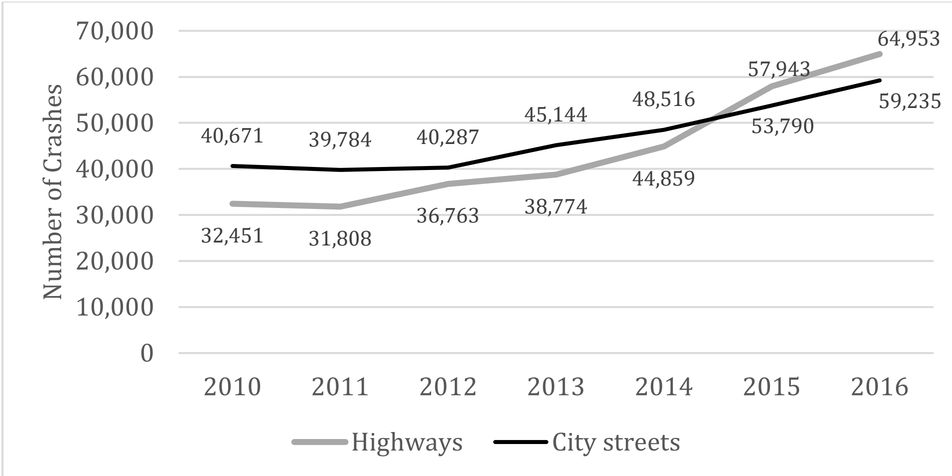


Figure 2 Number of crashes on highways and city streets 2010-2016

We present the statistics of vehicle crashes on city streets by vehicle type in Table 3 and Figure 3. Van crashes comprise 7-9% of all crashes on city streets, but the share is decreasing. Since 2012, van crashes consistently increased over time. Truck crashes comprise 5-6% of all crashes on city streets, and the share has stayed consistent since 2012. After a big drop in 2012, truck crashes increased significantly. Over time, the trend of truck crashes has followed that of all crashes, whereas van crashes have a unique trend over time.

Table 3 Number of crashes on city streets by vehicle type

Year	All crashes on city streets		Van crashes on city streets			Truck crashes on city streets		
	N	Relative to 2010	N	% share	Relative to 2010	N	% share	Relative to 2010
2010	40,671	100.0%	3,712	9.1%	100.0%	2,379	5.8%	100.0%
2011	39,784	97.8%	3,513	8.8%	94.6%	2,293	5.8%	96.4%
2012	40,287	99.1%	3,460	8.6%	93.2%	2,022	5.0%	85.0%
2013	45,144	111.0%	3,746	8.3%	100.9%	2,354	5.2%	98.9%
2014	48,516	119.3%	3,749	7.7%	101.0%	2,426	5.0%	102.0%
2015	53,790	132.3%	3,981	7.4%	107.2%	2,695	5.0%	113.3%
2016	59,235	145.6%	4,353	7.3%	117.3%	3,082	5.2%	129.6%
Changes 2010-2016	18,564	45.6%	641	-1.8%	17.3%	703	-0.6%	29.6%

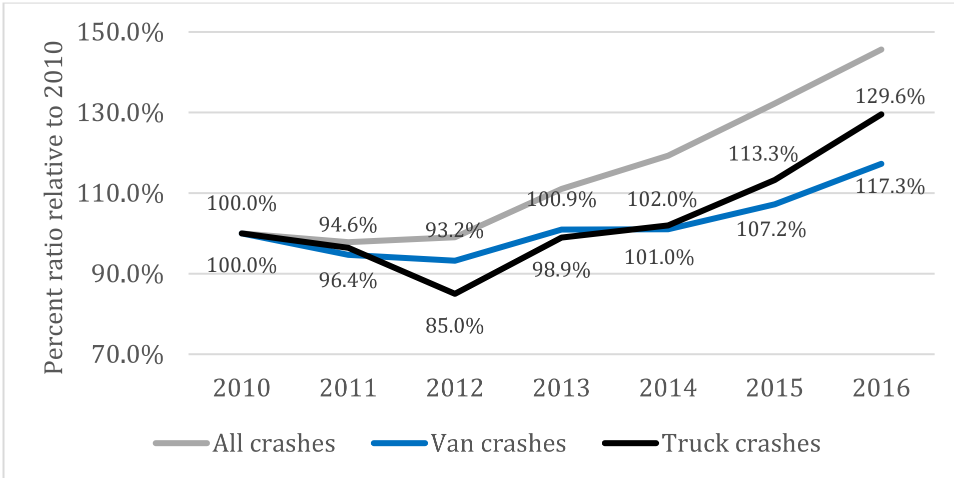


Figure 3 Trends in crash statistics on city streets by vehicle type 2010-2016

We present the statistics of severe crashes on city streets by vehicle type in Table 4 and Figure 4. Severe crashes followed the increasing pattern of all crashes (32.8% increase). Severe van crashes have stayed relatively consistent until 2016 (7.3% increase), but its extent of change is much smaller than that of all severe crashes. There has been a big drop in severe truck crashes over the entire period. In general, truck crashes comprise 5-6% of all crashes, and severe truck crashes comprise 2-3% of all severe crashes. Severe van and truck crashes have not followed the increasing trend of severe crashes.

Table 4 Number of severe crashes with a fatality or injury on city streets by vehicle type

Year	All severe crashes on city streets		Severe van crashes on city streets			Severe truck crashes on city streets		
	N	Relative to 2010	N	% share	Relative to 2010	N	% share	Relative to 2010
2010	15,172	100.0%	1,380	9.1%	100.0%	477	3.1%	100.0%
2011	14,809	97.6%	1,379	9.3%	99.9%	448	3.0%	93.9%
2012	15,071	99.3%	1,312	8.7%	95.1%	376	2.5%	78.8%
2013	15,846	104.4%	1,387	8.8%	100.5%	382	2.4%	80.1%
2014	16,735	110.3%	1,373	8.2%	99.5%	395	2.4%	82.8%
2015	17,934	118.2%	1,393	7.8%	100.9%	437	2.4%	91.6%
2016	20,151	132.8%	1,481	7.3%	107.3%	502	2.5%	105.2%
Changes 2010-2016	4,979	32.8%	101	-1.7%	7.3%	25	-0.7%	5.2%

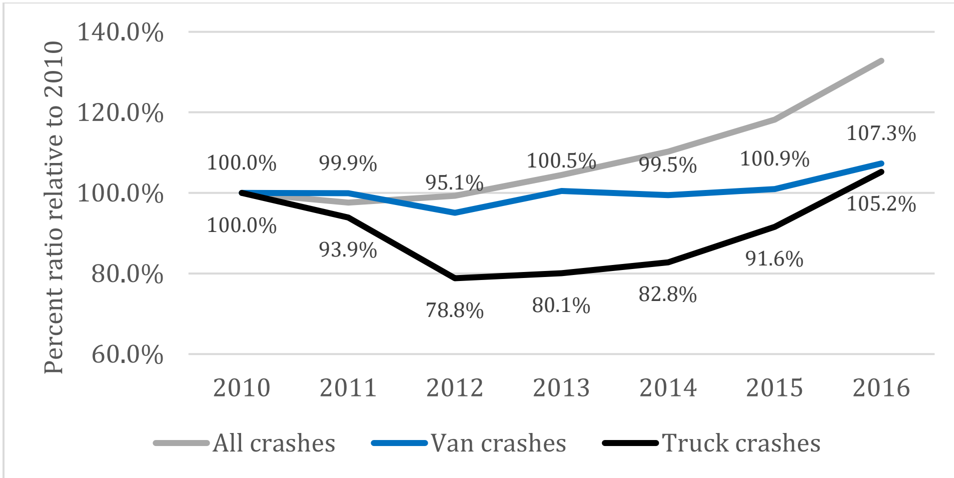


Figure 4 Trends in severe crash statistics on city streets by vehicle type 2010-2016

4.2 Population and Employment Data

We use (1) 2010 US Census and 2012-2016 American Community Survey to retrieve population and median household income statistics at the census-tract level (two periods) and (2) 2010 and 2015 Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LEHD LODES) to retrieve the number of employment at the two-digit NAICS industry sector levels (two periods). We define NAICS 31-33 Manufacturing, 42 Wholesale Trade, 44-45 Retail Trade, and 48-49 Transportation and Warehousing as the freight intensive sectors (Holguín-Veras et al., 2016). Compared to other sectors, the freight intensive sectors (FIS) generate and attract relatively more intensive freight trips. Thus, we expect that the locations with more FIS employment are more likely to have higher levels of freight movement, as well as a higher probability for freight vehicle crashes at the local level. We also use a relative diversity index (RDI), defined as Equation (2). A lower diversity index indicates more different an industry sector composition at location *i* to the industry sector composition of the entire DFW region (Duranton & Puga, 2000). We expect that locations with lower diversity index to have distinctive freight travel patterns.

$$RDI_i = \frac{1}{\sum_j |S_{ij} - S_j|}$$

Equation (2)

Where,

S_{ij} is the share of industry *j* in location *i*

S_j is the share of industry *j* in the region

As a spatial unit, we use a one-square-mile hexagon, which is approximately similar to the average area of the census tracts in 2016 US Census urbanized areas in the DFW region. The boundaries of census tracts are defined in a way that a census tract contains approximately 2,500-8,000 population. Also, the boundary generally follows visible features, such as major transportation networks (US Census Bureau, n.d.). The size and shape of a census tract vary with respect to population density. This variation makes employment analysis very complicated because the spatial distribution of employment does not necessarily correspond to that of the population (Giuliano, Redfearn, Agarwal, & He, 2012; Giuliano & Small, 1991). The size and shape of census tracts do not accommodate the level of employment densities. Thus, we developed a hexagon grid and transferred all data from the US Census, ACS, and LEHD to the hexagons by aerial apportioning. With the hexagons, we can compare population and employment activity in a consistent spatial unit and eliminate the need for normalization with respect to irregular areal size. Also, count and density can be used interchangeably. We conduct analysis using the hexagons in 2016 US Census urbanized areas (N=2,262) (Figure 1).

4.2.1 Understanding DFW's Urban Structure in 2015

In Table 5, we present the summary statistics of population and employment in the study area in 2015. It includes urban hexagons only and excludes approximately 17% of the population and 9% of employment outside of the urban areas. On average, one hexagon contains about 2,542 residents and 1,355 jobs. We also present the distribution by density quartiles. Here, the quartiles are separately defined in terms of population and employment densities. The fourth quartile includes the densest hexagons, in which 52% of the population and 75% of jobs are situated. Indeed, employment is far more concentrated in high-density hexagons relative to population.

Using the quartiles, we constructed combined categories of population-employment quartiles, the "Freight Landscape" as suggested in Giuliano et al. (2018). The distribution of hexagons with respect to the combined categories is presented in Table 6. The majority of hexagons fall in the categories where development levels are similar between population and employment. Namely, population and employment densities are generally correlated. For example, P1|E1, P2|E2, P3|E3, and P4|E4 comprise 43% of all hexagons. Relatively a small number of hexagons are in the categories with unbalanced development levels. For example, P1|E4 (industrial zone) and P4|E1 (high-density residential zone) comprise 2.2% and 0.7% of all hexagons, respectively. This distribution is very similar to that of Los Angeles, CA, except population densities in DFW are much smaller. The distribution and magnitude of employment densities in DFW are approximately 10% smaller than those of Los Angeles.

Table 5 Distribution of population and total employment by density quartile

	Quartiles	N	Sum	%	Mean	Median	Min	Max
Population	Q1	566	259,779	4.5%	459	447	0	875
	Q2	565	856,857	14.9%	1,517	1,487	883	2,199
	Q3	566	1,636,498	28.5%	2,891	2,852	2,199	3,663
	Q4 (highest)	565	2,995,993	52.1%	5,303	4,903	3,664	16,785
	Sum	2,262	5,749,128	100.0%	2,542	2,199	0	16,785
Employment	Q1	566	46,779	1.5%	83	70	2	184
	Q2	565	199,593	6.5%	353	343	184	558
	Q3	566	508,020	16.6%	898	846	560	1,433
	Q4 (highest)	565	2,310,634	75.4%	4,090	2,649	1,438	48,590
	Sum	2,262	3,065,025	100.0%	1,355	559	2	48,590

Table 6 Distribution of hexagons by population and employment quartile combinations

	Pop Q1	Pop Q2	Pop Q3	Pop Q4
Emp Q1	16.7%	5.5%	2.1%	0.7%
Emp Q2	4.9%	8.2%	7.1%	4.8%
Emp Q3	1.2%	6.0%	8.1%	9.7%
Emp Q4	2.2%	5.3%	7.7%	9.8%

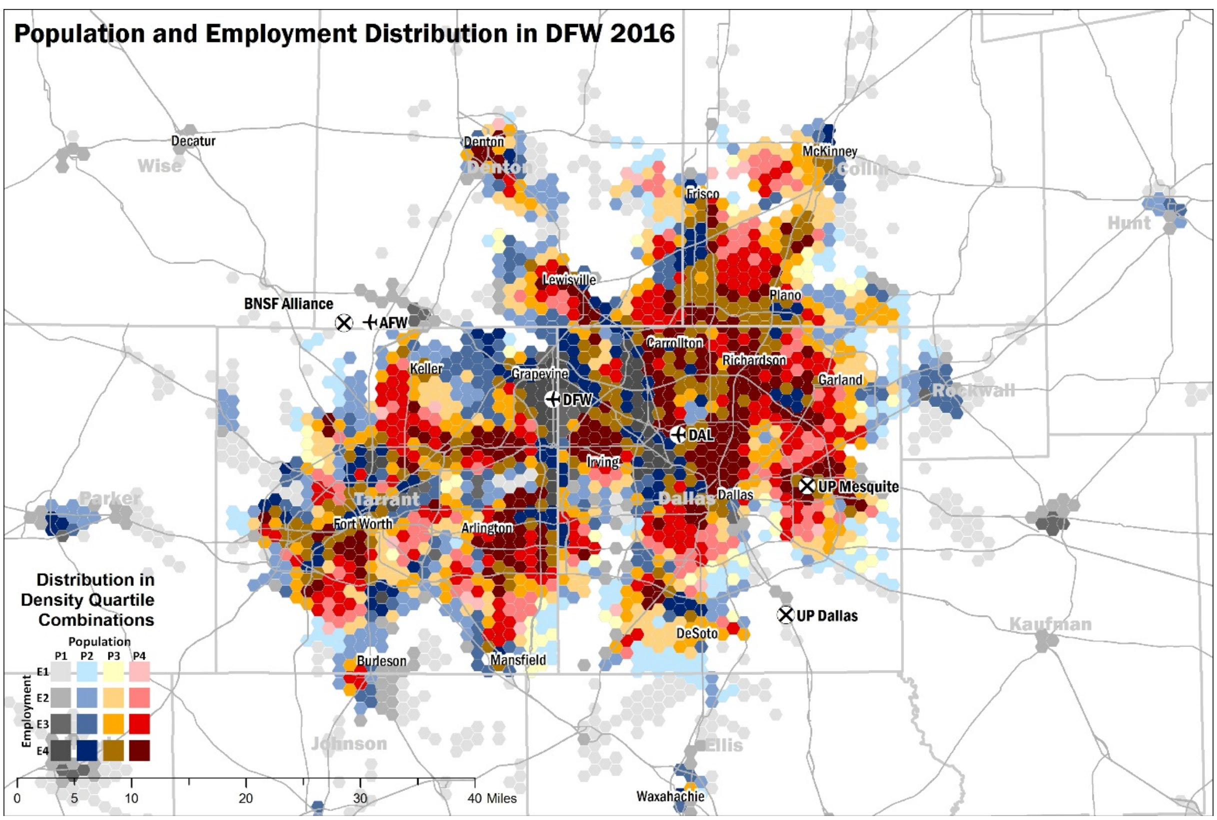


Figure 5 Freight Landscape – distribution of population and employment by density quartile combinations

In Figure 5, we present the spatial distribution of the combined quartile categories. The hexagons with the highest population and employment density (P4|E4) are located throughout a large area of the region, including the corridor between Dallas Downtown and Richardson (US Highway 75), the corridor between Dallas Downtown and Carrollton (Interstate 35E), Irving, Lewisville, Bedford, Arlington, and Fort Worth. The hexagons with low population and high employment (P1|E4) are around the D/FW International Airport and on the business corridor along Interstate 35E. These locations have intensive industrial, transportation, and warehousing businesses. As expected, the hexagons with medium densities are mostly in inner suburbs, and the hexagons with lower densities are on the periphery. This framework presents the variation in development patterns in terms of population and employment densities in a simple and intuitive manner.

4.2.2 Aggregation of the Sixteen Freight Landscape Categories

The sixteen combined quartile categories may be too many to be used as categorical variables in spatial analysis and econometric models. Hence, we ran k-means clustering to aggregate the sixteen categories into four land use categories (Table 7). The first category (LU1) is low population and high employment zones (P1|E4). The second category (LU2) is low population and low employment zones. The third category (LU3) is the zones with medium-level development. The fourth category (LU4) is medium-high population and high employment zones (P2|E4, P3|E4, and P4|E4).

Table 7 Aggregation of the 16 Freight Landscape categories

	Pop Q1	Pop Q2	Pop Q3	Pop Q4
Emp Q1	**Land Use 2**	**Land Use 2**	**Land Use 2**	**Land Use 2**
Emp Q2	**Land Use 2**	**Land Use 3**	**Land Use 3**	**Land Use 3**
Emp Q3	**Land Use 2**	**Land Use 3**	**Land Use 3**	**Land Use 3**
Emp Q4	**Land Use 1**	**Land Use 4**	**Land Use 4**	**Land Use 4**

To understand the characteristics of the four land use categories, we used ACS 2012-2106 and LEHD 2015 and calculated mean population and employment densities (Table 8). According to Holguin-Veras et al., (2016), the level of freight trip generation and attraction varies widely across industry sectors. The basic sectors include NAICS codes 11 (agriculture), 21 (mining), 22 (utilities), and 23 (construction). The freight intensive sectors include NAICS codes 31-33 (manufacturing), 42 (wholesale trade), 44-45 (retail trade), and 48-49 (transportation and warehousing). The service sectors include 51 (information), 52 (finance and insurance), 53 (real estate), 54 (professional), 55 (management), 56 (administrative), 61 (educational), 62 (health care), 71 (arts), 72 (accommodation), 81 (other services), and 92 (public administration). As expected, LU1 has very intensive FIS and service sector activity with a very low population. LU2 has low population and very low employment in all categories. LU3 has a high population and relatively low employment. LU4 has a high population and high service-oriented employment. The four land use categories have very distinctive development patterns. In Figure 6, we present the spatial distribution of the four land use categories. It is a simplified look of the development patterns of Dallas-Fort Worth but generally follows the patterns in Figure 5. LU1 is mainly in two locations: DFW International Airport and the industrial corridor along Interstate 35E. LU2 and LU3 are peripheral and inner suburbs, respectively. LU4 consists of high-density polycentric clusters. With no exception, all LU4 hexagons are located along with major highway networks.

Table 8 Comparison of the industry sector composition across the four land use categories

Land use	Area (mi^2)	Mean employment density			Mean population density
		1 Basic	2 Freight intensive	3 Service	
Land use 1	50	351	**1,805**	**1,830**	362
Land use 2	704	18	62	73	895
Land use 3	993	43	230	378	**3,196**
Land use 4	515	211	**1,049**	**2,840**	**3,743**
Sum	2,262	81	399	876	2,542

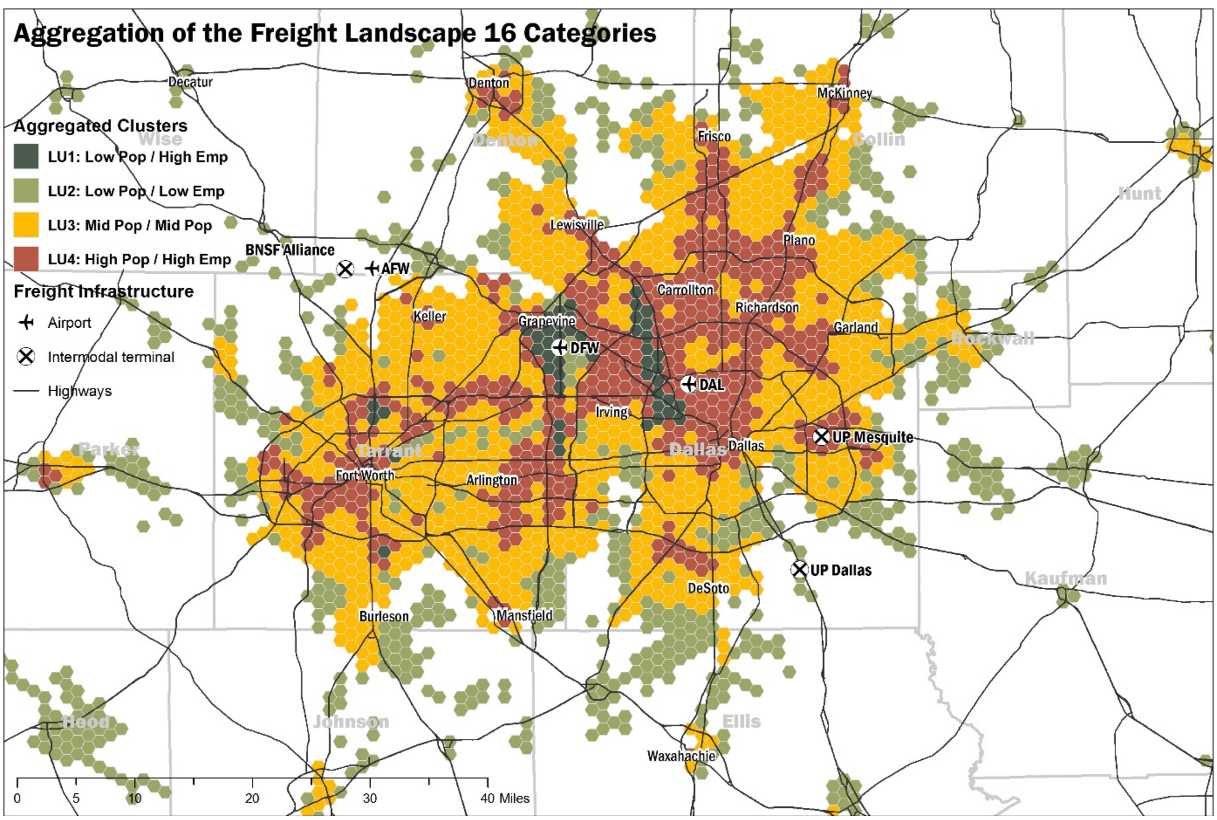


Figure 6 Aggregation of the Freight Landscape categories into four land use categories

4.2.3 Understanding Changes in DFW's Urban Structure from 2010 to 2015

The Dallas Fort Worth region has been one of the largest and rapidly growing metropolitan areas (US Census Bureau, 2018). Over the last five years, in our study area, the population increased 7.7%, employment 14.9%, and FIS employment 12.5% (Table 9). To have a clear understanding of the spatial distribution of the hexagons that gained activity the most, we identified the upper 90th percentile hexagons (N=226) with the largest gains for each of population, employment, and FIS employment, separately. In the upper 90th percentile hexagons, 40% of all population gains occurred, whereas 78% of all employment and 107% of FIS employment gains occurred. The bottom 90th percentile hexagons have lost 6,533 FIS employment over the last five years.

Table 9 Changes in population, employment, and freight intensive sectors 2010-2016

	2010	2015	Change	% change	Change in upper 90th percentile hexagons	% of total change
Population	5,337,788	5,749,128	411,340	7.7%	164,741	40.0%
Employment	2,666,632	3,065,025	398,393	14.9%	311,578	78.2%
Freight Intensive Sectors	801,756	901,748	99,992	12.5%	106,525	106.5%*

*The bottom 90th percentile hexagons lost FIS employment.

The spatial distribution of the 90th percentile hexagons varies significantly by population, employment, and FIS employment (Figure 7). In general, locations with the most development are not only in suburban and peripheral areas (Frisco, McKinney, Keller, and Mansfield) but also in central locations that already have intensive population and employment development levels. Locations with most population gains have very few overlaps with the locations with most employment gains. The general employment gains and FIS employment gains share a large portion of areas except for Dallas-Downtown and Plano areas. With no exception, all employment and FIS development occurred in locations along highways, whereas some population development occurred in locations remote from highway networks. Still, all developments have been approximately within 5 miles from highways, showing that access to highways is almost ubiquitous throughout the region.

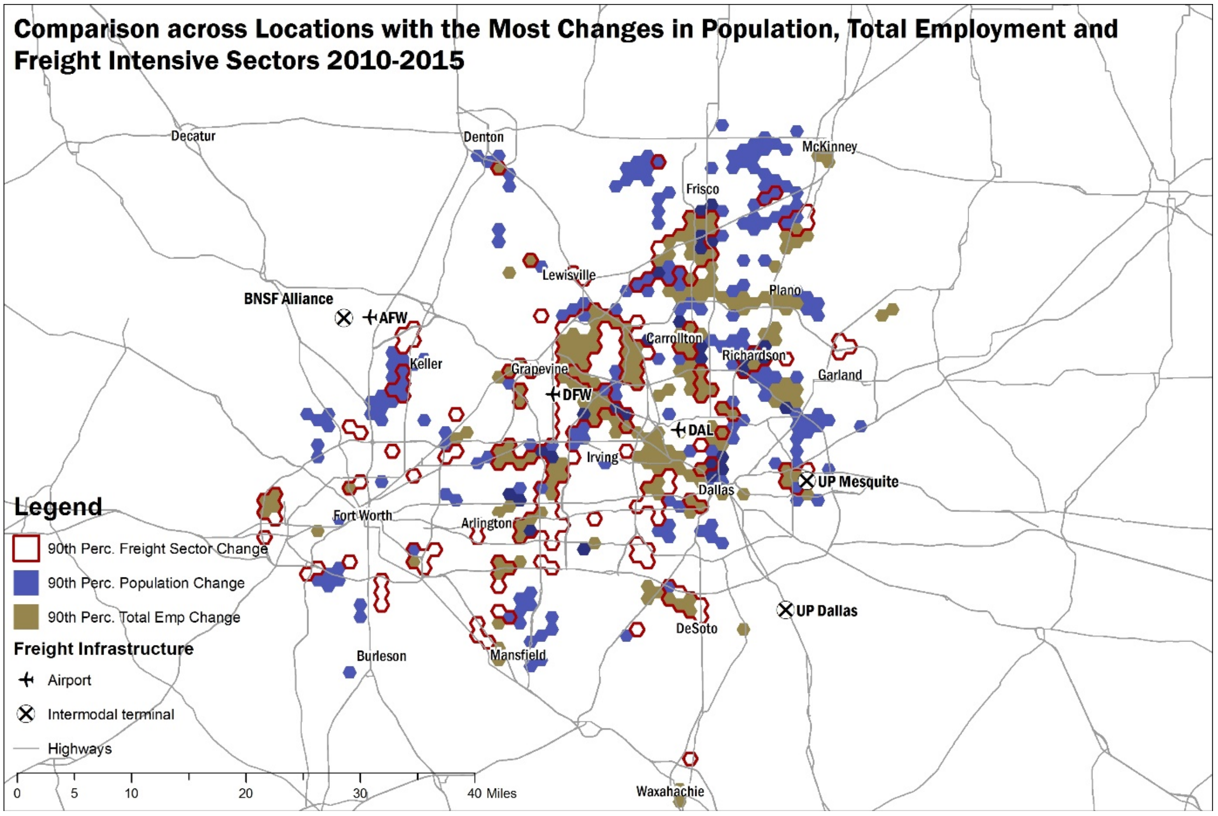


Figure 7 Comparison across the locations with the most changes in population, employment, and freight intensive sectors

4.3 Vehicle Movement Data

There is no information for intra-metropolitan vehicle flows, particularly freight vehicle flows, in the DFW region. Hence, we used the 2013 regional travel model estimates developed by the NCTCOG. The model provides link-level total and freight vehicle traffic counts post-equilibrium assignment and post-validation using actual traffic counts on the roads. We cut travel model networks with our hexagon boundaries, transferred traffic attributes to the hexagons, and calculated average vehicle miles traveled per network mile per hexagon for the total and freight traffic. The equation is as follows.

$$VMT\ per\ network\ mile = \frac{\sum VC_i \times mile_i}{\sum mile_i}$$

Equation (3)

Where,

VC is vehicle counts at link i

Mile is the length of link i

A hexagon notion is omitted

We excluded all highway traffic. We present the summary statistics in Table 10 and travel model networks in Figure 1. The distribution of all vehicle miles traveled per network mile is in Figure 8, and that of freight vehicle miles traveled per network mile is in Figure 9. Table 11 presents a summary of all the explanatory variable definitions.

Table 10 Summary statistics of VMT per network mile per hexagon

	N	Mean	SD	Median	Min	Max
All vehicle miles traveled per network mile	2,187	9,985.9	7,528.4	8,366.9	0.0	60,500.6
Freight vehicle miles traveled per network mile	2,187	410.4	365.6	316.6	0.0	3,661.2

Table 11 Summary of explanatory variable definitions

Variables	Definition
Transport supply variables	
• Miles to the nearest airport	Euclidean miles to the nearest airport from a hexagon
• Miles to the nearest intermodal terminal	Euclidean miles to the nearest intermodal terminal from a hexagon
• Miles to the nearest highway	Euclidean miles to the nearest highway ramp from a hexagon
Transport demand variables	
• Population	Number of populations in 2010 Census and 2012-2016 ACS
• Household income	Median household income from the same source above
• Employment	Number of employment in 2010 and 2015 LEHD LODES
• Relative diversity	The inverse of the sum of absolute differences of two-digit industry sector employment share between a hexagon and the regional average
• Freight intensive sector	Manufacturing, wholesale trade, retail trade, and transportation sectors
Vehicle movement variables	
• All vehicle VMT per mile	Sum of all vehicle miles traveled / sum of all network miles
• Freight VMT per mile	Sum of freight vehicle miles traveled / sum of all network miles

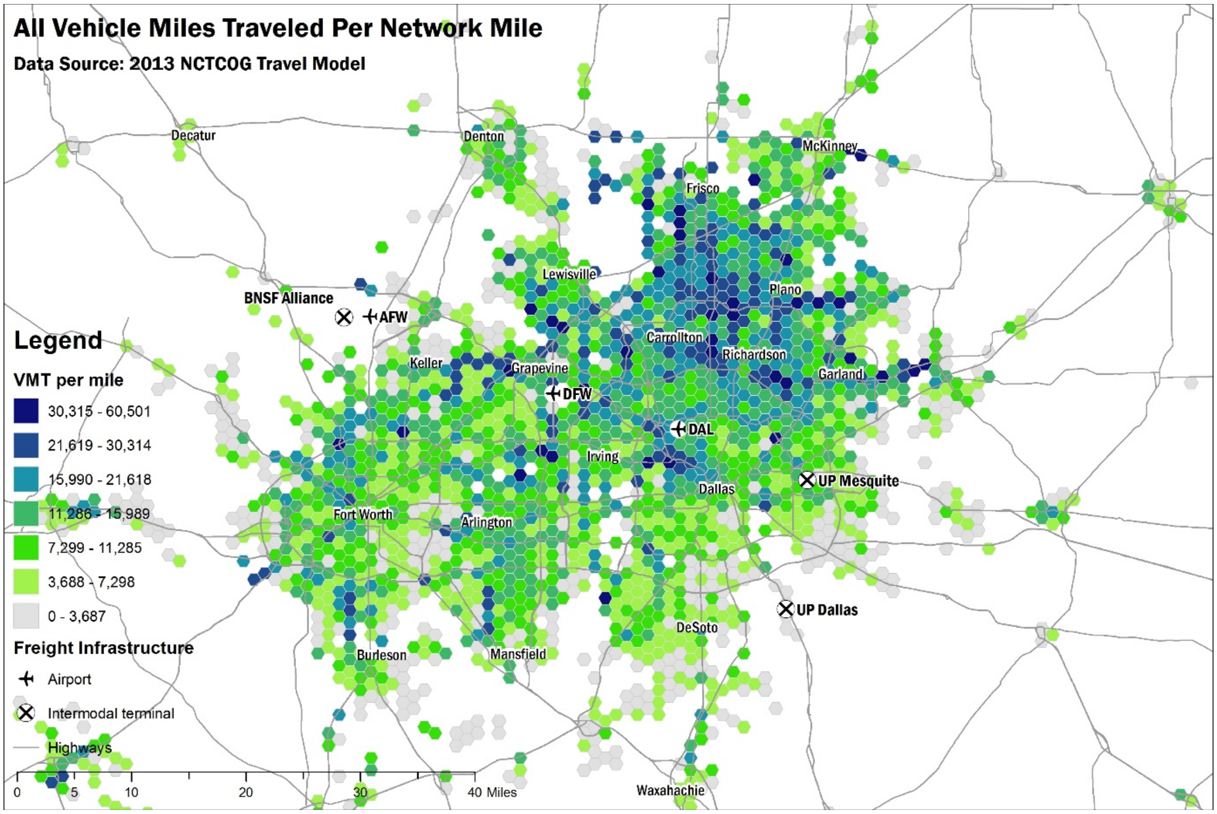


Figure 8 Spatial distribution of all vehicle miles traveled per network mile

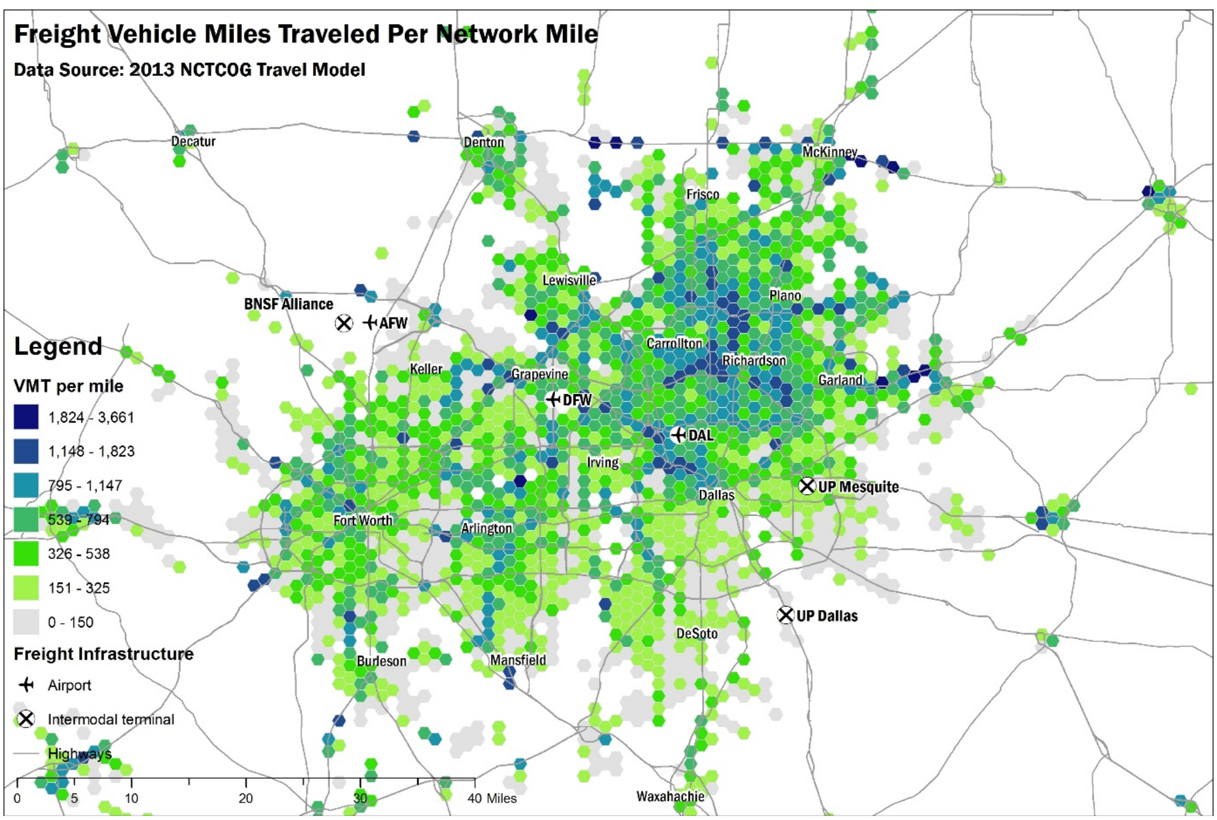


Figure 9 Spatial distribution of freight vehicle miles traveled per network mile

5 Results

We present the results of spatial analysis and econometric models in two sections. First, we use the four land use categories and the 90th percentile hexagons with most changes in terms of population, employment, and FIS employment to examine the distribution in 2016 and changes in distribution from 2010 to 2016 of vehicle crashes. It is to understand whether vehicle crash patterns are associated with development patterns over time. Second, we use cross-section and time-series models to examine which variables explain the spatial and temporal variation in vehicle crash patterns, controlling for all other factors.

5.1 *Trends in Vehicle Crashes in Dallas-Fort Worth 2010-2016*

5.1.1 Sub-metropolitan Distribution of Vehicle Crashes in 2016

In Table 12, we present the average number of all and severe vehicle crashes (with a fatality or injury) per hexagon by four land use categories in 2016. As expected, crash patterns vary significantly and have a reasonable correlation with the four land use categories. LU4, with the highest population and employment densities, has the highest all vehicle crash densities (52 all vehicle, 4 van, and 1.3 truck crashes per hexagon). LU3, with similar levels of population yet substantially lower employment densities, has almost half of crash densities than LU4. LU2, with low development levels, has almost one-tenth of crash densities than LU4. LU1, with intensive service/FIS employment yet with few populations, has truck crash densities similar to LU4. Van crash densities are similar to LU3 (high population). Severe crash densities have very similar patterns but with a third of magnitude relative to all crash densities. It is reasonable because severe crashes are a subset of all crash events (traffic failure events).

Table 12 Average number of all and several crashes per hexagon by vehicle type in 2016

	Area (mi^2)	N of all crashes per hexagon in 2016			N of severe crashes per hexagon in 2016		
		All veh.	Van	Truck	All veh.	Van	Truck
Land Use 1	50	16.94	1.56	2.66	5.88	0.50	0.68
Land Use 2	704	5.30	0.33	0.31	1.60	0.10	0.07
Land Use 3	993	26.39	1.93	1.19	8.83	0.68	0.32
Land Use 4	515	52.25	3.95	2.78	18.40	1.44	0.65
Sum	2,262	25.51	1.88	1.31	8.69	0.67	0.32

In Figures 10, 11, and 12, we present the spatial distribution of all crashes in 2016 by vehicle type. All vehicle crashes (Figure 10) are concentrated around Dallas Downtown, Cockrell Hill (southwest of Dallas), the city road corridors connecting Dallas and Richardson, Carrollton, and the Fort Wort areas. Van crashes (Figure 11) have a pattern similar to all vehicle crashes but are more concentrated in Downtown Dallas and northern parts of the region around Carrollton, Richardson, and Plano. Truck crashes (Figure 12) are more prevalent in areas between Downtown Dallas, Carrollton, and Richardson near DFW and DAL airports as well as areas around Fort Worth.

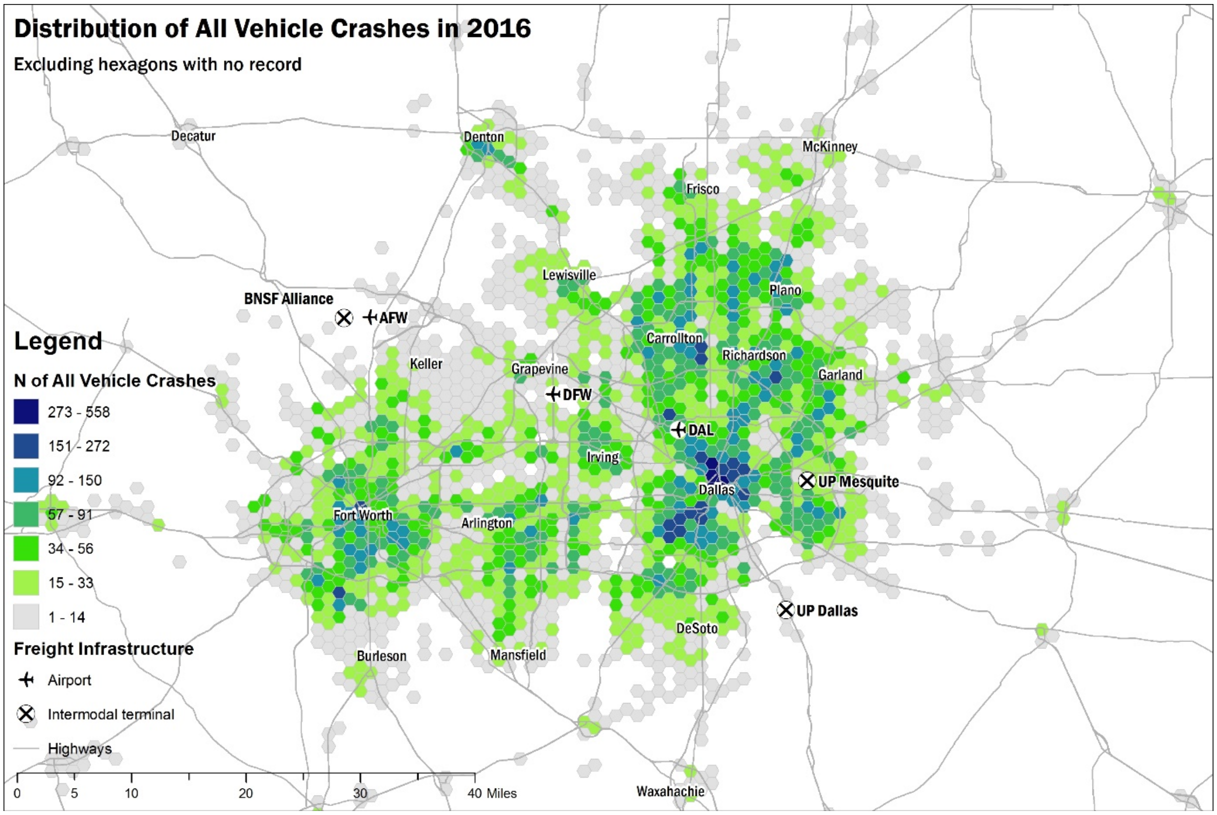


Figure 10 Distribution of all vehicle crashes in 2016

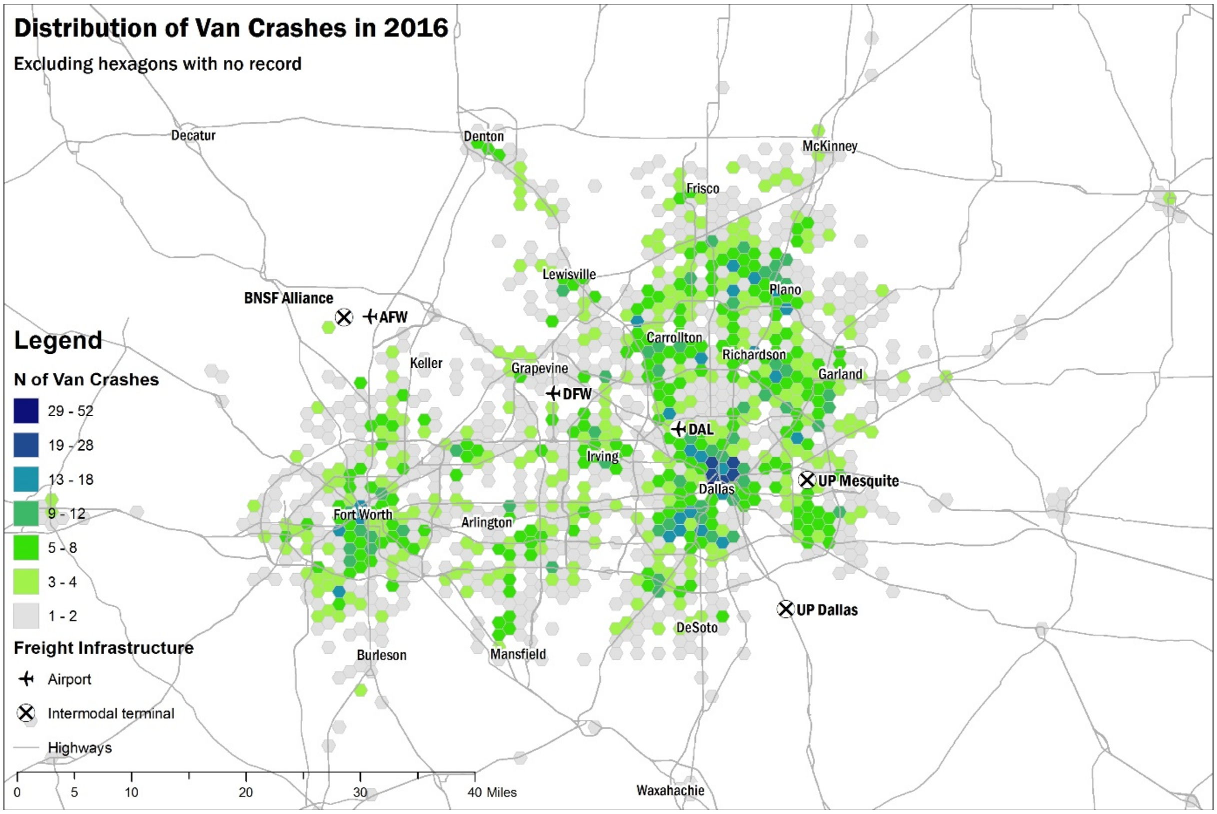


Figure 11 Distribution of van crashes in 2016

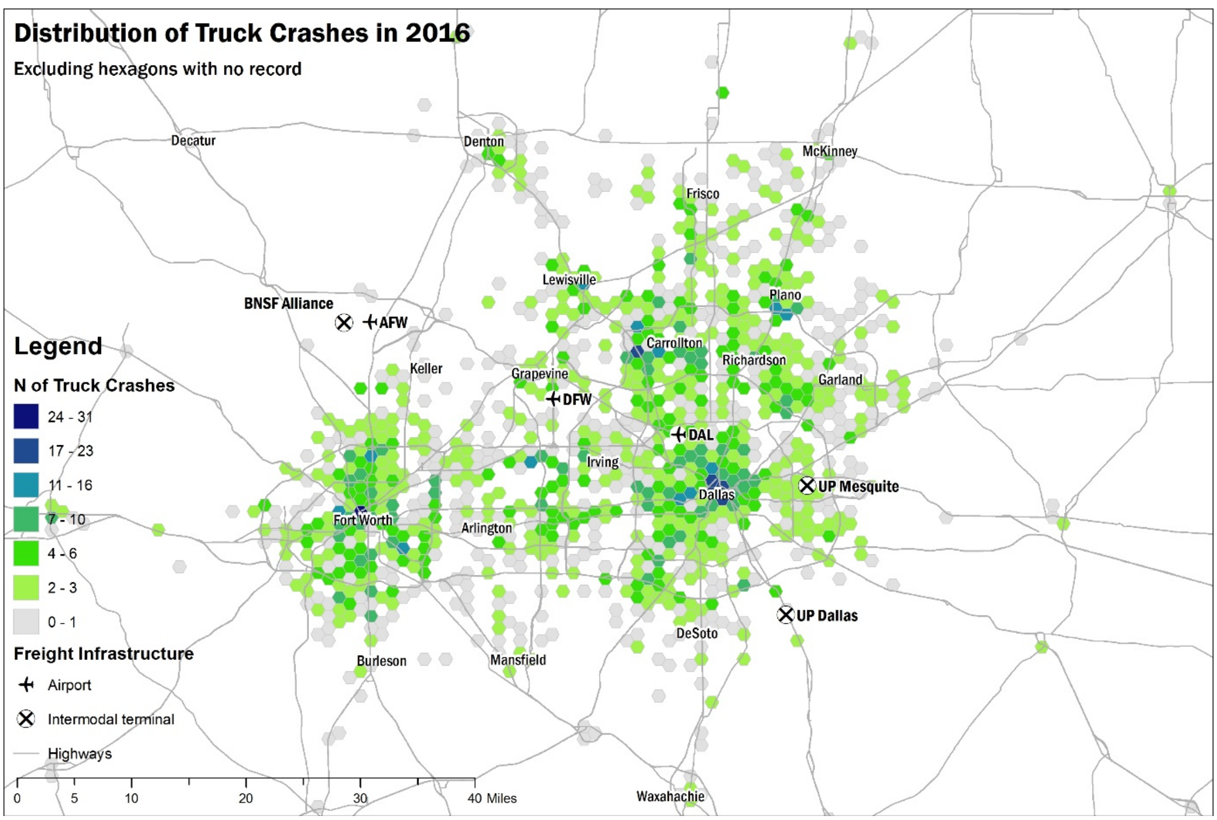


Figure 12 Distribution of truck crashes in 2016

5.1.2 Changes in Truck and Van Crashes over time

In Table 13, we present the percent changes in an average number of all and severe crashes per hexagon by land use category by vehicle type from 2010 to 2016. In general, changes in crash patterns are not evenly distributed. LU1 has experienced the most intensive increase in percent changes of all crashes across three vehicle types. Also, in LU2, despite its low development levels, truck crash density increased significantly. Except for LU1, changes in all vehicle crashes are distributed similarly across LU2, 3, and 4. Contrarily, changes in freight vehicle crashes tend to be concentrated in land use types with more intensive FIS businesses (LU1 and LU4). Changes in severe crash patterns are similar to those in all crashes. There are a couple of exceptions. The magnitude of changes is far smaller for severe crashes across land use categories. Changes in all vehicle severe crashes are evenly distributed across LU 2, 3, and 4. Severe all vehicle and truck crashes increased the most in LU1. It is notable that, in LU1, severe van crashes did not change over time.

Table 13 Changes in the average number of all and severe crashes per hexagon by vehicle type 2010-2016

	Area (mi^2)	Changes in N of all crashes per hexagon 2010-2016			Changes in N of severe crashes per hexagon 2010-2016		
		All veh.	Van	Truck	All veh.	Van	Truck
Land Use 1	50	**79.8%**	**56.0%**	**118.0%**	**50.8%**	0.0%	**30.8%**
Land Use 2	704	48.6%	32.9%	**58.1%**	29.5%	10.8%	19.5%
Land Use 3	993	42.4%	12.4%	10.0%	33.3%	4.2%	13.6%
Land Use 4	515	47.2%	17.5%	39.1%	32.0%	8.6%	10.6%
Sum	2,262	45.4%	16.4%	28.7%	32.6%	6.6%	13.3%

In Figures 13, 14, and 15, we present the spatial distribution of the changes in vehicle crashes from 2010 to 2016 by vehicle type. Most significant increases in all vehicle crashes are concentrated in a few locations in Dallas-Fort Worth, such as Dallas Downtown, Carrollton, and Fort Worth (Figure 13). Also, moderate increases are distributed throughout the region. Contrarily, spatial patterns of changes in freight vehicle crashes are not distinguishable. Carrollton, Richardson, and Fort Worth stand up for van crash changes in Figure 14. Dallas, Carrollton, and Fort Worth stand up for truck crash changes in Figure 15.

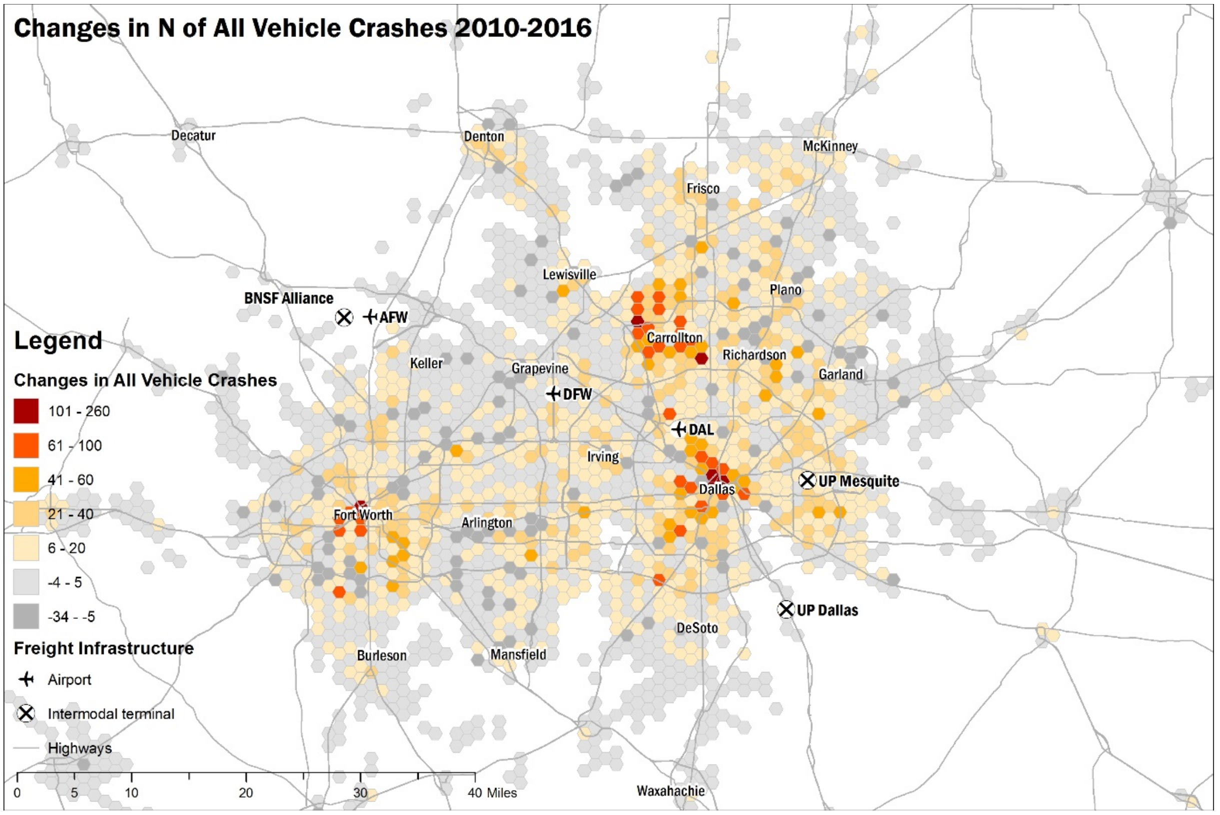


Figure 13 Distribution of changes in all vehicle crashes from 2010 to 2016

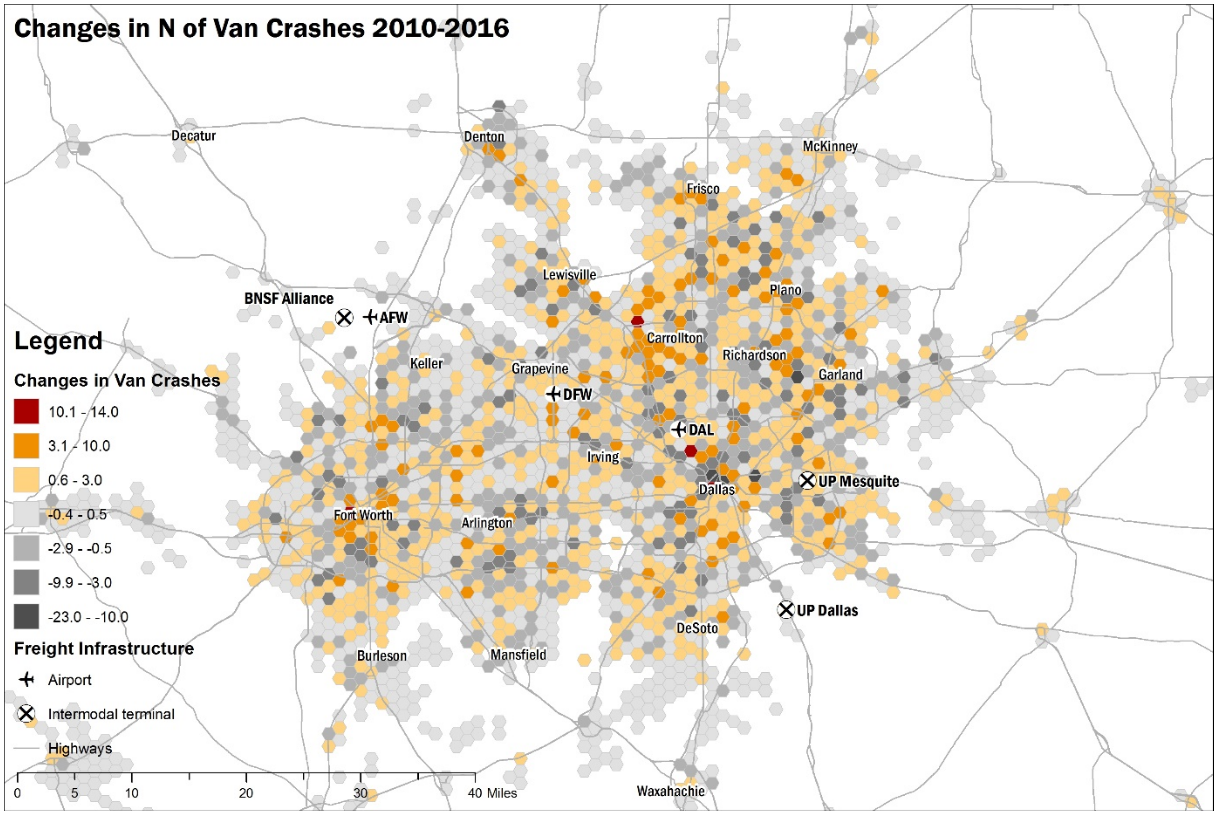


Figure 14 Distribution of changes in van crashes from 2010 to 2016

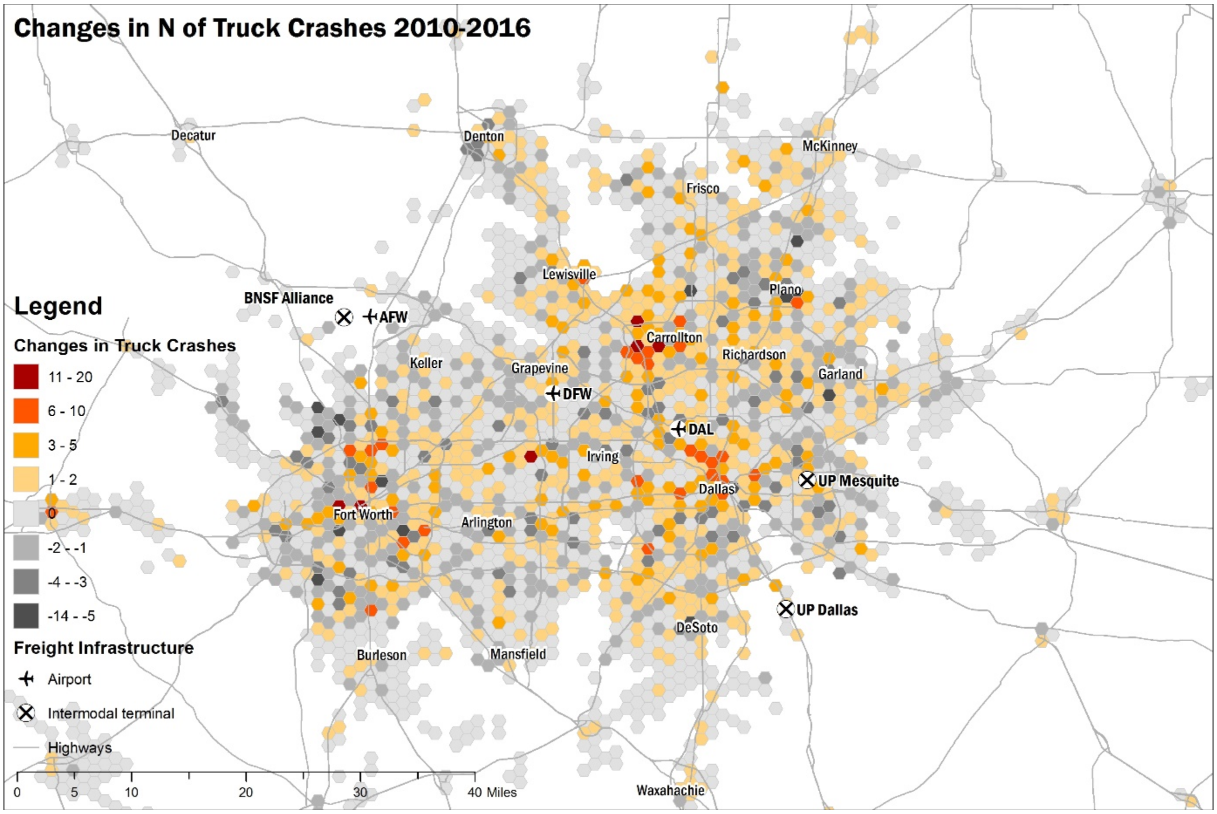


Figure 15 Distribution of changes in truck crashes from 2010 to 2016

We also examine the changes in vehicle crash patterns with respect to the hexagons with the most population, employment, and FIS employment gains. In Table 14, we present changes in all crashes per hexagon by development type by vehicle type. Between changes in crash counts per hexagon and changes in percentage, different patterns arose. In terms of the changes in crash counts, hexagons with intensive development gained more crashes (almost twice) for all vehicle crashes. For freight vehicle crashes, hexagons with intensive employment and FIS development gained more crashes (almost five times for truck crashes). In terms of changes in percentage, all vehicle crashes increased similarly across development types, whereas freight vehicle crashes show disparate patterns: a mixed pattern for van crashes; more truck crashes in intensive employment and FIS development hexagons. It is notable that the hexagons with less population development (bottom 90th percentile) gained more freight vehicle crashes. In Table 15, we present changes in severe crashes per hexagon by development type by vehicle type. The patterns of changes are similar to those of all crashes. Exceptions are that freight vehicle crashes decreased in hexagons with intensive population development. Arguably, one reasonable explanation may be that freight vehicle traffic existed before intensive population development might have moved to elsewhere after the area has been developed.

Table 14 Changes in all crashes per hexagon in terms of locations with intensive development

Changes in crashes in terms of	Development types	All vehicle		Van		Truck	
		Change per hex	%Δ	Change per hex	%Δ	Change per hex	%Δ
Population changes	Intensive (N=226)	15.76	44.6%	0.24	6.7%	0.26	14.5%
	The rest (N=2,036)	7.10	45.7%	0.27	19.2%	0.30	31.7%
Employment changes	Intensive (N=226)	14.46	45.2%	0.39	12.3%	**0.98**	**54.3%**
	The rest (N=2,036)	7.25	45.5%	0.25	17.4%	0.22	23.2%
Freight sector changes	Intensive (N=226)	10.69	46.2%	0.40	18.7%	**1.00**	**77.1%**
	The rest (N=2,036)	7.67	45.3%	0.25	16.0%	0.21	21.7%

Table 15 Changes in severe crashes per hexagon in terms of locations with intensive development

Changes in severe crashes in terms of	Development types	All vehicle		Van		Truck	
		Change per hex	%Δ	Change per hex	%Δ	Change per hex	%Δ
Population changes	Intensive (N=226)	4.04	29.0%	**0.00**	**-0.3%**	**-0.05**	**-9.6%**
	The rest (N=2,036)	1.93	33.6%	0.05	8.5%	0.05	18.2%
Employment changes	Intensive (N=226)	4.11	33.6%	0.13	11.1%	**0.18**	**35.7%**
	The rest (N=2,036)	1.92	32.4%	0.03	5.5%	0.02	8.4%
Freight sector changes	Intensive (N=226)	2.80	31.2%	0.09	9.9%	**0.18**	**47.1%**
	The rest (N=2,036)	2.07	32.9%	0.04	6.0%	0.02	8.2%

5.2 Understanding Trends in Vehicle Crashes in Dallas-Fort Worth, 2010-2016

5.2.1 2016 Cross-Section Models

We begin with a cross-section model that examines whether the count of vehicle crashes in 2016 has an association with development patterns, in terms of transport supply and demand proxies, controlling for traffic movement levels. After we found a high correlation between all employment and FIS employment densities, we included FIS employment only in the model. We use 2,157 hexagons that are covered by the transport network of the NCTCOG Regional Travel Model. In the previous section, we documented distinctive crash patterns across the four land use categories. Hence, we incorporate the categories as interaction terms with population and FIS employment densities to capture different levels of correlation across the land use categories. Six models are estimated for three vehicle types (all vehicle, van, and truck) and two crash types (all and severe crashes). Summary statistics are in Table 16. The final model is in Equation 4. A hexagon notation is omitted. For estimation, we use negative binomial model.

$$N_{crash} = exp(\beta_0 + \beta_1 * VMTPM + \beta_2 * Pop + \beta_3 * Pop * LU + \beta_4 * FIS + \beta_5 * FIS * LU + \beta_6 * Inc + \beta_7 * RDI + \beta_8 * Air + \beta_9 * Intm + \beta_{10} * Hwy + \varepsilon)$$

Equation (4)

Where,

N is the number of crashes;

β_n is coefficients to be estimated (n=0, 1, …, 10);

$VMTPM$ is all vehicle and freight VMT per network mile; all vehicle VMT is used for all vehicle model; freight VMT is used for van and truck models, included in a log form;

Pop is population density in ACS 2012-2016, included in a log form;

LU is land use categories (base category is LU2);

FIS is freight intensive sector employment density in LEHD 2015, included in a log form;

Inc is median household income in ACS 2012-2016, included in $10k;

RDI is a relative diversity index (see section 4.2);

Air is miles to the nearest airport, included in a log form;

$Intm$ is miles to the nearest intermodal terminal, included in a log form;

Hwy is miles to the nearest highway ramp, included in a log form;

ε is an error term.

Table 16 Summary statistics of explanatory variables

Variables	N	Mean	SD	Median	Min	Max
All vehicle crashes 2010	2,157	18.36	26.32	9	0	337
All vehicle crashes 2016	2,157	26.69	37.45	15	0	558
Van crashes 2010	2,157	1.70	3.11	1	0	51
Van crashes 2016	2,157	1.97	3.15	1	0	52
Truck crashes 2010	2,157	1.06	1.83	0	0	24
Truck crashes 2016	2,157	1.37	2.33	1	0	31
All vehicle severe crashes 2010	2,157	6.87	10.61	3	0	152
All vehicle severe crashes 2016	2,157	9.11	13.37	5	0	196
Van severe crashes 2010	2,157	0.66	1.35	0	0	20
Van severe crashes 2016	2,157	0.70	1.34	0	0	16
Truck severe crashes 2010	2,157	0.30	0.68	0	0	6
Truck severe crashes 2016	2,157	0.34	0.75	0	0	7
Population 2010	2,157	2,441	1,899	2,100	0	14,918
Population 2016	2,157	2,627	2,020	2,301	0	16,785
Employment 2010	2,157	1,228	2,522	490	1	53,373
Employment 2016	2,157	1,411	2,762	604	2	48,590
FIS employment 2010	2,157	368	587	147	0	6,707
FIS employment 2016	2,157	413	600	181	1	4,453
Median household income 2010	2,157	64,965	29,546	59,887	0	212,132
Median household income 2016	2,157	70,433	32,274	65,034	0	226,972
Relative Diversity Index 2010	2,157	1.30	0.34	1.25	0.62	2.83
Relative Diversity Index 2016	2,157	1.24	0.31	1.21	0.59	3.03
Miles to nearest airport	2,157	16.5	9.5	15.6	0.3	61.9
Miles to nearest intermodal tm.	2,157	17.8	8.7	17.5	0.1	54.6
Miles to nearest highway ramp	2,157	0.9	0.9	0.6	0.0	6.3
All vehicle VMT per mile (2013 BY)	2,157	10,125	7,487	8,459	0	60,501
Freight VMT per mile (2013 BY)	2,157	416	365	321	0	3,661

In Table 17, we present all crash model results for three vehicle types. Estimated coefficients for log-transformed variables (VMT per mile, population and FIS employment density, and miles to transport facility variables) are elasticity – the percent change of crash counts derived from one percent change of an explanatory variable. Estimated coefficients for all the other variables are semi-elasticity – the percent change of crash counts derived from one unit change of an explanatory variable. As a preliminary analysis, we ran stepwise regression models, including explanatory variables one by one, and found no multicollinearity among the explanatory variables. Overall, model goodness-of-fit statistics show that negative binomial models have a more appropriate fit than Poisson models (significant log alpha) and an acceptable level of explanatory power (0.11-0.16) relative to vehicle crash count models.

As expected, across vehicle types, vehicle movement variables (VMT per mile) are significantly and positively correlated with crash counts. Land use categories capture disparate effects on crash counts as a categorical variable as well as an interaction term combined with population and FIS densities. Population density has a positive, significant, and consistent effect across vehicle types. Population density has the largest elasticity for LU3 (0.753+0.182=0.935 for all vehicles; 0.992 for vans; 0.496 for trucks) and the smallest for LU1. FIS density also has a positive effect on vehicle crashes with the largest elasticity for LU4 across the three vehicle types. Its elasticity estimates are far smaller than that of population density (approximately 0.30-0.35 for all three vehicle types). Median household income has a significant and negative correlation with crash frequency for all three vehicle types. RDI is significant for all vehicle crashes: the higher relative diversity (more similar to the regional sector composition), the more all vehicle crashes. Locations with relatively more specialized industry sector compositions (e.g., industrial or service-oriented) than the regional average are likely to have a lower crash frequency. Miles to intermodal terminals and highways is significant (the closer to the facility, the more vehicle crashes), whereas miles to airports is not.

Table 17 Cross-section model results (all crashes)

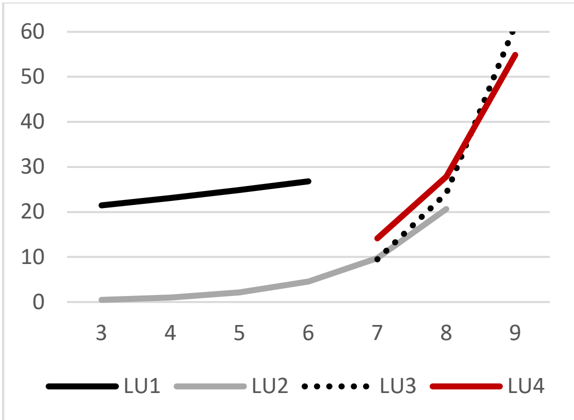
Negative Binomial Model	Number of all crashes					
Dependent variables	Model 1-1 All vehicles		Model 1-2 Vans		Model 1-3 Trucks	
Independent variables	Coef	Sig	Coef	Sig	Coef	Sig
Vehicle movement variables						
All vehicle VMT per link mile (log)	0.203	**				
Freight VMT per link mile (log)			0.187	**	0.221	**
Freight demand-side variables						
LU1 - low pop/high FIS emp	7.895	**	9.341	+	6.155	+
LU2 - low pop/low emp (base)	-		-		-	
LU3 - mid pop/mid emp	-1.154		-0.531		0.347	
LU4 - high pop/high serv. emp	-0.243		1.697		1.361	
Population density (log)	0.753	**	0.992	**	0.496	**
Pop den * LU1	-0.679	**	-1.001	**	-0.338	**
Pop den * LU2 (base)	-		-		-	
Pop den * LU3	0.182	+	0.127		-0.130	
Pop den * LU4	-0.074		-0.325	**	-0.348	*
FIS employment density (log)	0.099	+	0.194	**	0.101	
FIS den * LU1	-0.403		-0.289		-0.354	
FIS den * LU2 (base)	-		-		-	
FIS den * LU3	-0.027		-0.097		0.173	+
FIS den * LU4	0.197	**	0.175	+	0.308	**
Median HH income ($10k)	-0.071	**	-0.060	**	-0.093	**
Relative diversity index	0.136	*	0.096		0.042	
Freight supply-side variables						
Miles to airport (log)	-0.030		0.059		-0.045	
Miles to intermodal (log)	-0.143	**	-0.113	*	-0.143	*
Miles to highway (log)	-0.049	**	0.012		-0.048	+
Constant	-4.628	**	-9.011	**	-4.775	**
Log Alpha	-0.523	**	-0.640	**	-0.284	**
Log Likelihood	-8,134.6		-3,376.7		-3,018.0	
Pseudo R squared	0.111		0.161		0.119	
N	2,157		2,157		2,157	

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

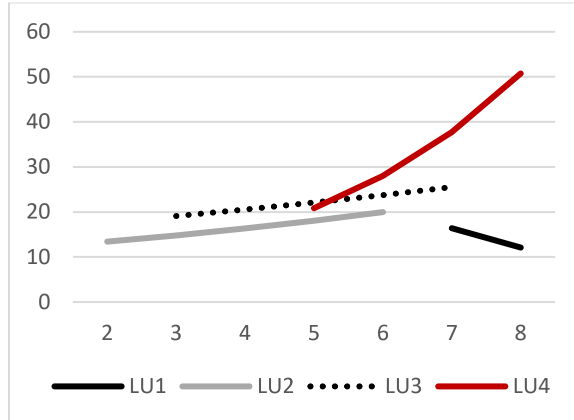
With the table alone, it is difficult to grasp the magnitude of the effect. In Figure 16, we present the margins plot of population and FIS densities, in combination with the land use interaction terms. The X-axis is population (left) and FIS (right) densities in natural logarithm, and the Y-axis is estimated margins of vehicle crashes. The curves of the margins plot are trimmed based on the sample distribution of population and FIS densities. Confidence intervals are not shown. Estimated coefficients and margins vary significantly with respect to crash and vehicle types as well as between population and FIS densities. It is reasonable because the distribution of crash counts (dependent variables) varies significantly across the various categories. To make the plot more comparable between density types, we adjusted the Y-axis scales according to the minimum and maximum values of the margin in Figure 16, all crash models, and Figure 17, severe crash models.

First, we analyze the effect of population density (left). Among land use categories 2, 3, and 4, despite different sizes of coefficients and interaction terms, the curves of margins plot show a pattern where the curves are nicely overlaid with each other with a reasonable similarity in terms of the estimated projectiles (an exponentially increasing pattern). Still, the margins plot for LU3 stands out: largest gradients (elasticity) and highest estimated margins at the peak of population density. They are even greater than those for LU4, in which population and FIS densities are much higher than LU3. Ewing et al. (2003) made a similar observation for all vehicle crashes. Controlling for all other factors, more vehicle crashes are expected in locations that have development patterns of a suburban area than central urban cores. Higher freight VMT per mile, as estimated in the regional travel model, explains part of the phenomena. Also, the margins plot for LU1 is distinguished – smaller marginal effects (gentler gradients), yet substantially greater margins for vehicle crashes in terms of population density. LU1 (intensive service/FIS employment and very few populations) hexagons are located either in and around the DFW International Airport or along the Interstate 35E corridor. The LU1 hexagons are also completely encompassed by LU4 hexagons (high population and service-oriented employment). Hence, we expect a significant level of conflict among residence, service, and FIS-oriented passenger/freight traffic in these areas.

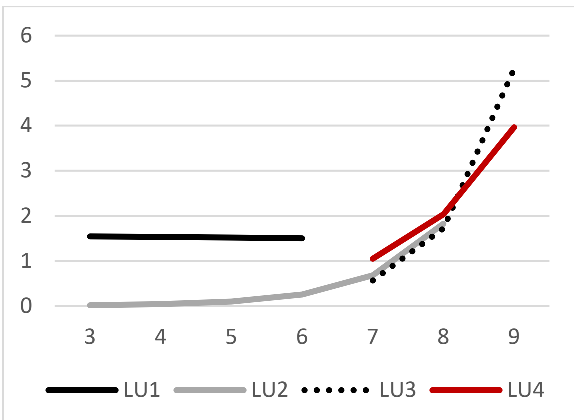
Second, we examine the effect of FIS density (right-side). In LU2 and LU3, FIS density has a small marginal effect. Rather, the margins plot of LU1 and LU4 stands out. In locations with very high population and service-oriented businesses (LU4), compared to other land use categories, FIS density has higher elasticities with vehicle crashes. Interestingly, in LU1 (with high FIS density levels), FIS density has almost no effect. Again, results imply that freight activity alone (e.g., as seen in LU1) does not sufficiently increase the likelihood of vehicle crashes, regardless of vehicle types. We may argue that it is rather the conflict between freight vehicles and other-purposed vehicles that increases the likelihood of vehicle crashes. It may be because of the differences among various vehicle types in terms of the travel behavior (trip time, duration, and origin/destination) and driving behavior (acceleration, deceleration, speed, and maneuver). More research is necessary in order to verify or focus this argument.



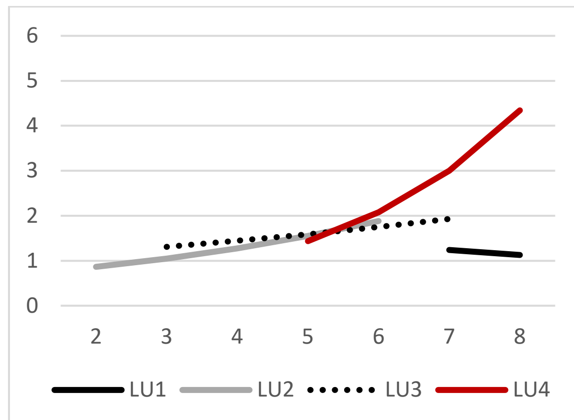
Margins plot – population density
Model 1-1 All vehicle crashes



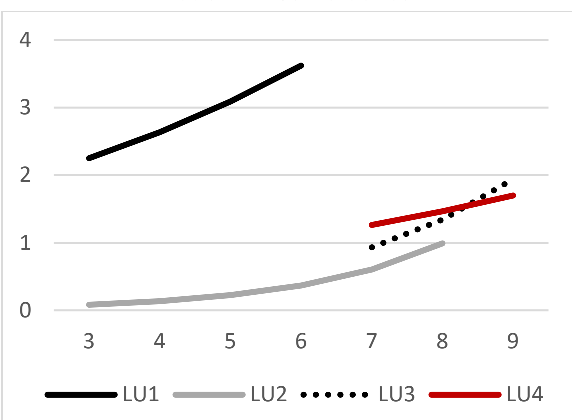
Margins plot – freight sector density
Model 1-1 All vehicle crashes



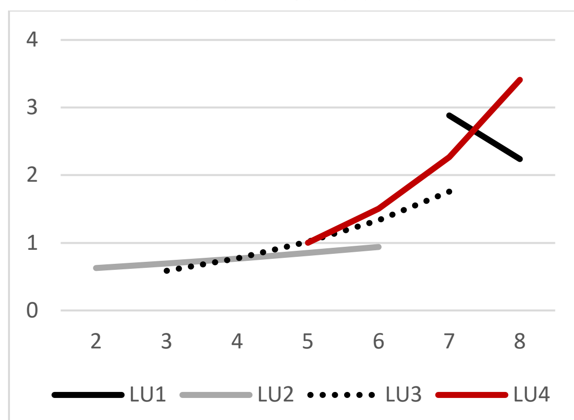
Margins plot – population density
Model 1-2 Van crashes



Margins plot – freight sector density
Model 1-2 Van crashes



Margins plot – population density
Model 1-3 Truck crashes



Margins plot – freight sector density
Model 1-3 Truck crashes

Figure 16 Margins plot of all crashes models

In Table 18, we present severe crash (incidents with at least one fatality or major injury) model results. Again, with stepwise models, we did not find multicollinearity among the explanatory variables for each of the three models. Overall, model goodness-of-fit statistics show that negative binomial models have an appropriate fit (significant log alpha) and an acceptable level of explanatory power (0.13-0.17) relative to vehicle crash count models.

The results of severe crash models are similar to those of all crash models. Vehicle movement variables (VMT per link mile) are positively and significantly associated with the frequency of severe crashes. Population and FIS employment, in general, have positive correlations across the four land use categories. The size of effect varies significantly across land use categories and vehicle types. Similar to all crash models, the elasticity between population density and severe crash frequency is far greater than that between FIS density and severe crash frequency. In LU2 and LU3, population density has the largest elasticity, greater than that in LU1 (high service/FIS density) and LU4 (high population and service employment density). FIS density generally has a positive correlation but with a varying extent across land use categories and vehicle types (largest in LU4). Median household income has a significant and negative correlation across the three vehicle types, yet RDI is significant only for severe truck crashes. Miles to intermodal terminals are generally significant and negative, yet miles to airport and highways show mixed results.

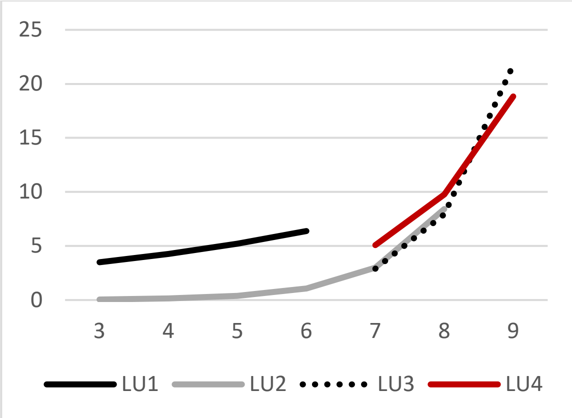
In Figure 17, we present margins plots for severe crash models. First, we examine the effect of population density (left). For land use categories 2, 3, and 4, even with different sizes of intercept and gradient estimates, the curves of margins plot show a similar projectile of estimated margins. LU3 has the steepest gradient (elasticity) and the largest estimate at the peak of population density. LU1, particularly for severe van crashes, stands out with the largest margins. Second, we examine the effect of FIS density (right). They have a pattern very similar to the margins plot for all crash models. Margins plot of LU1 and LU4 (largest) stands out. For all other land use categories and vehicle types, the correlation between FIS densities and severe crashes is not significant.

We document very similar margins plot patterns between all crash and severe crash models, particularly for land use categories 2, 3, and 4. It is reasonable because severe crashes are a subset of all vehicle crashes. With the margins plot exercise for all and severe crash models, we have two noteworthy observations: First, the factor that leads to more freight vehicle crashes might not simply be the volume of freight vehicles but the conflict among different types of vehicles with different trip purposes. This result is partly similar to the finding in Dong et al., (2015) in that truck percentages have a higher correlation with crash severity than the size of freight traffic volume. Second, the location with a higher probability of freight vehicle crashes might not simply be high FIS-density zones (e.g., LU1) but the locations where LU1 (high service/FIS density) and LU4 (high residential and service-oriented employment density) hexagons are adjoining. We support these claims with statistical and spatial analysis in the following section (see Section 6.1).

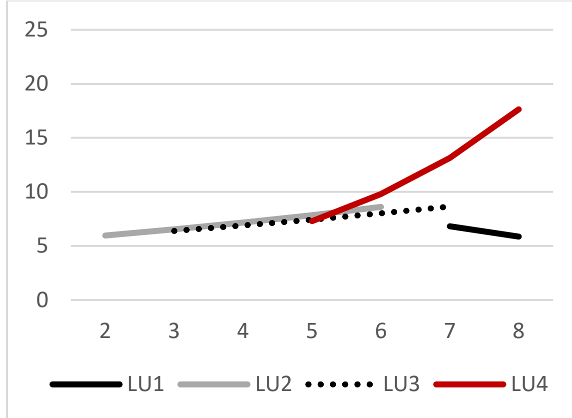
Table 18 Cross-section model results (severe crashes)

Model	**Number of severe crashes**					
Dependent variables	Model 2-1 All vehicles		Model 2-2 Vans		Model 2-3 Trucks	
Independent variables	Coef	Sig	Coef	Sig	Coef	Sig
Vehicle movement variables						
All vehicle VMT per link mile (log)	0.229	**				
Freight VMT per link mile (log)			0.171	**	0.210	**
Freight demand-side variables						
LU1 - low pop/high FIS emp	8.065	**	13.230	**	3.355	
LU2 - low pop/low emp (base)	-		-		-	
LU3 - mid pop/mid emp	0.218		-1.153		3.981	+
LU4 - high pop/high serv. emp	1.989	*	3.620	*	4.860	*
Population density (log)	1.032	**	1.098	**	1.084	**
Pop den * LU1	-0.831	**	-0.902	**	-0.855	**
Pop den * LU2 (base)	-		-		-	
Pop den * LU3	-0.023		0.209		-0.633	*
Pop den * LU4	-0.376	**	-0.470	**	-0.957	**
FIS employment density (log)	0.092	+	0.247	*	-0.021	
FIS den * LU1	-0.243		-0.879		0.606	
FIS den * LU2 (base)	-		-		-	
FIS den * LU3	-0.016		-0.129		0.212	
FIS den * LU4	0.202	**	0.044		0.487	*
Median HH income ($10k)	-0.079	**	-0.055	**	-0.140	**
Relative diversity index	-0.008		0.098		0.245	+
Freight supply-side variables						
Miles to airport (log)	-0.103	*	-0.036		0.005	
Miles to intermodal (log)	-0.144	**	-0.131	*	-0.029	
Miles to highway (log)	-0.023		0.046	+	0.002	
Constant	-7.515	**	-10.726	**	-10.261	**
Log Alpha	-0.620	**	-0.588	**	-0.440	*
Log Likelihood	-5,870.8		-2,038.5		-1,419.9	
Pseudo R squared	0.148		0.166		0.126	
N	2,157		2,157		2,157	

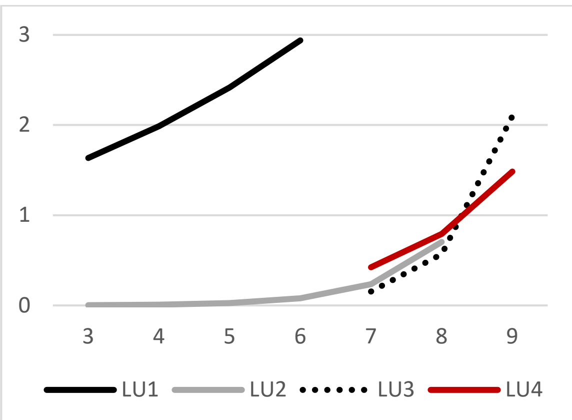
Note: +P < 0.10, *P < 0.05, **P < 0.01



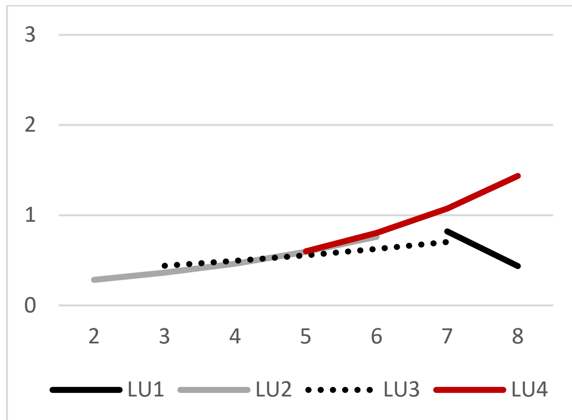
Margins plot – population density
Model 2-1 All vehicle severe crashes



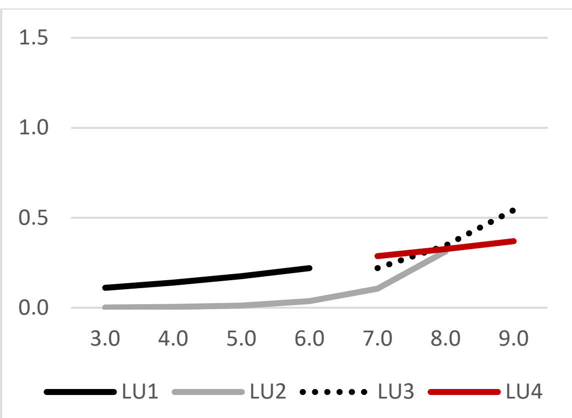
Margins plot – freight sector density
Model 2-1 All vehicle severe crashes



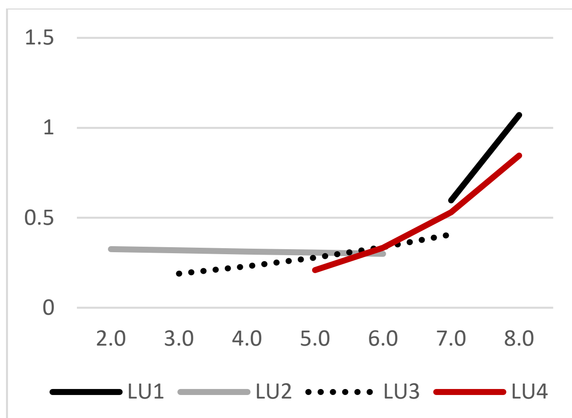
Margins plot – population density
Model 2-2 Severe van crashes



Margins plot – freight sector density
Model 2-2 Severe van crashes



Margins plot – population density
Model 2-3 Severe truck crashes



Margins plot – freight sector density
Model 2-3 Severe truck crashes

Figure 17 Margins plot of severe crash models

5.2.2 2010-2016 Time-Series Models

Now we examine a time-series model that tests whether the changes in the count of vehicle crashes from 2010 to 2016 have an association with the changes in development patterns, in terms of transport supply and demand proxies, controlling for traffic movement levels. Total employment density is omitted due to a high correlation with FIS employment density. We use the 2,157 hexagons covered by the NCTCOG Regional Travel Model. In the previous section, we documented distinctive crash patterns in and out of the hexagons with intensive development changes (population and FIS employment). Thus, we incorporate the hexagons as interaction terms with population and FIS employment densities. Six models are estimated for three vehicle types (all vehicles, vans, and trucks) and two crash types (all crashes and severe crashes). See Table 16 for summary statistics.

Note that population statistics are available only for two periods: 2010 Census and 2012-2016 ACS. Therefore, ours is a two-period time-series model (2,157 observations * 2 periods). For estimation, we use a fixed effects (FE) panel model. The fixed effects eliminate the correlation between the error term and time-invariant explanatory variables across entity (hexagon). The fixed effects model omits all time-invariant variables, including VMT per mile, miles to the airport, intermodal terminals, and highway ramps and examines the net effect of time-variant variables on the crash patterns. Hausman tests for all six models verify the use of fixed effects rather than random effects (Greene, 2008, chapter 9). Also, Wald tests for all six models, except for the severe van crash model, verifying the use of time fixed effects (in years). We use 2010 as a base category. The final model is depicted in Equation 4. A hexagon notation is omitted.

$$N_{crash,t} = \beta_0 + \beta_1 * Pop_t + \beta_2 * Pop_t * IDZ + \beta_3 * FIS_t + \beta_4 * FIS_t * IDZ + \beta_5 * Inc_t + \beta_6 * RDI_t + \beta_7 * Year + a + \varepsilon_t$$

Equation (4)

Where,

$N_{crash,t}$ is numberthe of crashes in time t;
β_n is coefficients to be estimated (n=0, 1, …, 7);
Pop is population density, included in a log form;
IDZ is intensive development zones (upper 90th percentile changes in population or FIS employment);
FIS is freight intensive sector employment density in LEHD 2015, included in log;
Inc is median household income, included in \$10k;
RDI is a relative diversity index (see section 4.2);
Year is time fixed effects;
a is entity fixed effects;
ε is an error term.

We provide all crash model results in Table 19 and severe crash model results in Table 20. Overall, model goodness-of-fit statistics show a significant level of explanatory power, particularly for all vehicle models. Adjusted R^2 statistics of all vehicle models (Model 3-1 and Model 4-1) are over 0.88 with significant F-statistics for both time-variant explanatory variables and entity fixed effects. All crash models for vans and trucks (Model 3-2 and 3-3) show statistically significant F-statistics. A large portion of the significance is due to entity fixed effects. Namely, the changes in time variant variables explain a small portion of the changes in freight vehicle crashes. Full model F-statistics of severe crash models for vans and trucks (Model 4-2 and 4-3) are not statistically significant. F-statistics of entity fixed effects are significant. Time fixed effects (year dummy), all but Model 4-2, are significant. T-tests for all six dependent variables (three vehicle types and two crash types) confirm the same pattern at $P<0.05$: average number of crashes per hexagon in 2016 is statistically significantly greater than that in 2010, except for severe van crashes (Model 4-2).

All vehicle model results are as expected. In Model 3-1, a one hundred percent increase in population and FIS employment over time leads to 7.6 and 3.7 unit decreases in all vehicle crashes, respectively for the hexagons outside of the intensive development zones (IDZs). In the IDZs, a one hundred percent increase in population leads to a substantial increase (26.8 units) in all vehicle crashes. The effect of FIS was not significantly different either inside or outside of the IDZs. A unit change ($10,000) in median income leads to approximately one unit decrease in all vehicle crashes. Change in RDI is not significant. Results for Model 4-1 are almost similar to those for Model 3-1, yet at the smaller magnitude. Results for van and truck models (Model 3-2, 3-3, 4-2, 4-3) are not as expected. Except for a few cases, controlling for all other factors, changes in population and FIS densities did not lead to statistically significant changes in freight vehicle crashes. Rather, significant year dummy coefficients (time fixed effects) and large F-statistics of entity fixed effects imply that key explanatory variables may have been missing. We also suspect that our dependent variables do not provide a sufficient variation over time at the hexagon level. We provide detailed explanations in Section 6.2.

Table 19 Time-series model results (all crashes)

Model	**Changes in all crashes**					
Dependent variables	Model 3-1 All vehicles		Model 3-2 Vans		Model 3-3 Trucks	
Independent variables	Coef.	Sig	Coef.	Sig	Coef.	Sig
Year dummy, 2016 (base: 2010)	9.455	**	0.385	**	0.265	**
Population density (log)	-7.628	*	-0.530		0.312	
Pop den * IDZ	34.463	**	0.330		0.270	
Freight sector density (log)	-3.675	**	-0.060		-0.144	
FIS den * IDZ	1.728		0.036		0.439	**
Median HH income ($10k)	-0.929	*	-0.110	*	0.029	
Relative diversity index	-0.136		0.101		0.071	
Constant	68.707	**	6.192	+	-1.339	
Full model F statistics: (7, 2150)	95.23		5.93		9.77	
Prob. > F	0.000		0.000		0.000	
Fixed effects F statistics (2156, 2150)	10.54		5.39		3.18	
Prob. > F	0.000		0.000		0.000	
Adjusted R^2	0.882		0.762		0.614	
N	4,314		4,314		4,314	

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

Table 20 Time-series model results (severe crashes)

Model	**Changes in severe crashes**					
Dependent variables	Model 4-1 All vehicles		Model 4-2 Vans		Model 4-3 Trucks	
Independent variables	Coef.	Sig	Coef.	Sig	Coef.	Sig
Year dummy, 2016 (base: 2010)	2.572	**	0.055		0.049	*
Population density (log)	-2.116		-0.145		-0.308	+
Pop den * High pop change zones	8.345	**	-0.229		0.121	
Freight sector density (log)	-0.756	**	0.027		0.041	
FIS den * High FIS change zones	0.419		-0.071		0.044	
Median HH income ($10k)	-0.338	*	-0.005		0.010	
Relative diversity index	0.048		-0.086		0.064	
Constant	21.024	*	1.979		2.100	+
Full model F statistics: (7, 2150)	51.33		0.65		1.44	
Prob. > F	0.000		0.711		0.186	
Fixed effects F statistics (2156, 2150)	11.28		2.74		1.62	
Prob. > F	0.000		0.000		0.000	
Adjusted R^2	0.887		0.565		0.334	
N	4,314		4,314		4,314	

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

6 Conclusions and Discussion

We examined the spatial distribution of vehicle crashes that involved at least one freight vehicle in the Dallas-Fort Worth metropolitan area. We also examined the changes in the spatial distribution of vehicle crashes from 2010 to 2016. We used the Texas Department of Transportation Crash Records Information System (CRIS), as the main data source for vehicle crash records from 2010 to 2016. We examined vehicle crashes in two severity classes (all vehicle crashes and the crashes that resulted in a fatality or injury) and three vehicle types (all vehicles, vans, and trucks). We used the vehicle body style information to define "truck" as truck, trailer, semi-trailer, pole trailer, and truck tractor and "van" as a van. We included all the crashes that occurred on city streets and excluded those on highways.

First, we examined the trends in vehicle crashes at the metropolitan level. From 2010 to 2016, all highway crashes increased 100.2%, whereas all city street crashes increased by 45.6%. Van crashes on city streets increased by 17.3%, and truck crashes increased by 29.6%. The extents for severe crashes were much smaller: 7.3% and 5.2% increases, respectively. Next, we examined the 2016 statistics and trends from 2010 to 2016. The unit of analysis is a one-square-mile hexagon, and we included 2,262 of them in urban areas, as the study area. Using population and two-digit NAICS industry sector employment counts, we identified four land use (LU) categories as well as the intensive development zones (IDZ). The characteristics of the four land use categories are as follows: land use 1 has low population and high service and freight intensive sector (FIS) employment densities, land use 2 has low population and employment densities, land use 3 has high population and relatively low employment densities, and land use 4 has high population and service-oriented employment densities. In IDZs, population and FIS employment increased the most from 2010 to 2016 (upper 90th percentile hexagons, N=226). We used the four land use categories to examine the potential association between development patterns and vehicle crash patterns. Overall, in 2016, crash patterns varied significantly and had a reasonable correlation with the land use categories: substantially more vehicle crashes in denser locations. Exceptions are the cases for land use 1 (more truck crashes, potentially derived from its high FIS activity). Severe crashes showed similar patterns. We used the LUs and IDZs to examine the potential association between changes in development patterns and changes in vehicle crash patterns. From 2010 to 2016, land use 1 experienced the largest increase in percent changes across three vehicle types regardless of crash severity. Different patterns arose across vehicle types. In terms of the percent change, all vehicle crashes increased similarly regardless of in and out of IDZs, whereas truck crashes increased significantly in IDZs. The patterns for van crashes were mixed.

Second, we examined the vehicle crash patterns using cross-section and time-series models. We used the freight landscape framework to explain the distribution of vehicle crashes with the proxies of freight supply and demand, controlling for vehicle movement. As proxies for transport supply, we used Euclidean miles to the nearest transport infrastructure, which includes cargo service airports, rail-to-truck intermodal terminals, and highway ramps. As proxies for transport demand, we used population and freight-intensive sector (FIS) employment densities, median household income, and a relative diversity index (RDI). LUs and IDZs are included in regression models as interaction terms in combination with population and FIS densities. As a proxy for vehicle movement, we used vehicle miles traveled per network mile, which are simulated and rectified estimates from the 2013 NCTCOG Regional Travel Model. For cross-section analysis, we used negative binomial model, and for time-series analysis, we use fixed effects panel model.

Cross-section models have a reasonable explanatory power. Vehicle movement variables are significantly and positively correlated with crash counts, consistently throughout the six models. Population and FIS densities have positive yet disparate sizes of effect when land use interaction terms are introduced. The elasticity between population density and vehicle crashes in LU3 is the largest. The elasticity between FIS density and vehicle crashes in LU4 is the second largest. We documented two interesting patterns. First, estimated numbers of crashes in LU3, in terms of population densities, controlling for all other factors, are greater than those in LU4, in which population densities are much higher than they are in LU3. Second, freight activity alone may not sufficiently increase the likelihood of vehicle crashes. Rather, it may be the conflict among residence, service, and FIS-oriented passenger and freight traffic. Median household income has a significant and negative correlation, whereas RDI shows mixed results. Access to intermodal terminals and highway ramps is significant. Severe crash models have a similar pattern, in general. It is reasonable because severe crashes are a subset of all vehicle crashes.

Time-series models have a significant level of explanatory power, particularly for all vehicle models. For freight vehicle models, a large magnitude of the explanatory power was derived from entity fixed effects. For all vehicle model, one percent increase in population and FIS employment over time is associated with 7.6 and 3.7 unit decreases in all vehicle crashes, respectively, outside of the IDZs. In the IDZs, one percent increase in population leads to a substantial increase (26.8 units) in all vehicle crashes. Generally, an increase in median household income is associated with a decrease in vehicle crashes. Time-series model results imply that key explanatory variables may be missing, and dependent variables may not provide a sufficient variation at the hexagon level.

6.1 Supporting Evidence for the Conflict Hypothesis

To support the conflict hypothesis, we compare the spatial distribution of freight vehicle crashes with (1) the hot spots of freight vehicle activity and (2) the locations with a potential conflict between service sector and FIS-oriented vehicle activities. In Figure 18, we present four maps: (upper left) the distribution of upper 90th percentile hexagons of service sector and FIS employment; (upper right) hot spot hexagons of freight VMT per network mile; (bottom left) hot spot hexagons of van crashes in 2016; and (bottom right) hot spot hexagons of truck crashes in 2016. As the service sector, we included all industry sectors in NAICS 51 information, 52 finance, 53 real estate, 54 professional, 55 management, 56 administrative, 61 educational, 62 health care, 71 arts, 72 accommodation, 81 other services, and 92 public administration. As the FIS, we included all industry sectors in NAICS 31-33 manufacturing, 42 wholesale trade, 44-45 retail trade, and 48-49 transportation and warehousing.

We used Getis-Ord Gi* Hot Spot Analysis to capture hot spots of activity. To be specific, the Hot Spot Analysis compares the local average of an activity to the global average that includes all hexagons. It produces Getis Ord Gi* statistics (z-scores and P-values). Gi* statistics represent the extent to which the local average is statistically significantly different from the global average. The Gi* statistics are calculated for every hexagon in the study (N=2,262). We defined the local hexagons as those within second-order queen contiguity at the author's discretion. For the Hot Spot Analysis, we used Esri ArcGIS desktop 10.4.

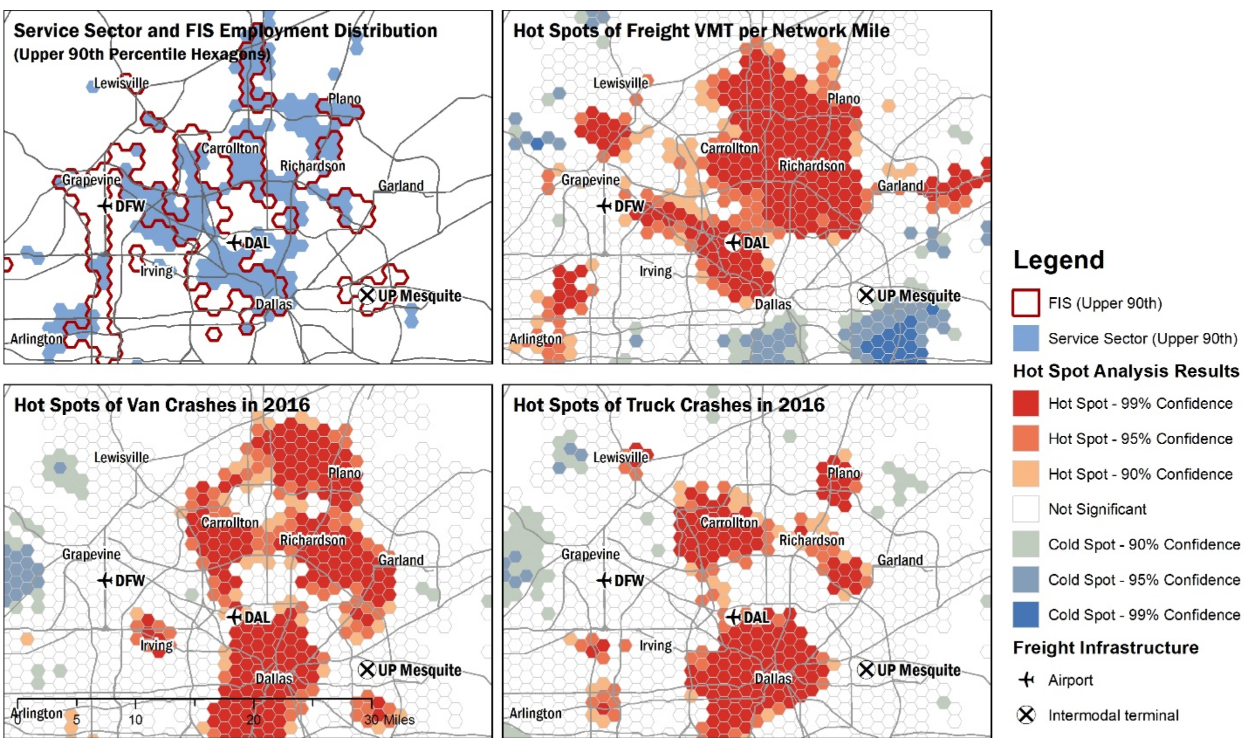


Figure 18 Comparison among the industry sector composition, VMT per network mile, and freight vehicle crashes

Illustrated in the upper left panel of Figure 18 is a map showing the distribution of the upper 90th percentile hexagons of the service sector and FIS employment. In the upper 90th percentile hexagons, 61% of service sector employment of the total 1.63 million and

47% of FIS employment of the total 0.90 million exist in 2015. The two groups of industry sectors share a considerable extent of the area in the eastern part of the region (east of the DFW International Airport). All upper 90th percentile hexagons are located along major highways. Shown on the upper right of Figure 18 is a map with hot spots of freight VMT per mile. The hot spots correspond solidly with the upper 90th percentile hexagons. We do not have information for traffic counts by vehicle type or trip purpose. However, we can assume that in these areas, the conflict is more likely among traffic with various trip purposes and vehicle types. Thus, more freight vehicle crashes are expected in the locations. The two maps in the bottom half of Figure 18 show the hot spots of van and truck crashes in 2016. Not all but the majority of the hot spots correspond to locations with potentially high vehicle conflicts. Thus, we presume with indirect evidence that conflict might lead to more freight vehicle crashes. Other factors, including personal, vehicular, behavioral, and road design aspects, may explain the freight crash patterns or their probability more in a direct manner. Lastly, the hot spots of freight vehicle crashes correspond very well to the municipality boundaries of Dallas, Carrollton, Richardson, Garland, Plano, and Fort Worth (not represented on the map). If borne out by future study, this calls for city-level measures to reduce vehicle crashes. All of these factors merit further research.

6.2 Explanations for the Lack of Explanatory Power of Time-Series Models

We provide two potential explanations for the lack of explanatory power of the time-series models for freight vehicle crashes. First, the variation across hexagons in term of the changes in freight vehicle crashes from 2010 to 2016 is small. Again, our dependent variables are counts of traffic failure events. They are not normally distributed, but with many zero observations, they rather fit the negative binomial distribution (Poisson-gamma mixture distribution). As presented in Table 3, van and truck crash increased by 17% and 30%, respectively. However, a large portion of the changes is concentrated in a small number of hexagons. Hence, except for the small number, the variation across hexagons in the number of freight vehicle crashes becomes very small (e.g., many observations that have zero crash record). In Figure 19, we present the frequency distribution of dependent variables. Approximately 43% and 50% of hexagons have zero observations in 2016 for van and truck crashes, respectively, and only 10% and 5% of hexagons have more than five van and truck crashes. On the contrary, only 9% of hexagons have zero observations for all vehicle crashes, and more than 70% of hexagons have more than five all vehicle crashes. For cross-section analysis, count data models (negative binomial) account for this “over-dispersion” with the Poisson-gamma mixture distribution assumption. However, the distribution is not assumed in time-series analysis. Moreover, the concentration of vehicle crashes in a small number of hexagons leads to the lack of variation in time-series dependent variables. In Figure 20, the frequency distribution of dependent variables shows a substantial difference between all vehicle and truck time-series models. Note that the X-axis scales are drastically different between the two. To alleviate this issue, we tried to use two-year worth crash records for both before (2010 and 2011) and after (2015 and 2016), but results did not change significantly.

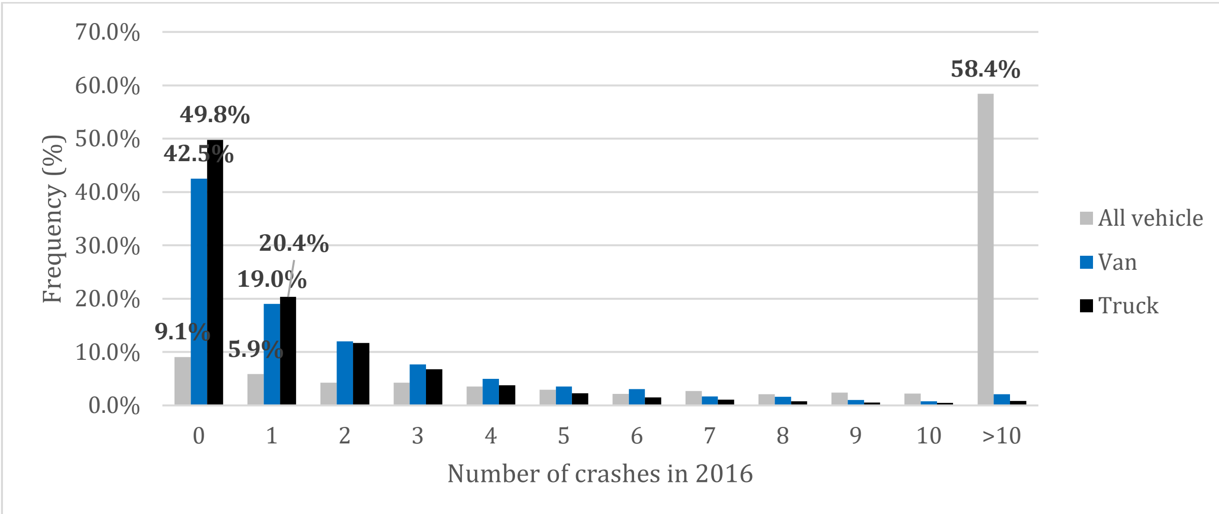


Figure 19 Frequency distribution of dependent variables for 2016 cross-section models

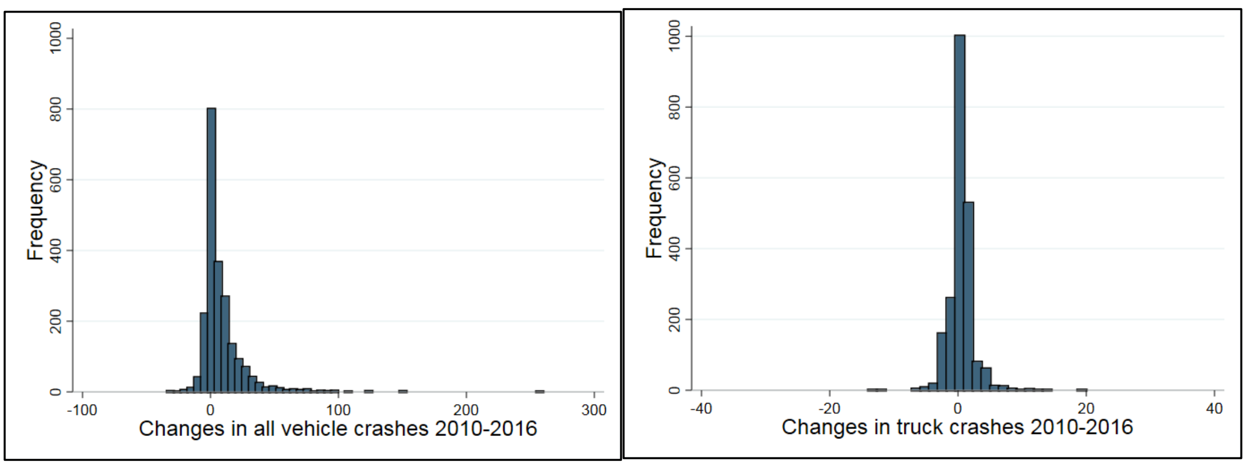


Figure 20 Frequency distribution of dependent variables for all vehicle and truck time series models

Second, longer-term time-series models are necessary. It is to have sufficient variations in terms of vehicle crash patterns, as well as more fundamentally, logistics and transportation business operations and people's consumption behavior on online platforms. We have already acquired crash records from 2003 to 2009. However, due to the inconsistency with respect to the definition of vehicle body styles, crash records of the previous periods cannot be used. TxDOT updated the definition, including many others, in 2010 and has purged the previous records from their CRIS database. Due to these limitations, we rely on statistical analysis results that have a broader category of land uses (upper 90th percentile hexagons with intensive land use changes) than the time series models (a hexagon).

This research also has other shortcomings. First, this research is subject to the ecological fallacy. This research uses a unit of analysis – a one square mile hexagon – that is equivalent to the size of an average urban census tract in the region and examines all vehicle crashes inside a hexagon using homogenous explanatory variables. Future studies should consider using various crash-level analysis frameworks. For example, discrete choice models having discrete outcomes (e.g., levels of crash severity) may be appropriate for examining the factors that explain the probability of a crash leading to various levels of severity. In that case, one must be able to examine vehicle speed, one of the critical factors for fatal/severe crashes yet excluded in this research. Second, this research is subject to spatial autocorrelation. Traffic flows of neighboring hexagons are more likely to be similar and affected by each other, so are vehicle crashes. Negative binomial and fixed effects panel models do not account for the spatial autocorrelation. Third, actual trip purpose and vehicle composition data may be necessary to support the conflict hypothesis with concrete evidence. No such information is available. Hence, we used the modeled and rectified estimates of freight vehicle volumes from the regional travel model. Further research is necessary to verify the conflict hypothesis.

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