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QUANTIFYING THE IMPACT OF TRANSPORTATION NETWORK COMPANIES (TNCs) ON TRAFFIC CONGESTION IN SAN FRANCISCO

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QUANTIFYING THE IMPACT OF TRANSPORTATION NETWORK COMPANIES (TNCs) ON TRAFFIC CONGESTION IN SAN FRANCISCO

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Engineering at the University of Kentucky

By

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ABSTRACT OF DISSERTATION

QUANTIFYING THE IMPACT OF TRANSPORTATION NETWORK COMPANIES (TNCs) ON TRAFFIC CONGESTION IN SAN FRANCISCO

This research investigates whether Transportation Network Companies (TNCs), such as Uber and Lyft, live up to their stated vision of reducing congestion by complementing transit and reducing car ownership in major cities. The objective of this research study is to answer the question: are TNCs are correlated to traffic congestion in the city of San Francisco? If found to be so, do they increase or decrease traffic congestion for the case of San Francisco? If and how TNC pickups and drop-offs impact traffic congestion within San Francisco? And finally, how does the magnitude of this measured command of TNCs on congestion compare to that caused by pre-existing conventional drivers of traffic and congestion change? Apart from answering these questions, it is also sought to establish a framework to be able to include TNCs, a seemingly fledgling mode of transportation but one that is demonstrably shaping and modifying extant transportation and mode choice trends, as part of the travel demand models estimated by any geographic jurisdiction.

Traffic congestion has worsened noticeably in San Francisco and other major cities over the past few years. Part of this change could reasonably be explained by strong economic growth or other standard factors such as road and transit network changes. The sharp increase in travel times and congestion also corresponds to the emergence of TNCs, raising the question of whether the two trends may be related. Existing research has produced conflicting results and been hampered by a lack of data.

Using data scraped from the Application Programming Interfaces (APIs) of two TNCs, combined with observed travel time data, this research finds that contrary to their vision, TNCs are the biggest contributor to growing traffic congestion in San Francisco. Between 2010 and 2016, weekday vehicle hours of delay increased by 62%, compared to 22% in a counterfactual 2016 scenario without TNCs. The findings provide insight into expected changes in major cities as TNCs continue to grow, informing decisions about how to integrate TNCs into the existing transportation system.

This research also decomposes the contributors to increased congestion in San Francisco between 2010 and 2016, considering contributions from five incremental effects: road and transit network changes, population growth, employment growth, TNC volumes, and the effect of TNC pick-ups and Drop-offs. It is so done through a series of controlled travel demand model runs, supplemented with observed TNC data. The results show that road and transit network changes over this period have only a small effect on congestion, population and employment growth are important contributors, and that TNCs are the biggest contributor to growing congestion over this period, contributing about half of the increase in vehicle hours of delay, and adding to worsening travel time reliability. This research contradicts several studies that suggest TNCs may reduce congestion and adds evidence in support of a recent empirical analysis showing that their net effect is to increase congestion. This research gives transportation planners a better understanding of the causes of growing congestion, allowing them to more effectively craft strategies to mitigate or adapt to it.

KEYWORDS: Traffic congestion, Causes of congestion, Transportation Network Companies (TNCs), Ride-hail, Uber, Lyft

Sneha Roy

March 27, 2019

QUANTIFYING THE IMPACT OF TRANSPORTATION NETWORK COMPANIES (TNCs) ON TRAFFIC CONGESTION IN SAN FRANCISCO

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I dedicate this work to my family, my advisors and my mentors

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CHAPTER 1. INTRODUCTION

1.1 Introduction

The purpose of this study is to quantify the impact on congestion created by the emergence of Transportation Network Companies (TNCs) in the city of San Francisco. The primary services provided by companies like Uber around the globe, Lyft in the United States, Cabify in South America, Ola in India, or Didi in China is described as ride-hailing, ridesourcing, or TNCs. They are app-based services providing mobility and rides as a service (MaaS) where rides are arranged through a mobile app to connect the passenger with a driver, often a private individual driving their personal vehicle (TRB Special Report 319, 2016). TNCs are one of a number of fledgling forms of shared mobility and one form of MaaS. The current system is commonly viewed as a bridge technology that may be replaced by fleets of self-driving cars if and when that technology is ready (Zmud and Sener 2017; Fagnant and Kockelman 2018).

Transportation Network Companies (TNCs) have grown rapidly in recent years (Iqbal 2019). In 2016, TNCs were 15% of all intra-San Francisco vehicle trips, which is 12 times the number of taxi trips, while in New York in 2016 (TNCs Today 2017, SFCTA), TNC ridership equaled that of yellow cab and doubled annually between 2014 and 2016 (Shaller 2017). Presently, TNCs are not a fringe mode of transportation any more, and given their substantial presence on our road networks, it is vital to assess their impact on important traffic performance metrics. This research also proposes a method to do this, the data set that would be required to complete such an analysis and points out various factors that should be studied to reach at a conclusive statement to carry out a study at a scale that it has been carried out on in this study.

With this growth, the question of their effect on the broader transportation system becomes important. The Uber mission statement at one point included a claim that they are tackling the problem of “reducing congestion in major cities by getting more people into fewer cars” (Uber n.d.), while the founder of Lyft claims inspiration from a college urban planning class and presents a vision of reduced dependence on cars with road space dedicated to other uses (Zimmer 2016). Supporters of this vision group TNCs with other shared mobility and argue that “Shared modes largely complement public transit, enhancing urban mobility” (Feigon and Murphy 2016) and “TNC use is associated with decreases in respondents’ vehicle ownership and single-occupancy vehicle trips” (Feigon and Murphy 2018). It is true that by wielding their potential to incentivize pooled rides, TNCs can inherently increase capacity of the existing roadway network. TNCs can make carpooling and ridesharing more accessible to the masses as compared to when users had to schedule rides themselves and potentially, only with commuters they personally knew. While this is true, it is imperative to seek if in their current state of operation provides any quantifiable evidence to this being the case.

Do TNCs really live up to this stated vision? The remainder of Chapter 1 illustrates that there have been a limited number of existing studies on the topic, and the results of those studies have been mixed. The major challenge is that existing research has been hampered by a lack of data (Cooper et al. 2018). While we live in the era of Big Data, those data are not necessarily available for research purposes. Specifically, the TNCs have a wealth of data, including details of the trips made, driver movements, and potentially location data of customers purely from the TNC apps running in the background of user's smartphones. Requests to a major TNC to access a privacy-protected and aggregate version of these data for this research were denied. Instead, this research relies on a data set scraped from the Application Programming Interfaces (APIs) of the two largest TNCs. This data set was collected by researchers at Northeastern University in partnership with the San Francisco County Transportation Authority (SFCTA) (Jiang et al. 2018; Cooper et al. 2018) and made available for this research. It provides a snapshot of TNC use in San Francisco for a 6 week period in Fall 2016, and is a unique opportunity to quantify the use of TNCs and their effect. The data and their processing are described in further detail in Chapter 2.

A parallel set of research is examining the effect of TNCs on transit ridership (Mucci 2017; Graehler, Mucci, and Erhardt 2019). This research is concerned with the effect of TNCs on traffic congestion. Specifically, it aims to answer the question: Do TNCs increase or decrease traffic congestion in San Francisco and by how much?

1.2 Literature Review: The Effect of TNCs on Congestion

Clewlow and Henao (2019), in a recent report, presented a framework (**Figure 1**) that makes it possible to understand the effect of the presence of TNCs on congestion. This framework proposes multiple steps and asks several questions, answers to which would ideally address the probable correlation between TNCs and congestion (and other indicators of network performance like Vehicle Miles Traveled).

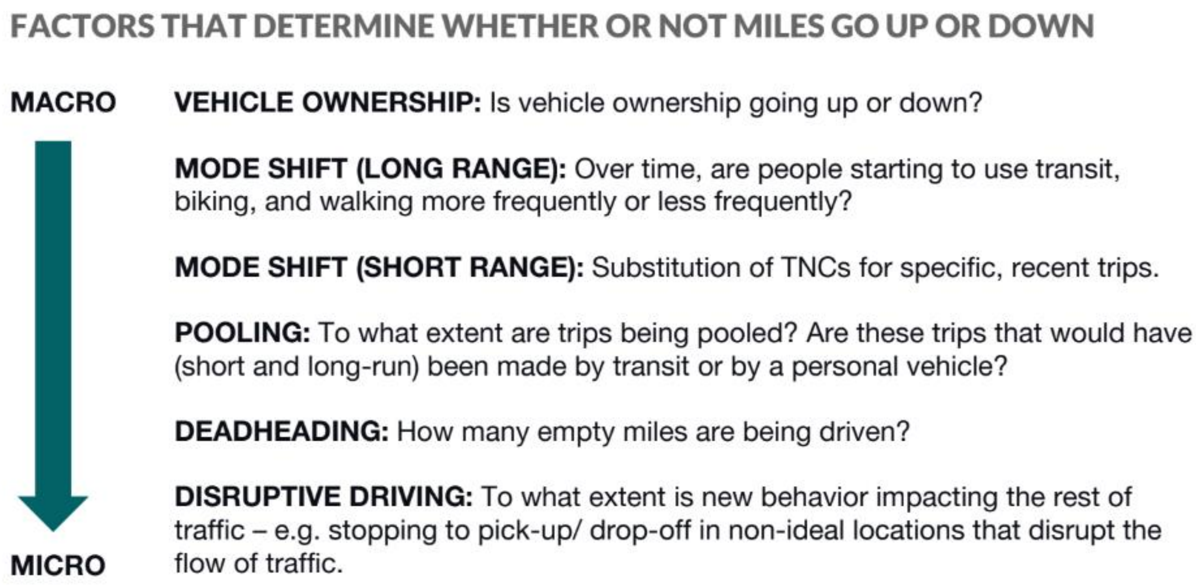


Figure 1 Defining a framework to attain answer to the question: Does TNC use increase or decrease VMT?
Source: Clewlow and Henao 2019, TRB 2019 workshop presentation

The referred framework, however, is devoid of spatial and temporal differences across the network within any proposed study area. These left-out spatial and temporal trends are critical in the discussion about whether TNCs affect traffic congestion and travel time since TNCs, as a factor, are not independent of any interaction between them and the pre-existing drivers of congestion. Instead, they are an *additional* potential source of congestion. Their contribution to congestion occurs in combination with the conventional drivers of congestion and this combined output, i.e., the present-day traffic congestion, can only be precisely quantified when tracked through staggered points in time and space. As controlled experiment within the same temporal snapshot has not been possible in several past, recent and concurrent studies, this study has drawn comparisons between congestion data sourced from the same study area across two snapshots of time.

1.2.1 Vehicle Ownership

Some have speculated that by providing a convenient alternative to owning a car, TNCs could incentivize people to own fewer cars, and by extension induce them to shift other trips to transit or non-motorized modes, potentially reducing their total vehicle travel (Feigon and Murphy 2016; Feigon and Murphy 2018). TNCs do have the potential to reduce the existing reliance on private cars in the longer scheme of things. The TNCs themselves present a vision of the future in which they reduce traffic congestion and allow roads to be repurposed to other uses (Uber Newsroom 2017; Zimmer 2016). Clewlow and Mishra (2017) found that while ride-hailing transit users have lower vehicle ownership rates than non ridehailing transit users by about 6%-11%, about 91% of TNC users have not made any changes with respect to vehicle ownership. While at present it might be too soon to predict the long-reaching effect on vehicle ownership as a result of TNC use at this time since the average lifetime of a private vehicle in the United States is about 15 years (Weisbaum 2006), they also found no difference among non-transit users in vehicle ownership rates between ridehailing users and non-ridehailing users. This potentially indicates that usage of transit might be a more telling feature that differentiates vehicle owners from non-owners for the long term as compared to TNC usage.

1.2.2 Mode Shift (Long Range)

Existing studies have produced a spectrum of assessments about the impact of TNCs on long term modal shifts. Studies published by the Shared Use Mobility Center (SUMC) and Hall et al. (2018) demonstrate how increasing use of TNCs can result in increasing patronage for public transit. TNCs have the potential to 'fill in the gaps' of transit, making transit more lucrative and accessible for people, especially at non-peak service hours. The SUMC report argued that shared mobility services have great untapped potential to serve as bridges between trip beginning points to historically established transit pick up points. Hall (2018) in his paper described the effect of Uber penetration on the ridership of fixed-route, fixed-service transit facilities using a difference in difference calculation framework and found that greater Uber penetration complemented transit, and promoted off-peak travel since people now have greater assurance of reaching home post alighting from transit (especially smaller transit agencies) run vehicles. Clewlow and Mishra (2017) found that TNC usage could be attributed to bring about a 3% rise in transit usage due to improved accessibility. The same study also found that the substitutive versus complementary nature of ride-hailing varies greatly based on the type of transit service in question, a notion measured and confirmed by a dedicated transit ridership study by Mucci et al. (2018).

However, the long-term effect of TNCs on transit ridership is an ambiguous subject as established by the conclusions of a number of different studies. Theoretically, TNCs are also likely to siphon off otherwise loyal transit patrons by offering a more personalized travel experience for the individual traveler. If this possibility of TNCs acting as competitors to transit rather than serving as their complement becomes reality, they can potentially choke the network by increasing in-use Passenger Car Equivalents manifold. Some existing studies have remarked upon this substitution versus addition effect of TNCs. Henao (2018) found that about 22% of TNC trips within his sample database were defected from public transit modes. On the same track, a report on the TNC use patterns in the greater Boston region by Gehrke et al. (2018) found that this transit-to-TNC substitution rate is about 42%. This, admittedly, was higher than some other concurrent research studies. Clewlow and Mishra (2017) found this statistic to be about 15% in a nationwide study of disruptive transportation, whereas another recent MBTA customer satisfaction survey study by the Massachusetts Department of Transportation found the defection rate to be about 30%. In light of such conflicting long-range travel trends that TNC usage purportedly causes, it is imperative to study their effect in a greater, more quantifiable manner.

1.2.3 Mode Shift (Short Range)

Previous studies to interpret how TNCs affect the existing transportation environment have also included a comprehensive analysis of the methods such companies employ to incentivize and consequently, improve the operation of TNC cabs within the roadway network.

Whether a trip made by TNC adds traffic to the road also depends on which mode would have been used for the trip if TNC were not available. Between 43% and 61% of TNC trips substitute for transit, walk, or bike travel or would not have been made at all (Rayle, Dai, Chan, Cervero and Shaheen 2016; Clewlow and Mishra 2017; Henao 2017; Gehrke, Felix and Reardon 2018), adding traffic to the road that otherwise would not have been there. Henao (2018) found through surveying active TNC riders that about 10% of the riders in his sample would have otherwise biked or walked. This category of modal substitution represents induced demand for trips facilitated by the accessibility of TNCs, that is, these trips would otherwise not have been made by automobile modes. Clewlow and Mishra (2017) found the combined percentage of non-auto modal shift and induced additional trips to be between 49% to 61%. The report on Boston travelers by

Gehrke, Felix and Reardon (2018) found the non-auto modal shift to be about 12% whereas induced travel demand to be about 5%. Overall, it found the combined percent of additional trips as a substitution to transit, walk/bike and no-trip modes to be about 59%.

1.2.4 Pooling

A popular adage to the increasing popularity of TNCs is the shared or pooled ride feature. In operation, it is similar to carpooled trips except for the fact that TNCs provide for greater ease of use for riders wanting to carpool without being responsible for the scheduling themselves (the app does it for them). Pooled rides are a great way to increase vehicle occupancy, and to reduce VMT and deadheading. However, in its current state of operation, where pooled rides are only offered to densely populated and/or geographical locations of heavy TNC use, the actual share of pooled rides opted for would help quantify whether these benefits could be regarded eponymous with the rapid rise of TNC use. The study of Boston travelers by Gehrke, Felix and Reardon (2018) concluded that about 80% of all TNC trips were non-pooled. Similarly, Schaller (2019) reported that about 78% of all ride-hailing trips made within New York city were standard, unpooled trips. Keeping in mind the low adoption rates of pooled TNC rides in such densely populated urban areas currently, it is unlikely that the cornucopia of benefits associated with pooled trips can be attributed to the present day use of TNCs.

1.2.5 Deadheading

Deadheading, or out-of-service movement, is the movement of a vehicle with no passenger. TNCs and taxis deadhead to look for fares or reposition before or after a paid trip. Out-of-service travel is estimated at about 50% of TNC vehicle miles traveled

(VMT) in New York (Shaller 2017) and 20% in San Francisco (TNCs Today 2017, SFCTA).

A novel study by Henao (2018) asserted that for every 100 miles of TNC use that clocks with a passenger inside a car, drivers traveled an additional 69 miles in deadheading. This study was specifically designed to answer questions related to how TNCs affect Vehicle Miles Traveled (VMT), deadheading, land use problems like parking and ethno- demographic travel behavior. Two interconnected datasets, namely, “driver dataset” and “passenger dataset” were created. The former exclusively incorporated data that TNCs make publicly available, like travel times and distances, passenger cost, and driver earnings. The latter was obtained through creating a targeted experiment wherein the researcher drove as an Uber/Lyft driver to track the number of hours and miles spent traveling with and without passengers. Some other metrics obtained through this method were recording pickup and drop-off locations, time spent travelling between the location of accepting a ride and picking a passenger up, “cruising to park time”, etc. Randomness of passenger destinations helped to create a holistic purview for the research and so did shifting the time at which the researcher/driver chose to drive around. The starting location was varied as well to upkeep the randomness of the experimental data. The study found that the time efficiency rate for ride-sourcing was about 39% when accounting for the commuting time at the start and end of a shift (from the driver’s perspective), whereas the mileage efficiency rate was about 59%. This study also examined the shift in mode through designing a survey which was handed over to passengers riding the researcher’s Uber/Lyft wherein individual responses to counterfactual modes were inquired about. This information was categorized and disseminated based on date and time of rides, age, gender, travel distances, number of people carpooling if the alternative mode was carpool, relation to other modes of transportation, number of passengers and trip-mode replaced. Based on the responses, the study concluded that the increase in VMT attributable to use of ride-sourcing in Denver is about 85%. Also, with the advent of increased mobility that TNCs promise, an increase of 12% in total number of trips was estimated.

1.2.6 Disruptive Driving

TNC pick-ups and drop-offs (PUDO) contribute to congestion on urban streets by disrupting traffic flow in the curb lane, similar to the congestion effects found in areas that rely heavily on taxis (Golias and Karlaftis 2001). Simulation studies using taxi-to-passenger cars equivalence factors found that effects of taxi traffic in Athens were dependent on the number of lanes. Whether non-curb lanes sufficed to accommodate disrupted traffic from taxi pickups and drop-offs influenced the total number of seconds for which the regular flow of traffic was interrupted. Another significant problem with taxi traffic, which for the purpose of quantifying TNC pickups and drop-offs for this study, is analogous to TNC traffic, was found to be the location of the (PUDO) stops; that is, in the context of Athens, a city that relies heavily on taxis, the curbside stopping of taxis to drop-off-/pick-up passengers. It was surmised that by assuaging this problem, traffic speeds in the central business district could be increased by about 12% during morning peak hours. The central business district and the core areas of San Francisco, in recent years, has also been found to rely heavily on TNCs and curbside pickups and drop-offs of passengers. This has the potential to cause similar disruptions to the traffic flow.

1.2.7 Spatial Distribution

How TNCs are spread across the city is an important subject to examine. Areas of the city where they are the most popular among commuters and consequently, the most profitable to operate in would have a significant bearing on the total increment of travel time, vehicle delay and/or decline in speed that they are assessed to be contributing to in the network. Existing research has found that TNCs in urban centers such as those of San Francisco and New York City are the most concentrated in the downtown cores (Feigon & Murphy 2018, Shaller 2018, and TNCs Today SFCTA 2017).

Figure 2 Weekday Pickup Hotspots – TNCs Today Report 2017; The dense yellow links in the northeast quadrant of the city represent the substantially high number of pickup activities taking place here as compared to the rest of the city.

This valuation seems intuitively sensible, since TNCs could be assessed to be most popular among people looking to forgo daily commute through private passenger cars in areas charging high parking rates, vis-à-vis the traditional central business districts/downtown areas. In addition, one can understandably assume an inherent correlation between the demographic that could be supposed to be giving up private ownership of cars and those who are employed in or frequently visit the downtown core areas of such cities during peak hours. TNC volumes being the highest in such areas pose an operational problem: such areas are already highly congested to begin with. Even a small addition in the total traffic volumes in these areas would lead to a significant decline in the operational conditions of the network, leading to increased hours of delay, vehicular emissions and traffic gridlocks (explained later in Chapter 2). **Figure 2** shows a map referred from TNCs Today, a report published by the San Francisco County Transportation Authority in 2017, that demonstrates how TNCs are mostly concentrated in the core areas that are already prone to frequent network performance failures.

1.2.8 Temporal Distribution

When do TNC trips occur? Evaluating this question bears significant impact on checking if and how much TNCs Dr.aw from the share of conventional modes of transport including public transit as forms of daily commuter transport. Also, if TNC trips are made during peak hours, how much traffic volume does this new mode effectively add to the network? TNC trips are originally considered to be mostly made during off peak hours and weekends, for example, trips to restaurants, bars and entertainment centers in the evening period during weekdays and towards the evening shoulders during weekends. Recently collected TNC volume data by Feigon and Murphy (2018) for

Chicago, Washington DC, Los Angeles, Nashville and Seattle is shown in **Figure 3**. Total TNC pickup data for San Francisco is shown in **Figure 4**. While trends of TNC use vary across the various cities, it should also be noted that there exist certain fundamental differences between the distribution of modes, demographics, population densities and metropolitan/urban area setting across these cities. Densely populated cities like San Francisco, Chicago and Washington DC have lower levels of solo car commuting, fewer cars per household, and greater levels of transit ridership per capita. Nashville, with the least dense population, was observed to have the highest proportion of car commuters, and the lowest per capita transit ridership (Feigon and Murphy 2018). In Seattle's compact core, commute mode split and car ownership are like the three dense-core cities (Feigon and Murphy 2018). **Figure 5** displays a TNC volume graph featured in the TNCs Today report by the San Francisco County Transportation Authority (SFCTA) that tracks TNC presence by time of day during weekdays.

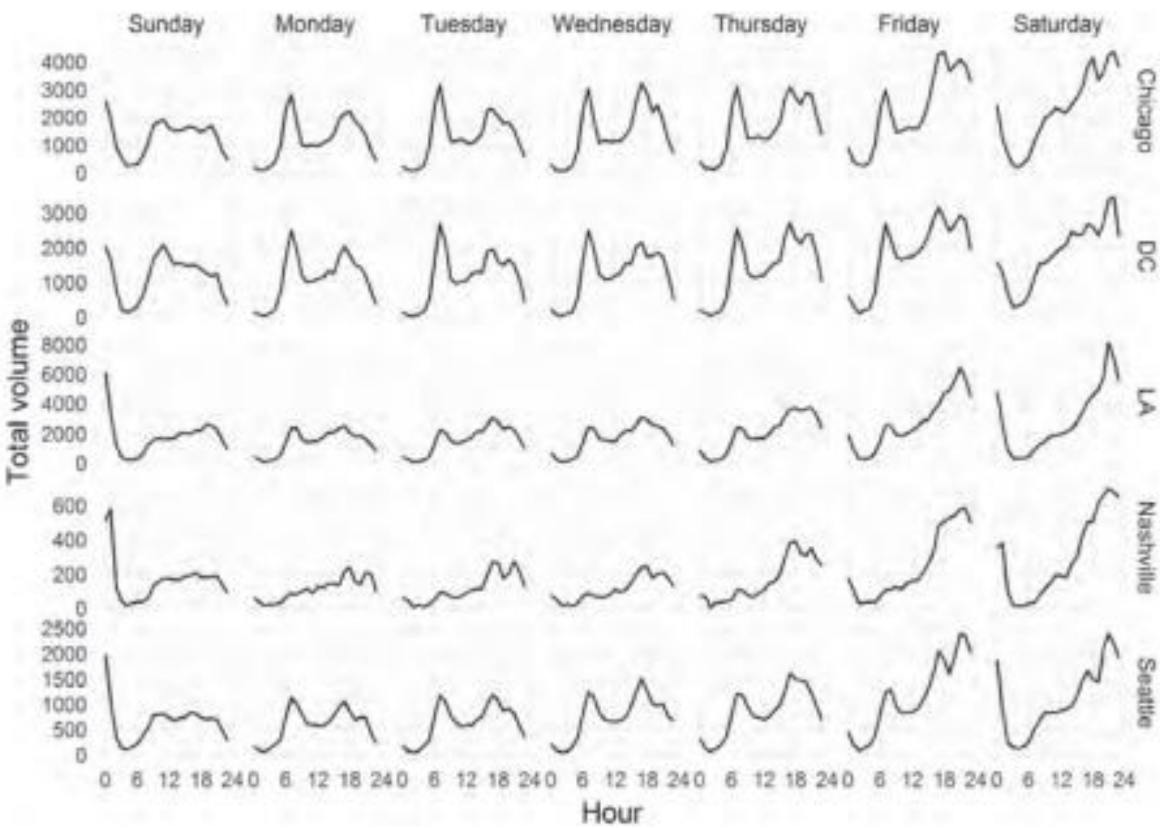


Figure 3 Total TNC trip volume by hour and day in the five study regions. Panels are organized by day (columns) and region (rows), with hours of each day on the bottom horizontal scale. Source: TNC trip data (Feigon and Murphy 2018)

Figure 4 TNC pickups by hour and day, San Francisco. Panels are organized by day, with hours of each day on the bottom horizontal scale. Source: SFCTA modeled data of intracity trips in the city of San Francisco (Feigon and Murphy 2018)

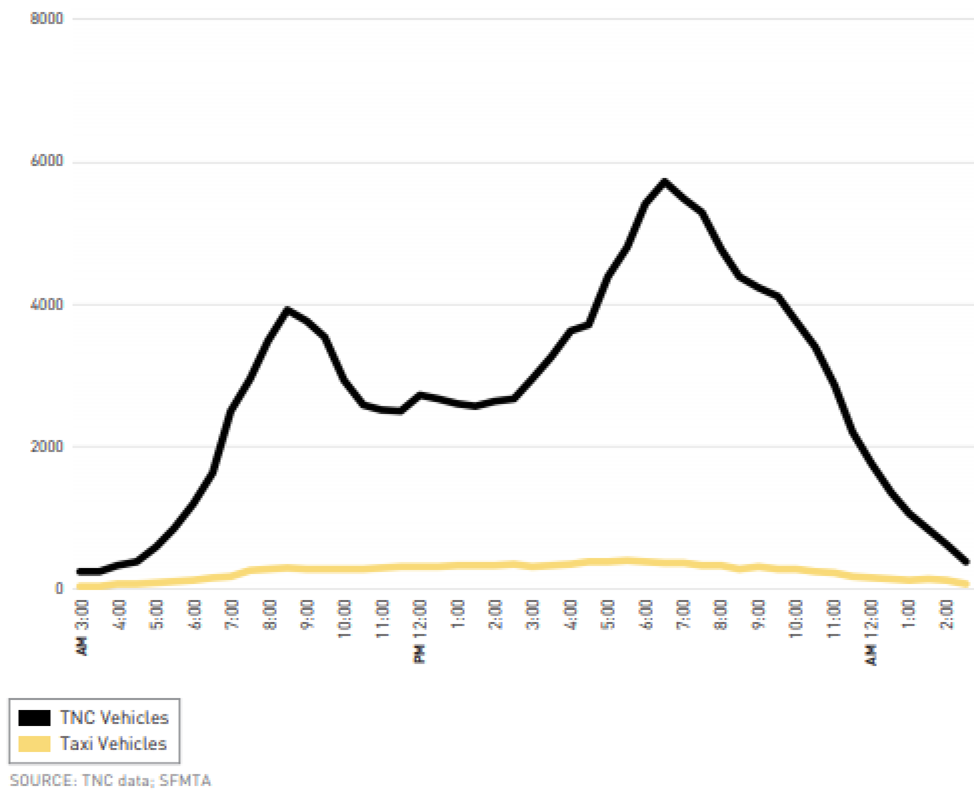


Figure 5 Intra-San Francisco TNC and Taxi vehicles on street on an average Wednesday by time-of-day. Source: TNCs Today by San Francisco County Transportation Authority (SFCTA – 2017)

It can be observed by looking at the graphs in **Figure 3**, **Figure 4** and **Figure 5** that while it is true that most TNC trips are made in the evening hours following the evening commuter peaks, there exist significant weekday diurnal peaks in the hourly volume peaks for all the cities included in study by Feigon and Murphy (2018). The number of TNC trips are seen to be consistent with the population densities of the respective cities, the diurnal nature of the morning and evening peaks mostly being a commonality among all the study areas. This observation supplicates the question whether TNCs should be started to being treated as any other major pre-existing mode of transport exhibiting similar diurnal volume peak trends and competing with conventional modes of public transit. Conclusions regarding the widespread use and presence of TNCs similar to the above made observations can be drawn from a survey-based study by Gehrke, et al. (2018) for the case of Boston. Survey responders indicated that the highest share of home-based trips are made to work, thus rationalizing the diurnal nature of peaks observed in the **Figure 3**, **Figure 4** and **Figure 5**. Neither that much evidence was gathered for TNCs being used as modes for first and last mile trips for transit-based trips to work that could potentially otherwise explain the peaks observed for TNC usage. This research also confirmed the earlier made observation that TNCs are most popular for after-work evening trips during weekdays.

1.2.9 Net Effect

It can be successfully established from the inferences of the previous titles of the chapter that researching the overall effects of TNCs on congestion and travel mode adoption is an important endeavor for transportation professionals. However, studies assessing the net effect of TNCs on congestion have produced mixed results, for example some of them concluded that: 1.) TNCs decrease congestion (Li and Hong 2016): They combined data from Uber and the Urban Mobility Report, and empirically examined whether and how the entry of Uber car services affects traffic congestion using a difference-in-difference framework. They compared cities with and without Uber services and measured travel time index, delay cost, delay time and commuter stress index while controlling for roadway geometry variables and traveler characteristics. 2.) TNCs add to VMT or increase congestion. Henao (2017) demonstrated that TNCs introduce substantial deadheading which is even more pronounced due to their sheer numbers and found that increase in VMT is significantly correlated to TNC presence; Shaller (2017, 2018) concluded that most trips in New York City are non-pooled and that

TNC presence was expressively associated with increased hours of delay; Gehrke, Felix and Reardon (2018) found that increased TNC use was directly associated with decline in public transit ridership and increased sensitiveness to transit fares., or 3.) TNCs “did not drive the recent increase in congestion” (City of New York 2016), or been inconclusive (Rayle et al. 2016; Clewlow and Mishra 2017).

Another recent survey-based study of Uber users in Santiago, Chile by Tirachini and Gomez-Lobo (2019) found that unless such ride-hailing services considerably increase, popularize and/or incentivize shared or ‘pooled’ rides, their usage significantly adds vehicle kilometers traveled on to the network. Their study used Monte Carlo simulations to the possible realms of the model parameters used to assess TNC use behavior among ride-hailing patrons.

1.3 Other Relevant Literature

This section includes a review of other relevant literature that does not directly address the mechanisms by which TNCs may affect congestion.

1.3.1 Other Congestion-Related Studies

Some earlier studies explored the impulse and effect of TNC’s. A report outlining the compact urban development impact on congestion published in 2016 by Mosammam et al. analyzed latest traffic data, which is *presumed to reflect TNC vehicles* on the road (TNCs were not explicitly monitored, measured or counted, but a real time traffic network was analyzed that has significant TNC presence), to measure the annual delay per capita. This delay was calibrated against the expected rise in delay due to the projected increase in background traffic on account of increasing population, employment, income, fuel price, change in highway capacity, vehicle miles travelled, compactness index and GDP growth within the defined study boundaries. Congestion here was defined in terms of travel time and the elasticities of the various explanatory variables were calculated. Data was sourced from INRIX and Urban Sprawl Statistics from the Texas Transportation Institute (TTI). The results indicated that higher per capita income was correlated to higher transit passengers, whereas steeper fuel prices were found to be correlated with a reduction in traffic congestion for both TNCs and private vehicles. The study space for this research indubitably qualifies to be playing home to such a demographic. This prerogative also raises a corresponding question about the viability and equitability of TNC services in areas of the city that are not as profitable to such private service providers as others as they currently poise to draw ridership shares from transit services.

Increase in freeway capacity was associated with greater travel times and delays. Whether this is due to additional demand induced by an increased freeway capacity, the impact of the introduction of newer modes of transportation (TNC's), or reflective of altered and adjusted rush hour congestion characteristics needs to be determined by resolving the data further. Compact urban sprawling and average annual delay were found to be positively correlated and their combined consequence were believed to have effectively cancelled out each other.

1.3.2 Regulatory Environment

A report on Transportation Network Companies by the Texas Transportation Institute (TTI) (Goodin and Moran, 2016) states that as of May 2016, 33 states and the District of Columbia have enacted legislation to legalize and regulate TNC activity. This may include amending permits and operation fees, insurance, licensing and financial responsibilities, passenger protections, etc. Consequently, these prices trickle down to the user base, which when combined with the monetary value of time, might end up costing the users higher than their perceived fare.

1.3.3 Socioeconomic Characteristics of TNC Users

An assessment of UberX wait times in Greater Seattle by Hughes and Mackenzie (2016) revealed the associated socioeconomic identifiers. Spatial regression with locally weighted regression heat maps were generated to indicate specific time of the year, time of day, and geographically evaluated location indicators that influence wait times in the city. By extending the definition of wait time, it can be established that these attributes were indicative of factors which would relate to better served areas and population. It was gauged that transportation network companies offer higher performance in dense urban areas. Whether this suggests a supplement or a competition to public transit, which also operates in dense inner-city zones, understandably due to higher demand, needs to be evaluated by further studies. A few other manifestations of this study were that areas with lower average per capita income nevertheless experience better service. The outcome of population density is weakest shortly after the morning rush hour, and that of employment density is weakest around the evening rush hour. A possible explanation for this is that the pool of available drivers in high-density residential areas depletes following the morning rush, while the same happens in high-density employment centers following the afternoon rush.

In another study, Nguyen-Phuoc, Currie and De Gruyter (2017) examined the interrelationship between socioeconomic indicators, public transport and the susceptibility of mode shift to passenger car in the role of a driver, i.e., using passenger cars in lieu of either TNCs or transit, using a multinomial logit model. This research was a survey-based study. The idea behind reviewing the statistics related to this study for this research is to operate under the assumption that individuals with propensity to replace seamlessly public transport were nearly as likely to substitute public transit with shared mobility vehicles. Majority of the survey responders indicated the affinity to shift to car as a driver, whereas larger proportion higher income individuals expressed the same tendency. More trips to the central business district (CBD) would be in the risk of being cancelled in comparison to trips made to non-CBD areas in the event of a disruption to public transit since transit most heavily serves the core and downtown areas of the city. If the results of this study are indicative of analogous trend for TNC usage, these areas within an urban environment are intuitively more likely to attract TNC users with similar trip purposes with respect to another group of travelers like say, educational trip makers.

1.3.4 Factors Affecting TNC Use

Mo, Lee, Wang and Cheung (2017) sought to quantify passenger tolerance for increased travel time through their study to maximize the utilization of the Shared Dial-A-Ride (SDAR) service. Interestingly, no additional monetary discount was provided to passengers whose travel times were increased through shared mobility and the incumbent tolerance to the increment in delay was observed. The study surmised that a 10-minute tolerance in pick-up and drop-off times resulted in an 8.4% rise in the number of passengers served. The takeaway from this exercise would be to scout for a similar threshold for travel time when comparing transit service users and TNC users and the shift from one mode to another through the study period, while accounting for the demographics and urban characteristics of the study area.

An intercept survey-based research study comparing taxi and ride-sourcing trips and user characteristics in San Francisco (SF) by Rayle, Shaheen, Chan, Dai and Cervero (2014) identified three SF hotspots for ride-sourcing to question riders. This limited the socioeconomic characteristics of the urban area as well as the demographic features of the survey responders. Keeping an account of this, the key independent attributes were transit time reduction exclusively due to ride-sharing, ease of payment, short wait-times, fastest route to reach destination, reliability, unavailability of another mode, avoiding driving under influence, parking unavailability and/or undependability, parking cost, comfort and safety, fare, ease of access, and impact of vehicle ownership. It should be noted that wait times for TNC's in San Francisco are significantly lower than those for taxi services. The authors also prompt their concern about the possibility to have underestimated taxi trip waiting times, which is assumed five minutes for the purpose of this study. Intuitively, insurance and operational costs associated with owning a vehicle in San Francisco and the safety laws regarding TNC's helped make ride-sourcing an attractive option to the central business district crowd in SF. Additionally, many responders replied that they utilized TNC's primarily as a mode to access public transit thus considerably reducing their total transit time. Remarkably, this is seen to have resulted in a small, induced travel effect within people who took trips they would not have otherwise taken and walked instead. Quantifying this demand generation would be one of the chief tasks in the current research study.

Shirgaokar (2017) looked to determine the barriers that prevent seniors from accessing TNC services. This study, which included independent elements like gender, season (change in mobility demand due to season), ambiguity and unfamiliarity with online financial transactions, and technological challenges associated with online ride-hailing, revealed that older women are more likely to seek training and take a stab at using TNC services than older men.

1.3.5 Simulation Studies of the Integration with Other Modes

Martinez and Viegas (2016) studied the impact of the newly prosperous urban shared mobility alternatives through an agent-based simulation for the city of Lisbon, Portugal. The typical features of the simulation were high acceptability of the assigned rides and nested categories each for passenger car based transit and larger vehicle transit options. This study examined the ramifications on congestion if passenger cars and public transport are replaced by shared mobility services. Even low occupancy transit systems ended up reducing vehicle miles travelled and congestion when deployed in conjunction with shared mobility services. However, the study did not include the rather disruptive use-case of a complete (or near complete) substitution of public transport by shared mobility services.

Burnier, Jacobi, Torng and Gross (2014) computed the percent utilization and average time spent travelling in a bid to uncover the impact of coordinating human services with transportation. Coordination between existing modes of transportation and services like TNCs was the independent variable that proved intuitively that better coordination between the two increased resource utilization. However, when applied to individual travelers, this model was inconclusive in determining the result of human service coordination. Vakayil, Gruel and Samaranayake (2017) attended to integrate shared-vehicle mobility-on-demand systems with public transit by invoking the NetworkX library of Python to derive link-level travel times and corresponding fares. This study did not use simulated data and instead, made use of the car2go data interface. Empty and occupied vehicles were justly differentiated in this study owing to their difference in nature in impacting travel-times and affecting the demand-fare dynamics. Irrespective of mode choice and fleet size, vehicular emissions, as well as congestion was observed to have been reduced when mass transit and AMoD operated in complement. However, only the effect of car2go AMoD with pre-existing mass transit services were considered in this study and it is presumed that the inclusion of more AMoD may change the conclusions.

1.3.6 Airport Access

Airport travel is another major trip attractor especially in the case of TNCs. Hermawan and Regan (2017) performed a nested logit model study to quantify the elasticity if travel time and cost related to such trips. Data from On-Demand, application based ride services like Lyft Line and Uber Pool, shared TNC services most popular for airport travel was used. It is widely speculated that TNC's foraying into higher occupancy vehicle territories is both beneficial, in terms for congestion reduction, as well as damaging, if a perceived encroachment into designated passenger share of public transit services is taken into account. This coupled with the fact that TNC services are currently only about 55% of the average fare of hauling a taxi, it was estimated that if fares were to increase to match the cost of taxis, the demand for TNC's would fall from 9% to 7%. Meanwhile, if fares were cut by 50% and travel time increased by ten minutes, the demand would rise by about 1.5%, successfully offsetting the approximate time value of money as implied by Mo et al (2017). In addition, a negative binomial study carried out by Contreras and Paz (2017) concluded that the decrease in taxicab ridership in Las Vegas, Nevada was a function of the comparatively delayed advent of TNCs in the city. On the contrary, a survey-based, mode choice model development by Chavis and Gayah (2016) asserted that familiarity trumps over insignificant monetary gains through a study which exercised a multinomial logit model on wait times, walk times, GPS tracking services and financial savings.

1.3.7 The Effect of TNCs on Transit Ridership

It is important to assess the impact of the rising popularity on transit, both in terms of ridership as well as service reliability when addressing the question on traffic congestion. This is because by adhering to the concept of independent and irrelevant alternatives (IIA), any new mode of transportation will be expected to be drawing equally from the existing modes. By this tenet, TNCs can be projected to potentially add more vehicles to the network as it bites into the passenger share of transit services.

Mucci (2017) explored transit ridership trends for system of interest ‘MUNI’, the bus and light rail system in light of the growing popularity of TNCs in San Francisco. Transit ridership trends in San Francisco has undergone a major shift or a ‘diverging growth’ during the past decade (Erhardt et al. 2017) with bus ridership declining and rail ridership growing significantly. Direct Ridership Models (DRMs), with a fairly precise predicting power (within 10% of the total observed change), were employed to determine what factors were influencing MUNI light rail and bus ridership. This study found variables like employment and housing density to be correlated to each other. Mucci used fixed-effects panel models to assign an intercept to every stop to remove any existing spatial correlation. TNC variables were introduced to the panel models to quantify their effect on MUNI bus and light rail ridership. It was found that the addition of a TNC variable and elimination of multi-collinearity helped the panel models predict ridership better than the daily and time-of-day DRMs, both within 5% of the observed change. TNCs were found to complement MUNI light rail and compete with MUNI buses, an observation that seems intuitively rational as TNCs are more comparable to buses in terms of fares and typical lengths of trips than to light rails, a mode for which they can be assumed to provide first and last mile rides. Mucci inferred from his research study that TNCs contributed to a 7% growth in light rail ridership and were responsible for a 10% decline in bus ridership. These findings suggested that TNCs have a complex relationship with transit modes and that any assumption treating the two modes as one should be avoided.

The Shared Use Mobility Center (SUMC) of San Francisco express their perception as they study the influence of Transportation Network Companies and the way they streamline urban traffic and transit demands. In this report they summarized a survey study in which transit agencies of seven major cities participated (Murphy, Feigon and Colin 2016). In this study, SUMC envisioned that shared-use mobility will reduce congestion and costly parking requirements, thus effectually redefining land use in certain parts of the city. It is noteworthy that while it is relatively easy to police and improve zoning ordinances to reduce parking requirements that are located near transit and include Travel Demand Management (TDM) measures, defining the same for shared mobility contributed by TNC operations is more complicated. Currently, qualified TDM programs include carpooling, vanpooling, on-site car share parking, transit passes, electric vehicle charging, alternative fuel vehicle priority parking, guaranteed ride home, telecommuting, parking cash out, education and programmatic support, emergency transportation, transit shuttles and bicycle commuter facilities.

Notably, the Associated Press depreciated the use of the term ‘ridesharing’ to be associated with TNCs as they are considered to be operating more as a ‘ride-hailing' service rather than a ridesharing or carpooling service, says Zenner (2015). While there are web-based applications designed to facilitate traditional carpooling, such as Waze Carpool and Carma, they often need to face stigmas associated with lumping these two modes together when evidentially, only about 20% of all TNC trips are pooled (Shaller 2017). Traditional carpooling operates such that commuters or riders travelling on common routes are matched using application-based services to optimize their routes and travel time. ‘Slugging’ is also a common practice in large metropolitan areas where drivers pick up strangers from ‘designated’ carpooling zones to be able to use exclusive carpool lanes and/or reduction in tolls associated with carpoolers. TNCs, on the other hand, are more closely analogous to Demand Response Transportation (DRT), even when it comes to shared rides. Traditional providers of DRT services, most popularly for paratransit riders, have financially struggled to keep up with expenses owing to fixed variable like scheduled dialysis appointments for senior citizens (Herzog 2018). He notes that in order to cut down operational costs, a growing number of paratransit agencies are choosing to reimburse passengers for trips provided by taxi companies or TNCs as they can be up to 70% cheaper than conventional paratransit (Cmar 2017). While TNCs may provide your passengers a fashionable user experience (through an app), many drivers do not have the same kind of professional training to serve elderly and disabled passengers as paratransit drivers. TNCs cannot, in their current state, be thought to replace paratransit service providers. As such, there is a clear need to study the intricacies of such policies on the standard network performance metrics.

In tow with the conclusions of Rayle et al. (2014), SUMC shares the vision of bike-sharing, ride-sourcing and other shared modes serving as feeder transportation or first/last mile connections to transit trips. The effect of the presence of TMC's on transit operations as well as transit ridership is yet to be calibrated, although it is reasonable to believe that few users would likely want to swap a 15-mile train ride for a daily ride-sourced trip in rush-hour traffic. Lyft has noted that 25% of its trips in the San Francisco area are to or from Caltrain stations. To estimate the benefits of TNC's, controlled experiments need to be carried out to assign an impact-portfolio to each mode of public transport, namely, MUNI bus, MUNI rail, Caltrain, etc. as well as the ride-sourcing modes, which would compare transportation behavior with and without shared-use modes.

This vision is shared by a study conducted by Hall et al. (2018) which assessed the heterogeneity among the different classifications of transit facilities that TNCs can possibly affect. A difference-in-difference methodology was used to estimate the effect of Uber, standardized by their market penetration in different locations across the United States and their time of entry into the said market. It observed an overall increase in transit ridership in areas with larger population where people taking transit can simultaneously afford TNC fares as well as in smaller transit agencies. On the other hand, larger transit agencies and smaller metro areas recorded a decrease in average transit ridership that correlated to TNC operations. This study also found that greater popularity and use of TNCs related to a decrease in rail ridership while a boost in bus ridership was observed. This is in contrast to other studies that stated that since TNC trip lengths are comparable to those by buses as opposed to rails, transit ridership of buses were affected negatively. Such studies also claimed that TNCs serve as effective first and last mile modes that potentially increased the accessibility to rails for longer trips. As evident, there remains a unambiguity in conclusions between studies carried out in different locations and with distinct methodologies.

1.3.8 Relevance to Automated Vehicles

Hyland and Mahmassani (2017) proposed a taxonomy of shared autonomous vehicle-fleet management problems to inform future transportation mobility, keeping in view the growing interest of TNC services (including Uber, Lyft, Google, etc.) to employ AV fleets. A mesoscopic classification to optimize the AV fleet management problems by ascertaining new categories was carried out. This may prove helpful when creating the estimation datasets for analyzing TNC data in future studies relating travel time optimization and presence of AVs (TNCs or otherwise). These include identifying the underlying network, congestion on travel links independent of being a function of the user vehicles, fleet size elasticity, pricing, arc directionality (to or from destination in both home based or non-home based trips), pick-up versus Drop-off trips, objective (vis-à-vis minimizing cost, maximizing profit, minimizing travel time, minimizing number of functioning vehicles in the network, minimizing vehicle miles travelled: these categories would be analogous to classifying between public service transport options against private sector services), accept/reject decision, and reservation timeframe (essentially time-of-day), etc..

1.4 Vision for present study

1.5 Overview of research stages

This research study first employs an empirical approach to determine the coefficients associated with introducing this new mode of transportation as a function of travel time. The primary motive at this stage of the study is to determine if TNCs and their respective operational maneuvers are identified as significant contributors to the difference (increase) in travel time (or in other words, increase in network congestion) observed between two points in time that are addressed in this study. This effect is notably attenuated by the background factors like the increase in employment and population, change in network and transit operations, change in trip making incentives and travel behavior of commuters in general that would naturally have increased traffic congestion during this period. After being found so, a parameter is estimated that denotes the magnitude to which they are assessed to be affecting this increase in travel time. This coefficient has then been applied to the activity-based model deployed by the county of San Francisco by introducing TNC volumes as additional loads on the model network. A model-based analysis is thus borne that incrementally tests the individual contribution of each major background factor to the increase in traffic congestion (represented by travel time and delay) and travel time reliability (represented by Planning Time Index) within the primary arterial network. These quantifications of delay contributions are compared to those made by TNCs and their pickup and drop-off maneuvers to quantitatively gauge the degree to which TNCs have affected the standard network performance measures within the study area.

CHAPTER 2. THE EMPIRICAL STUDY

2.1 Introduction

Transportation planners and policy makers are interested in understanding the congestion effects of TNCs as they face decisions about how to regulate TNCs and how to integrate them into the existing transportation system (Kuhr, Bhat, Duthie and Ruiz 2017; Moran and Laslev 2017). There is a need for further research to adjudicate these differences, but research on the topic has been hampered by a lack of data (Gerte, Konduri and Eluru 2018; Cooper, Castiglione, Mislove and Wilson 2018). This debate has been entered to address the question: Do TNCs decrease or increase traffic congestion?

This is done for the case of San Francisco, where a data set scraped from the Application Programming Interfaces (APIs) of the two largest TNCs provides a unique insight into their operations. These data were collected and processed as described by Cooper et al. (2018). The data was further processed to associate TNC volumes, pick-ups and drop-offs to each road segment in San Francisco by time-of-day.

This section of the research is structured as a before-and-after assessment between 2010 conditions when TNC activity is negligible and 2016 conditions when it is not, focusing on the change in average weekday conditions. Measures of roadway conditions in both years were derived from GPS-based speed data licensed from INRIX. The relationship between the change in TNC activity and the change in roadway travel time was estimated, assuming zero TNCs in 2010.

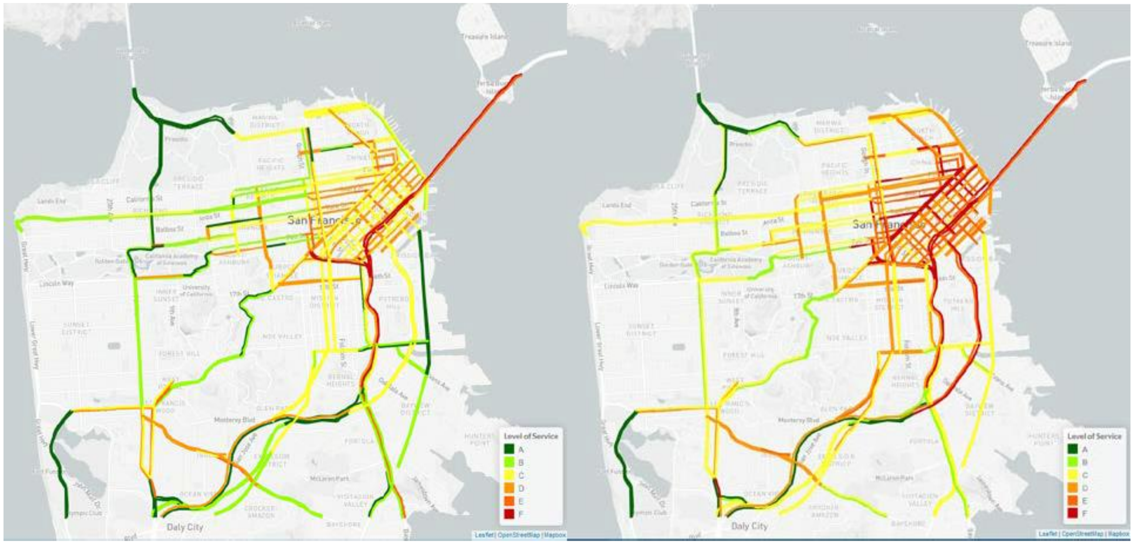
To control for other factors that may also affect congestion over this period, San Francisco's travel demand model, SF-CHAMP, was used which produces estimates of traffic volumes on all roads in San Francisco and is sensitive to changes in population and demographics, employment, transportation networks and congestion. Since SF-CHAMP's initial development (Jonnalagadda, Freedman, Davidson and Hunt 2001), it has been further enhanced (Erhardt, Charlton, Freedman, Castiglione and Bradley 2008; Zorn, Sall and Wu 2012), extensively tested (Outwater and Charlton 2006), and successfully applied to analyze policy and infrastructure changes (Castiglione, Hiatt, Chang and Charlton 2006; Brisson, Sall and Ang-Olson 2012). The version of SF-CHAMP used in this study was calibrated to 2010 conditions, and does not account for TNCs. This means that when the model is run for current-year inputs, it represents a counterfactual case where TNCs do not exist.

The relationship between demand and traffic speed is non-linear, such that adding vehicles in already congested conditions has a bigger effect than adding them in uncongested conditions. Therefore, it is not just the total VMT change that matters, but when and where that change occurs. The analysis was conducted directionally for segments known as Traffic Messaging Channels (TMCs), which average 0.3 miles long. For each year, all the data was aggregated to these TMC links and averaged across days to represent average weekday conditions for five times-of-day (TODs). These link-TOD-year combinations are more detailed than past TNC studies which are either more aggregate, i.e., carried out on a system wide or network-wide scale as opposed to roadway link-scales (Shaller 2017; Feigon and Murphy 2018; Li, Hong and Zhang 2016; City of New York 2016), or based on smaller user surveys (Rayle et al. 2016; Clewlow and Mishra 2017; Feigon and Murphy 2016; Henao 2017; Gehrke, Felix and Reardon 2018) that cannot be expanded to the network link level.

After estimating the relationships between the change in travel times, TNCs and control variables, the estimated model was applied to evaluate network performance metrics for 2010, 2016 and a counterfactual 2016 scenario with no TNCs. The congestion levels in these two scenarios were compared to evaluate the research question.

2.2 Observations and Hypotheses

Like New York (Shaller 2017; City of New York 2016), San Francisco has experienced a notable increase in congestion over the past few years (San Francisco County Transportation Authority 2017) (**Figure 6**). The speed data used in this study confirm this trend, showing that the average speed decreases from 25.6 miles per hour (mph) in 2010 to 22.2 mph in 2016, and that the vehicle hours of delay (VHD) increase by 63% over the same period. Delay is defined as the difference between the congested travel time and the travel time under free-flow conditions. Areas with lower LOS increased manifold in 2016 as compared to those observed in 2015.



A **B**

Figure 6 PM peak period roadway level-of-service (LOS) in San Francisco in (A) 2009 and (B) 2017 (San Francisco County Transportation Authority 2017). LOS grades roadways by vehicle delay, with LOS A representing free flow and LOS F representing bumper-to-bumper conditions. Data and an interactive mapping tool are available at congestion.sfcta.org.

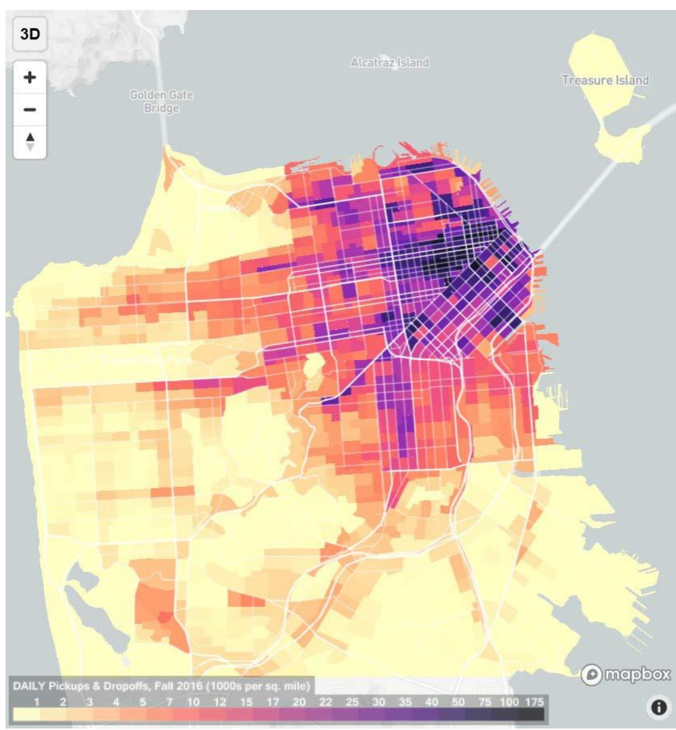


Figure 7 Daily TNC pickups and drop-offs for an average Wednesday in Fall 2016 (TNCs Today SFCTA 2017). Darker colors represent a higher density of TNC activity (pickups in this case). Data and an interactive mapping tool are available at tncstoday.sfcta.org.

This change corresponds to the period in which TNCs emerged. **Figure 7** shows the distribution of the TNC pick-ups and drop-offs for an average Wednesday in Fall 2016. The data show that TNCs are concentrated in the downtown area, consistent with findings elsewhere (Feigon and Murphy 2016; Clewlow and Mishra 2017), and in the locations where level-of-service (LOS) deterioration is worst.

Several other changes also may affect congestion. Between 2010 and 2016, San Francisco population grew from 805,000 to 876,000 (U.S. Census Bureau 2016) and employment grew from 545,000 to 703,000 (U.S. Bureau of Labor Statistics 2016). Important network changes include a rebuild of the Presidio Parkway, the introduction of turn restrictions on Market Street, several "road diets", and bus improvements (SFMTA). These changes have been accounted for through SF-CHAMP. In addition, a list of active construction projects during the 2016 analysis period was reviewed to evaluate whether these construction activities were associated with disproportionate speed decreases and was not found that they were.

The data do not show the share of ride-splitting in San Francisco, but it is between 13% and 20% elsewhere (Henao 2017; Gehrke, Felix and Reardon 2018), with some of those trips carrying no additional passengers (TRB Special Report 319, 2016; Gehrke, Felix and Reardon 2018). Rail ridership grows substantially over this period and bus ridership does not (Erhardt 2016), consistent with other findings that TNCs may complement rail and compete with bus (Clewlow and Mishra 2018; Mucci 2017). A meaningful change in car ownership was not observed, with an average of 1.08 cars per household in 2010 and 1.10 cars per household in 2016 (U.S. Census Bureau).

In addition to the 20% of TNC VMT that is out-of-service, 70% of San Francisco TNC drivers live outside the city (TNCs Today SFCTA 2017). While this was not explicitly tracked in this study, the drivers' commutes into the city may also add more VMT to the network.

Some argue that TNCs have little effect on traffic operations because they occur in the evening when congestion is less severe (Feigon and Murphy 2016; Feigon and Murphy 2017). The data show that 43% of TNC VMT occur between 6:30 PM and 3 AM, but they also show that 26% of TNC VMT occurs in the 3-hour AM or PM peak periods, compared to 40% for 4-hour peaks in Boston (Gehrke, Felix and Reardon 2018).

Given these observations, it is suggested that the gap between the background changes predicted by SF-CHAMP and the observed change in travel times is an indicator of TNC impact. Specifically, it is hypothesized that:

1. If TNCs have no effect on congestion, the background changes should reasonably predict the observed travel time changes.
2. If TNCs decrease congestion, then the observed change in travel time should be better than the background changes would predict.
3. If TNCs increase congestion, then the observed change in travel time should be worse than the background changes would predict. The gap is expected to be the widest for times and locations with high levels of TNC activity.

To test these hypotheses, this study was structured as a before-and-after assessment between 2010 conditions where TNC activity is assumed to be negligible and 2016 conditions when they are not. For each year, an estimation data file is compiled with one observation on each road segment and time-of-day combination. The data represent average weekday conditions in the fall of each year.

Fixed-effects panel data models were estimated where the dependent variable was the observed travel time converted to implied volumes using volume-delay functions (VDFs). This time-implied volume is the model's dependent variable, and the conversion ensures that it is linearly related to the background and TNC volumes. The physical interpretation of this conversion would be that instead of treating congested travel time as the dependent variable in the panel regression model, "volume implied by congested travel time" be treated as the y-variable now. Since travel time is a function of volume, back-applying the volume-delay function (VDF) gives us an estimate of the traffic volume that brought about the observed congested travel time in the first place. The fixed-effects models estimate coefficients based on the change between 2010 and 2016 conditions. There is precedent for using both before-and-after analysis and panel data models in transportation analysis, including to study changes in congestion (Hanna, Kreindler and Olken 2017), TNC growth (Gerte, Konduri and Eluru 2018), and the effects of new technology (Tang and Thakuriah 2012). The estimated coefficients are applied to produce a modeled estimate of 2010 and 2016 network conditions, as well as a 2016 counterfactual scenario that excludes the effect of TNCs.

2.3 Data

The analysis relies on three sources of data: background traffic estimates, TNC data and network wide link-level speed data. Those data and their processing are described below.

2.3.1 Background Traffic Estimates

To estimate the net effect of TNCs on congestion, it is necessary to control for other factors that are also expected to change congestion levels, including changes to population, employment and road, any significant construction projects or public activities expected to impact traffic, and transit networks. To control for these changes, this research uses San Francisco's travel demand model, SF-CHAMP.

SF-CHAMP is an activity-based travel demand microsimulation model that is sensitive to a broad array of conditions that influence travelers' choices. The model predicts the typical weekday travel patterns for approximately 7.5 million San Francisco Bay Area residents, including choices of vehicle availability, activity participation, destinations, travel modes, and travel times. The simulated travel patterns are sensitive to changes in population and demographics, employment, transportation networks and congestion. The model incorporates detailed information about demographics and land use, using block, block group, and tract level geographies, and six broad employment sectors. It also incorporates a detailed representation of the entire Bay Area multimodal transportation system including roadways, transit routes, and non-motorized facilities, as well as information about how these change by time-of-day. The core behavioral components are based on detailed travel surveys and capture time and cost tradeoffs and other factors that influence traveler choices, such as the effects of demographics and the availability and quality of alternatives. The model has been used extensively in practice for almost two decades to evaluate long range transportation plans, transportation infrastructure investments, pricing policies, and land use development proposals.

SF-CHAMP uses a detailed representation of the road network, including a link for every street and in the city, along with attributes that include length, number of lanes, capacity, turn restrictions, and facility type. The outputs include an estimate of the average weekday traffic volume and congested travel time on each link for each of five times-of-day (TODs): 3-6 AM, 6-9 AM, 9 AM-3:30 PM, 3:30-6:30 PM, and 6:30 PM-3:00 AM.

The analysis uses version 5.2.0 of SF-CHAMP, run using 2010 and 2016 inputs. The model runs uses actual inputs, not forecasts, avoiding inaccuracies associated with errors in the inputs. The referred input inaccuracies were dealt with by cross examining the SF-CHAMP recorded congested speed (or speed-implied volume, explained later in the chapter) with that observed in real-time within the INRIX database. This version of SF-CHAMP was calibrated to 2010 conditions, and does not account for TNCs. Normally this would be a limitation, but in this case it is beneficial because it means that when the model is run for 2016 population, employment and network inputs, it represents a counterfactual case where TNCs do not exist.

2.3.2 TNC Data

Complementing SF-CHAMP are the TNC data, which were collected and processed as described by Cooper et al. (2016). The raw data show the locations and timestamps of out-of-service TNC vehicles collected in 5-second increments for a 6-week period in Fall 2016, totaling about 12 terabytes of raw data. When a driver accepts a ride, that vehicle no longer appears in the traces, and after the driver drops off the passenger, the vehicle re-appears. This structure allows the analyst to infer that a trip was made between those two points. The point at which the driver disappears from the trace is inferred as the location of a passenger pick-up, and the point at which it reappears is inferred as the passenger drop-off location. There is some uncertainty associated with the pick-up location because the driver must travel from his/her current location to the location where the passenger is waiting, but given the density of TNCs in San Francisco, the passenger wait time is usually short. City-wide, the average wait time is 3 minutes (Emerging Mobility Evaluation Report SFCTA 2018), and in popular experience, it is often 1-2 minutes in the core of the city. The TNC data were further processed for this study in several ways. The out-of-service TNC vehicles were attached to directional SF-CHAMP road links by time-of-day using a spatial matching process that accounts for the trajectory of points. The in-service TNC volumes were attached to directional road links by assigning each to the shortest path between the inferred pick-up and drop-off locations, where the shortest path is calculated based on the congested SF-5 CHAMP networks.

Finally, the pick-up and drop-off locations were assigned to directional road links, allowing for their effect on congestion to be measured. The end-result is a set of SF-CHAMP road networks that include the background traffic volumes and other link attributes and are annotated with 2016 TNC activity. These are for average weekday conditions, segmented by SF-CHAMP's five time periods. To the extent that in-service TNC volumes substitute for other auto trips, some overlap is expected between these and the background SF-CHAMP volumes.

To understand the potential effect of the error in pick-up locations, a different assumption was tested. Rather than assuming that the pick-up occurs at the point where the ride is accepted, it could instead be assumed that pick-ups are symmetrical with drop-offs. To test this assumption, a sensitivity test was run in which a model was estimated that includes only Drop-off locations, and excludes pick-up locations. In doing this, a model that includes only Drop-offs has a drop-off coefficient that is about twice as large as the pick-up/drop-off (PUDO) coefficient was arrived at. This is logical, because there are half as many drop-offs as there are PUDO. This is true since by definition, each TNC trip connects one pick-up to one drop-off. Therefore, it has two PUDO. Though it is correct to note that the pick-up and drop-off of a trip occur in different locations, nonetheless, it was observed that a correlation exists between the pick-ups and drop-offs, suggesting that on TMCs where one TNC picks up a passenger, there is often another who drops a different passenger off. This is what one would expect, given that TNC trips are concentrated in the northeast quadrant of the city, and that drivers have an incentive to find a new ride near their Drop-off location to minimize any deadheading. It was assumed that the Drop-off coefficient should be about twice as large as the PUDO coefficient. This occurs because there are half as many Drop-offs as PUDO. Since the size of the descriptive variable is reduced, the model estimation produces a larger coefficient to result in a similar net effect. This does not have a large effect on the overall result. Some potential limitations are addressed in Appendix A.

2.3.3 Speed Data

Archived speed data were used from INRIX, a commercial vendor, that is available in 5-minute increments for each day from 2010 through the present, allowing both the average travel time and reliability metrics to be calculated. Spatially, the data are available directionally for segments known as Traffic Messaging Channels (TMCs), which in San Francisco average about 0.3 miles in length, or about 3 city blocks. TMCs exclude many local roads, but otherwise provide good coverage throughout the city.

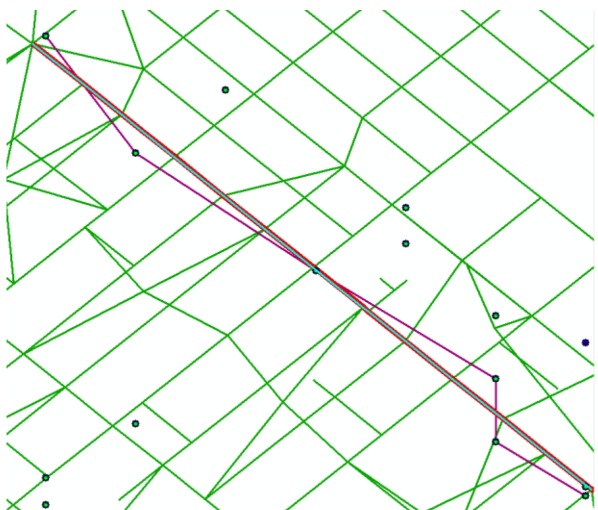
Links associated with TMCs carry about 70% of the total VMT in San Francisco. This study uses INRIX speed data, at a 5-minute temporal resolution, for non-holiday weekdays for the 6-week period in November and December 2016 when TNC data were collected, and for a comparable 6-week period in November and December of 2010. The data is provided for each TMC segment with day and time stamps. A reference speed is also available in the dataset representing speed under uncongested condition.

The speed data depend upon probe vehicles and therefore varies in confidence scores depending upon the time of day and presence of vehicles on each TMC link that provides this data. For the purpose of this study, INRIX speeds pertaining only to the highest INRIX confidence score are used to calculate a reliable estimate for link-resolved travel-time. Further, a comprehensive evaluation of the data was conducted, including a comparison to speed data from San Francisco's Congestion Management Program (CMP) (Congestion Management Program SFCTA 2017). TMC links with unreasonable speeds were excluded from the analysis. For example, a surface street running parallel to a freeway showed unreasonably high speeds, which, it is suspected, is the link picking up probe vehicles from the adjacent freeway. Additional data assurance is performed to identify and exclude data labeled with the wrong travel direction.

2.3.4 Relating Multiple Networks

The study derives quality, network identification, geometric and operational data from three networks: INRIX TMC links, CHAMP links and Congestion Management Program defined links (CMP). CHAMP segments are usually smaller than TMC links; the three networks relate to each other as shown in **Figure 8**. In essence, the length of the CMP segments are longest, followed by TMC and CHAMP respectively. In the table shown in **Figure 8**, each row corresponds to one CHAMP segment. In this initial step, each CHAMP segment is associated with the same number of TMC's as its corresponding CMP link. For example, CHAMP segment 24499-24494 is associated with CMP segment 1, which in turn is associated with five TMC segments. In the subsequent step, each CHAMP segment will be assigned a shape file with its corresponding TMC's and the nearest neighboring TMC segment will be sought and assigned to it.

A straightforward spatial join between SFCHAMP and TMC segments is impractical due to two reasons: a.) Excessive run time due to the sheer volume of CHAMP segments, and b.) The TMC shapefile is not an accurate overlay on the CHAMP network.



1	cmp_segid	A	B	AT	TMC-1	TMC-2	TMC-3	TMC-4	TMC-5
2	1	24499	24494	0	105-10568	105-10567	105-10566	105N10565	105-10565
3	1	24500	24499	0	105-10568	105-10567	105-10566	105N10565	105-10565
4	1	24522	24500	0	105-10568	105-10567	105-10566	105N10565	105-10565
5	1	24526	24522	0	105-10568	105-10567	105-10566	105N10565	105-10565
6	1	24528	30012	0	105-10568	105-10567	105-10566	105N10565	105-10565
7	1	24530	24563	0	105-10568	105-10567	105-10566	105N10565	105-10565
8	1	24532	24528	0	105-10568	105-10567	105-10566	105N10565	105-10565
9	1	24534	52721	0	105-10568	105-10567	105-10566	105N10565	105-10565
10	1	24542	24534	0	105-10568	105-10567	105-10566	105N10565	105-10565
11	1	24563	24542	0	105-10568	105-10567	105-10566	105N10565	105-10565
12	1	24564	24530	0	105-10568	105-10567	105-10566	105N10565	105-10565
13	1	24666	24564	0	105-10568	105-10567	105-10566	105N10565	105-10565
14	1	30012	24526	0	105-10568	105-10567	105-10566	105N10565	105-10565
15	1	30731	24666	0	105-10568	105-10567	105-10566	105N10565	105-10565
16	1	52721	24532	0	105-10568	105-10567	105-10566	105N10565	105-10565

Legend:

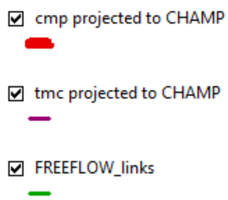


Figure 8 Example demonstrating how links from three different networks were conjoined to form the resultant link which in turn, formed the main analysis network. The red link(s) are the links of interest in this particular case. This image is spatially magnified to the scale of 1:5000. Note how link nodes (denoted by blue colored points) do not align with the link nodes (ends) of other networks. This figure demonstrates the uncertainty of GPS points.

It does not follow the roadway network because the TMC shapefile was generated by a straight-line interpolation between the TMC start and end latitudes and longitudes. Due to this, in the worst case scenarios like the one shown below, a TMC segment in the N-S direction may intersect or be closer to a CHAMP segment in the E-W direction. In cases not as extreme as this, there may still exist a discrepancy between the appropriate TMC correspondence and the associated CHAMP segment. Thus, a shapefile containing exclusively those TMC’s that correspond to a CHAMP segment for each CHAMP segment in the network is created. This creates a list of TMC's "in the running" only among from which each CHAMP segment is subjected to nearest neighbor analysis. Next, these associations were validated manually. The end result of this data preparation process is a unified data set with one observation for each directional TMC. Associated with that TMC will be the INRIX travel times and speeds, measures of TNC usage, and measured transferred from SF-CHAMP including the facility type, number of lanes, and background traffic estimates. A paired data set is created, allowing us to measure the change of each between 2010 and 2016.

Some TMC segments are "filler segments". Links lying between two stop bars at a traffic signal or unsignalized intersections, links denoting the change in direction of a roadway, etc. are some examples of filler segments. Since these links are extremely short in length (typically, shorter than 0.025 miles), and more importantly, not representative of a typical roadway segment, they are excluded from the analysis. In total, 23% of TMCs were excluded from the analysis, but these TMCs account for less than 4% of the total TMC road length. The thick lines are TMCs. The colored lines in **Figure 9** are those for which data exists in this study, while the thick gray lines are TMCs that have been excluded from the analysis. The TMCs excluded most of the local roads in residential neighborhoods, but have good coverage of minor arterials and above, as well as a smaller number of collectors/locals. Roads associated with TMCs carry about 70% of the VMT in San Francisco. In terms of TMCs that are excluded, 23% of TMCs have been excluded, but this accounts for only 4% of the total road length associated with TMCs. This is because many of the exclusions are for very short TMCs, less than 0.025 miles long. Below, summarizes the reasons TMCs have been Dropped from the analysis.

To incorporate the predicted volume obtained from the SF-CHAMP model, as well as normalizing the growth in background traffic attributable to the typical non-TNC factors, it is required to create an association between the TMC network and the SF-CHAMP network. The remaining TMC links are associated with the corresponding SF-CHAMP links. In most cases, SF-CHAMP links aggregate to TMC links. In instances when a CHAMP segment is longer than a TMC segment, multiple TMC segments were merged together to form one composite TMC segment and correspond to the said CHAMP segment. In a few cases, such as in some of the more complex freeway interchanges, a clean correspondence could not be identified between the SF-CHAMP links and the TMC links. Those cases are excluded from the analysis.

In order to create a temporally bound and uniform data framework, the 5-minute speed data were aggregated to average weekday measures for each of the five SF-CHAMP time periods. During this aggregation, several speed metrics were calculated, including the mean, the standard deviation, the 5th percentile and the 20th percentile. The highest observed average hourly speed on each TMC link over the observation period was assigned as the free-flow speed for that link. Examination of this dataset shows that the free-flow speed on a segment remained largely unchanged between 2010 and 2016.

Table 1 Summary of Reasons for Dropping TMC Links

Reason Dropped	Number	Length
Bad INRIX Data	10%	20%
Flagged in Manual QA/QC	4%	20%
Incorrect Segment	3%	7%
Interchange	9%	27%
Intersection Segment	3%	3%
No CHAMP Link Found	2%	3%
Very short TMC Links	69%	21%
Total of all Dropped TMCs	100%	100%

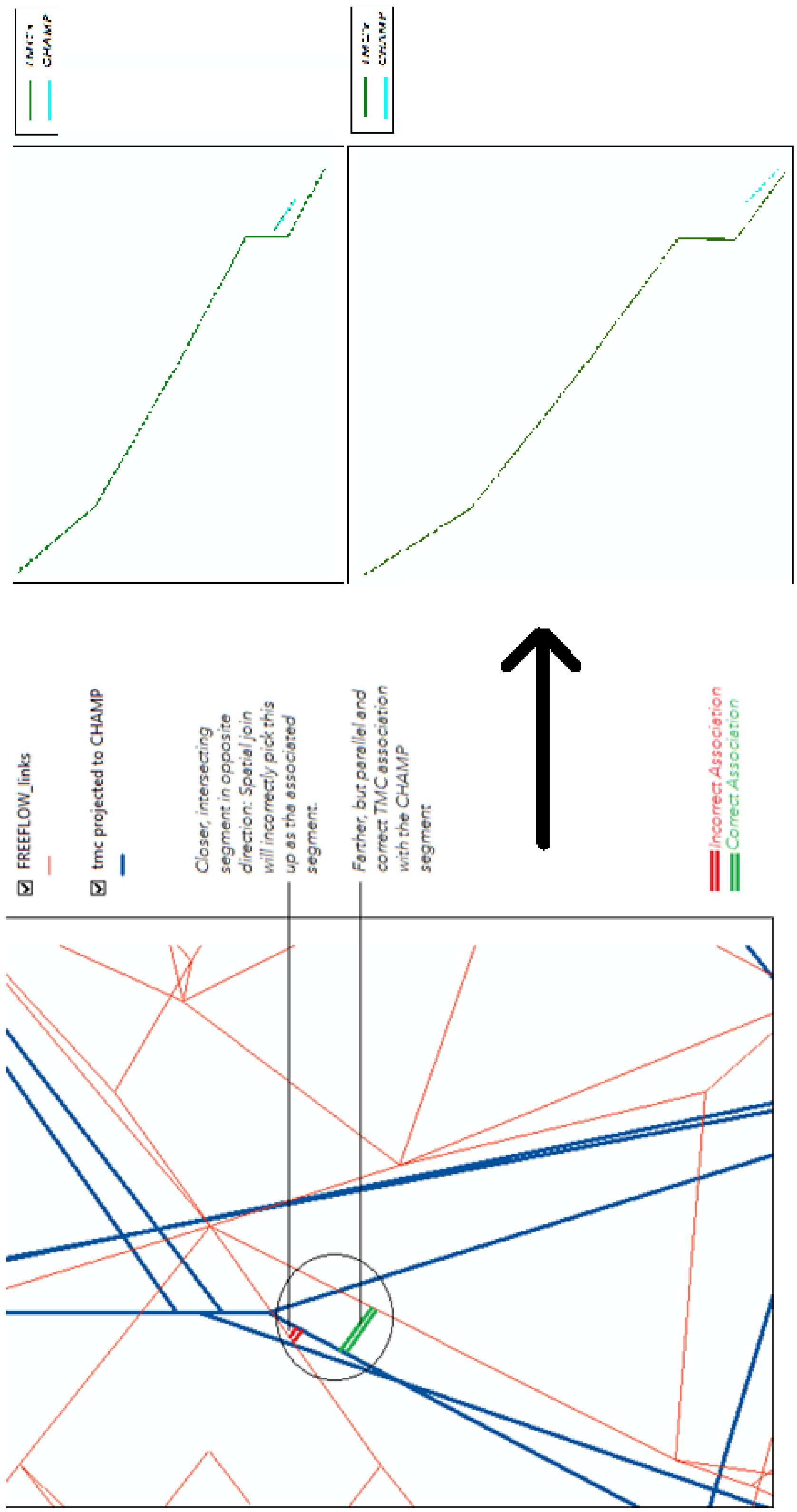


Figure 9 A diagrammatic representation of automating the TMC-CHAMP association process

2.3.5 Merging the Data

The data are merged, such that TMC links serve as the common spatial units for the remainder of the analysis. When the data are aggregated from SF-CHAMP links to TMC links, the link attributes are aggregated as well. Volumes and capacities are combined using a length-weighted average. There are two measures of distance: one from the SF-CHAMP links and one from the TMC links. The SF-CHAMP links are more spatially accurate, so the sum of the SF-CHAMP link length is used as the primary measure of length in the combined data set. In the event where multiple TMC segments need to be aggregated, the space mean speed is estimated by dividing the combined TMC length by the sum of travel time across all TMCs. The speed is then applied to the length of the combined SF-CHAMP links.

All of this is done for both 2010 and 2016 scenarios. The 2010 and 2016 data are matched for each TMC segment, and if there is missing data in one or the other, both records are Dropped. This can happen, particularly in the 3-6 AM time period, if there are insufficient probe vehicles to achieve the highest confidence score in the INRIX data. The end result is a matched panel with 2010 and 2016 for a total of 7082 TMC link-TOD combinations. This corresponds to 1450 TMC links with up to five times-of-day each.

2.4 Methods

Figure 10 pictorially represents the mathematical framework proposed to address the research problem. The null hypothesis assumed in this diagrammatic representation is an ideal scenario in which TNCs add no additional vehicles on to the network, that is, every TNC vehicle replaces an otherwise existing passenger car. It has been established that the total traffic volume in 2016 is the combination of TNC and non-TNC volumes. In **Figure 10**, V_2 is defined as the organically increased volume in the year 2016, irrespective of the presence/introduction of TNCs. $V_{Overlap}$ represents the number of passenger cars that are double counted for being part of the natural increase in traffic as well as being identified as a TNC vehicle. V_2 is therefore representative of the traffic volume which would have existed had TNCs not existed within the network, that is, the predicted traffic volume in 2016 by travel models such as SFCHAMP (used in this study). This volume is also termed as 'background growth volume'. In the current context, V_2 is the number of vehicles in the network that includes the volume of conventional passenger vehicles in conjunction with those vehicles that are substituted by TNCs. In addition, V_{TNC} is the number of vehicles identifying themselves as TNCs in the network.

To estimate the effect of TNCs, a fixed-effects panel data regression model was used (Greene 2003). The fixed-effects standardize the link-dependent unexplained constancy or variance that might affect the regressed variable. Some examples of link-specific characteristics are location of links near high foot traffic, recreational areas, special roadway geometry, etc. The temporal unit used by the panel is '2', warranted by the before-after nature of the study. Each data point in the dataset is a unique combination of a TMC, time of day (TOD) and observation year. Since there are only two points in time, this is equivalent to estimating an ordinary least squares (OLS) model on the change on each TMC for each time-of-day.

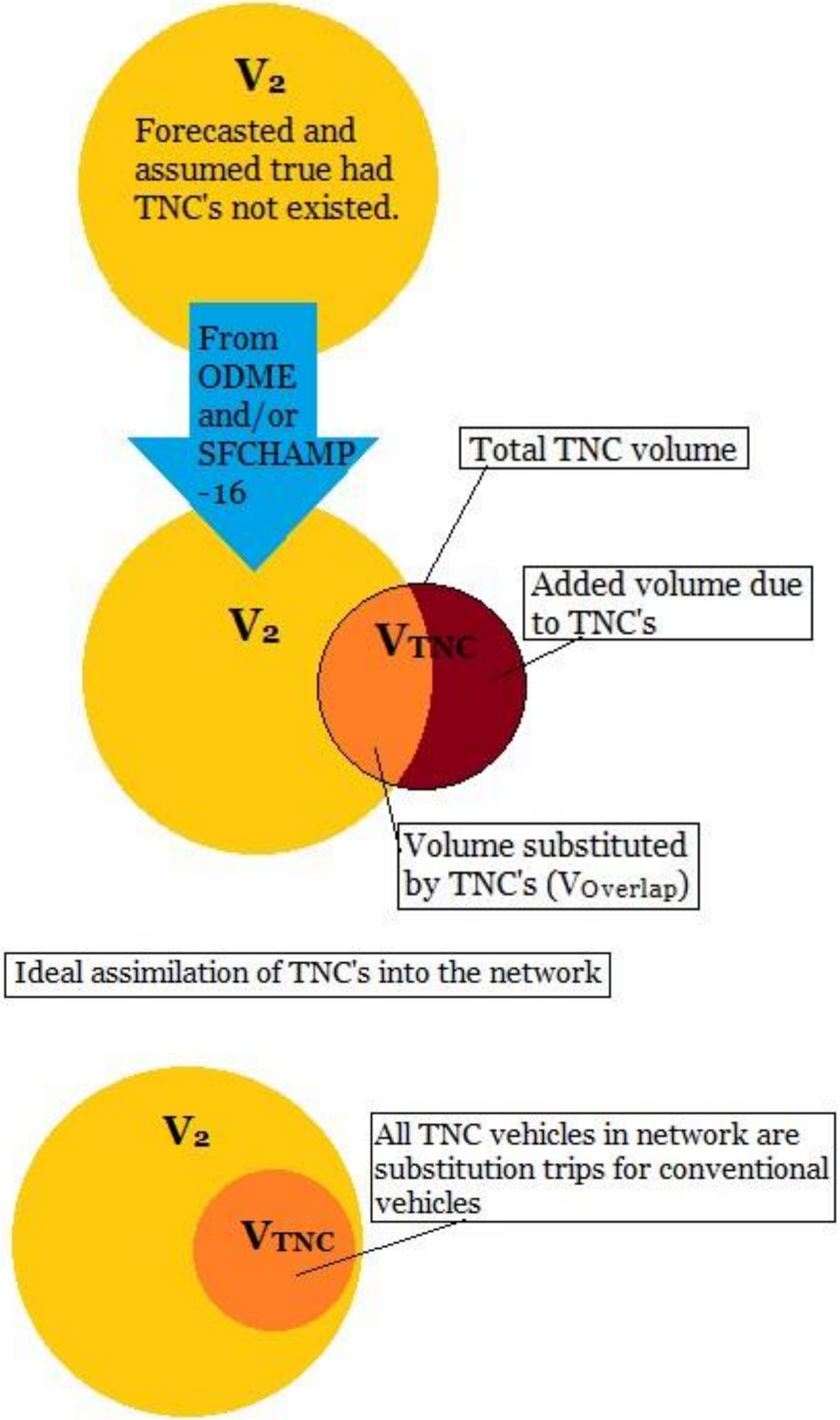


Figure 10 Pictorial representation of the mathematical framework followed by the statistical models

2.4.1 Converting Travel Time to Implied Volume

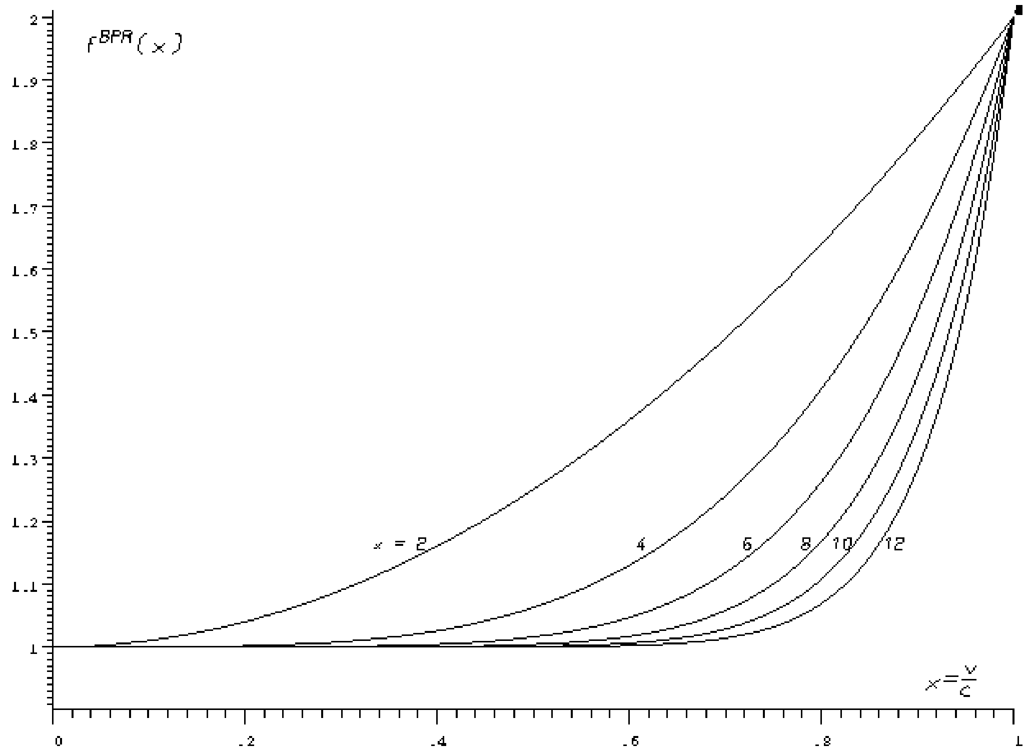


Figure 11 A typical volume delay function with multiple curves for multiple volume-to-capacity ratios represented in the x-axis. Source: Heinz Speiss at www.spiess.ch/emme2/conic/conic.html

A challenge in estimating the regression models required to evaluate the relationships between the congestion and volume-impacted travel-time that they assume a linear relationship between the dependent variable and the regressors, but the relationship between volume and travel time is non-linear as shown in **Figure 11** and take the form given in Equation 1. To deal with this, the volume-delay functions (VDFs) from SF-CHAMP were used to convert the observed travel times into implied passenger car equivalent (PCE) volumes. The original volume delay functions take the form:

$$T = \gamma T_0 \left(1 + \alpha \left(\frac{v}{c}\right)^{\beta}\right) \qquad \text{Equation 1}$$

where T is the congested travel time, T_0 is the free-flow travel time, V is the traffic volume in PCEs, C is the link capacity, and α and β are calibrated parameters explained later in this section. Solving for V, one gets:

$$V_1 = C\left(\frac{\frac{\gamma T}{T_0}-1}{\alpha}\right)^{1/\beta} \qquad \text{Equation 2}$$

where the subscript on V_1 is used to designate a time-implied volume as opposed to an expression of travel-time influenced by traffic volume, as derived from the travel times. The panel models use V_1 as their dependent variable. It is in units of PCEs, so is linearly related to the volume measures in the descriptive variables: volume, capacity, link travel time and free flow travel time. The expression given in Equation 2 relate travel-time linearly to volume through the use of the parameters α, γ and β. The values of the parameters α and β used for this study were those ascertained in the SF-CHAMP model. They are characteristics of the functional classification, roadway geometry and average daily traffic of the roadway links for which the volume delay function is being evaluated. Another parameter that affects the valuation of the function is γ. This is an empirical factor used by SF-CHAMP to scale up the volume-delay function evaluation for certain arterial and freeway roadway functional classes for which, it is ascertained by the regional transportation planners, the Bureau of Public Roads (BPR) VDF is not sufficiently steep enough. Volume to capacity ratios are another parametric requirement that need to be normalized for the respective number of lanes. The values of these parameters are presented in **Table 2**.

Table 2 Parameter values for volume-delay function used in SF-CHAMP assignment model

Roadway Classification	α	β	δ
Freeway-to-Freeway Connector	0.83	5.5	1.3
Freeway	0.83	5.5	1
Expressway	0.71	2.1	1
Collector	0.6	8.5	1.8
Ramp	0.83	5.5	1.3
Major Arterial	0.6	3.5	1.8
Alley	0.6	8.5	1.8
Local Street	0.6	8.5	1.8
Minor Arterial	0.6	3.5	1.8
Super Arterial	0.6	3.5	1.8

The analysis is conducted for five multi-hour time-periods, so it is important that all volumes and capacities be either hourly, or for the period as a whole. Here, they are defined for the period as a whole, and scale the hourly capacities to the period total using the same peak-hour factors (PHFs) that are used by SF-CHAMP. The PHF values for the five times of day are mentioned in Table 3.

Table 3 Peak Hour Factors by five times of day used in SF-CHAMP assignment model

Time of Day	PHF
EA - Early (AM) Morning: 03:00-06:00	0.463
AM - Morning (AM) Peak: 06:00-09:00	0.348
MD - Midday: 09:00-16:00	0.154
PM - Evening (PM) Peak: 16:00-19:00	0.337
EV - Evening: 19:00-03:00	0.173

2.4.2 Congestion Effects of Pick-ups and Drop-offs

In considering the effect of TNC pick-ups and Drop-offs (PUDO) on congestion, it is useful to consider other scenarios in which a vehicle movement has an effect on congestion beyond simply driving on the roadway. Several examples where this occurs include taxis (Golias and Karlaftis 2001), delivery trucks (Chiabaut 2015), and movements into or out of on-street parking spaces (Yousif 1999; Biswas, Chandra and Ghosh 2017). Wijayaratna (2015) provides a useful method for considering the congestion effect of on-street parking that follows the capacity adjustment approach used frequently in the Highway Capacity Manual (HCM) (Transportation Research Board 2010). The approach scales the capacity of the road lane adjacent to the on-street parking based on the share of time that the lane is blocked. To model the effect of TNC PUDO, a similar approach has been adopted, but the PUDO effect has been defined in PCEs so it is in the same units as the dependent variable, and express the effect as:

$$\beta_{AvgDur} * \frac{\mathrm{PUDO} * \mathrm{PHF}}{3600} * \frac{\mathrm{c}}{\mathrm{L}} \qquad \text{Equation 3}$$

Where PUDO is the number of pickups and Drop-offs (PUDO) in the period, PHF is the peak hour factor to convert the PUDO to an hourly value, C is the capacity of the link, L is the number of lanes, and β_{AvgDur} is an estimated model parameter. For simplicity, this term, excluding the estimated coefficient, has been expressed as V_{AvgDur} β_{AvgDur} can be interpreted as the average duration for which each PUDO blocks or disturbs traffic in the curb lane. In congested conditions, this can be longer than the duration of the stop itself, because it can take some time for a queue to dissipate if it builds up behind a stopped vehicle and for traffic to recover to its pre-PUDO condition. β_{AvgDur} can also be shorter than the actual duration of a stop if there is some probability that the stopping vehicle can pull out of traffic, or if volumes are low enough that the probability of a vehicle arriving behind the stopped vehicle is low.

2.4.3 Fixed Effects versus Random Effects versus Mixed Effects Panel *Regression Model*

Fixed-effects panel data models (Greene 2013) are estimated where the dependent variable is a transformed version of the observed travel time, and the descriptive variables include the background traffic levels, TNC volumes and TNC pick-ups and Drop-offs (PUDO). Any changes occurring within the individual data points between 2010 and 2016 not accounted for by the independent variables of the regression model will be absorbed by the error terms. Another panel regression tool, the random effects test, can be run when endogeneity exists between the explanatory variable(s), that is, when different entities acting as the descriptive variables have the tendency to affect the outcome in a manner exclusive to their identity. A fixed effects model accounts for any extant constancy across individual explanatory variables. Fixed effects are estimated using least squares (or, more generally, maximum likelihood) and random effects are estimated with shrinkage and partial pooling as opposed to fixed effects ("linear unbiased prediction" in the terminology of Robinson, 1991). It is possible to have a dataset where both these effects are exhibited (mixed effects model). Therefore, using the fixed effects linear model for the panel data was arrived at by performing the Wu-Hausman test, which checks for endogeneity between the explanatory variables in addition to determining whether a random effects model should be used to explain the distribution of the y-variable in the panel dataset instead. The Durbin-Wu-Hausman test checks whether the use of the random effects model (which is more data sensitive and thus rigorous) can be rejected (use of the random effects model is the null hypothesis being tested). It does so by testing the significance of the differences between variances of the explanatory variables under each of the two testing scenarios, thus also commenting on any significant endogeneity existing between the regressing x-variables. The Wu-Hausman test statistic is defined in Equation 4 below:

$$H = (b_1 - b_0)' \, (Var(b_0) - Var(b_1))^{+}(b_1 - b_0) \qquad \text{Equation 4}$$

Where $^{+}$ denotes the Moore-Penrose pseudoinverse (of the matrix '$\mathrm{Var}(b_0) - \mathrm{Var}(b_1)$'). Under the null hypothesis, this statistic has the chi-squared distribution asymptotically with the number of degrees of freedom equal to the rank of matrix $\mathrm{Var}(b_0) - \mathrm{Var}(b_1)$. b_0 and b_1 are coefficients of the two independent variables being tested for endogeneity.

The Wu-Hausman test rejected the presence of endogeneity between any combinations of x-variables used in the final model (also explained later by the post-hoc model validation test through Variance Inflation Factor calculations).

2.4.4 Model Estimation

As explained in the section above, to estimate the effect of other factors on the change in implied volume, a fixed-effects panel data regression model is used (Greene 2003). The fixed-effects standardize the link-dependent unexplained constancy or variance that might affect the regressed variable. Some examples of link-specific characteristics are location of links near high foot traffic, recreational areas, special roadway geometry, etc. Since these characteristics do not change between the 2010 and 2016, their influence is absorbed into the fixed effect, preventing them from biasing the other parameter estimates. The temporal unit used by the panel is '2', warranted by the before-after nature of the study. Each data point in the dataset is a unique combination of a TMC, time of day (TOD) and observation year. Since there are only two points in time, this is equivalent to estimating an ordinary least squares (OLS) model on the change on each TMC for each time-of-day. The estimated model can be expressed as:

$$V_{\mathrm{I:i,t}} = \beta_1 V_{\mathrm{SF}} + \beta_2 V_{TNC:i,t} + \beta_3 FT_{MajArt:i} * V_{AvgDur:i,t} + \beta_4 FT_{\mathrm{MinArt:i}} * V_{AvgDur:i,t} + \beta_5 PRESIDIO_{i,t} * V_{I:i,2010} + FE_i + \varepsilon_{i,t} \qquad \text{Equation 5}$$

Where the entities i are TMC links by time-of-day, and the time periods, t, are either 2010 or 2016, and each is used to index the remaining variables. $V_{I:I,t}$ is the time-implied volume. $V_{AvgDur: I, t}$ is the volume predicted by SF-CHAMP in passenger car equivalents, giving some additional weight to trucks and buses. $V_{AvgDur: I, t}$ is the average duration variable, as defined above. $FT_{MajArt: i}$ is a binary facility type flag indicating whether or not the link is a major arterial, and $FT_{MinArt: i}$ is a binary facility type flag indicating whether or not the link is a minor arterial. These facility type flags do not change between the two years. $PRESIDIO_{i, t}$ is a binary flag identifying links on the Presidio Parkway and Veterans Boulevard, where there was major construction in 2010 but not in 2016. $PRESIDIO_{i ,t}$ is defined to be 0 in 2010 and 1 in 2016 such that the effect of a change can be estimated. $V_{I:I, 2010}$ is the time-implied volume in period 1 (2010), which allows the effect of the construction change to be proportional to the starting volume on the link, as opposed to additive and the same on every link. FE_i is the fixed-effect, which is effectively a constant on each entity, and $\varepsilon_{i,t}$ is a random error term. In this specification, the Presidio flag $PRESIDIO_{i, t}$ and the TNC terms ($V_{TNC:i,t}$, $V_{AvgDur: I, t}$) are zero in 2010, so the 2010 time-implied volume is simply a function of the SF-CHAMP volume plus the fixed effect and an error term. Each observation within the constructed panel database is therefore a unique combination of year (2010 or 2016) and one of the five mentioned times of day. Each such observation lists the INRIX travel-time-implied volume which acts as the measure of speed, a Presidio Parkway flag, In-service and out-of-service TNC volume, and the PCE-worth of each pickup and drop-off maneuver occurring within the respective time frame.

2.4.5 Model Application

After the model was estimated, it was applied to all links to predict the $V_{\mathrm{I:I,t}}$ for 2010 and 2016. It is also applied to predict a 2016 counterfactual scenario with no TNCs by setting $V_{\mathrm{TNC:I,2016}}$ and $V_{\mathrm{AvgDur:I,\ 2016}}$ to zero, and otherwise applying the model to 2016 data. These predicted PCEs are then used to calculate the travel times using the volume delay functions (Equation 6).

The non-PCE volume on each link is calculated as:

$$V_{\mathrm{i,t}} = V_{SF-CHAMP:i,t} + \beta_2 V_{TNC:i,t} \qquad \text{Equation 6}$$

Where $V_{\mathrm{i,t}}$ is the traffic volume in units of vehicles instead of PCEs and $V_{\mathrm{SF\text{-}CHAMP:i,t}}$ is the SF-CHAMP volume. β_1 is excluded such that the full SF-CHAMP traffic volume is counted, (but) not their estimated effect on speed. The inclusion of β_2 (which is less than one) accounts for the partial overlap between the TNC volumes and the background volumes. These volumes are combined with the link lengths to calculate vehicle miles traveled (VMT), and combined with travel times to calculate vehicle hours traveled (VHT) and vehicle hours of delay (VHD). The average speed is calculated as VMT / VHT. The same volumes are used in combination with observed travel times to calculate observed VHT, VHD and average speed. In addition, a set of reliability metrics are calculated as described below.

2.4.6 Travel Time Reliability Metric

This study employs planning time index 80 (PTI80) as the measure of travel time reliability. It is defined as:

$$\mathrm{PTI80} = \frac{\mathrm{T}_{80}}{\mathrm{T}_0} \qquad \text{Equation 7}$$

Where T_{80} is the 80th percentile travel time and T_0 is the free flow travel time. A PTI80 value of 1.5 means that for a 30 minute trip in light traffic, 45 minutes should be planned to ensure on time arrival 80% of the time.

PTI80 can be calculated directly using measured travel times, or estimated as a function of the travel time index (TTI) (Cambridge Systematics Inc. et al 2012), which is the ratio between the average travel time and the free-flow travel time. The estimated relationship for each observation i takes the form:

$$\mathrm{PTI80}_i = \gamma_1 \mathrm{TTI}_i^{\gamma_2} \qquad \text{Equation 8}$$

Where γ_1 and γ_2 are estimated model parameters. These parameters were estimated for this study from the observed travel time data from both 2010 and 2016, with one observation for each TMC, TOD, and year combination. The relationships are specific to each facility type. Table 4 shows the results of that estimation.

Table 4 Estimated relationships between PTI80 and TTI

Facility Type	γ_1	γ_2	R-squared
Freeways and Expressways	1.029	1.498	0.831
Arterials	1.101	1.361	0.862
Collectors and Locals	1.131	1.440	0.762

PTI80 is calculated for each TMC link, TOD and year combination, and aggregated to the network level using a VMT-weighted average. The idea of following through on calibrating SF-specific parameters establishing the relationship between Travel Time Index and Planning Time Index was subsequently hatched after making a previous attempt to import facility type-specific relationships between PTI80, free flow speeds and travel time indices from chapter LR3 of the SHRP2 study detailing advisories about extant interrelationships between the three quantities since quality-controlled speed data was available on hand.

2.5 Model Estimation Results

Table 5 shows the model estimation results from the fixed-effects models. The SF-CHAMP background volume parameter estimate is 0.92, not significantly different from 1. This is logical, because it is expected that each vehicle added in background traffic should have an effect on congestion of adding 1 vehicle to the implied volume. The Presidio Parkway scaling factor accounts for major construction that was underway on those links in 2010 but not 2016, and is equivalent to reducing the 2010 implied traffic volume by 36%.

Two measures of time and location-specific TNC activity are studied as part of this dataset. The TNC volume parameter measures the net effect of TNCs. If TNCs purely substitute for other car trips, the estimated TNC parameter should be 0 as they substitute for other vehicles already counted in the background volumes. Negative values would be consistent with TNCs reducing traffic, while a value of positive 1 would be consistent with TNCs purely adding to background traffic. The estimated coefficient of 0.69 can be interpreted as an addition of 1 TNC vehicle, partially offset by a subtraction of 0.31 non-TNC vehicles.

The PUDO parameters represent the average number of seconds that a pick-up or Drop-off disrupts traffic in the curb lane. Locally collected data show that the average time needed for a passenger to board or alight from passenger vehicles such as TNCs and taxis is about 1 minute. The higher average impact durations estimated in these models suggest that the traffic disruption persists after the stopped vehicle departs because additional time is needed for traffic flow to recover to its pre-PUDO condition.

The estimated model was applied to assess network-wide performance metrics for three scenarios:

- 2010: Reflecting observed 2010 conditions, when no TNCs were present;
- 2016 No TNC: Represents a counterfactual scenario of what 2016 conditions would be if there were no TNCs;
- 2016 with TNC: The full application of the model to 2016 conditions.

Table 5 Fixed-effects panel estimation results with TNC variables included

Parameter Estimates			
Variable	Parameter	Standard Error	T-statistic
SF-CHAMP background volume	0.9172	0.0541	16.952
Presidio Parkway scaling factor	-0.3648	0.0189	-19.327
TNC Volume	0.6864	0.0720	9.5387
Average impact duration of TNC PUDO on major arterials (s)	144.75	7.7195	18.751
Average impact duration of TNC PUDO on minor arterials (s)	79.486	12.114	6.5617
Model Statistics			
Number of Entities		7081	
Number of Time Periods		2	
R-squared between groups		0.5819	
R-squared within groups		0.2985	

2.5.1 Model Diagnostics

Since the estimated model includes both TNC volumes and TNC PUDO as the descriptive variables, it was imperative that one considers about the possibility and implications of multicollinearity within these two explanatory variables. Any existing correlation between the TNC volume and the TNC PUDO terms was observed by testing different model specifications. If the PUDO variables are removed, the TNC volume coefficient increases in magnitude, and vice-versa. This also suggests that it may be difficult to precisely estimate how their combined descriptive power is allocated between these two variables, so the risk is the possibility of over-estimating one while under-estimating the other. However, the risk may be greater in excluding one of the two variables, because the effect of the other may be overestimated. When this experiment was done, it was found that the remaining variables in the model, including the SF-CHAMP volume, stay quite stable. This means that one can be more confident in attributing the TNC volume and PUDO effect to TNCs and the potential to falsely allocate the blame of worsening traffic congestion is largely restricted within these two variables. This minimizes the propensity of encountering the “missing variable” conundrum within the estimated parametric model.

To further check whether multicollinearity poses a challenge to the current interpretation of the model results, the standard symptoms of multicollinearity within the variables of concern were sought out. It was noted that each variable of concern exhibited individually significant slopes and the correlations among pairs of predictor variables were not large. The latter was done by calculating the Variance Inflation Factor (VIFs) for all the descriptive variables.

A VIF quantifies how much the variance (and consequently, their contribution to the R-squared of the model) is inflated. VIFs test not only for the pairwise correlation between variables, but for multicollinearity, which could be due to a combination of variables. VIFs above ‘5’ are generally considered to indicate high levels of collinearity. It is known that the variance of the estimated coefficient b_k in a model where only one predictor ‘x’ exists is:

$$\mathrm{Var}(b_k)_{min} = \frac{\sigma^2}{\sum_{i=1}^{n} \left(X_{ik} - X_{(avg)k}\right)^2} \qquad \text{Equation 9}$$

Where, σ = Standard deviation of the variable of which b_k is a coefficient,

X_{ik} = value of the predictor ‘x’ at the i^{th} data point,

The ‘min’ subscript denotes the minimum possible value for the variance of the coefficient b_k since only one predictor variable is considered in this specific example

On the other hand, if one considers a model where more than one predictor variables exist, where some of the other predictors are correlated with the predictor X_k, then the variance of b_k gets inflated, that is, it does not stay confined to its minimum value calculated in Equation 9. It can then be shown that the variance of b_k is:

$$\mathrm{Var}(b_k)_{min} = \frac{\sigma^2}{\sum_{i=1}^{n} \left(X_{ik} - X_{(avg)k}\right)^2} \text{ X } \frac{1}{1-R_k^2} \qquad \text{Equation 10}$$

Where, R_k^2 is the R^2 value obtained by regressing the k^{th} predictor on the remaining predictors. The greater the linear dependence among the predictor X_k and the other predictors, the larger is the value of R_k^2. Also, the larger the R_k^2 value, the larger is the variance of b_k.

The variance inflation factor is obtained by comparing the increase in R-squared by adding each successive regressor variable for all pairs of variables included in a model. A Variance Inflation Factor exists for each of the k predictors in a multiple regression model, or in this case, the panel regression model. Since a VIF is a measure of the "inflation" of the variance *due to* the presence of correlation between the explanatory variables within a model, a VIF of 1 indicates that there exists no correlation between the k^{th} predictor and the remaining predictors variables implying that the variance of b_k is not inflated at all. The generally accepted norm is that VIFs exceeding '4' warrant further investigation into the inclusion of the represented correlated variables, and VIFs exceeding '10' exhibit signs of severe multicollinearity requiring correction. Therefore, one can calculate the ratio of the two variances, the inflated variance to the minimum variance, and come up with the expression:

$$\mathrm{VIF_k} = \frac{1}{1-\mathrm{R_k^2}} \qquad \text{Equation 11}$$

Table 6 presents the calculated VIFs. We see that none of the VIFs are close to 5, which as mentioned before, would have presented a cause for concern related to variable endogeneity.

Table 6 Variance Inflation Factors (VIFs)

Variable	VIF
CHAMP_VOL	1.5
TNC_VOL	2.4
AVG_DUR_MAJOR_ARTERIALS	1.7
AVG_DUR_MINOR_ARTERIALS	1.2
BASE_INRIX_VOL_PRESIDIO	1.0

It was observed that the VIFs are modest and do not indicate a major cause for concern.

Endogeneity is the correlation between the X variable and the error term in a model. **Figure 12** shows a scatterplot of the fitted values versus the model's residuals. It does not show any obvious correlation. The possibility of endogeneity due to a missing variable, including speculation about what such a missing variable may be has been discussed before. It can also be noted that the use of a fixed effects model (as opposed to a cross-sectional model) is considered to be a preferred intervention when endogeneity is a concern. This is because any confounding factor that is present cross-sectionally but stable in time simply falls out of the model.

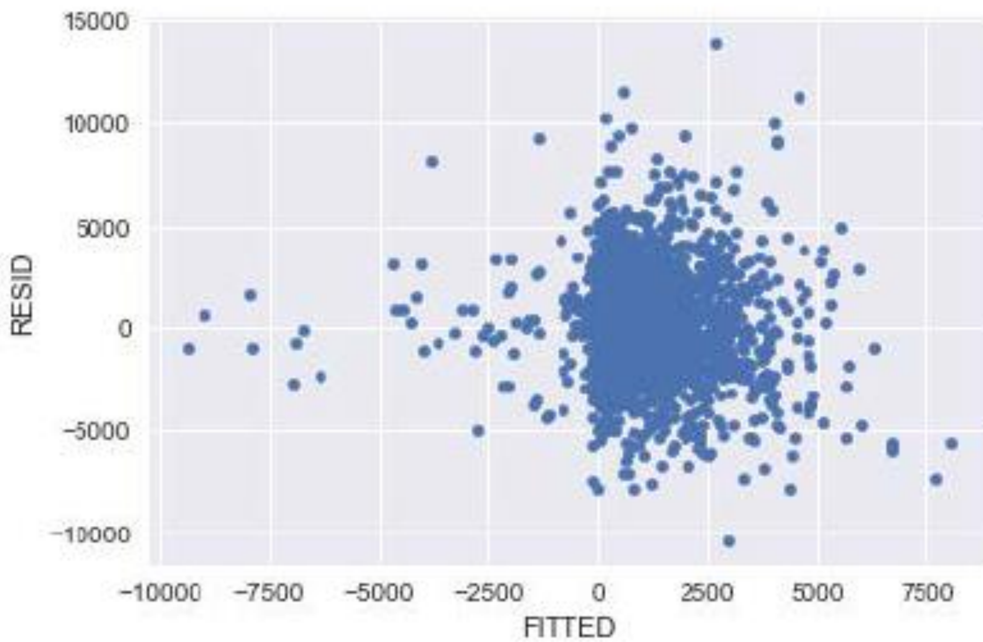


Figure 12 Correlation between fitted values and residuals

2.5.2 Supplemental Model Estimation

One notable variation in the models tested relates to the proposed hypothesis that TNCs have no effect on traffic congestion. If this were true, one would expect the change in background volume alone to reasonably predict the change in time-implied volume

(V_1). Table 7 shows the estimation results testing this hypothesis. It includes only two of the above parameters: the background volume as estimated by SF-CHAMP, and a scaling factor applied to the Presidio Parkway and Veterans Boulevard. The Presidio parameter can be interpreted as a travel time increase equivalent to reducing the 2010 implied traffic volume by 39%. The background volume is highly correlated with V_I, with a coefficient of 1.78. This suggests that time-implied volumes are increasing by 78% more than SF-CHAMP would predict. It appears that the employment, population and network changes do not fully describe the congestion changes observed during this period, and more terms are needed to do so.

Since the distribution of congestion effects is not uniform throughout the network or throughout the day, it is desired that one look into the variations that occur when the dataset is sliced across different times of day and across various categories of areas across the city. **Figure 13** maps the speed difference between the TNC scenario and the no-TNC counterfactual for four times of day. TNCs have a larger effect on congestion in the downtown area and on arterial roadways. One might argue that since the inner core and downtown areas have always been congested to begin with, it is only natural that the worst decline be experienced within those areas. It should be noted that the dependent variable in the fixed-effects model is the INRIX-implied volume, which is linear with respect to changes in the traffic volume. The positive coefficients on TNC volume and TNC PUDO suggest that the INRIX-implied volume increases more on TMCs and in time periods with high TNC concentrations that would be expected from other background factors. Changes beyond what is expected that are concentrated on other links, occur uniformly, or occur randomly would be absorbed by the model's error term, not by these coefficients. TNCs are also shown to have a disproportionately large effect on evening congestion, but they also increase congestion in the peak periods: a 48-52% increase in VHD in the AM and PM periods with TNCs, versus an 18-23% increase for the no-TNC counterfactual.

The more complete specification, as reported in **Table 5**, has a better fit and further, includes a coefficient on the SF-CHAMP volume that is close to 1. This means that once the effects of TNCs has been accounted for, the change in SF-CHAMP volume reasonably predicts the remaining change. A number of variations on this specification were attempted before arriving at the preferred model. For example, specifications were tested that split the TNC volume into separate in-service and out-of-service volumes or segmented the PUDO coefficients in different dimensions. One notable variation relates to the hypothesis that TNCs have no effect on traffic congestion. If this were true, one would expect the change in background volume alone to reasonably predict the change in time-implied volume ($V1$). Estimating such a model reveals that the background volume is highly correlated with $V1$, with a coefficient of 1.78. This suggests that time-implied volumes are increasing by 78% more than SF-CHAMP would predict. It appears that the employment, population and network changes do not fully describe the congestion changes observed during this period, and more terms are needed to do so.

Table 7 Fixed-effects panel model estimation results only accounting for background traffic

Parameter Estimates			
Variable	Parameter	Standard Error	T-statistic
SF-CHAMP background volume	1.7816	0.0468	38.052
Presidio Parkway scaling factor	-0.3869	0.0202	-19.144
Model Statistics			
Number of Entities		7081	
Number of Time Periods		2	
R-squared between groups		0.7192	
R-squared within groups		0.1941	

2.6 Model Application Results

The model was applied to all TMCs, as described in *Section 2.4.5* for three scenarios: 2010, 2016 without TNCs, and 2016 with TNCs. Table 8 presents network performance metrics for these three scenarios. VMT grows by 13% between 2010 and 2016, with almost half of the VMT increase attributable to TNCs. Vehicle hours traveled (VHT), vehicle hours of delay (VHD) and average speed using both modeled travel times and, where available, observed travel times have been calculated. In the absence of TNCs, VHT would be 12% higher in 2016 than 2010, VHD would be 22% higher, and average speed would be 4% lower. With TNCs, VHT is 30% higher, VHD is 62% higher and speeds are 13% lower. The R-squared within groups is 0.2985 and the R-squared between groups is 0.5819. These values are in line with what can be reasonably expected for a system like transportation. The explanatory variables that are included in the model are highly significant.

In addition, travel time is becoming less reliable, as measured by the planning time index 80 (PTI80). PTI80 is the ratio between the 80th percentile travel time and the free-flow travel time. It is a measure of the day-to-day variability of travel time. The PTI80 value of 1.8 means that for a 10-minute trip in uncongested condition, 18 minutes should be planned to ensure on time arrival 80% of the time. Between 2010 and 2016, PTI80 increases by 15% with TNCs or 6% without.

Table 8 Network Performance Metrics in Base Year, Counterfactual Year 2016 and Actual Year 2016 along with Percent Difference between Base Year and the others

	Network Performance Metrics								
		Based on Modeled Travel Time				Based on Observed Travel Time			
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
2010	4,923,449	205,391	64,863	24.0	1.83	204,686	64,158	24.1	1.83
2016 No TNC	5,280,836	230,642	79,449	22.9	1.94	N/A	N/A	N/A	N/A
2016 with TNC	5,559,412	266,393	105,377	20.9	2.12	269,151	108,134	20.7	2.21
	Percent Change from 2010								
		Based on Modeled Travel Time				Based on Observed Travel Time			
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
2016 No TNC	7%	12%	22%	-4%	6%	N/A	N/A	N/A	N/A
2016 with TNC	13%	30%	62%	-13%	15%	31%	69%	-14%	21%

The changes summarized in Table 8 are not evenly distributed throughout the network or throughout the day. **Figure 13** shows the speed difference between the 2016 scenario with TNCs and that for the no-TNC counterfactual. The warmer colors show a greater drop in speed with the addition of TNCs. The figures show that the speed drops are concentrated in the northeast quadrant of the city, which includes the downtown area, the most existing congestion, and the highest density of TNC use.

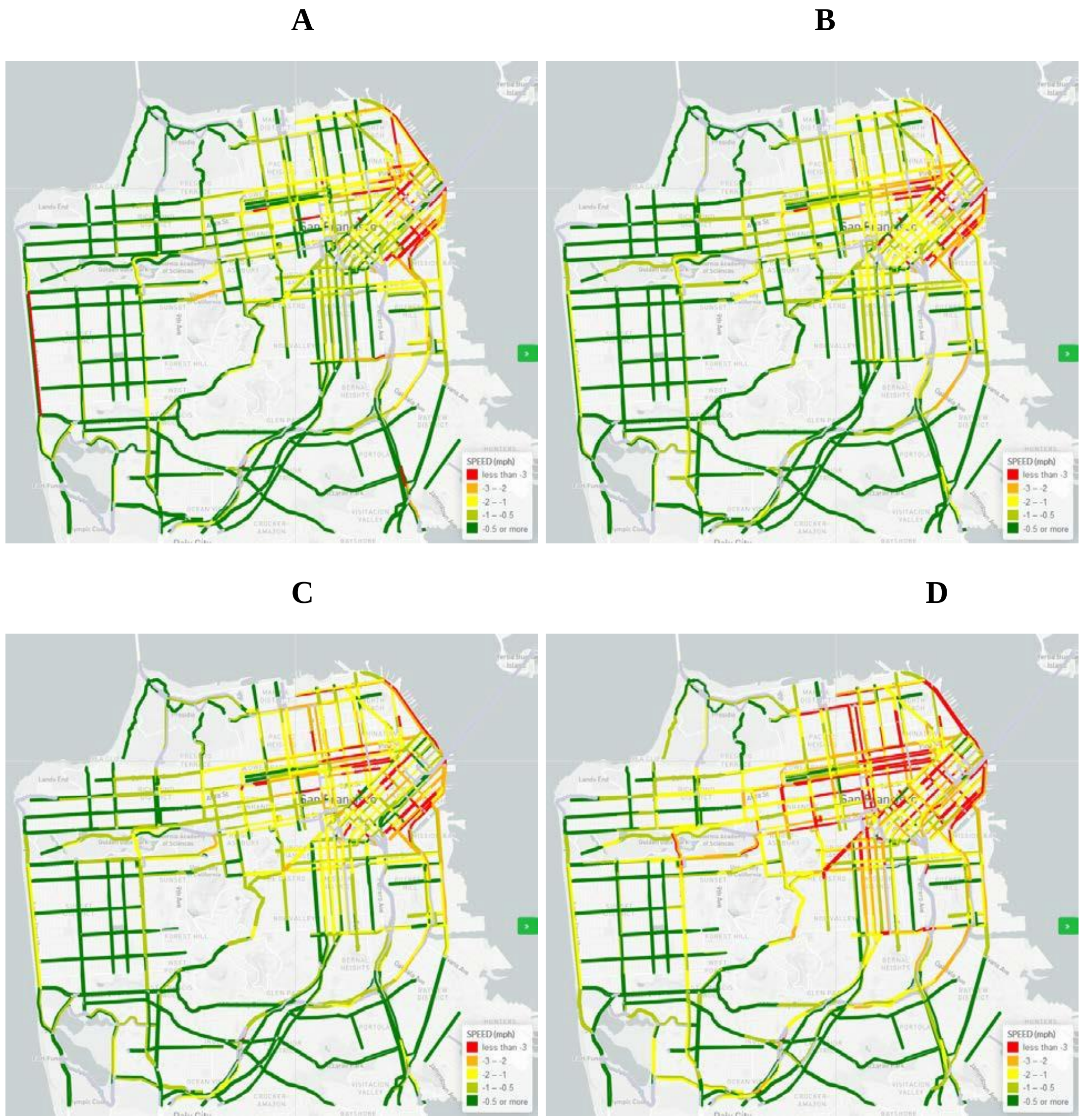


Figure 13 Speed (mph) difference between 2016 scenario with TNCs and a counterfactual 2016 scenario without TNCs for (A) 6-9 AM, (B) 9 AM-3:30 PM, (C) 3:30-6:30 PM, and (D) 6:30 PM-3:00 AM.

Table 9 shows the network performance metrics segmented by time-of-day. The results show that the 2016 scenario with TNCs higher VMT, VHT, VHD and BTI80 and lower speeds than the 2016 no TNC scenario throughout the day, including in the AM and PM peak periods.

Table 9 Modeled and Observed Network Performance Metrics by Time-of-Day and Percent Changes from the Base Year

Time-of-Day	Scenario	Network Performance Metrics								
			Based on Modeled Travel Time				Based on Observed Travel Time			
		Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
6:00 AM-9:00 AM	2010	805,002	32,718	10,180	24.6	1.79	32,955	10,417	24.4	1.95
	2016 No TNC	860,180	36,661	12,509	23.5	1.90	N/A	N/A	N/A	N/A
	2016 with TNC	891,673	40,739	15,467	21.9	2.04	40,651	15,379	21.9	2.33
9:00 AM-3:30 PM	2010	1,848,690	77,735	24,391	23.8	1.74	77,125	23,781	24.0	1.69
	2016 No TNC	1,988,010	88,154	30,587	22.6	1.86	N/A	N/A	N/A	N/A
	2016 with TNC	2,065,117	99,575	39,288	20.7	2.02	101,153	40,867	20.4	2.19
3:30 PM-6:30 PM	2010	1,027,916	49,206	19,485	20.9	2.43	48,137	18,415	21.4	2.32
	2016 No TNC	1,086,243	54,516	23,005	19.9	2.58	N/A	N/A	N/A	N/A
	2016 with TNC	1,126,449	61,819	28,832	18.2	2.80	64,097	31,111	17.6	2.68
6:30 PM-3:00 AM	2010	1,107,141	41,199	9,917	26.9	1.52	41,983	10,700	26.4	1.59
	2016 No TNC	1,196,599	46,103	12,224	26.0	1.59	N/A	N/A	N/A	N/A
	2016 with TNC	1,316,689	58,572	20,473	22.5	1.82	57,306	19,207	23.0	1.86
3:00 AM-6:00 AM	2010	134,700	4,532	890	29.7	1.39	4,487	844	30.0	1.39
	2016 No TNC	149,803	5,208	1,124	28.8	1.43	N/A	N/A	N/A	N/A
	2016 with TNC	159,485	5,689	1,316	28.0	1.47	5,943	1,570	26.8	1.51
Total	2010	4,923,449	205,391	64,863	24.0	1.83	204,686	64,158	24.1	1.83
	2016 No TNC	5,280,836	230,642	79,449	22.9	1.94	N/A	N/A	N/A	N/A
	2016 with TNC	5,559,412	266,393	105,377	20.9	2.12	269,151	108,134	20.7	2.21

Time-of-Day	Scenario	Percent Change from 2010								
			Based on Modeled Travel Time				Based on Observed Travel Time			
		Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Plannin g Time Index 80
6:00 AM-9:00 AM	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	12%	23%	-5%	6%	N/A	N/A	N/A	N/A
	2016 with TNC	11%	25%	52%	-11%	14%	23%	48%	-10%	19%
9:00	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 9, continued" on 2nd page of table

AM-3:30 PM	2016 No TNC	8%	13%	25%	-5%	7%	N/A	N/A	N/A	N/A
	2016 with TNC	12%	28%	61%	-13%	16%	31%	72%	-15%	30%
3:30 PM-6:30 PM	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	6%	11%	18%	-5%	6%	N/A	N/A	N/A	N/A
	2016 with TNC	10%	26%	48%	-13%	15%	33%	69%	-18%	16%
6:30 PM-3:00 AM	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	8%	12%	23%	-3%	4%	N/A	N/A	N/A	N/A
	2016 with TNC	19%	42%	106%	-16%	19%	36%	79%	-13%	17%
3:00 AM-6:00 AM	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	11%	15%	26%	-3%	3%	N/A	N/A	N/A	N/A
	2016 with TNC	18%	26%	48%	-6%	5%	32%	86%	-11%	8%
Total	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	12%	22%	-4%	6%	N/A	N/A	N/A	N/A
	2016 with TNC	13%	30%	62%	-13%	15%	31%	69%	-14%	21%

Table 10 Network Performance Metrics by Area Type

		Network Performance Metrics								
			Based on Modeled Travel Time				Based on Observed Travel Time			
Area Type	Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
Regional Core	2010	380,981	28,578	10,214	13.3	2.05	28,529	10,165	13.4	2.08
	2016 No TNC	431,106	34,200	13,516	12.6	2.22	N/A	N/A	N/A	N/A
	2016 with TNC	481,326	46,321	23,202	10.4	2.86	46,652	23,533	10.3	2.87
Central Business District	2010	1,128,774	57,469	19,526	19.6	2.13	56,550	18,608	20.0	2.01
	2016 No TNC	1,213,840	65,430	24,459	18.6	2.28	N/A	N/A	N/A	N/A
	2016 with TNC	1,314,005	78,652	33,814	16.7	2.52	80,327	35,489	16.4	2.67
Urban Business	2010	1,960,197	63,672	18,420	30.8	1.70	63,357	18,105	30.9	1.74
	2016 No TNC	2,107,126	71,715	23,113	29.4	1.81	N/A	N/A	N/A	N/A
	2016 with TNC	2,193,400	78,972	28,060	27.8	1.93	79,536	28,624	27.6	2.08
Urban	2010	1,453,498	55,673	16,704	26.1	1.73	56,249	17,280	25.8	1.76
	2016 No TNC	1,528,763	59,297	18,361	25.8	1.76	N/A	N/A	N/A	N/A
	2016 with TNC	1,570,681	62,448	20,301	25.2	1.82	62,635	20,489	25.1	1.82

Table 10, continued” on 2nd page of table

Area Type	Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
Total	2010	4,923,449	205,391	64,863	24.0	1.83	204,686	64,158	24.1	1.83
	2016 No TNC	5,280,836	230,642	79,449	22.9	1.94	N/A	N/A	N/A	N/A
	2016 with TNC	5,559,412	266,393	105,377	20.9	2.12	269,151	108,134	20.7	2.21

		Percent Change from 2010								
			Based on Modeled Travel Time				Based on Observed Travel Time			
Area Type	Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Plannin g Time Index 80	Vehicle Hours Travele d	Vehicle Hours of Delay	Average Speed (mph)	Plannin g Time Index 80
Regiona l Core	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	13%	20%	32%	-5%	9%	N/A	N/A	N/A	N/A
	2016 with TNC	26%	62%	127%	-22%	39%	64%	132%	-23%	38%
Central Business District	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	8%	14%	25%	-6%	7%	N/A	N/A	N/A	N/A
	2016 with TNC	16%	37%	73%	-15%	18%	42%	91%	-18%	33%
Urban Business	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	13%	25%	-5%	7%	N/A	N/A	N/A	N/A
	2016 with TNC	12%	24%	52%	-10%	14%	26%	58%	-11%	19%
Urban	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	5%	7%	10%	-1%	2%	N/A	N/A	N/A	N/A
	2016 with TNC	8%	12%	22%	-4%	5%	11%	19%	-3%	4%
Total	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	12%	22%	-4%	6%	N/A	N/A	N/A	N/A
	2016 with TNC	13%	30%	62%	-13%	15%	31%	69%	-14%	21%

Table 10 shows the network performance metrics segmented by area type. **Figure 14** shows a map of the area types. The metrics show that the effect of TNCs is biggest in the densest area types. There are six area type categorizations mapped in this figure, namely, the regional core, central business district, urban business district, urban, suburban and rural. For example, in the regional core, the model shows that VHD is 112% higher in 2016 than in 2016, compared to only 13% higher for the no-TNC counterfactual. **Table 11** documents the results of the analysis segmented by the three facility types. It is observed that the facility type arterials (both major and minor) are the most severely affected functional classifications when the increase in travel time is

compared both to the base year as well as the counterfactual 2016 scenarios. This implication also falls in accordance with the existing research which designates arterials as the most common hotspots for pickups and Drop-offs and general TNC presence.

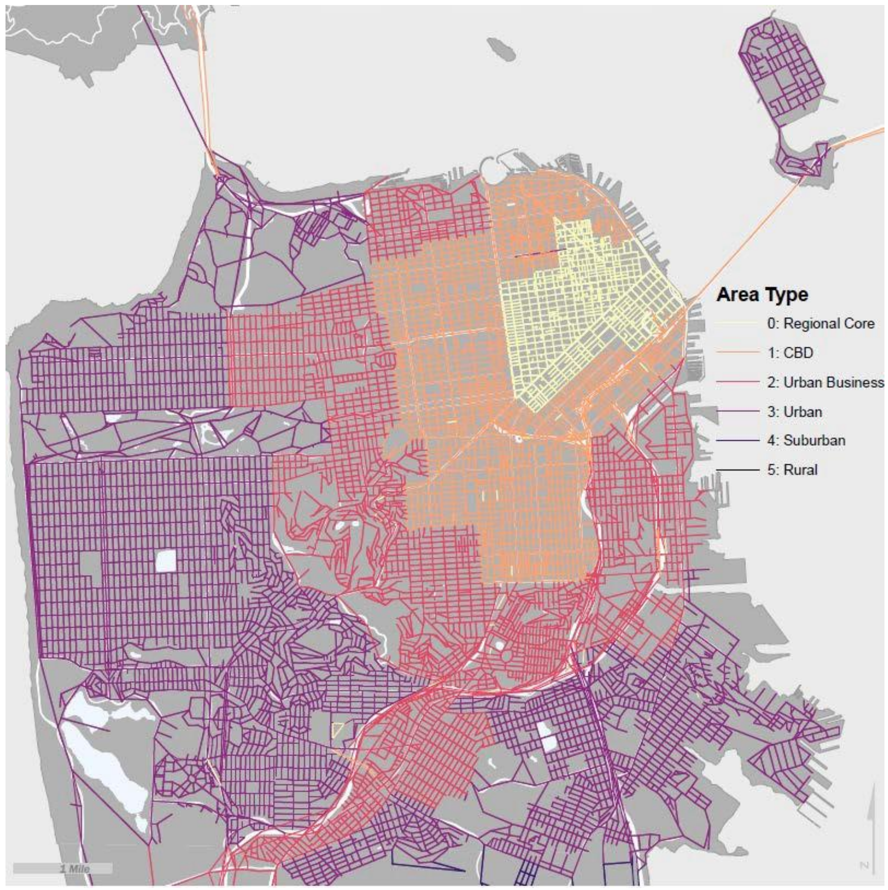


Figure 14 Area type map on SF-CHAMP links

Table 11 Modeled and Observed Network Performance Metrics by Facility Type and Percent Changes from the Base Year

		Network Performance Metrics								
			Based on Modeled Travel Time				Based on Observed Travel Time			
Facility Type	Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
Freeways & Ramps	2010	2,201,707	47,332	13,368	46.5	1.77	46,651	12,687	47.2	1.75
	2016 No TNC	2,347,348	51,807	15,602	45.3	1.85	N/A	N/A	N/A	N/A
	2016 with	2,416,922	54,503	17,233	44.3	1. 91	56,401	19,132	42.9	2.16

Table 11, continued" on 2nd page of table

	TNC									
Major Arterials	2010	1,943,506	102,528	33,687	19.0	1.91	102,817	33,976	18.9	1.94
	2016 No TNC	2,102,905	117,620	42,919	17.9	2.05	N/A	N/A	N/A	N/A
	2016 with TNC	2,241,568	139,511	59,512	16.1	2.33	139,680	59,682	16.0	2.29
Minor Arterials	2010	524,855	37,767	12,639	13.9	1.93	37,520	12,392	14.0	1.87
	2016 No TNC	560,389	41,534	14,700	13.5	2.01	N/A	N/A	N/A	N/A
	2016 with TNC	605,131	49,020	20,006	12.3	2.26	49,578	20,564	12.2	2.23
Collectors & Locals	2010	253,381	17,765	5,170	14.3	1.69	17,698	5,103	14.3	1.72
	2016 No TNC	270,194	19,681	6,229	13.7	1.76	N/A	N/A	N/A	N/A
	2016 with TNC	295,791	23,360	8,625	12.7	1.93	23,492	8,757	12.6	1.98
Total	2010	4,923,449	205,391	64,863	24.0	1.83	204,686	64,158	24.1	1.83
	2016 No TNC	5,280,836	230,642	79,449	22.9	1.94	N/A	N/A	N/A	N/A
	2016 with TNC	5,559,412	266,393	105,377	20.9	2.12	269,151	108,134	20.7	2.21

		Percent Change from 2010								
			Based on Modeled Travel Time				Based on Observed Travel Time			
Facility Type	Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
Freeways & Ramps	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	9%	17%	-3%	5%	N/A	N/A	N/A	N/A
	2016 with TNC	10%	15%	29%	-5%	8%	21%	51%	-9%	24%
Major Arterials	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	8%	15%	27%	-6%	8%	N/A	N/A	N/A	N/A
	2016 with TNC	15%	36%	77%	-15%	22%	36%	76%	-15%	18%
Minor Arterials	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	10%	16%	-3%	4%	N/A	N/A	N/A	N/A
	2016 with TNC	15%	30%	58%	-11%	17%	32%	66%	-13%	19%
Collectors & Locals	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	11%	20%	-4%	4%	N/A	N/A	N/A	N/A
	2016 with TNC	17%	31%	67%	-11%	14%	33%	72%	-12%	15%
Total	2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
	2016 No TNC	7%	12%	22%	-4%	6%	N/A	N/A	N/A	N/A
	2016 with TNC	13%	30%	62%	-13%	15%	31%	69%	-14%	21%

2.7 Discussion

Our results show higher VMT and more congestion in the 2016 TNC scenario than in the no-TNC counterfactual. These results are consistent with the subset of TNC rider surveys that were able to assist in drawing a conclusion about the net VMT effect of TNCs (Henao 2017; Gehrke, Felix and Reardon 2018), and they provide complementary evidence to the subset of surveys that were inconclusive regarding the net effect of TNCs on VMT (Rayle et al. 2016; Clewlow and Mishra 2017). The results of this study are also consistent with the most recent findings in New York that TNCs add VMT and increase congestion (Shaller 2017).

2.7.1 Comparison to existing literature

Our findings differ from the conclusions of several other studies (Martinez and Viegas 2017; Feigon and Murphy 2016; Feigon and Murphy 2018; Li, Hong and Zhang 2016; City of New York 2016). The relationship between the findings of this research and those of these other mentioned studies are discussed below.

A study by Li, Hong and Zhang finds "reasonable evidence that the entry of Uber significantly decreases traffic congestion in the urban areas of the U.S." (Li, Hong and Zhang 2016). This study estimates models of the change in annual congestion in metropolitan areas from 1982 to 2014 as measured by the Urban Mobility Report (Schrank, Eisele, Lomax and Bak 2015). It introduces a binary variable into the model based on the year of Uber's entry into each market and uses the negative coefficient estimate as the basis for their conclusion. There are two issues with this approach. First, it does not reflect spatial detail in the distribution of TNCs, which are heavily concentrated in downtown areas, so the aggregate nature of the study may obscure the underlying effect. Second, it does not capture the quantity of TNC use, which varies between cities and continues to grow after entering a market. This study does better on both accounts.

The City of New York (2016) used New York's travel demand model to develop 2010 and 2020 VMT estimates, and examined e-dispatch trip records in comparison to those total VMT estimates. They based their conclusion that TNCs did not drive the recent increase in congestion on a projection that TNCs largely substitute for yellow taxi trips, and on a lack of evidence for congestion effects associated with PUDO. The results show that, at least in San Francisco, substitution for taxis and cars only offsets a portion of the TNC volume, and they provide evidence of a PUDO effect.

Simulations, such as the "Portugal Study", showing large benefits from ride-splitting assume full participation and centralized optimization (Martinez and Viegas 2017). These assumptions do not reflect the way in which TNCs operate today. While the present data do not include vehicle occupancy, other survey data show a modest share of ride-splitting (Henao 2017; Gehrke, Felix and Reardon 2018), and the current study results suggest that it is not sufficient to offset the ways in which TNCs add to congestion. Such simulations can be useful in establishing the positive potential of ride-splitting if such a system were effectively managed to achieve socially desirable outcomes, but do not imply that TNCs will achieve those outcomes on their own.

Two notable studies by Feigon and Murphy (2016 and 2018) promote the idea of TNCs as a complement to public transit. These studies base their conclusions primarily on data summaries generated from surveys of shared mobility users. Feigon and Murphy conclude that because TNC use is high in the evening and weekend periods when transit service is less frequent, TNCs largely complement public transit and enhance urban mobility. However, their own data show (Feigon and Murphy 2018), and ours confirm, that TNC use is also high during the peak periods when congestion is worst and transit service is frequent. Feigon and Murphy find that a greater use of shared modes is associated with more frequent transit use (2016). However, this finding should not be taken to imply a directional relationship, as it could be that frequent transit users are likely to switch some trips to TNC, adding traffic to the roads. Feigon and Murphy also note that TNC use is associated with decreases in respondents' vehicle ownership and private vehicle trips.

While this may be true for specific users, no aggregate changes were observed in vehicle ownership in San Francisco between 2010 and 2016. Further, this finding only accounts for the subtraction of private vehicle trips, not the addition of TNC vehicle trips. The results of this study indicate that the net effect of TNCs is to add more vehicles to the road.

2.7.2 Limitations

Some limitations of this study are worth being cognizant of and are addressed in this section.

1. The analysis relies on VDFs that are limited in their ability to capture the underlying complexity of traffic flow (Chiu et al. 2011). They should be viewed as a means of understanding the aggregate relationships observed in the data, not of the expected operations at a specific location.
2. While the predicted background traffic changes account for several important control variables, there remains a risk that the present results are confounded by another

factor. For example, this analysis controls for demographic and socioeconomic changes over this period, but like all travel models, SF-CHAMP assumes that the relationship between those inputs and the resulting travel behavior remains stable. If there are major behavioral changes over this period, it could affect the result. Similarly, some have hypothesized that growing freight and commercial vehicle traffic, attributable to the rise in e-commerce (Pettersson, Hiselius and Koglin 2018, Uber spokespeople 2018), may be an important contributor to growing congestion. SF-CHAMP accounts for the growth in delivery trucks and freight traffic as per the standard increase in demand of these services generated by the growing population and employment. Whether delivery trucks themselves are responsible for the growth in congestion cannot be measured specifically since data encompassing this mode of transport is not available and is outside the purview of this study. It is assumed that this effect is accounted for in the background traffic growth. One additional thing to keep in mind is that the empirical study implied that the most severe worsening in congestion is observed in the core of the city. This is reasonable since this area was the most congested to begin with and thus lies on the extreme right and exponential area of the volume delay curve. Presence of Commercial Vehicle Loading Zones (CVLZs) are the norm in this part of the city and it is very uncommon, not to mention, impractical/very challenging, for delivery trucks to park anywhere other than these designated zones in this part of the city. CVLZs are present in most arterial roadways within the city, which is why it is found safe to assume that their contribution to increasing congestion in the city is not underestimated. This analysis reflects growth in truck travel associated with growing employment, but it does not account for structural changes such as a large shift from in-person to online shopping. Such a shift could increase delivery truck volumes, but decrease personal shopping trips (Petterson, Hiselius and Koglin 2018). The net effect of this trade-off is not clear, and depends on factors such as how efficiently the delivery vehicle can chain multiple deliveries together, what time-of-day the different trips would occur, and whether the deliveries are to commercial locations in the downtown area or to less congested residential areas. Unfortunately, the commercial vehicle data necessary to evaluate that effect is found lacking.

As the possibility of other uncontrolled factors are considered, it is worth keeping in mind a few aspects of this research. To have an effect, any uncontrolled factors must be different between 2010 and 2016. Also, these estimation results show that congestion is growing more than expected specifically on the links and in time periods with high levels of TNC activity. The most problematic factors would be those that are spatially and temporally correlated with TNCs, occurring on those same links in the same time periods.

3. The analysis presented here is specific to a single city with a dense urban core and a rich transit system. The data show that TNC use is heavily concentrated in the densest portion of that city, consistent with evidence from other cities (Feigon and Murphy 2018). While one may expect similar results in other comparable cities, further research is needed to confirm that expectation. Moreover, a framework supplemented with comparable datasets to carry out similar studies in areas not surrounded by a coastline and heavy traffic along it unlike San Francisco, has been attained. Given a background traffic modelling/estimating platform such as SF-CHAMP, a database of

TNC trips enlisting in-service and out-of-service TNC volumes, pickup and drop-off locations and volumes, consistent estimates of speed and travel time reliability, this study can be replicated for similarly dense metropolitan cities. The effects of TNCs may be quite different in smaller cities, in less compressed roadway networks, less dense areas, or in places with very different combinations of populations, detour route options or regulatory environments. In such cases, it is expected that a vigorous activity-based model, such as SF-CHAMP, will be designed to be sensitive enough to respond to rerouting maneuvers that could potentially calm down extremely congested conditions.

Several extensions would complement this research: better understanding the contributors to background growth, assessing the TNC effect on transit ridership, and considering how worsening congestion and travel time reliability affect transit operations. Finally, the study should be repeated elsewhere to understand how the results vary in cities of different sizes and compositions.

2.8 Conclusions

This study examines the effect of TNCs on traffic congestion and reliability in San Francisco. It is intended to adjudicate between competing arguments about whether TNCs decrease or increase congestion.

The results show that the observed changes in travel time are worse than the background changes would predict. The estimated TNC volume and PUDO coefficients show that travel times get worse on roads with more TNC activity than on roads with less

TNC activity after controlling for background traffic changes. This result supports the hypothesis that TNCs increase congestion, at least in San Francisco.

The results show some substitution between TNCs and other car trips, but that most TNC trips are adding new cars to the road. The estimated models show that TNC vehicles stopping at the curb to pick-up or drop-off passengers have a notable disruptive effect on traffic flow, especially on major arterials.

The model is applied to estimate network-wide conditions for 2016 and for a counterfactual scenario that estimates what conditions would be in 2016 if there were no TNCs. Both are compared to a 2010 baseline, before TNCs. VMT, VHT and VHD increase by 13%, 30% and 62%, respectively, from 2010 to 2016. Without TNCs, those same metrics would have increased by 7%, 12% and 22%. Average speeds decrease by 13%, compared to a 4% decrease without TNCs. TNCs are associated with worsening travel time reliability, thus requiring travelers to further buffer their travel times if they wish to consistently arrive on-time. These results lead us to conclude that TNCs are the biggest factor driving the rapid growth of congestion and deterioration of travel time reliability in San Francisco between 2010 and 2016, exceeding the combined effects of population growth, employment growth and network changes. These findings are of interest to transportation planners, to policy makers, and to the general public in San Francisco and other large cities. It is in the public interest that decisions about the regulation of TNCs, the allocation of curb space and right-of-way, and the integration of new mobility services with existing transit operations be based on independent analysis as presented here.

CHAPTER 3. THE MODEL-BASED VALIDATION STUDY

3.1 Overview

In this section, the research detailed in the preceding chapter has been built upon to further decompose the factors contributing to the rapid growth of congestion in San Francisco between 2010 and 2016. Following a review of the possible explanations for growing congestion, each of them is evaluated by conducting a series of controlled experiments using the regions travel demand model, SF-CHAMP. In doing so, Axelrod's model of simulation as a "third way of doing science" was followed (Axelrod 2006). As mentioned in the previous chapter, to evaluate the effect of TNCs, an observed TNC trip table derived from data scraped from the Application Programming Interfaces (APIs) of two TNCs (Cooper et al. 2018) had been incorporated. This section builds upon the results of the previous section which was an assessment of the TNCs' effect on congestion by considering TNCs' substitution with other modes in a more direct and thorough fashion, by considering diversion effects within the network, and by decomposing the factors affecting congestion in more detail. In that chapter, it was established that congestion increased sharply between 2010 and 2016 due to factors not solely limited to the conventional drivers of congestion. While it was inferred that a rise in congestion and travel time was inevitable between the two study years due to the rapid increase in both population and employment in this post-recession period of study, it was also proven that not all of the decline in network performance can be attributed to these typical factors of congestion growth alone. The analysis detailed in chapter 2 empirically estimated the increase in total vehicle hours traveled in a counterfactual 2016 scenario to be about 12% as compared to base year (2010) conditions. The observed increase in same was about 31% in 2016 and the modelled increase in VHT in 2016 was about 30%. Similar differences between the year 2010, counterfactual 2016 and observed (along with modelled conditions for 2016) 2016 were observed for other performance measures like average speed, vehicle hours of delay and planning time indices as well. This chapter aims to explain the staggering difference between the actual (both modelled and observed) conditions in 2016 and that modeled for the counterfactual scenario while also attempting to unravel the distinct contributions of the three conventional factors of congestion growth: population, employment and changes in network that make up the 12% increase in the no-TNC scenario. The results of this study aim to provide transportation planners and policy makers with a better understanding of the problem, so they can more effectively evaluate and manage congestion.

3.2 Possible Causes

There are a number of possible explanations for the causes of increased traffic congestion over this period. The focus here is on the change between the two study years, allowing cross- sectional factors, such as different urban forms or different population compositions that may be important in describing congestion in different cities to be discounted unless they are assumed to have changed over the analysis period. The factors that are reasonably thought to have changed apart from the variable of interest in this study, ‘TNCs’, are described below, drawing, where appropriate, from relevant literature.

3.2.1 Socioeconomic Factors

It is well-established that levels of congestion and vehicle miles traveled are related to socioeconomic factors, including population, employment and household income (Marshall 2016; Chang, Lee, and Choi 2017; Bastian, Börjesson, and Eliasson 2016; Stapleton, Sorrell, and Schwanen 2017). This is logical as more people living in an area, going to work, and going shopping or to socialize should generate more vehicle demand and more congestion, although the effect is not necessarily linear as factors such as density and the built environment are at play as well (Ewing and Cervero 2010). In San Francisco between 2010 and 2016, median household income increased from $79,000 to $104,000 in 2016 dollars (U.S. Census Bureau, n.d.). This sharp increase in income also signal a considerable rise in population and employment within the city. During the study period, population grew from 805,770 to 876,103 (U.S. Census Bureau, n. d.), whereas number of jobs in the county increased from 545,000 in 2010 to 703,000 in 2016 (Bureau of Labor Statistics, n. d.) .

From a policy perspective, congestion is sometimes viewed as an indicator of success because of its correlation to economic factors (Marshall 2016; Mondschein and Taylor 2017). Hence, while it is clearly desirable to minimize congestion, it should not be sought to achieve that goal simply through lower economic performance. Therefore, it is important to understand and account for the share of the growth in congestion that is attributable to these socioeconomic factors versus other factors over which planners may be able to exert more control, as is done in this section of the research study.

3.2.2 Road and Transit Network Changes

Changes to the road and transit networks are expected to affect the level of congestion, with more arterial capacity cross-sectionally associated with less congestion (Marshall 2016), although capacity increases are generally viewed to be at least partially offset by induced demand (Cervero 2002; Kavta and Goswami 2018; Litman 2018). Similarly, increased transit service can be expected to reduce congestion (Aftabuzzaman 2011; Nguyen, Currie, and Young 2015).

There are several relevant transportation network changes in San Francisco over this period, including the reconstruction of the Presidio Parkway, the rollout of the Muni Forward transit improvements, the introduction of turn restrictions on Market Street, and a number of “road diet” projects (SFCTA 2017; SFMTA 2017). The road and transit expansion projects are expected to reduce congestion, the net effect of the turn restrictions is not clear, and the road diets are worth considering as a potential source of increased congestion. Road diets are reconfigurations of streets that reduce car capacity, often with corresponding improvements to add bicycle lanes, improve conditions for pedestrians, and slow travel speeds (Burden and Lagerwey 1999). Several studies have considered livability enhancements associated with road diets (Sohn 2011), and found positive safety benefits (Huang, Stewart, and Zegeer 2002; Pawlovich et al. 2006; Noland et al. 2015). Their effect on travel times has been found to be modest, and sometimes insignificant (Burden and Lagerwey 1999; Noland et al. 2015; Figliozzi and Glick 2017). These road diets and other network changes in this analysis are accounted for to examine their effect on congestion in the context of San Francisco.

3.2.3 Non-Recurring Congestion

Some of the literature on the causes of congestion focuses on distinguishing between recurring and non-recurring congestion (Cambridge Systematics, Inc. and Texas Transportation Institute 2005; Soltani-Sobh et al. 2017). These studies break out the portion of congestion due to recurring causes such as capacity constraints and signal timing, versus those that vary from day to day, such as bad weather, traffic incidents and work zones, although the magnitude of the effect is based on a limited number of corridors and varies dramatically between the studies.

This section of the analysis focuses primarily on recurring congestion, as measured by average weekday travel speeds. It does, however, implicitly consider non-recurring congestion through the use of travel time reliability metrics. Travel time reliability is a measure of the day-to-day variation in travel time, and is affected by the non-recurring factors described above. As recurring congestion increases, traffic flow becomes less stable and travel times can be subject to large increases given a minor disruption. Recent research explored this issue, and developed a methodology to estimate travel time reliability as a function of the travel time index (TTI), which is the ratio of the average congested travel time to the free flow time (Cambridge Systematics, Inc. et al. 2012). The locally estimated reliability functions are applied based on travel time and area type from Chapter 2 to generate travel time reliability metrics for unravelling the effect of the different contributors to traffic congestion in this section of the analysis.

3.2.4 Magnitude of TNC operations in San Francisco

Profiling TNC activities in San Francisco (San Francisco Count Transportation Authority 2017) found that there were about 170,000 TNC vehicle trips on a typical weekday, which is about 15% of intra-San Francisco vehicle trips. An average TNC trip is 2.6 miles long, and the trips are heavily concentrated in the densest and most congested parts of San Francisco. On weekdays, TNC trips follow a time-of-day 20 distribution with peaks during the AM and PM peak periods. About 20% of TNC vehicle miles traveled (VMT) are out-of-service or deadhead miles in which the vehicle is traveling with no passenger beyond the driver. In addition, most TNC drivers come from outside San Francisco, adding more VMT the network as they drive into the city to find passengers. Data on the growth of TNCs in San Francisco is not directly available, but worldwide, the cumulative rides booked on Uber and Lyft grew from 200 million in 2014 to over 2 billion in 2016 (Dogtiev 2018). In New York, the number of trips served per month doubled annually between 2014 and 2016 (Shaller 2017).

Some have argued that TNCs are likely to reduce traffic congestion by encouraging ridesharing, complementing transit, or enabling people to own fewer cars (Uber 2017; Zimmer 2016; Feigon and Murphy 2016, 2018). However, as established earlier, several factors compete with these and were demonstrated to cause TNCs to increase congestion, including deadheading and pick-up and Dropping-off maneuvers. In the previous chapter, it was found, through an empirical evaluation combining the scraped usage data with speed data from probe vehicles, that TNCs are a net contributor to increased congestion in San Francisco. Specifically, it was determined that vehicle hours of delay increased by 62% between 2010 and 2016 and that TNCs are responsible for two-thirds of that increase. In this section, some unanswered questions are assessed from the empirical study. First, the empirical evaluation only considered the contributions of TNCs versus every other conventional factor to increased congestion, whereas here, these conventional factors are decomposed in more detail. Secondly, the empirical study's consideration of TNCs substitution with other modes was implicit, finding that 69% of TNC volumes are new traffic without considering which other modes those trips are drawing from. Here, that modal substitution has been broken out. Third, that study did not explicitly consider the effects of re-routing. One would expect that as traffic congestion becomes worse on main streets, a portion of traffic be diverted to parallel routes including local and collector streets. This follow-up analysis accounts for that possibility using a more detailed road network. Collectively, this model-based analysis serves to test the conclusions of the empirical study using a different methodology, and to provide more information that is detailed.

3.3 Data and Methods

This analysis considers the change in congestion in San Francisco between 2010 and 2016. This was achieved using six scenarios, with each building incrementally upon the previous scenario. **Table 12** shows a summary of these six scenarios, and the inputs used for each.

Table 12 Summary of Scenarios Tested to unpack the Effects of Background Factors and Compare them to TNCs

Scenario	Network	Population	Employment	TNC Volumes	TNC PUDO	Notes
2010 Base Case	2010	2010	2010	No	No	2010 Base Conditions
Network Change	2016	2010	2010	No	No	
Population Change	2016	2016	2010	No	No	
Employment Change	2016	2016	2016	No	No	No-TNC counterfactual
TNC Volume	2016	2016	2016	Yes	No	
TNC PUDO	2016	2016	2016	Yes	Yes	Best estimate -actual 2016 conditions

Each scenario was tested using San Francisco's SF-CHAMP travel demand model (Jonnalagadda et al. 2001; Zorn, Sall, and Wu 2012). SF-CHAMP is an activity-based travel demand (Bowman and Ben-Akiva 2000; Davidson et al. 2007) model that simulates the daily movements of individual travelers for a synthetic population in the 9-county San Francisco Bay Area. It has a long history of being successfully used to evaluate a range of policy and planning scenarios (Castiglione et al. 2006; Sall et al. 2010; Brisson, Sall, and Ang-Olson 2012). The version 5.2.0 is used in this study, which was calibrated to 2010 conditions and does not, on its own, include TNCs as a mode. Instead, TNCs are accounted for, as described later in this chapter. The remaining inputs, including transportation networks, population and employment data are not forecasts, but have been updated to reflect actual 2010 and 2016 conditions.

For each scenario, five network performance metrics are reported: vehicle miles traveled (VMT), vehicle hours traveled (VHT), average speed, vehicle hours of delay (VHD) and planning time index 80 (PTI80). VMT and VHT are standard metrics. Average speed is in miles per hour (mph) and calculated as VMT / VHT. Delay is defined as the difference between congested travel time and what the travel time would be under free-flow conditions. PTI80 is a measure of travel time reliability defined as the ratio of the 80th percentile travel time to the free-flow travel time. It indicates how much extra time a traveler must plan on to arrive on-time 80% of the time. Following is a discussion of additional details related to how each of the six scenarios are modeled.

3.3.1 2010 Base Case

This first base conditions for the year 2010, assuming no TNCs are present. This serves as a constant comparison scenario against which all subsequent traffic assignments and their resultant performance statistics are measured. This scenario was run using the best available estimate of 2010 socioeconomic conditions, and with a set of networks that are consist with the 2016 networks except for project-related changes.

3.3.2 Network Change

Starting from the 2010 base case, this scenario incorporates the road and transit network changes that occurred between by 2016, while retaining the 2010 socioeconomic inputs and assuming no TNCs. This also includes any accounted prolonged construction activities on the network during the study period. Any potential impacts on lane obstructions, lane closures or turn restrictions introduced in this period as a result of these factors are accounted for in this scenario.

3.3.3 Population Change

Starting from the network change scenario, the population change scenario accounts for the growth in population and the change in demographics that occurred between 2010 and 2016. Because SF-CHAMP operates using a synthetic population (Beckman, Baggerly, and McKay 1996; Müller and Axhausen 2011), it was necessary to re-generate that synthetic population before running the model. This was done using 2016 totals for the number of households in each traffic analysis zone (TAZ), as well as 2016 control totals for household size, income and demographics, but the 2010 control totals for the number of workers per household were retained. This was done to separate out the effect of the growing population and changing demographics from the effect of those same people having a higher level of employment and therefore traveling more frequently to and from work.

3.3.4 Employment Change

Starting from the population change scenario, the employment change scenario accounts for the change in employment between 2010 and 2016. To do this, the 2016 employment in each TAZ by industry was incorporated, with those employment estimates based on a combination of data from state unemployment insurance records and city Planning Department data. The synthetic population was also regenerated to include 2016 control totals for workers per household, reflecting a higher employment rate within the population.

3.3.5 TNC Volume

Starting from the employment change scenario, the TNC volume scenario accounts for the net effect of adding TNC vehicles to the network. There are three related components to this effect. Deadhead or out-of-service TNC vehicles purely add traffic to the network. In- service TNC trips (those carrying a passenger) also add traffic to the network, but if they substitute for taxi or car trips, there would be a corresponding reduction in traffic generated by those modes. If in-service TNC trips substitute for transit, walk or bike trips, then there is no corresponding reduction in traffic by other modes. The same is true if the TNC trips represent induced demand, meaning that they would not have occurred if TNCs did not exist. To understand the net effect of in-service TNC trips on traffic volumes, it is necessary to estimate which modes those trips would have used, if TNC were not available. SF-CHAMP does not, on its own, account for TNCs as a travel mode. One important reason for this is that data were not previously available with which to calibrate a model. For this study, the newly available scraped TNC data to evaluate the TNC effects is used.

3.3.5.1 Processing TNC volume data

For this study, those data was further processed to associate out-of-service TNC volumes with directional links in the SF-CHAMP road network. The said data were also processed to create an observed TAZ-to-TAZ trip table of TNC trips. Both represent average weekday, non-holiday conditions and are limited to trips with both ends in San Francisco. The TNC data were collected over a six-week period in November and December 2016.

SF-CHAMP uses a multi-class user-equilibrium traffic assignment for each of five times-of- day (TODs): 6:00-9:00 AM, 9:00 AM-3:30 PM, 3:30 PM-6:30 PM, 6:30 PM-3:00 AM and 3:00-6:00 AM. Both the TNC out-of-service volumes and in-service trip tables were segmented by these same five TODs. The out-of-service TNC vehicles are accounted for by including them as a pre-loaded volume in the traffic assignments. The TNC in-service vehicles were accounted for by including the trip tables as an additional class in the traffic assignments. To estimate how much non-TNC vehicle demand should be reduced due to substitution with TNC trips, some additional processing was conducted as described below. Because the geographic scope of the data collection method used was limited to the San Francisco County, only TNC trips with both ends in San Francisco were considered for the purpose of this research.

Prior to carrying out the traffic assignment, the simulated trips from SF-CHAMP are compiled into TAZ-to- TAZ person trip tables, segmented by mode and TOD. This was begun by converting the observed in-service TNC vehicle trip tables to person trips, assuming an average occupancy of 1.49 passengers (excluding the driver) per vehicle.

This average occupancy is calculated from the occupancy rates reported in a survey of TNC users in Boston (Gehrke, Felix, and Reardon 2018). The study data of this research do not reveal the demographic or socio-economic characteristics of TNC users, nor do they directly reveal what TNC users otherwise would have done if TNC were unavailable. Therefore, a simple assumption is made to estimate what otherwise would have happened: it is assume that within a zone pair and a TOD, the introduction of a new mode (TNC) draws from all other modes proportionally to their existing mode share. This is equivalent to the well-known independence of irrelevant alternatives (IIA) property of the multinomial logit model. For example, if a zone pair previously contained 90 car trips and 10 transit trips, and the data for this research show 10 TNC person trips for that zone pair, it is assumed that 9 of those trips substitute for car, and one substitutes for transit, leaving 81 car trips, 9 transit trips and 10 TNC trips for the same total person trips. If the total TNC person trips in a zone pair exceeds the total number of trips on other modes, it is not allowed that the non-TNC trips turn negative. Instead, it is assume that TNC trips first substitute for all available non-TNC trips, and any excess TNC trips are added as “non-shifted” trips. These non-shifted TNC trips could theoretically represent induced demand, but it is also possible that they occur simply because of imperfect data in either the modeled trip tables or the TNC trip tables in a detailed zone system.

The end result of this process is a modified set of person trip tables by mode and TOD, with fewer trips than the original trip tables due to some of those trips shifting to TNC. **Table 13** summarizes the change in intra-San Francisco person trips that is output from this process. The results show that 26% of TNC trips substitute for car trips, 1%

substitute for taxi, 14% for transit and 44% for walk or bike. The remaining 15% of TNC trips are "non-shifted" and are not substituted for another mode. In terms of the change to existing trips by mode, the results show that introducing TNCs reduces the number of car trips by 5.1%, taxi trips by 8.1%, transit trips by 6.1% and walk and bike trips by 7.5%. These results are based on the existing mode shares in those zone pairs at the appropriate time-of-day, so they suggest that TNCs are more likely to occur in zone pairs with a high walk, bike or transit mode share than car.

Table 13. Change in Intra-San Francisco Person Trips

Table 13 Change in Intra-San Francisco Person Trips

Mode	Person Trips without TNCs	Person Trips with TNCs	Difference	Percent Difference	Percent of TNC Trips
Car	1,269,769	1,205,143	-64,626	-5.1%	26.1%
Taxi	33,008	30,334	-2,674	-8.1%	1.1%
Transit	556,407	522,492	-33,916	-6.1%	13.7%
Walk & Bike	1,440,941	1,332,261	-108,680	-7.5%	44.0%
TNC	0	247,267	247,267	N/A	100.0%
Total Trips	3,300,125	3,337,496	37,371	1.1%	N/A

The person trip tables are converted to vehicle trips by dividing by the average occupancy: 1 for drive alone, 2 for shared ride 2, and 3.5 for shared ride 3+. The original TNC trip table is in vehicle trips already and does not require further conversion. **Table 14** shows the change in vehicle trips when TNCs are introduced using this method. Within San Francisco, 166,000 TNC trips are added to the network. This is partially offset by a reduction of 48,000 car trips and 1,600 taxi vehicle trips. These results suggest that about 70% of TNC trips are new vehicle trips that add traffic to the network, adding a net of 116,000 vehicle trips to the network, which is a 12% increase in intra-San Francisco vehicle trips.

Table 14 Change in Intra-San Francisco Vehicle Trips

Mode	Vehicle Trips without TNCs	Vehicle Trips with TNCs	Difference	Percent Difference	Percent of TNC Trips
Car	946,197	897,721	-48,476	-5.1%	29.2%
Taxi	19,884	18,273	-1,611	-8.1%	1.0%
TNC	0	165,951	165,951	N/A	100.0%
Total Trips	966,082	1,081,945	115,863	12.0%	69.8%

To generate the estimates for the TNC Volume scenario for the purpose of this research study, these modified car and taxi vehicle trip tables were assigned to the network, along with the TNC in-service vehicle trip table and the TNC out-of-service preloaded volumes.

3.3.6 TNC Pick-ups and Drop-offs (PUDO)

Starting from the TNC volume scenario, the TNC PUDO scenario also accounts for the disruptive effect of curbside TNC pick-ups and drop-offs on traffic flow. Past research has shown delivery trucks, taxis and TNCs stopping curbside to load or unload passengers or freight are important contributors to urban traffic congestion (Golias and Karlaftis 2001; Chiabaut 2015; Erhardt, Roy, Cooper, Sana, Chen and Castiglione in review).

To account for this effect, the approach developed in Chapter 2 has been followed that converts each PUDO into passenger car equivalents using the capacity of the curb lane and the amount of time each PUDO blocks or disrupts traffic in the PUDO. The average duration coefficient estimated the average number of seconds that a PUDO blocks or disrupts traffic in the curb lane. This was assessed to be 145 seconds and 79 seconds in the previous chapter for major and minor arterials respectively (it was found to be insignificant for collectors and local streets), which is what is plugged into the model when the network is preloaded using PUDO numbers for the said facility type(s). The higher values on higher-class roads suggest that it can take some time for traffic to recover to its pre-PUDO state on higher volume facilities.

The TNC data allow for the pick-up location to be inferred based on where the driver accepts a ride and the drop-off location to be inferred based on where the vehicle becomes available again after serving a passenger. It is expected that the drop-off locations are more spatially accurate because the vehicle may drive some distance before picking up a passenger, although with a high density of TNCs as found in San Francisco, this distance is usually modest. For this study, each PUDO in the observed TNC data is associated with a directional SF-CHAMP link by time-of-day. The above conversion is then applied to PCEs, and those PCEs are included as a 'preload' in the traffic assignments. These PCEs are counted for their effect on congested travel times, but not when tabulating the total traffic volume on the link. The results of this scenario represent the best conceivable estimates of actual 2016 conditions.

3.4 Results

Table 15 shows the network metrics for the six tested scenarios. The first set of numbers

shows the totals from each set of assignments, and the second set shows the change from the previous scenario. The third set of numbers shows the cumulative percent change relative to the 2010 base case, and the fourth set shows the percent of the total change associated with each increment. These metrics are reported for all links in San Francisco, excluding centroid connectors, summed across the five times-of-day.

Table 15 Network Performance Metrics for Tested Scenarios mentioned in Table 14

Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
			Network Metrics		
2010 Base Case	8,105,226	371,147	21.8	154,992	2.24
Network Change	8,111,757	372,388	21.8	155,965	2.25
Population Change	8,468,384	393,354	21.5	166,907	2.29
Employment Change	8,734,445	411,398	21.2	177,485	2.34
TNC Volume	9,289,667	448,174	20.7	196,492	2.38
TNC PUDO	9,292,047	453,359	20.5	201,343	2.42
			Change from Previous Scenario		
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
Network Change	6,532	1,241	-0.1	973	0.01
Population Change	356,626	20,966	-0.3	10,942	0.04
Employment Change	266,061	18,044	-0.3	10,578	0.06
TNC Volume	555,223	36,776	-0.5	19,007	0.04
TNC PUDO	2,379	5,185	-0.2	4,852	0.03
Total Change	1,186,821	82,212	-1.3	46,352	0.18
			Percent Change from 2010 Base Case		
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
Network Change	0%	0%	0%	1%	0%
Population Change	4%	6%	-1%	8%	2%
Employment Change	8%	11%	-3%	15%	5%
TNC Volume	15%	21%	-5%	27%	7%
TNC PUDO	15%	22%	-6%	30%	8%
Total Change	15%	22%	-6%	30%	8%
			Percent of Total Change		
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
Network Change	1%	2%	4%	2%	6%
Population Change	30%	26%	19%	24%	21%
Employment	22%	22%	22%	23%	31%

Table 15, continued" on 2nd page of table

Change					
TNC Volume	47%	45%	37%	41%	23%
TNC PUDO	0%	6%	17%	10%	17%
Total Change	100%	100%	100%	100%	100%

For the total effect of all changes, the results show VMT increasing by about 1.2 million or 15%, VHT increasing by 82,000 or 22%, average speed decreasing by 1.3 mph or 6%, and VHD increasing by 46,000 or 30%. They also show that travel times become less reliable over this period, as indicated by the PTI80 increase.

The results show that across all categories, TNC volumes are the largest individual contributor to increased traffic congestion, and network changes are the smallest individual contributor. Considering TNC volumes and PUDO together, TNCs are associated with 47% of the VMT increase, 51% of the VHT increase, 55% of the speed decrease and 51% of VHD increase. TNCs are associated with 41% of the increase in PTI80. Depending on the metric, one can summarize these results as TNCs being associated with about half of the increase in congestion over this period.

The possibility was considered that these results may be affected by the order in which the scenarios are run as well. To test for this possibility, running select scenarios in a different order was attempted, and it was found that while the numerical results did change, the relative ordering of the contribution from each scenario remained the same.

Also, the network metrics were compared to an equivalent set of metrics calculated using observed travel times. One can only compare the 2010 Base Case and the TNC PUDO scenarios, each of which is the best possible estimate of actual conditions in their respective year given the research methodology of this study. The observed travel time data was sourced and used from the commercial vendor INRIX, who derive their estimates from probe vehicle traces. The data are for non-holiday weekdays for the six-week period in 2016 when the TNC data were collected and the corresponding six-week period in 2010. They are filtered and processed in the same manner as in the previous chapter. The observed speed data are available on road segments known as traffic messaging channels (TMCs), which average about 3 city blocks in length and cover major roads in San Francisco. The comparison is therefore limited to network links that underlie TMCs, with observed speeds allocated to the underlying SF-CHAMP links. Modeled traffic volumes are used with both modeled and observed travel times for calculating VHT, VHD, average speed and PTI80.

Table 16 shows the results of this modeled versus observed comparison. The comparison shows that the modeled speeds are 4% too slow in 2010, and 5% too fast in 2016, and thus the model substantially underestimates the observed drop in speed between the two years. The equivalent is true of VHT. The model reasonably captures the observed VHD in 2016, but overestimates it in 2010, so underestimates the increase in VHD by 43%. Similarly, the model reasonably estimates PTI80 in 2016, but overestimates it in 2010, thus underestimating the degree to which reliability deteriorates.

The changes are not uniformly distributed throughout the network or across times of day. A deeper dive is taken into how these changes vary over the time of day in the next chapter. **Figure 15** shows the change in congested speed for each scenario, relative to the previous scenario, for four times-of-day. To make the plots more readable, the results are limited to segments associated with TMCs.

Table 16 Modeled vs Observed Network Performance Metrics for 2010 and 2016; Percent Changes from 2010 to 2016 for Links at SF-CHAMP level disaggregation

Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
Using Modeled Travel Times					
2010 Base Case	5,476,943	226,437	24.2	90,103	2.07
TNC PUDO	6,179,581	271,741	22.7	115,955	2.22
Change	702,638	45,305	-1.4	25,852	0.15
Using Observed Travel Times					
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
2010	5,476,943	216,932	25.2	67,941	1.82
2016	6,179,581	284,636	21.7	113,619	2.19
Change	702,638	67,704	-3.5	45,678	0.37
Percent Difference					
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Average Speed (mph)	Vehicle Hours of Delay	Planning Time Index 80
2010	0%	4%	-4%	33%	13%
2016	0%	-5%	5%	2%	1%
Change	0%	-33%	-59%	-43%	-58%

3.5 Discussion

Our analysis in this section examined the contributors to growing traffic congestion in San Francisco through a series of controlled experiments with a travel demand model. Four of the six scenarios tested were relatively straight-forward model runs. The remaining two scenarios, which considered the effect of TNC volumes and TNC PUDO required revisions to the standard modeling process to reasonably represent TNCs.

For the TNC Volume scenario, out-of-service TNCs were included as a preload in network assignment as mentioned before, and an observed TNC trip table was assigned for in-service TNCs. Modification of the existing trip tables was also required to account for trips that switched to TNCs, and it was done by assuming that the substitution to TNCs was proportional to the existing mode shares within a given zone pair and time-of-day. The results of that analysis show that 27% of TNC person trips substitute for car or taxi trips, 58% substitute for walk, bike or transit trips, and 15% are added with no substitution for another mode. Past surveys of TNC users show that 43% to 61% of TNC trips substitute for transit or non-motorized modes or would not otherwise have been made (Rayle et al. 2016; Clewlow and Mishra 2017; Henao 2017; Gehrke, Felix, and Reardon 2018).

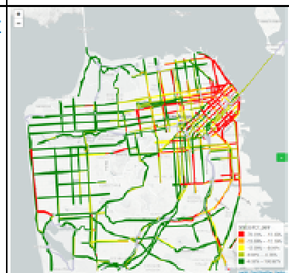
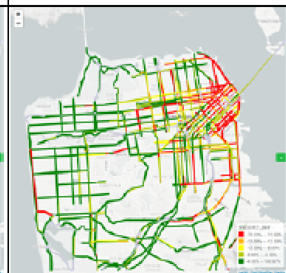
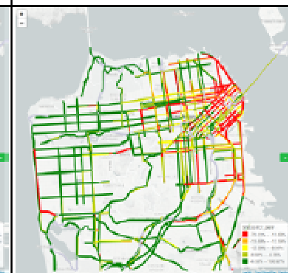
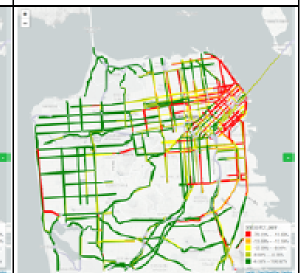
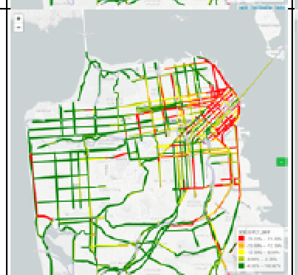
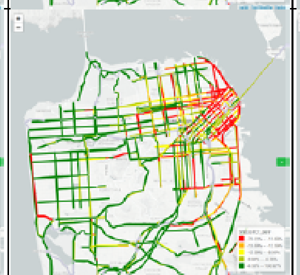
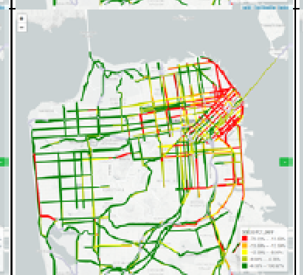
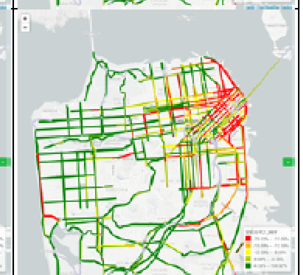
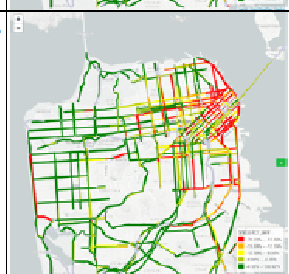
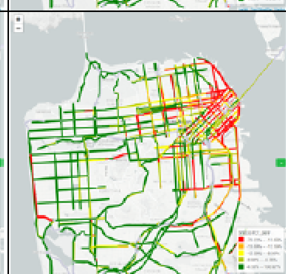
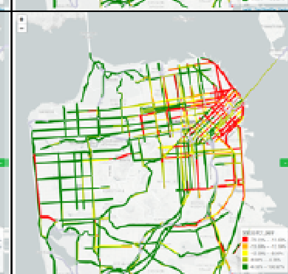
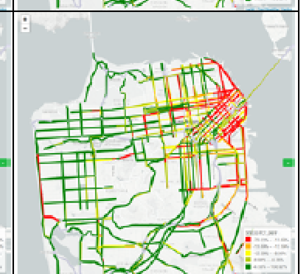
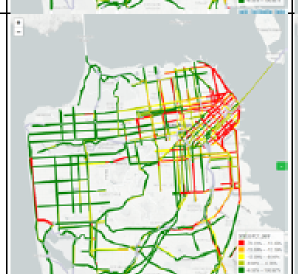
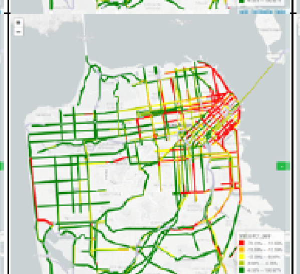
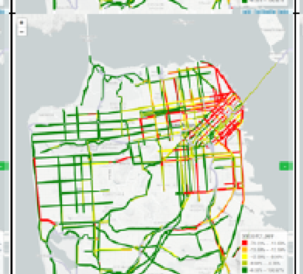
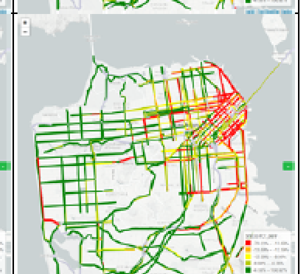
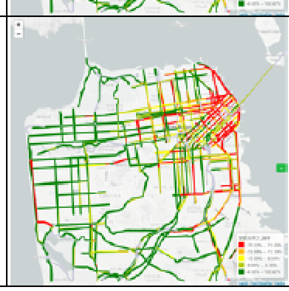
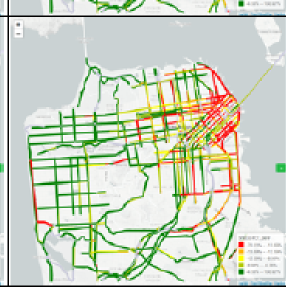
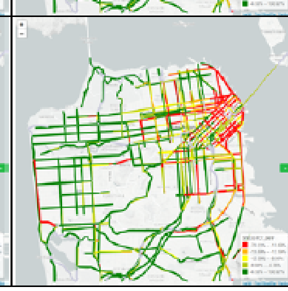
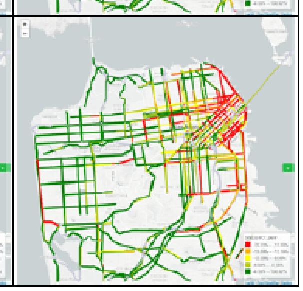
Scenario	Time-of-Day			
	6:00-9:00 AM	9:00 AM-3:30 PM	3:30-6:30 PM	6:30 PM-3:00 AM
Network Change				
Population Change				
Employ-ment Change				
TNC Volume				
TNC PUDO				

Figure 15 Change in Speed Compared to Incrementally Added Scenarios, by Time-of-Day; Color Red represents highest and most significant drops in speed, Yellow represents moderate drop in speeds while Green represents least pronounced drops in speed

The results for non-car substitution are within this range, but they exceed this range when the non-shifted trips are included. San Francisco is a dense city with a high non-car mode share, so it is logical for the non-car substitution to be higher, although a more sophisticated mode choice analysis may show a greater tendency to substitute with one mode or another. It makes sense that TNCs would substitute heavily for walk, bike and transit modes because TNC trips tend to be heavily concentrated in downtown areas (Feigon and Murphy 2018; Clewlow and Mishra 2017; Erhardt et al. in review) where non-car mode shares are highest. TNC trips also tend to be short, averaging 2.6 miles long (San Francisco Count Transportation Authority 2017), compared to an average trip length of 0.7 miles for walk, 2.3 miles for bike, and 9.8 miles for car (National Household Travel Survey 2009). For transit in San Francisco, the average trip length is 2.3 miles for local bus, 2.7 miles for light rail, 13.5 miles for heavy rail, and 26.6 miles for commuter rail (National Transit Database 2016c, 2016b, 2016a). Due to the similar lengths, it is logical that they would substitute for bus trips while complementing longer rail trips (Clewlow and Mishra 2017; Mucci 2017; Graehler, Mucci, Erhardt 2019).

When converted to vehicle trips, the study results show that 70% of in-service TNCs are new vehicle trips that add traffic to the roads. The empirical evaluation of TNCs in San Francisco found that the net effect of each additional TNC vehicle on a link contributed 0.69 PCEs to congestion, which is equivalent to adding one TNC vehicle partially offset by a subtraction of 0.31 other vehicles (Chapter 2). Most TNC drivers in San Francisco come from outside San Francisco (San Francisco Count Transportation Authority 2017), and it appears that they do so because there is high demand for TNCs in places with a high density of people who would otherwise be without a car. As inferred from the empirical analysis of chapter 2, each such additional TNC vehicle can be potentially counted as adding almost 0.69 passenger car equivalent (PCE) to the network which would not have been present otherwise in addition to increasing vehicle miles traveled outside the city limits. That 0.69 estimate included both in-service and out-of-service TNCs, and this estimate is reasonable in comparison. When applied to 2010 and 2016 conditions, the model underestimates the observed increase in congestion. One explanation for this difference may be that it reflects limitations of the model's volume-delay functions (VDFs). If the VDFs are not steep enough they may show modest travel time degradation at too low of a volume-capacity ratio, and travel times may not increase fast enough once the volume-capacity ratio passes a certain critical threshold. Such a shape would be consistent the observations here where the base year speeds show too much congestion, but that congestion does not increase fast enough.

Much attention has been given to developing better volume delay functions for traffic assignment models, and rightly so given the challenges in balancing the desire to match speeds, traffic volumes and to achieve a stable model convergence (Akcelik 1991; Dowling and Skabardonis 2008; Cetin et al. 2012; Foytik, Cetin, and Robinson 2013; So Jaehyun (Jason), Stevanovic Aleksandar, and Ostojic Marija 2017; Slavin, Lam, and Nandur 2015). The recalibration of these VDFs is left as a future improvement, as it is taken for now as a limitation of the analysis. Although the VDFs used by SF-CHAMP do include scaling factors for high density roads (the parameter δ), if the shape of the VDFs is the source of the difference between the modeled and observed travel times, then one would expect the absolute contribution of all contributors to growing congestion to be higher than is reported here. This difference between modeled and observed changes could also be explained by some other change that is not accounted for in this analysis, such as the effect of TNC trips with one or both ends outside San Francisco city limits.

A second limitation is that an assumption that TNCs Dr.aw from all other modes within a zone pair and time of day proportionally to the existing mode shares has been relied upon. It is reasonable to expect that TNC users are more likely to substitute for some modes than others, but no data has been found to know which, or by how much. Therefore, it would be valuable the travel survey data sufficient to estimate a full set of mode choice models in order to better understand this substitution. Given the rapid growth of TNCs, that data collection effort would need to be contemporary, and it may require a design to oversample TNC users in order to capture sufficient observations for model estimation. Finally, it would be valuable to extend this analysis to other cities, subject to data availability, to understand how the results may vary based on the size and other characteristics of the city.

When applied to the set of six scenarios, the study results show that network changes result in a small increase in congestion, which is consistent with past evaluations of the effect of road diets on car travel times (Noland et al. 2015; Figliozzi and Glick 2017). Population growth and employment growth both contribute to increased congestion, again consistent with other evidence (Marshall 2016; Chang, Lee, and Choi 2017). The present study results show that TNC volumes contribute about half of the VMT increase over this period and are associated with 37% of the decrease in speed. TNC PUDO do not add additional vehicle miles, but they are associated with another 1% of the speed decrease over this period. Both contribute to worsening reliability. While the precise magnitude differs due both to a different methodology and a broader set of links considered, these results confirm the recent empirical assessment that TNCs are the biggest single contributor to increasing congestion in San Francisco (Erhardt et al. in review). These results consistent with a portion of research in chapter 2 showing that TNCs contribute to increased traffic and congestion and other existing literature (Henao 2017; Henao 2018; Schaller 2017; Gehrke, Felix, and Reardon 2018; Schaller 2018) whereas differ from claims that TNCs primarily complement transit and reduce congestion (Uber n.d.; Zimmer 2016; Feigon and Murphy 2016, 2018; Li, Hong, and Zhang 2016). Another subset of studies could not Dr.aw conclusions about the net effect of TNCs on traffic volumes (Rayle et al. 2016; Clewlow and Mishra 2017). Several of the assessments suggesting that TNCs may reduce congestion are either based on theoretical arguments (Uber n.d.; Zimmer 2016; Feigon and Murphy 2016, 2018) or on very aggregate data (Li, Hong, and Zhang 2016), so it appears that when detailed data are available, they point in the same direction.

3.6 Conclusions

In this section, the rapid increase in congestion observed in San Francisco between 2010 and 2016 was examined, and the factors contributing to that increase were decomposed. It was done through a series of virtual experiments using a travel demand model. This analysis revealed that standard factors, including network changes, population growth and employment growth all contributed to increased congestion, but that those factors alone were insufficient to explain the full increase.

The effects of TNCs on congestion using a unique data set scraped from the APIs of two TNCs were further considered. Those TNC data allow us to directly observe out-of-service TNC trips, and allow us to infer the locations and timing of in-service TNC trips. Both of these were accounted for in the analysis, and the substitution of TNC trips for other modes was considered by assuming that they Dr.aw from existing modes within a zone pair and time-of-day proportionally to the existing mode shares. Because TNC trips are concentrated in zone pairs with a high walk, bike and transit mode share, this analysis suggests that TNCs Dr.aw more from walk, bike and transit modes than from car modes. In addition to the 100% of out-of- service TNC trips that add traffic to the roads, it was found that 70% of in-service TNCs are new vehicle trips that add traffic to the roads. The result is that TNCs are associated with about half the increase in VMT between 2010 and 2016 and TNC volumes are the biggest single contributor to increased congestion over this period. In addition, It was also revealed that TNCs stopping curbside to pick-up and drop-off passengers disrupt traffic flow and contribute to increased congestion.

These results provide more evidence to confirm the conclusion that TNCs increase congestion in San Francisco, and counter the arguments that they decrease congestion. The results show that road and transit network changes are only a small factor in the growing congestion over this period, and provide an understanding of the role that the high growth in population and employment play. The results are important to transportation planners and policy makers as they decide how to best manage congestion and provide mobility within their cities.

CHAPTER 4. COMBINED EMPRICAL AND MODEL-BASED RESULTS, AND RESULTING POLICY CONSIDERATIONS

4.1 Overview

This chapter delves deeper into the perceptions gained by the empirical study and the model-based study from chapters 2 and 3. The big picture question that these chapters answer are if TNC's affect congestion independently when employment, population and network capacity shifts (such as for a bus or bicycle lanes, turn restrictions, etc.) are accounted for. When compared to the conventional factors that bring about a standard increase in traffic congestion, the contribution of TNCs were attributed to approximately 50% of the net change in congestion in San Francisco between 2010 and 2016. This was defined by the following congestion measures: vehicle hours of delay, vehicle miles travelled, vehicle hours travelled Planning Time Index (signifying travel time reliability) and average speeds. Employment and population growth, encompassing citywide non-TNC driving activity by residents, local and regional workers, and visitors, are primarily responsible for the remainder of the change in congestion. In this chapter, the conclusions of the previous chapters are sliced into various classes, such as time of day, most affected areas of congestion, scenario analyses and identifying the chronology of declining roadway performance in the city. This chapter also draws parallels between the empirical study and the model based analyses to arrive at a more assertive quantification of the impacts of TNCs on the studied roadway performance measures. The delay statistics drawn using the results of the estimated parameters in the empirical analysis, though pointing towards the same direction as that concluded by the model-based study, are applicable for a more restricted network coverage when compared to those asserted by the model-based study. The empirical study exclusively covers network links embodied by TMC link coverage provided by INRIX. It is known that vehicle rerouting, modified demand and trip generation and traffic assignments influenced by changing affinities to newer modes of travel are often subjected to changes in even seemingly inconsequential traffic volumes, especially on congested networks. The model-based study, in addition to covering the links that INRIX does, also takes into account the changes in network imparted by lower classes of network links (CHAMP network links). Therefore, in the model based study, the total vehicle miles travelled, and vehicle hours travelled and delay quantifiers are therefore scaled to a higher order. Here, the parameter estimate based performance quantifiers were scaled from the empirical study to the order of the model based study in order to arrive at a comparable, ascendable and unequivocal estimate of the network performance metrics. According to the model-based study, TNCs were accountable for the following rises in network congestion.

1.) Daily vehicle hours of delay (VHD) on the roadways studied increased by about 40,000 hours during the study period. It was estimated that TNCs account for 51% of this increase in delay, and for about 25% of the total delay on San Francisco roadways and about 36% of total delay in the downtown core in 2016, with employment and population growth accounting for most of the balance of the increase in delay.

2.) Daily vehicle miles travelled (VMT) on study roadways increased by over 630,000 miles. It was estimated that TNCs account for 47% of this increase in VMT, and for about 5% of total VMT on study roadways in 2016.
3.) Average speeds on study roadways declined by about 3.1 miles per hour. It was estimated that TNCs account for 55% of this decline.

4.2 Methodology

As mentioned in the network preparation section of Chapter 2, TMC links sourced from INRIX were associated and aggregated to corresponding CHAMP links to import operational and geometric link characteristics. In order to compare the performance metrics produced by the two analysis methodologies, links that were common to both the empirical and model-based analyses were extracted from the CHAMP links dataset. The two discussed stages of analysis result in network performance metrics for a total of five scenarios, three of which are available in both stages of analysis: 2010 Base, 2016 Counterfactual, and 2016 with TNCs. For the three overlapping scenarios, the relative contribution of TNCs to the change in congestion is similar in direction and magnitude, with the empirical analysis (which directly reflects observed speed changes) showing a somewhat greater share of the increase in congestion attributable to TNCs. This allows for making two-way comparisons between INRIX-observed speeds (from empirical study) and parametrically predicted speeds (from empirical study) with the corresponding data, model-predicted speeds with TNCs and PUDO included in the traffic assignment (from model-based study) and the speeds predicted by a traffic assignment that did not include TNCs/PUDO. It should also be noted that in the SF-CHAMP model based analysis, addition of TNC volumes (and accounting for capacity reduction on arterials due to PUDO) to the network potentially redistributes traffic over the network, theoretically improving lane capacity usage in a (more expansive than the empirical analysis) network that also includes lower class road links. This is a categorical difference between the scales of exploration by the two methods that serves as a potential source of discrepancy between the results of the two analyses. As such, the distinguishing feature of both stages of the analysis was that they were performed at disaggregate levels, using the previously described directional TMC segments, and across five times of day. The spatial and temporal details are important because adding vehicles does not always have the same effect on travel speeds. For example, an additional vehicle on an uncongested segment in the early AM has a very different effect on delay than an additional vehicle on a downtown segment during the PM peak. **Table 17** shows the relative contribution of TNCs to each of the congestion metrics for the two stages of the analysis.

4.2.1 Intermediate observations and discussion

It was observed that the estimated attribution of total increase in delay to TNC operations and PUDO maneuvers in the empirical study was categorically lower than that forecasted by the scenario analysis based study where each contributing factor was incrementally assigned towards recalculating the delay. The objective of combining the two study methodologies is to arrive at a conservative, yet quantifiable estimate of the share of TNCs and PUDO to total increase in VMT, VHT, VHD and worsening of travel time reliability. The main merit of the scenario based study can be inferred by recognizing its capacity to classify and separate the four main identified sources that increase network congestion within San Francisco. From this study, one can extract its main takeaway: the ratio of attribution of each of the four factors to declining network performance as opposed to relying completely on the absolute increase in delay it states occurred (or would have occurred, in the case of the counterfactual scenario) between the study years. On the other hand, the empirical analysis commendably determines the ratio of absolute increase of delay and vehicle hours travelled from 2010 to the counterfactual year 2016, and the present-day year, 2016. This can be verified by comparing the close to equal increase in ratios predicted by the fixed effects model and the real-time data sourced from INRIX. Thus, to keep the claim of TNCs' contribution to declining network performance limited to the lower bound of the speculating spectrum, the shares of delay from the scenario analysis were applied to the total change in congestion from the empirical analysis in order to obtain the best estimate of the specific contribution of each factor to changes in network performance. **Table 17** demonstrates how the contribution of TNCs to the decline of performance measures compare to each other in the two stages of the analysis after the described scaling procedure was completed. As an example, let us assume that on a particular network link, the empirical analysis predicts a total of 20% increase in delay between 2010 and 2016 (that includes TNC volume and the parameter estimates of 0.67, 144 seconds and 78 seconds on TNC volumes and pickups and drop-offs respectively). Further, assume that the SF-CHAMP model based scenario predicts a 40% contribution of TNCs and PUDO to total increase in delay between 2010 and 2016 on the same link. In this case, the fraction "40%" was applied to the total increase in delay (20%), and conclude that the contribution of TNCs to increase in delay is 8%.

Table 17 Contribution of TNCs to Change in Congestion by Analysis Stage

Metric	Empirical Analysis	Scenario Analysis
Vehicle Hours of Delay	64%	51%
Vehicle Miles of Travel	44%	47%
Speed	65%	55%

4.3 Validation of Assumptions Tying the Empirical and Model-based Analysis Together

The first stage of this study quantifies the contribution of TNCs to changes in congestion in San Francisco between 2010 and 2016 by estimating a statistical fixed-effect panel regression model and then applying this model to identify the relationship between the change in TNC activity and the change in roadway congestion measures between 2010 and 2016, assuming zero TNCs in 2010 and observed TNC levels in 2016. Estimates of the combined effect of the growth of non-TNC factors such as population, employment, and network changes are derived from the SFCHAMP activity-based model system. Because the estimated model relies on the transformation of the observed speed data as the dependent variable in the regression analysis, this stage has been referred to as the empirical analysis. In the second stage, a scenario analysis, the SF-CHAMP activity-based demand model was again used, this time to systematically estimate the individual contributions to changes in roadway congestion of the factors of transportation network supply change, population change, employment change, and TNCs. The estimated parameter on the SF-CHAMP background volume is approximately 0.92, not significantly different than 1. This is logical, because it is expected that each vehicle added in background traffic should have an effect on congestion of adding about ‘1’ vehicle to the implied volume. The Presidio Parkway scaling factor accounts for major construction that was underway on those links in 2010 but not 2016. Two measures of time and location-specific TNC activity have been included. The TNC volume parameter measures net effect of TNCs. If TNCs purely substitute for other car trips, the estimated TNC parameter should be 0 as they substitute for other vehicles already counted in the background volumes. Negative values would be consistent with TNCs reducing traffic, while a value of positive 1 would be consistent with TNCs purely adding itself to background traffic. The estimated coefficient of 0.69 can be interpreted as meaning that TNCs do not purely add to traffic through induced travel or shifts from non-vehicular modes.

4.4 Combined Results

What should be noted here is that in the densest part of the city, TNC activities are highest, irrespective of the fact whether they replace or add volume to the network. While one is aware that these areas lie in the exponential area of the volume delay curve, which implies that even a slight increase in traffic volume has the potential to significantly worsen congestion. Just as one should keep in mind that this is where one would expect congestion to worsen the most, at the same time, it is also true that these are the areas where even a minor addition of volume brought about by TNCs (as opposed to their stated vision of substitution) could potentially make network performance expressively worse.

Figure 16 shows a breakdown of the shares of the four calculated factors that affect the increase in vehicle delay, VMT and VHT. For all the three performance measures portrayed in the figure, it can be seen that TNCs are the leading source of influence. It can be argued that the impact of TNCs is more pronounced since they are added to the already present contribution of the other three factors, it is still relevant since the other pre-existing factors would have been present nevertheless and TNCs are the newest source of change. Also, contributing to the influence of TNCs are the popularity of TNCs in the downtown core, the most congested area of the city to begin with, and their most profitably viable hours of operation (detailed later in this chapter), peak hours, where again, the network is the most congested to begin with.

The model-based analysis from Chapter 3 indicated that daily vehicle hours of delay increased on study roadways from approximately 65,000 hours in 2010 to over 105,000 hours in 2016 with TNCs, an increase of 62%. In the counterfactual 2016 scenario, where TNCs are unavailable and travelers use other modes, the daily vehicle hours of delay are approximately 79,000, an increase of 22% over 2010. This suggests that TNCs are responsible for about 25% of the total delay on monitored streets (the difference between 105,000 hours and 79,000 hours of delay in 2016). It also illustrated how much each of the factors contributes to changes in delay between 2010 and 2016. TNCs account for 51% of the increase in delay. Population change and employment change are responsible for just under 47% of the increase in delay, and network changes account for only about 2% of additional delay.

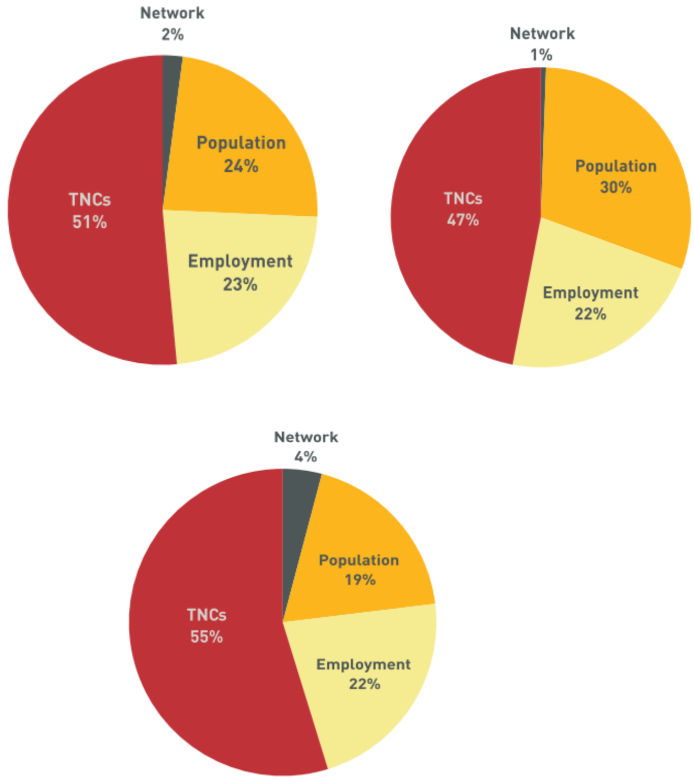


Figure 16 (a) Share of Change in Total Vehicle Hours of Delay by Factors (b) Share of Change in VMT by Factors (c) Share of Change in VHT by Factors. Source: TNCs and Congestion, SFCTA (Collaborated work)

4.4.1 TNC effects on Congestion by Time of Day

TNC usage varies by time-of-day, and thus affects congestion differently at different times of day. An additional vehicle on the roadway during congested time periods results in more congestion than an additional vehicle during uncongested time periods. The following summaries use five times of day derived from the SF-CHAMP model, which vary in length: the AM peak, PM peak, and early AM periods are 3 hours long, while the midday and evening periods are 6.5 and 8.5 hours long, respectively. The figures below demonstrate that TNCs significantly contribute to increased congestion across all times of day, especially in the evening, but during the AM and PM peaks and the midday as well.

Figure 17 compares the VHD from 2010 to the 2016 No TNC scenario in which TNCs don't exist, and to the 2016 with TNC scenario. This figure shows that TNCs increased VHD in all time periods relative to 2016 No TNC scenario. The greatest total increases in delay occurred during the midday and evening period. It was observed that the mid-day period, which is not traditionally associated with the highest daily traffic volumes, contributes largely to the increase in delay due to the fact that pre-existing delay is much lower during mid-day than during the other time periods. Deadheading per in-service TNC (scaled to hourly volumes) is much more in mid-day than the other periods once peak-hour traffic volumes are used to normalize this measure. One can also argue that the evening shoulder, post the peak-hour evening rush is contributed to mostly by induced demand by people going out for dinner and entertainment who would have otherwise walked, taken the transit (as these modes would likely be much less crowded, cheap and travel-time reliable at these hours) or resorted to non-motorized modes of traffic. TNCs increase delay in the evening from 23% without TNCs to 106% in reality, increase the delay in the midday from 25% without TNCs to over 60%, and also increase delay significantly in the PM and AM peak periods albeit making ride-splitting and car sharing more lucrative and practicable. This is in contrast with their stated vision that by making first and last mile rides to transit centers more accessible, they could theoretically reduce travel time, increase transit ridership and in extension, take more vehicles off the road than those being added. Even if no further performance measure is considered, their contribution to the increase in overall person/vehicle delay itself contradicts this vision.

Figure 18 illustrates the total increase in delay between 2010 and 2016, as well as the share of this delay caused by TNCs, network changes, population changes and employment changes. During the AM peak, midday, and PM peak periods, TNCs cause between 43% and 48% of the increased delay and about 20% of total delay. Employment growth and population growth combined account for just over half of the increased delay, which would have been experienced in a counterfactual world and for all practical purposes, unavoidable under the existing infrastructure. In the evening time period, TNCs are responsible for almost 70% of the increased delay, and for about 40% of the total delay.

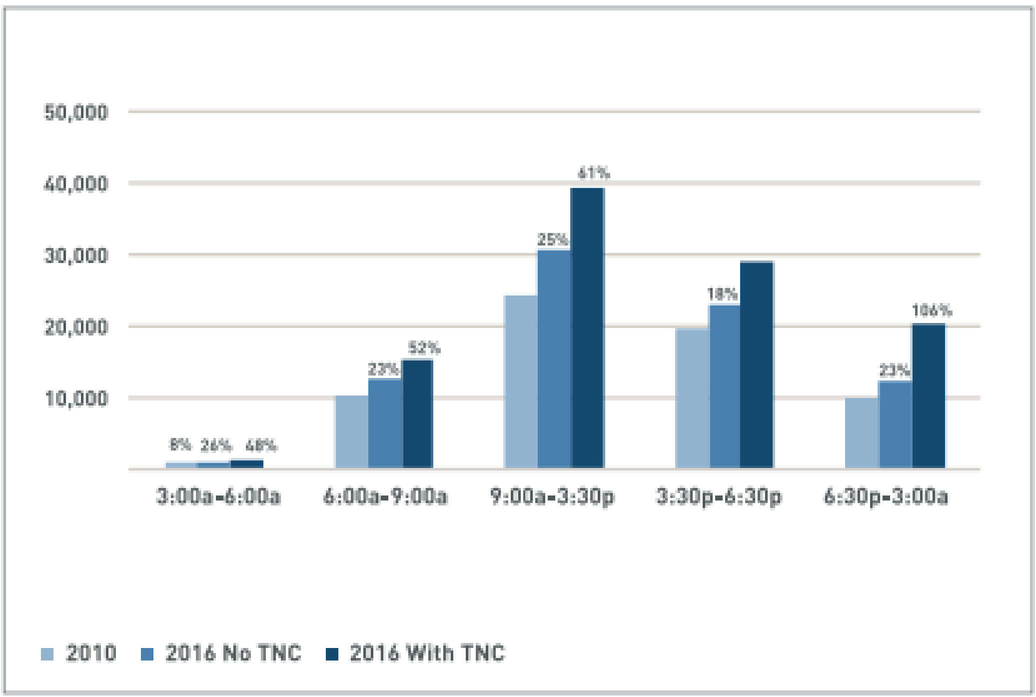


Figure 17 Vehicle Hours of Delay by Time Period. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows the total hours of delay experienced by the network fleet in 2010 and 2016. The x-axis shows the 5 time periods within the day: Early AM, AM peak, Mid-day, PM peak and Evening shoulder

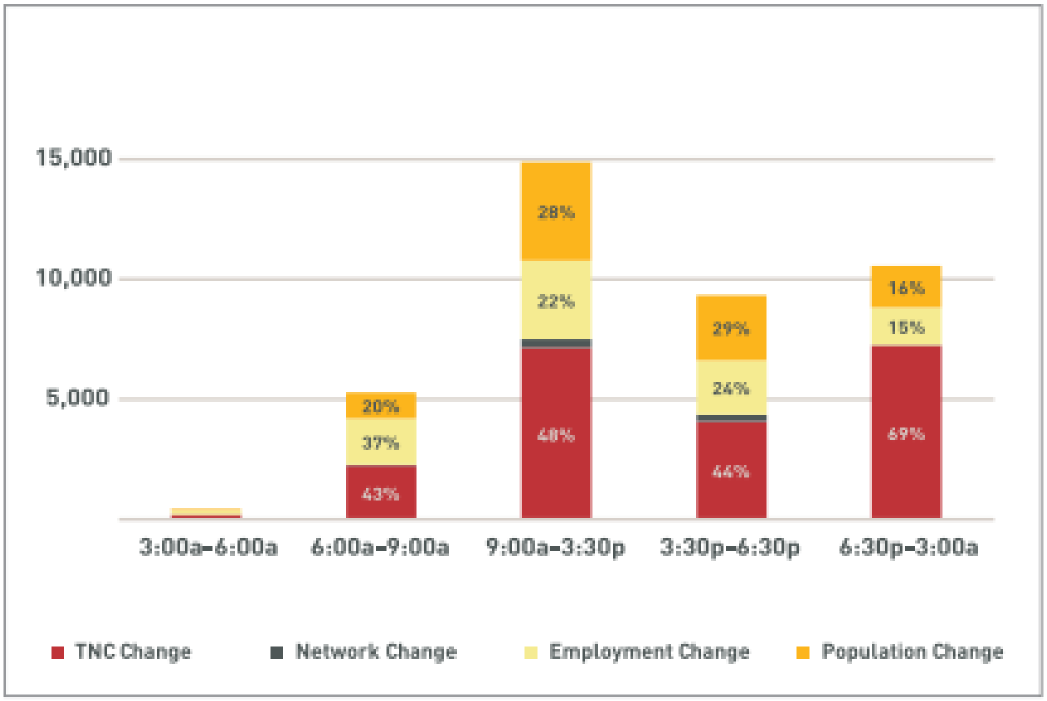


Figure 18 Change in vehicle hours of delay by time period by contributing factors. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows the total hours of delay experienced by the network fleet in 2010 and 2016, the x-axis shows the five times of day: Early AM, AM peak, Mid-day, PM peak and Evening shoulder

Figure 19 compares the VMT from 2010 to the 2016 No TNC scenario in which TNCs do not exist, and to the 2016 with TNC scenario. This figure shows that TNCs increased VMT in all time periods relative to 2016 No TNC scenario, with the greatest increases occurring during the midday and evening period. VMT effectively equips us with a performance measure that can be used to quantify extra TNC miles, and by extension, deadheading miles given in-service TNC vehicle miles can be attributed to substituting counterfactual volumes, as opposed to additional volumes. **Figure 20** illustrates the total increase in VMT between 2010 and 2016, as well as the share of this delay caused by TNCs, network changes, population changes and employment changes. TNCs contribution to increased VMT varies by time period. During the AM peak, midday, and PM peak periods, TNCs cause about 40% of the increased vehicle miles travelled, while employment and population growth combined are responsible for about 60% of the increased VMT. However, in the evening time period, TNCs are responsible for over 61% of the increased VMT and for about 9% of total VMT.

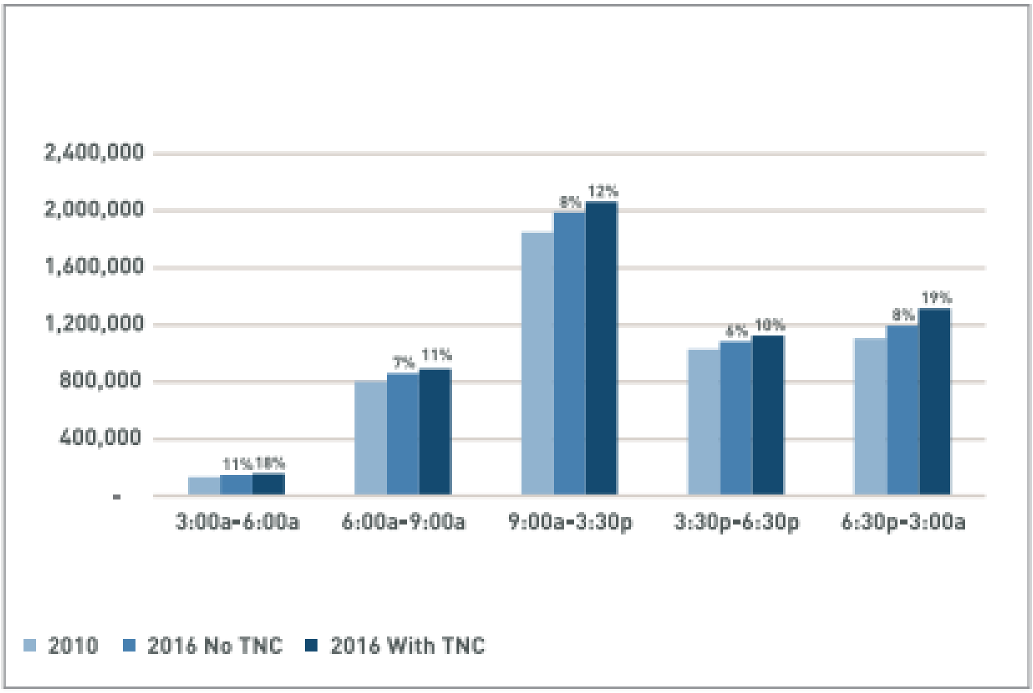


Figure 19 VMT by Time Period. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows the total vehicle miles travelled by the network fleet in 2010, 2016 no-TNC scenario and 2016 with TNCs included, the x-axis shows the five times of day: Early AM, AM peak, Mid-day, PM peak and Evening shoulder

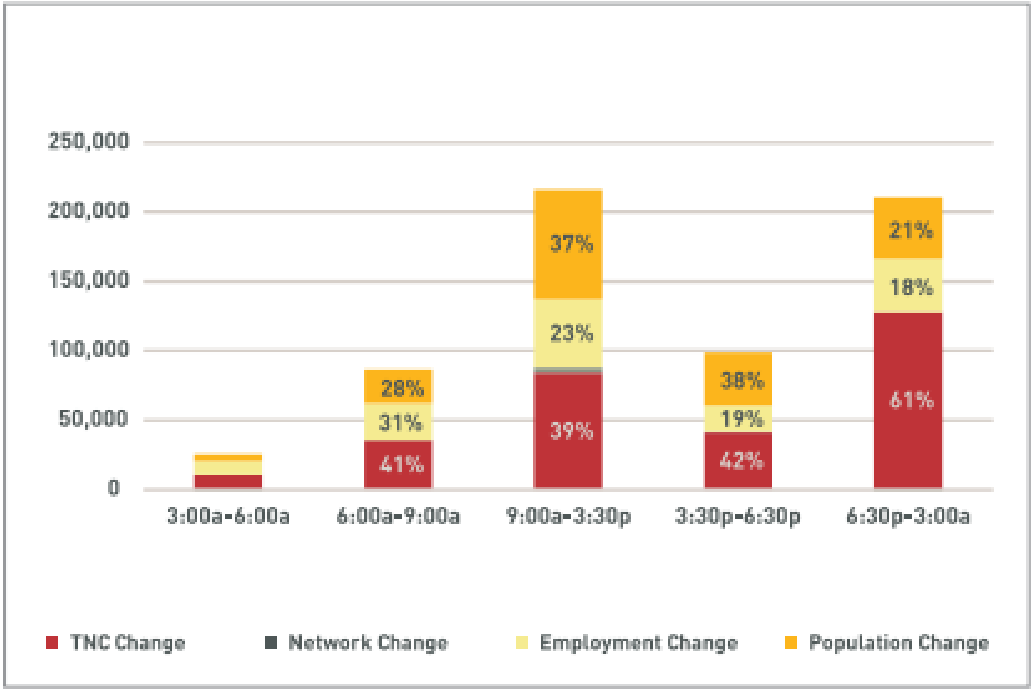


Figure 20 Change in VMT by time period by contributing factors. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows the change in total vehicle miles travelled, the x-axis shows the five times of day: Early AM, AM peak, Mid-day, PM peak and Evening shoulder

Figure 21 compares speeds from 2010 to the 2016 No TNC scenario in which TNCs don't exist, and to the 2016 with TNC scenario. This figure shows that average speeds have declined across all time periods, but that this decline has been exacerbated by TNCs. **Figure 22** shows the decrease in average speeds between 2010 and 2016, as well as the share of this delay caused by different factors. The decline in average evening speeds has been most precipitous, dropping over 4 miles per hour, with almost 75% of this change attributable to TNCs. Speed decreases during the other time periods were about 3 miles per hour, with about 45%-55% of this decrease caused by TNCs.

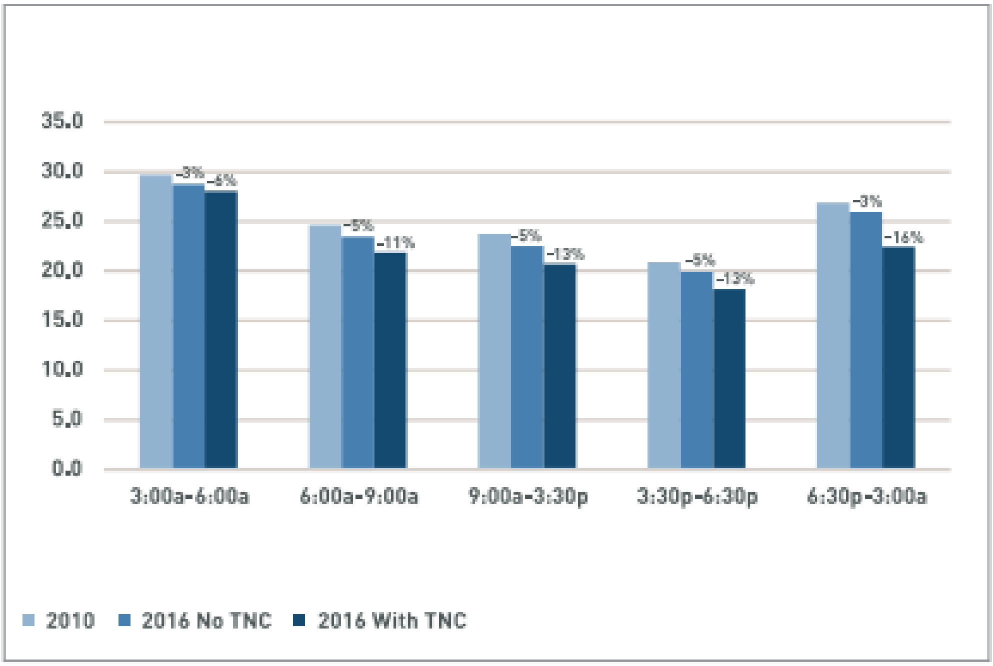


Figure 21 Speed in mph by time period. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows average speed for the network fleet in 2010, 2016 no-TNC scenario and 2016 with TNCs included, the x-axis shows the five times of day: Early AM, AM peak, Mid-day, PM peak and Evening shoulder

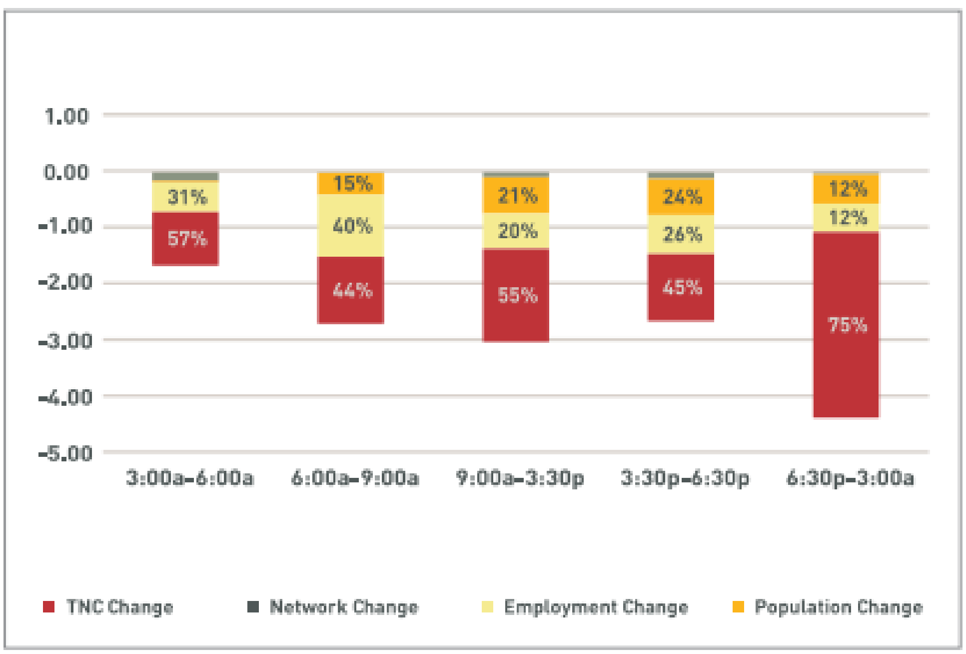


Figure 22 Change in average speed between 2010 and 2016 by time period by contributing factors. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows change in average speed for

the network fleet in 2010, 2016 no-TNC scenario and 2016 with TNCs included, the x-axis shows the five times of day: Early AM, AM peak, Mid-day, PM peak and Evening shoulder

4.4.2 TNC effects on Congestion by Supervisory Districts

TNC usage varies across the city, and thus affects congestion differently in different neighborhoods. An additional vehicle on the roadway in more congested areas results in more congestion than an additional vehicle in less congested areas. The following sections first use maps to illustrate overall changes in the congestion measures on the INRIX segments, followed by supervisorial district-level charts. **Figure 23** illustrates the 11 San Francisco Supervisor districts. The subsequent figures demonstrate that TNCs significantly contribute to increased congestion, especially in the densest parts of the city. **Figure 24** shows the percent increase in VHD between the 2016 No TNC scenario in which TNCs do not exist, and to the 2016 with TNC scenario. It indicates that the greatest increases in delay occurred in the core northeastern quadrant, as well as along key corridors such the Mission corridor.

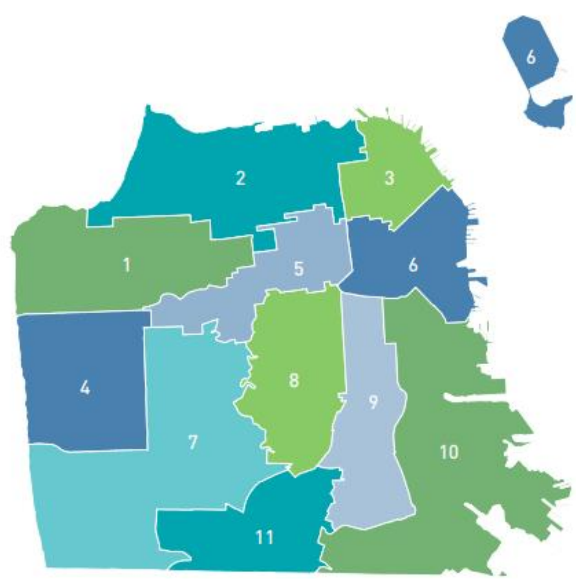


Figure 23 San Francisco Supervisory Districts. Source: TNCs and Congestion, SFCTA (Collaborated work)

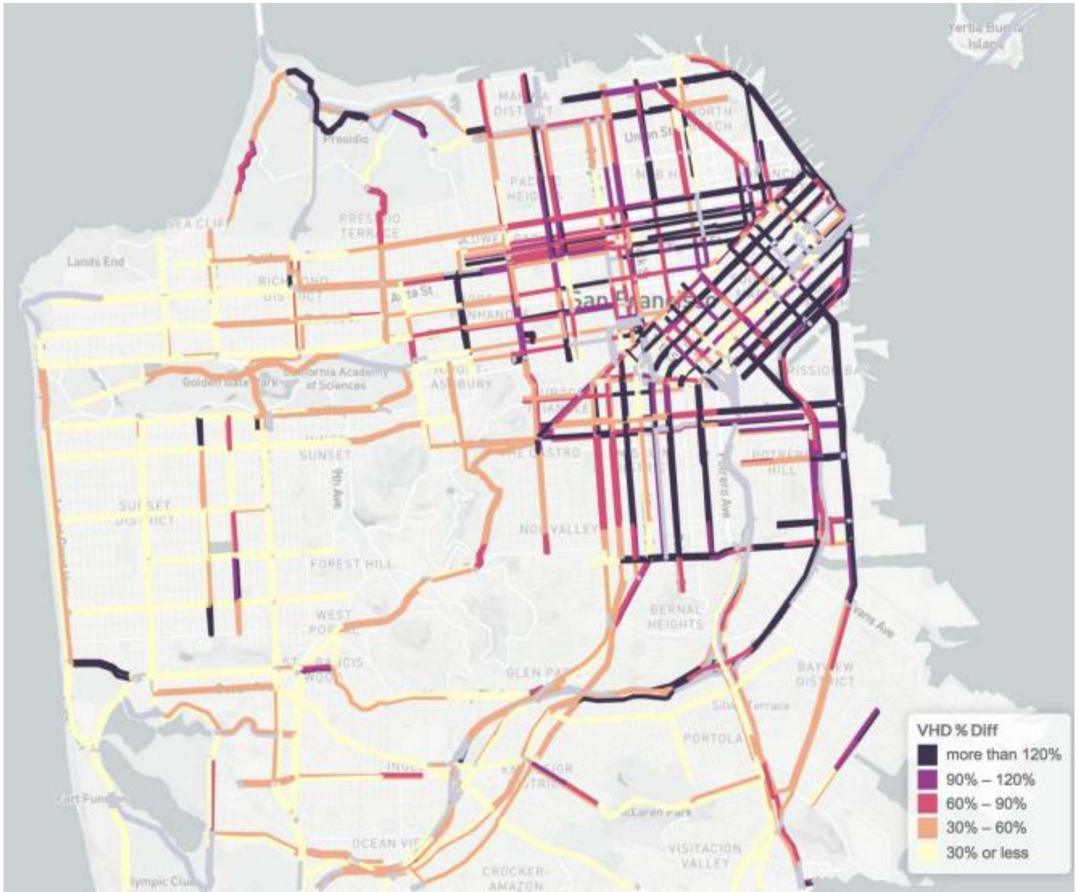


Figure 24 Percent change in delay between 2010 and 2016 by INRIX segments. Source: TNCs and Congestion, SFCTA (Collaborated work)

Figure 25 compares the delay from 2010 to that in 2016 counterfactual scenario that does not account for any TNCs, and to the present-day 2016 scenario that does account for TNC operations including pickups and drop-offs. It shows that TNCs increased delay in all districts relative to the counterfactual 2016 scenario. The greatest total increase in delay occurred in District 3 and District 6. The greatest relative increase in delay occurred in District 3, while the greatest total amount of delay occurred in District 6. **Figure 26** illustrates the total increase in delay between 2010 and 2016, as well as the share of this delay caused by TNCs, network changes, population changes and employment changes. The greatest increases in delay occurred in Districts 3 and 6, with approximately 73% of the increase in delay in District 3 due to TNCs, and about 45% of the increase in delay in District 6 due to TNCs.

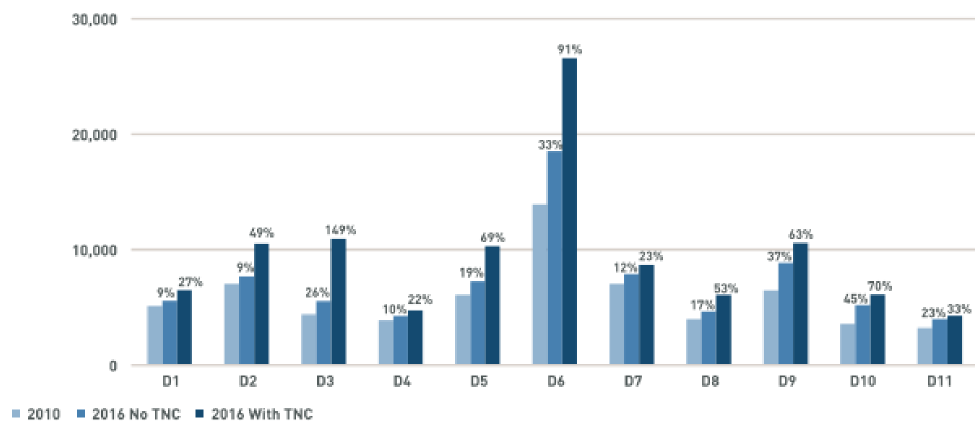


Figure 25 Delay by Supervisory Districts. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows total hours of vehicle delay for the network fleet in 2010, 2016 no-TNC scenario and 2016 with TNCs included, the x-axis shows the eleven supervisor districts within San Francisco

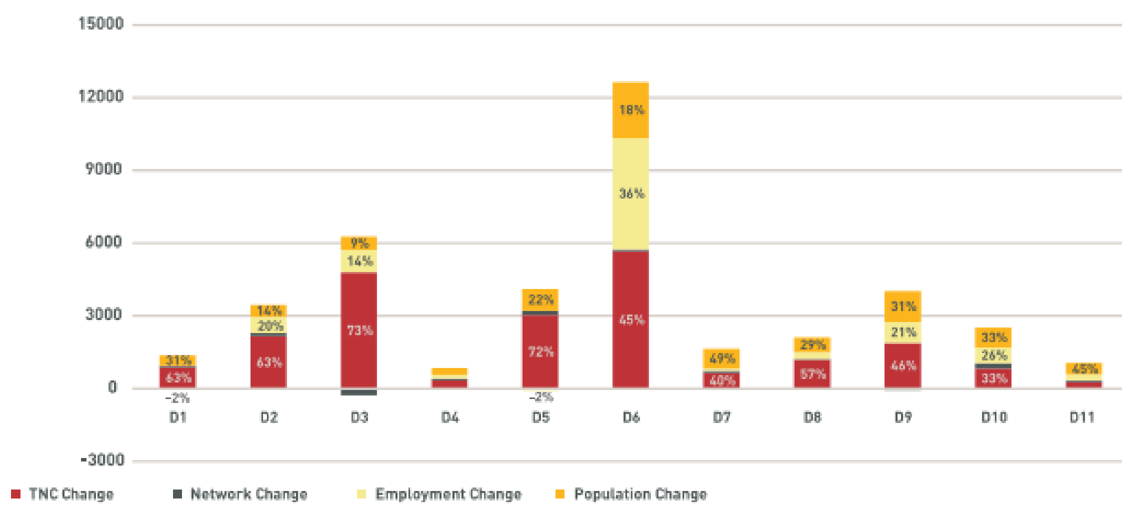


Figure 26 Hours of Delay by Supervisory Districts showing contribution of various factors. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows total hours of vehicle delay for the network fleet in 2016, the x-axis shows the eleven supervisor districts within San Francisco

It is estimated that approximately 36% of total delay in District 3 and District 6 combined is due to TNCs based on the percentage shares applied to the total increase in delay derived using the empirical analysis. The remaining districts exhibit increases in delay between 25% to 70% with the contribution of TNCs ranging from 20% to 45%. **Figure 27** shows the percent increase in VMT between the 2016 No TNC scenario in which TNCs don't exist, and to the 2016 with TNC scenario. It indicates that the greatest increases in vehicle miles travelled occurred along key corridors, and with general increases in the northeast quadrant.

Figure 27 Percent change in Vehicle Miles Travelled between 2010 and 2016. Source: TNCs and Congestion, SFCTA (Collaborated work)

Figure 28 compares the VMT from 2010 to the 2016 No TNC scenario in which TNCs don't exist, and to the 2016 with TNC scenario. The percentage change shown is relative to the 2010 Base scenario. This figure shows that TNCs increased VMT in all districts relative to 2016 No TNC scenario, with the greatest total increases occurring in Districts 6 and District 10, and the greatest relative increase occurring in District 3.

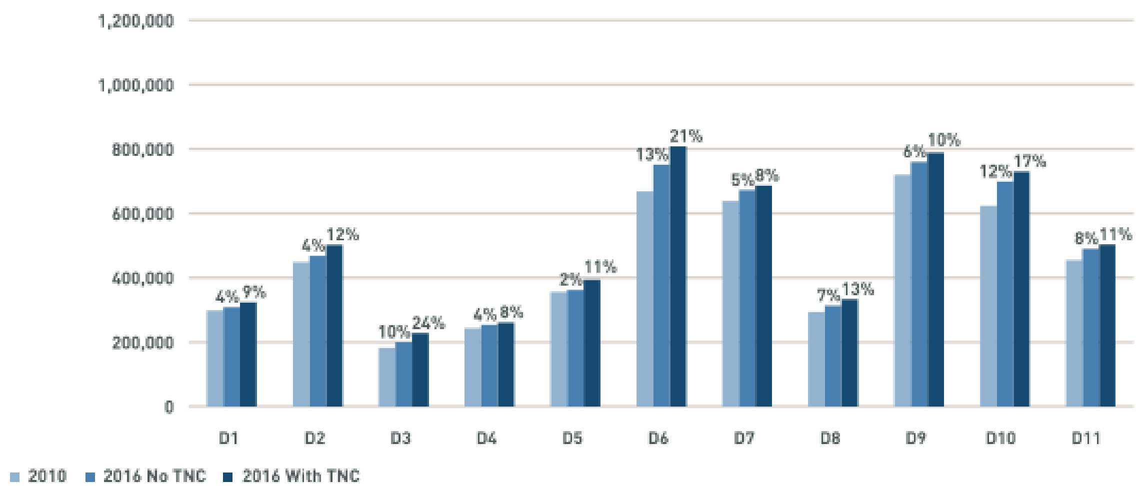


Figure 28 Vehicle Miles Travelled by Supervisory Districts. Source: TNCs and Congestion, SFCTA (Collaborated work). The y-axis shows total vehicle miles traveled for the network fleet in 2010, 2016 no-TNC scenario and 2016 with TNCs included, the x-axis shows the eleven supervisor districts within San Francisco

Figure 29 Change in Vehicle Miles Travelled by Supervisory Districts by Factor. Source: TNCs and Congestion, SFCTA (Collaborated work). The y-axis shows total vehicle miles traveled for the network fleet in 2016, the x-axis shows the eleven supervisor districts within San Francisco

Figure 29 illustrates the total increase in VMT between 2010 and 2016, as well as the share of this delay caused by TNCs, network changes, population changes and employment changes. As noted, the greatest total increases occurred in Districts 6 and 10. TNCs accounted for 44% and 35% the increased VMT in these districts, respectively. While the total increase in VMT in Districts 3 and 5 were less than observed in other districts, the share of this increase attributable to TNCs in these districts was over 70%, the highest in the city.

Figure 30 Percent Change between 2010 and 2016 in Speed by INRIX segments*. Source: Data Visualization tool by SFCTA (Collaborated work)

*The Data visualization tool developed in collaboration with Bhargava Sana at the San Francisco Transportation Authority can be found at http://tncsandcongestion.sfcta.org/

Figure 30 shows the percent decrease in speed between the 2016 No TNC scenario in which TNCs don't exist, and to the 2016 with TNC scenario. It indicates that the greatest decreases in speeds occurred South of Market, Downtown, and along the Embarcadero and with general increases in the northeast quadrant.

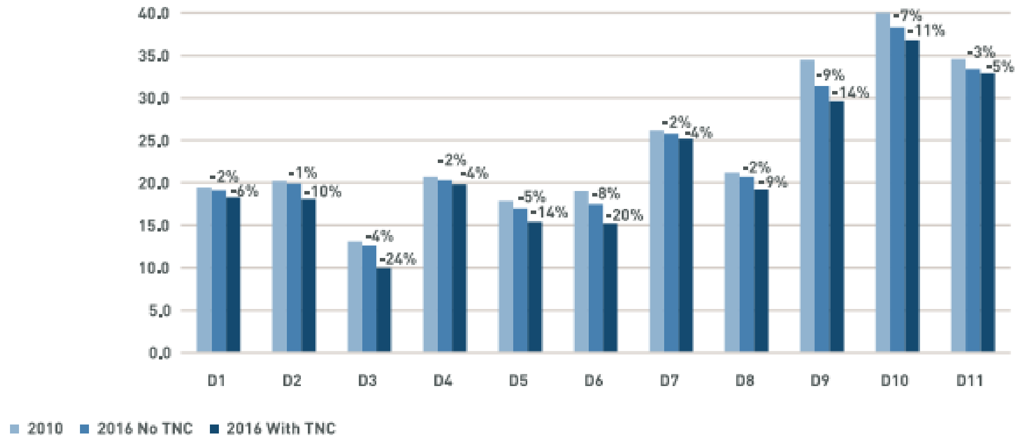


Figure 31 Speed in mph by supervisory districts. Source: TNCs and Congestion, SFCTA (Collaborated work): The y-axis shows the average speed for the network fleet in 2010, 2016 no-TNC scenario and 2016 with TNCs included scenario, the x-axis shows the eleven supervisor districts within San Francisco

Figure 30 compares speeds from 2010 to the 2016 No TNC scenario in which TNCs don't exist, and to the 2016 with TNC scenario. The percentage change shown is relative to the 2010 Base scenario. This figure shows that average speeds have declined in all districts, with the greatest relative declines between the 2016 No TNC and 2016 With TNC scenarios occurring in Districts 3, 6, 5 and 9. Overall speeds were lowest in District 3 and highest in District 10. **Figure 31.** exhibits the decrease in average speeds in each District between 2010 and 2016, as well as the share of this delay caused by different factors. The greatest declines in speed occurred in Districts 9 and 10. While almost 50% of this decline was due to TNCs in District 9, only 27% of the decline in District 10 was due to TNCs. Districts 3 and 6 also experienced notable declines in speed, with 82% of the decline in speed in District 3 attributable to TNCs. Note that more than half of the decline in speeds in District 6 is attributable to employment and population growth.

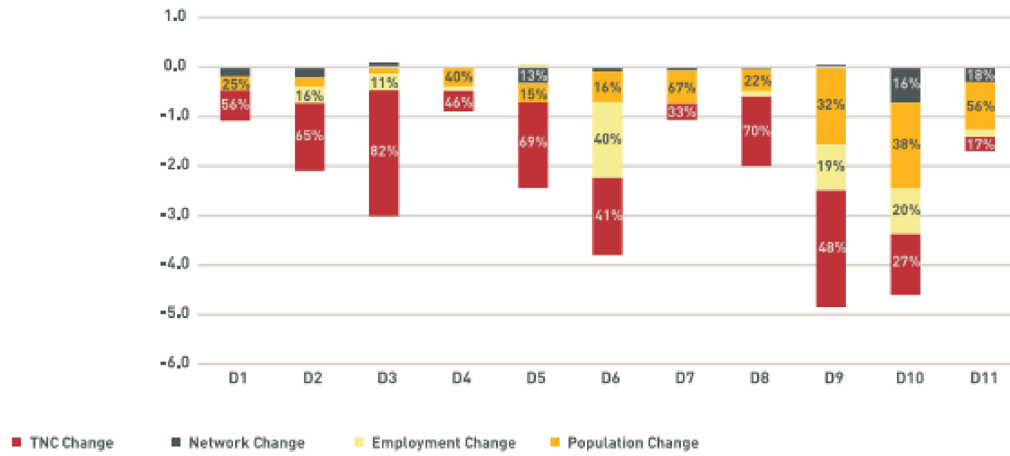


Figure 32 Change in speed by supervisory districts by factor. Source: TNCs and Congestion, SFCTA (Collaborated work):): The y-axis shows the change in average speed for the network fleet between 2010 and 2016, the x-axis shows the eleven supervisor districts within San Francisco

4.5 Possible Policy Interventions

Several potential cases for policy changes can be suggested as outcomes of the findings of this research study. It should be borne in mind that these policy-based interventions are recommended based solely on its academic theory merit-based implications and should not be treated as holistically evaluated suggestions. It should be kept in mind that the operational cost of a TNC ride is much more than the user pays for it. In fact, passenger fares only cover about 40% of the total cost of each ride (Cole 2016). Investor capital foots the remaining 60%. These trips could be more expensive since the facility cost of owning and operating each TNC vehicle is paid by the non-users. Any additional cost difference between TNCs and public transit comes from operating smaller, less expensive modes. Keeping aside even the operational cost, it can be argued that the true cost of running a TNC vehicle on the road spills over both user and investor footed expenses. The monetary value of the benefit notched by a TNC rider is a function of a combination of factors like total time saved by not taking public transit, delay caused to passengers who did choose to ride public transit by increasing net operating vehicles and revenue lost by public transit which, in the long term, can potentially turn public transit sufficiently unprofitable which may lead to service cuts to traditionally underserved or unprofitable areas. Within the foreseeable future, if and when TNC service providers run out of investor capital, and offering rides at a fraction of what their costs are is not economically feasible any longer, the fares of such rides is estimated to increase. If public transit fails to keep up with the competition it receives from TNC operations owing to their deep discounts, transportation, a basic requirement within and a pointer of the health of any economy, will become an untenable luxury for the multitudes. Even today, TNCs are not accessible to every section of the society partly due to their functioning platform and partly due to user unawareness. Transportation equity provided by public transit can therefore not be guaranteed or replaced solely or exclusively by privately held and operated travel facilitators.

Factoring in all these costs is a necessary endeavor to attain the true user benefit derived out of using a TNC over the pre-existent modes as TNCs have yet to exhibit their sustainability to maintain their ever intensifying grasp on travel mode shares sans the massive losses they are presently experiencing at the cost of their investor capital (Somerville 2017). Owing to the number of hours of delay and loss in travel time reliability that have been demonstrably attributed to the presence and operation of TNCs through this study, there exist several strategy programs and steps that can be taken to limit and mitigate the effect of TNCs within a congested roadway network as that of San Francisco. Some of them are mentioned here:

4.5.1 Congestion Pricing

A system of surcharging riders and drivers based on time of day could be an effective tool to utilize to discourage excessive vehicles from operating within peak congestion hours. Vehicles subject to increase congestion in historically observed peak hours could possibly be charged to use public-owned facilities and creating excessive demand. The revenue generated through congestion pricing can be further reinvested in the system to improve existing mobility options, such as increasing frequency of trains and other public transit modes on high-demand routes, maintenance and operation of transit cars and stations, increasing the incentive to use public transit over passenger cars. There are a number of different ways through which congestion pricing can be executed in the transportation domain within San Francisco. For instance, a system exclusively (or preferably, staggeringly) charging single occupancy vehicles (SOVs) over shared rides can be deployed, which attains a two-way advantage: it promotes ridesharing/carpooling increasing vehicle occupancy, and at the same time, encourages people to get off of passenger cars, effectively reducing demand of passenger-car based rides, and use public transit, increasing travel time reliability of transit. Another way to execute congestion pricing would be to charge drivers, based on the type of passenger car being used, for using traffic-clogged roadways primarily during peak hours. The two-fold hindrance thus created: firstly, potentially reduced travel time reliability and increased travel time by using an already congested network facing the driver, and secondly, the impending surcharge to use the non-optimally functioning roadway, would help divert/reduce the total number of cars attempting to use the facilities off the most densely congested parts of the city. This monetary value of the mentioned surcharge can be exercised by either a fixed or a dynamic pricing system that can be designed keeping in mind the most effectively and justly ascertain the user-cost of the roadway facilities depending upon the complexity and time-sensitiveness of the congestion being priced. In a dynamic pricing system, the value of the surcharge will be a proportional and continuously derived function of the total number of vehicles operating within the city (or a defined congested area) bounds. Alternatively, a fixed system of surcharge varying across the five times of days using historic traffic counts within each of those periods could be a simplistic approach to the same. The pricing could also be made subject to a function of the occupancy, real-time or average, of the vehicle in order to incentivize HOVs.

4.5.2 Cordon Capping of Vehicles

A fixed-time cap on the total number of commercially operated passenger cars, synonymous to a fleet that is mostly comprised of TNCs in the present-day scenario, can also be a working solution to decreasing and averting the number of passenger cars operating in the most densely congested part (mostly downtown or the northeastern quadrant) of San Francisco. A geometric cordon within which the cap will be effective can be established which targets the most problematic areas within the jurisdiction. Within these boundaries, only a fixed number of passenger cars, identified by the type (TNCs, taxis, privately owned vehicles, buses, vans, and any other modes of private transportation) under which each vehicle can be classified, would be allowed to operate. This number will have to be ascertained after a dedicated study of operational conditions that arise as an outcome of a specific number of functional vehicles. Through this move, transportation planners can exercise substantial control over the performance of the sought after network which can then be suitably optimized . In a pilot move by the city of New York as part of which the city established a cap on the number of ridehailing service passenger cars operating within the city, the proposed requirement (which was eventually voted on and approved) applied only to the “high-volume for-hire service” (those that provide equal to or more than 10,000 trips per day) cars so as not to affect singly owned vehicles. This move has the potential to provide at least a semblance of regulation of municipalities over the operations of TNCs. Another customization to this proposal could be limiting or charging the total time each vehicle, HOV or otherwise, spends inside the cordon, in order to be more equitable to commuters desiring to travel to the inside of the cordon and enabling minimum time spend within the set boundary.

4.5.3 Conversion of Parking Spaces into TNC Pickup/Drop-off Zones

In light of the potential benefits of the rising popularity of TNCs, it can be argued that parking requirements within the city do not hold as much prominence as they did in the pre-TNC era. It should be kept in mind that in a city as congested as San Francisco, parking is limited to begin with. Nevertheless, a case can be made for several on-street parking spots to be potentially converted into dedicated pickup and drop-off zones. This move could be directed towards reducing the number of TNC pickups and drop-offs being made on haphazard locations on the curb lane across the city that evidently affects traffic flow on these lanes as demonstrated in this study. Commuters shifting from driving their own vehicles and thus requiring fewer parking spots than in an otherwise unsubstituted for travel modes can therefore be benefitted from conversion of a number of parking spots into PUDO zones. This move will also be helpful in creating amendable regulations related to TNC pickups and drop-offs such that TNC drivers would then have clearly marked places to maneuver PUDO from and failure to comply with such regulations can be accordingly and suitably handled.

4.5.4 Potential Collaboration between the City and TNCs to Regulate or Incentivize TNC services to Transit Stations

In order to combat the declining transit ridership and TNCs potentially affecting transit mode shares as discussed in detail in chapter 3, a successful collaboration between the city and TNCs has the potential to enhance traffic flow, transit operations, transit ridership, TNC and transit revenue generation, and overall enhanced rider and commuter experience greatly. A systematic arrangement to incentivize TNC trips to and from transit stations would increase transit ridership while also taking additional passenger cars introduced as an outcome of rising popularity of TNCs off the network. The user cost benefit gained in an efficiently planned commuting provision, such as this, can then be split between the providers of this system proportionally. The enhancement of mobility as a consequence of such a system should be explored in context of demarcated service zones defined by the catchment areas of existing and emerging public transit modes and that of TNCs. Instinctively, it can be inferred that the congestion benefits of a move of such nature would be considerable and need to be further quantified through simulations or pilot studies. A few such collaborative studies are already in motion such as that declared between the Cincinnati Mobility Lab and Uber, undertaken by the Ohio-Kentucky-Indiana Regional Council of Governments in partnership with the Southwest Ohio Regional Transit Authority and the Transit Authority of Northern Kentucky. A greater push towards moves of such nature based on the successful completion and a thorough review of the outcomes of these pilot studies are the need of the hour to tackle successfully the growing congestion problem in high density urban areas such as San Francisco (Acton, Delagardelle, Kester and Vachiraadisorn 2017; Kuhr, Bhat, Duthie and Ruiz 2017). A few other examples of undertaken pilot initiatives are mentioned below:

a.) The Pinellas Suncoast Transit Authority (PSTA) branded as ‘Direct Connect’ (Pinellas Suncoast Transit Authority 2016),

b.) Dallas Area Rapid Transit (in collaboration with Lyft and MV Transportation) aimed at paratransit users (Shared Use Mobility Center 2017),

c.) Cascades East Transit partnership with Uber in Central Oregon for providing transportation and/or transit discounts for special events (Cascades East Transit 2017),

d.) The Go Centennial pilot partnership with CH2M, the city of Centennial, the Denver South Transportation Management Association, Lyft, the Southeast Public Improvement Metropolitan District (SOUND), Via Mobility Services (Via) and Xerox (Conduent) addressing first and last mile transportation services to transit centers (Xerox Press release 2016),

e.) The Regional Transportation Commission of Southern Nevada (RTC) and Lyft in Las Vegas aimed at providing enhanced service to Southern Nevada Transit Coalition paratransit users. (Regional Transportation Commission 2018)

A move of this measure could also be considered as a step in the direction of a fruitful partnership between the municipality and the private TNC companies paving a way for bidirectional and rational dialog between the two agencies where the city earmarks certain facilities for the unhindered operation of TNCs while also ensuring smooth and uninterrupted flow of traffic on its own facilities.

4.5.5 Allocation of Urban Right-of-Way

Another possible avenue to research potential policy programs to accommodate the growing urban TNC presence more sustainably would be a predetermined allocation of right of way to each mode of transportation operational on a specific network. Execution of this policy can be based on varying geographical scales ranging from a few blocks, for example, limited to the core or downtown areas of the city where the impact of any additional mode of personal transportation is felt the most, to possibly a supervisory district level. Regulations dividing up the right-of-way (ROW) into multiple fractions to promote a more equitable distribution of travel time among users of the facility could be proposed. This, in its essence, is not unlike the red-carpet lanes assigned to buses and streetcars to promote public transit in the central business district and the downtown areas in San Francisco during the busiest hours of the day. The ROW can be distributed within both conventional and non-conventional modes like bikes, pedestrians, transit, passenger cars, TNCs, light rails, etc. How much ROW gets allocated to each of these modes in order to arrive at the most optimum user-cost (time cost) balance can be a possible subject for future research.

4.6 Future Work

This study can be expanded to include the contexts of multiple cities, differing in size, population, popularity of transit and demographic characteristics. Attributes like deadheading, parking requirements, right-of-way allocations are extremely dynamic in a future that promises the emergence of autonomous vehicles and any policy change should be subject to thorough reviews and studies of what that means in terms of the quality of mobility in the present (and future) world. As carpooling services offered by TNCs continue their widespread assimilation, it is imperative to differentiate between the impacts caused by single occupancy and pooled TNC services in terms of network performance. Any such study investigating distinctions between these highly correlated modes would require exceedingly granular data. Therefore, potential data sharing agreements, promoting data-driven, accurately informed inference-drawing and consequently, decision-making, between cities and companies like Uber and Lyft are the need of the hour. This study extricated TNCs as a mode from other conventional modes used to conventionally model travel demand which can be further benefitted by finer spatial and temporal resolution of TNC data. Accounting freight and delivery truck volume and studying their dedicated effect on congestion in congested urban areas such as San Francisco would also help increase the practice-readiness of research studies like this one. Development of state-of-the-art volume delay functions that more accurately represent current traffic behavior and relationships between increasing traffic volume and travel time including novel modes such as TNCs and autonomous vehicles would also greatly advantage the field-relatability of similar research studies.

4.7 Conclusions

The objective of this research study was to find out if TNCs are correlated to traffic congestion in the city of San Francisco. Since TNCs are demonstrated to have both positive and negative repercussions on factors like vehicle ownership, change in total and personal vehicle delay and transit ridership and popularity that have significant implications on traffic congestion, if found correlated, this research investigated whether they increase or decrease traffic congestion for the case of San Francisco. How do TNC pickups and drop-offs influence traffic congestion within San Francisco? And lastly, how does the magnitude of the impact of TNCs on congestion compare to that caused by pre-existing conventional drivers of traffic and congestion change?

It was established that network performance in San Francisco declined between 2010 and 2016, increasing congestion. The San Francisco Transportation Authority's Congestion Management Program (CMP) monitoring indicated that average AM peak arterial travel speeds decreased by 26% when compared to that in 2009, while PM peak arterial speeds have decreased by 27% during this period. Vehicle hours of delay on the study network increased by 40,000 hours for a typical weekday, while weekday vehicle miles travelled on study roadways typically increased by over 600,000 miles. Travel time reliability too has taken a deep hit. It is also equally noteworthy that during the study period, significant changes occurred within San Francisco. Roadway and transit networks changed, including the rebuilding of Doyle Drive (Presidio Parkway), the laying of transit red carpet lanes was implemented, and the bicycle network was expanded. Additionally, San Francisco added 70,000 new residents and over 150,000 new jobs, and these new residents and workers were expected to add more trips to the city's transportation network. Finally, new mobility alternatives, most discernibly TNCs, emerged. The duopoly of TNCs have witnessed a rapid evolvement to become an important travel option in San Francisco. By late 2016, TNCs were estimated to generate over one million intra-San Francisco vehicle trips in a typical week, accounting for approximately 15% of all intra-SF vehicle trips (Cooper et al. 2018). The number and share of TNC trips in San Francisco have unquestionably continued to increase since 2016, which was the observed treatment period for this study. The combined effects of all these changes on traffic congestion in San Francisco was studied as part of this research using a two-stage approach. In the first step, an empirical relationship between the increasing number of passenger cars within the network and the volume of TNCs, and the number and location of TNC pickups and drop-offs was established. This empirical model was validated against the observed present-day network conditions to control for its accuracy. Next, the observed network performance measures were compared to a modelled no-TNC scenario to ascertain their lone-factor impact on the calculated performance measures. In the second stage of the research, multiple SFCHAMP traffic assignments were run incrementally introducing each above-mentioned driver of congestion change to get an estimate of the contribution of each factor to the growing congestion in the study area. In order to avoid overestimating the effect of TNCs the fractional empirical constant obtained in the first stage of the research was applied to TNC volumes and TNC pickups and drop-offs that scaled down their culpability to the total increase in VMT, VHT and VHD on the network in light of their positive accountability in substituting single use vehicles within the network.

The results show that despite some substitution between TNCs and other car trips, most TNC trips are adding new cars to the network and that TNC vehicle trips have significantly underwritten the increased traffic congestion within the city. After normalizing this increase in congestion for the weight of increased employment and population, and transportation network changes, TNCs are estimated to have caused 51% of the total increase in vehicle hours of delay, 47% of the total increase in vehicle miles traveled, and 55% of the overall decline in speeds citywide between 2010 and 2016. That the effect of TNCs on congestion varies considerably by time-of-day should be noted in light of this study's significant policy repercussions. During the major portion of a typical weekday, approximately 40% to 50% of the increase in vehicle hours of delay is inferable to TNCs, but during the evening peak and shoulder, almost 70% of the increase in vehicle delay is attributable to TNCs. Similarly, during most of the day approximately 40% on the increase in vehicle miles traveled is due to TNCs, but in the evening TNCs account for over 60% of the overall increased VMT. Average travel speeds have declined by about 2 to 3 miles per hour during most of the day, with TNCs accounting for about 45% to 55% of this decrease. However, evening speeds declined by almost 4.5 miles per hour on the study network, with TNCs having been estimated to cause 75% of this decrease. The effects of TNCs on congestion also varies significantly by location. The greatest surges in vehicle hours of delay occurred in supervisorial districts 3, 5 and 6. Over 70% of the increase in delay in Districts 3 and 5, and about 45% of the increase in delay in District 6 occurred due to TNCs. Vehicle miles traveled went up most significantly in Districts 6 and 10, with TNCs accounting for 41% and 32% of this increase respectively. While the total increase in VMT in Districts 3 and 5 were less than observed in other districts, the share of this increase attributable to TNCs in these districts was between 65% and 75%, the highest in the city. Average speeds have declined in all districts, with the greatest relative declines occurring in Districts 3, 6, 5 and 9.

Table 18 recalls the framework referred in Chapter 1 and seeks to summarize the issues raised by extant literature and points to the ones answered in this research study. Broadly, we conclude that TNCs are an important contributor to growing traffic congestion in San Francisco.

Table 18 Summary of results and issues tackled by this research

Topic	Evidence
Car Ownership	No change
Mode Shift (long-range)	No evidence
Mode Shift (short-range)	70% of TNC trips are new vehicle trips, substituting for walk, bike or transit
Pooling	No direct evidence. Literature: 13-20% select shared option
Deadheading	20% of VMT (50% in NY)
Disruptive driving	Each pick-up or drop-off leads to 140s of disruption on major arterials and 80s on minor arterials
Interaction with other traffic	Evidence
Spatial Distribution	Concentrated in downtown area, further exasperating existing congestion
Temporal Distribution	Heaviest in PM peak and into the evening, with a second peak in the AM

APPENDIX A: Addressing possible limitations and concerns raised

A.1 Section 2.4.2 TNC Data

Duplicate traces are removed to avoid double-counting drivers who work for both TNCs and vehicles recorded by multiple clients. While this assumption potentially adds error to the pick-up location estimation, there is no evidence to suggest that it systematically overestimates the impact of pick-ups, nor is it evidenced to suggest that pick-ups are more likely to happen in isolated areas (not covered by the TMC network used in this analysis). In inspecting this data, locations were reviewed that showed a high frequency of pick-ups and a high frequency of drop-offs. Locations that stood out in the inspections of both pick-ups and drop-offs included the streets surrounding Union Square, major hotels, and 4th Street in front of the Caltrain station. In fact, a recent pilot program implemented by Lyft recognizes that pick-ups on main streets are both common and problematic, and seeks to divert them to side streets, as shown in **Figure A 1**. Recognizing that there is some error in the method to identify the pick-up location, it is aimed to bound that error and to understand the potential effect of that error. In terms of bounding the error, the error is expected to be larger for trips with a longer wait time because there is an opportunity for the driver to travel farther during that wait time.

Another potential issue with measuring PUDO impacts is that they are expected to vary by time-of-day. To begin with, it was acknowledged that the number of PUDO varies by time-of-day, but the PUDO coefficients were calculated as a constant across the five different times-of-day. To address the potential concern mentioned above, a model was tested that segments the PUDO coefficients by time-of-day. In the resulting model, the time-of-day differences on minor arterials were not statistically significant, and the time-of-day differences on major arterials were marginally significant. Given the limited benefit of this more detailed specification, the more parsimonious model was preferred that was begun with prior to testing this additional hypothesis.

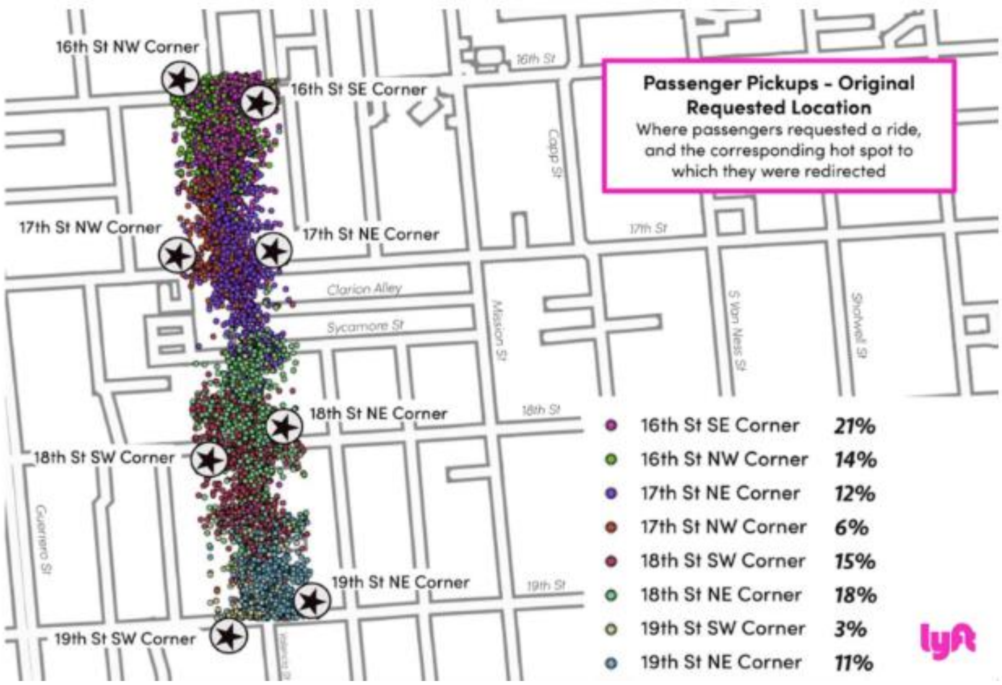


Figure A 1 Data from Lyft pilot program to divert pick-ups from Valencia Street to less congested side streets.

A.2 Section 2.7 Additional Model Estimation

A concern that speed limit changes can potentially affect the baseline speed at which a typical vehicle is assumed to operate on an arterial in a two-fold answer is addressed here. Like mentioned before, in this study, delay is defined as the difference between average travel time and free flow travel time. Therefore, demonstrating the relationship between free flow speed and the corresponding speed limit on each network link should intrinsically suffice in establishing the association between baseline speeds and operating speeds. As part of this study, speed limits were not used to arrive at estimates of free flow speed/travel time. Instead, the highest average hourly weekday speeds derived on link-level granularity assessed from five-minute interval real time speed data sourced from INRIX were established as free flow speeds. Consequently, in order to address potential concerns that speed limit reductions on certain links would definitively result in lowering of baseline (free-flow) speeds, whether the extant estimates of free flow speeds are significantly correlated with the changes in speed limits has been ascertained. In order to do that, z-tests were carried out on three snapshots of the free flow speed data corresponding to the two sets of free flow speed estimates, one each for the years 2010 and 2016. Links where speed limits were updated between the two study years within the INRIX network were identified. The three sets of data correspond to

a.) Links where speed limits were reduced in 2016 from those posted in 2010,

b.) Links where no speed limit changes were observed, and

c.) Combined set of links in a.) and b.).

Since the universe of this discussion is comprised of the arterials and freeways of the county of San Francisco, it can be assumed that the standard deviation of the free flow speed estimates are known. Since these variances are known, a z-test can be used in lieu of a t-test since z-test assumes that the observations belong to a normal distribution rather than the Student t-test distribution (t-test assumes this). Another argument in support of using the z-test over a t-test is that since the population variances have already been input, when the z-test are carried out, one does not have to make a choice between using equal or unequal variances t-test. The results of the z-test (shown in **Table A 1**) demonstrate that in none of the three cases were the free flow speeds significantly different between the years 2010 and 2016. This, in extension, also suggests that the changes observed in free flow speeds between the two years are not a function of the speed limit drops deployed within the study network.

Table A 1 Z-test for exploring relationship between speed limit reductions and free flow speed estimates

z-test: Two Sample for Means						
Scenarios	Speed Limit Reductions Only		No Speed Limit Changes		All links combined	
Free Flow Speed for year	2010	2016	2010	2016	2010	2016
Mean	38.23	40.01	37.41	38.14	37.44	38.25
Known Variance	147.84	217.47	175.5	284.1	174.2	280.16
Observations	137	137	1855	1855	1992	1992
Hypothesized Mean Difference	0		0		0	
z	-1.09		-1.47		-1.69	
P(Z<=z) one-tail	0.1373		0.0709		0.0456	
z Critical one-tail	1.6449		1.6448		1.6448	
P(Z<=z) two-tail	0.2746		0.1418		0.0912	
z Critical two-tail	1.9600		1.9600		1.9600	

A.3 Section 4.2 Methodology

A.3.1 Accounting of visitor travel

Visitor travel in San Francisco has also increased significantly between 2010 and 2016. According to research prepared for the San Francisco Travel Association, the number of annual visitors to San Francisco increased 58% from 15.9 million in 2010 to 25.2 million in 2016 (Armstrong 2011; Bay City News 2017). The SF-CHAMP model includes visitor travel. Further investigation reveals that the reporting of visitor numbers changed in 2015, such that numbers before 2015 include only leisure visitors, while numbers after 2015 include total visitors (San Francisco Center for Economic Development 2012, 2015, 2016; San Francisco Travel Association 2016). Therefore, the actual growth in tourism in

San Francisco is much less than the earlier mentioned 25.2 million, as summarized in **Table A 2**.

Table A 2 Annual Visitors to San Francisco

Year	Leisure Visitors (millions)	Total Visitors (millions)	Growth from 2010
2010	15.9		
2011	16.4		3%
2012	16.5		4%
2013	16.9		6%
2014	18.0		13%
2015	18.9	24.6	19%
2016*	19.4	25.2	22%

* Leisure visitors in 2016 are interpolated based on the growth in total visitors.

In the 2010 base case, visitor travel represented approximately 4.5% of all intra-San Francisco travel. However, the SF-CHAMP model does not produce a 58% increase in visitor travel because the number of hotel rooms in San Francisco, which have not increased significantly increased during this time-period primarily influences it. The increase in visitor travel may be at least partially explained by the growth in the number of home share options such as AirBnB. In 2015, it was estimated that there were 34,000 hotel rooms, and almost 5,000 AirBnB listings in San Francisco (Pender 2015). In SF, visitors use TNCs and transit more than passenger vehicles. Research for the San Francisco Travel Association shows that TNCs are the third most commonly cited transportation mode for intra-San Francisco visitor travel, exceeded only by BART and Muni (two transit operators in San Francisco), and followed by cable cars, personal automobiles, rental cars and taxis. Therefore, while one cannot precisely estimate the share of increased congestion due to visitor travel, it is likely small due to the overall size of the visitor market and the preference for visitors to use non-auto modes. In addition, recent survey data indicates that TNCs are used less frequently by visitors than Muni and

BART, although this is likely changing as TNCs become more ubiquitous. Increases in pedestrian travel might also impede traffic flow due to turning movements or other conflicts, but there is no data available to indicate whether increases in pedestrians in San Francisco have reduced auto speeds.

A.3.2 Addressing freight volume in San Francisco

Online shopping, and by extension, freight and delivery truck traffic are expected to have significantly increased during the study period as well. There is no observed data on the size of the universe of commercial and freight delivery services in San Francisco, nor any observed data on how this has changed between 2010 and 2016. The SF-CHAMP model does include a basic truck and commercial model driven by employment and population assumptions, and thus there are higher numbers of truck and commercial vehicles in SF-CHAMP in 2016 than in 2010. There is observed data from the San Francisco Planning Department about the durations of TNC (2018), taxi and commercial and freight delivery durations, and the duration of deliveries is, unsurprisingly, significantly longer that TNC pick-ups and drop-offs. However, commercial and freight deliveries typically use commercial vehicle loading zones, and do not interrupt flow. In fact, recent data from the San Francisco Police Department indicates that in the densest parts of San Francisco, TNCs (not commercial vehicles) account for 2/3 of congestion related traffic violations and for over 75% of citations for blocking lanes of traffic (Rodriguez SFPD 2017).

To summarize, the SF-CHAMP model does incorporate some growth in commercial and freight delivery volumes, and a recent study by the SFPD shows that TNC loading and not deliveries are the dominant cause of flow-impeding traffic violations. Changing demographics may also contribute to increased TNC usage, as the National Household Travel Survey indicates that people with higher incomes appear to make more TNC trips. Finally, while this research does address changes in network capacity resulting from major transportation and land use projects, due to a lack of data it could not incorporate temporary unpermitted disruptions in traffic resulting, for example, from short-term construction activities.

A.3.3 Incorporating an interim year of analysis to account for possible sources of disruption in traffic trends between 2010 and 2016

One might argue that the period between 2010 and 2016 was subjected to severe economic hardship and consequent financial recovery. Due to the existence of the massive disruption of demographic trends and employment that theoretically shaped the travel patterns one encounters today, the question of forecast accuracy begs crucial examination; fortunately this is a problem that has been studied to some degree in the literature. An important aspect of that is to understand the reasons for forecast inaccuracies. One distinction that is commonly made is between the accuracy of inputs to the travel model, versus the accuracy of the model itself. Inputs include factors such as population and employment by TAZ and fuel price. In the example of the 2008-2011 recession, a 2010 forecast made in 2005 that did not anticipate the recession would likely over-predict traffic in 2010, while a 2015 forecast made in 2010 that did not anticipate the economic growth coming out of the recession would likely under-predict traffic in 2010. In a review of traffic forecast accuracy, Nicolaisen and Driscoll (2014) found that every study they reviewed cited these auxiliary forecasts as an important source of forecast inaccuracy. Andersson et al (2017) went further to quantify how much forecasts could be improved if they got these inputs correct, using the case of past forecasts in Sweden. They found that adjusting the forecasts based on the actual population growth, fuel price, fuel economy, car ownership and GDP reduced the root mean square error of the forecasts from 0.38 to 0.12. They concluded that, “A very large share of forecast errors can be explained by input variables turning out differently than what was assumed in the forecasts.” This is a testimony of the explanatory strength of the models. What is important to bear in mind here is that this analysis is not a true forecasting exercise. Instead, it is a form of modeling exercise where the actual level of economic/employment growth coming out of the recession is known. While this model differs from those tested by Andersson et al (2017), it is reasonable to expect that knowing the inputs improves the accuracy of the modeling exercise. What remains important is that the relationship between employment levels and the level of travel remains consistent. In particular, it is important that that one locates the employment in the correct TAZs by the correct industries. Typically one can do this from a combination of data sources ultimately derived from unemployment insurance records, but this process requires a sufficient quality control effort to ensure that records are located on the correct side of a street, and are distributed to the locations where employees actually work, rather than to the headquarters of a company. It is standard practice in travel forecasting to develop and calibrate a model for base-year conditions, and apply that model to predict conditions in a different year. The travel demand model used to assess traffic conditions based on accurate data to reflect changes in the input parameters (e.g. population and employment) in this study makes this assessment different than traditional forecasting exercises where future conditions are predicted. Here, it is sought to model the past. It is envisioned that an interim year would exhibit growth in congestion comparable to the ones projected for 2010 and the counterfactual 2016. The network performance statistics for an interim year, say 2012, would be worse than those in 2010 and better off than those for 2016. The objective of this study is not to comment on the absolute condition of the network, and the performance measure thereof, but to capture, as precisely as possible, the worsening of these conditions over the study years. In order to test this hypothesis, the model was run using the previously estimated parameters for background traffic (assuming zero or negligible TNC volumes) for the year 2012. The SF-CHAMP model based estimation showed that with respect to 2010, a 2% increase in VMT was observed in 2012. This was predicted to be 7% in a counterfactual 2016 year with no TNCs and 12% in the modelled year 2016 with TNCs present (Refer **Table A 3**). The primary purpose of a travel forecasting model is to make predictions that go beyond a base year, especially when economic conditions and other factors change dramatically. In applying the model in this way, one is following in more than five decades of established practice. Whether a model calibrated for 2010 conditions would accurately predict 2016 traffic volumes in the absence of TNCs cannot be directly established using the SF-CHAMP model alone since the observed 2016 traffic volumes include TNCs, a mode that SF-CHAMP calibrated for 2010 does not account for. The counterfactual scenario tests this. Thus, the question of validity of the model now shifts to that represented by the counterfactual scenario used to compare the outputs of the empirical analysis. One approach to validating the robustness of SF-CHAMP model would be to compare a similar activity-based model with a proven stellar record of accomplishment forecasting future travel demand calibrated for an analogous base year and subjected to near equal (or more aggressive) urban growth. A study of the temporal stability of important structural relationships built into travel models (Mwakalonge and Badoe 2014) is referred to here. This study used data from three household surveys in the Greater Toronto area in the years 1986, 1996 and 2006. It found, for example, that the root mean square error of 2006 mode choice predictions made from 1996 was 1%, and for predictions made from 1986 it was 3.2%. Note that Toronto grew very rapidly over this period, much more so than San Francisco did between 2010 and 2016. In order to further validate this assumption of SF-CHAMP being able to correctly evaluate traffic volumes and network conditions in 2016 in the absence of TNCs, the estimated empirical model was applied to the year 2012, a year when TNCs could still be assumed to be a fledgling mode of transportation. The year 2012 was selected since Lyft began operations in June 2012, and UberX (the lower cost service) started in July 2012. It is expected that in 2012, the effect of TNC would still be small, but one is unsure about their magnitude in 2012. In order to determine the predicted 2012 conditions, first, an SF-CHAMP model for a 2012 scenario was run, including the appropriate population and employment changes from 2010. Then those SF-CHAMP results were used to apply the existent panel model in the same way as it was applied to predict the 2016 counterfactual scenario, with the TNC variables set to zero. The results are listed in **Table A 3**.

The results suggest that the predicted VMT, VHT, VHD, average speed and PTI80 all fall between the predicted 2010 and 2016 No TNC conditions, as one would expect. They are closer to 2010 conditions than to 2016 No TNC conditions, which one would also expect given the difference in years and the rates of growth in those years.

Table A 3 Network Performance Metrics including intermediate years

Scenario	Network Performance Metrics								
		Based on Modeled Travel Time				Based on Observed Travel Time			
	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
2010	4,923,449	205,391	64,863	24.0	1.83	204,686	64,158	24.1	1.83
2012	5,028,567	211,077	67,376	23.8	1.84	N/A	N/A	N/A	N/A
2016 No TNC	5,280,836	230,642	79,449	22.9	1.94	N/A	N/A	N/A	N/A
2016 with TNC	5,559,412	266,393	105,377	20.9	2.12	269,151	108,134	20.7	2.21
	Percent Change from 2010								
		Based on Modeled Travel Time				Based on Observed Travel Time			
Scenario	Vehicle Miles Traveled	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80	Vehicle Hours Traveled	Vehicle Hours of Delay	Average Speed (mph)	Planning Time Index 80
2010	0%	0%	0%	0%	0%	0%	0%	0%	0%
2012	2%	3%	4%	-1%	0%	N/A	N/A	N/A	N/A
2016 No TNC	7%	12%	22%	-4%	6%	N/A	N/A	N/A	N/A
2016 with TNC	13%	30%	62%	-13%	15%	31%	69%	-14%	21%

The goal of this exercise was to compare these results to the 2012 estimates of VHT, VHD, average speed and PTI80 based on observed travel times, as derived from the INRIX data. Unfortunately, an unexpected barrier was run into in the ability of this research to do so, which is that the 2012 INRIX data are no longer available. The regional partner of this study, the Metropolitan Transportation Commission (MTC) is the entity that contracts with INRIX to provide travel time data. They recently switched to a new data product called Roadway Analytics, based on a different segment definition, referred to as XD segments. The earliest date for which these XD data are available is 12/31/2013, making a 2012 (or 2013) comparison impossible, even if one could assume the data were consistent with the TMC based data. Both MTC staff and INRIX staff were directly reached out to in an effort to have them recover an archived version of the 2012 data. After several weeks chasing these data, INRIX claims that the 2012 data no longer exist.

In lieu of a comparison to the INRIX, the accessible speed trend data is presented instead, which is from San Francisco's Congestion Management Program (CMP) that monitors AM and PM peak period travel speeds on designated roadways biennially. **Table A 4** shows the observed auto speeds on arterials in the designated CMP network, and the percent change in auto speed from 2009. These speeds are not directly comparable to the speeds reported in **Table A 3** because they cover different links, are limited to the peak periods, and are collected in odd-numbered years. Nonetheless, **Table A 4** does show that there is only a small speed decrease in the 2009 to 2013 period, versus a much larger speed decrease in the 2013 to 2017 period. This larger speed decrease aligns with the emergence of TNCs. The smaller speed decrease in the 2009 to 2013 period supports the idea that the modeled 2010 to 2012 speed change is reasonable.

Table A 4 Observed Arterial Speeds from Congestion Management Program

Year	Average Auto Speed on Arterials		Percent Change from 2009	
	AM	PM	AM	PM
2009	18.4	16.7	0%	0%
2011	17.6	16.6	-4%	-1%
2013	17.1	16.0	-7%	-4%
2015	14.6	12.7	-21%	-24%
2017	13.6	12.2	-26%	-27%

SF-CHAMP was initially developed in the early 2000s (Cambridge Systematics, Inc. 2002; Jonnalagadda, Freedman, Davidson and Hunt 2001). It has undergone several enhancements since its initial development (Erhardt, Charlton, Freedman, Castiglione and Bradley 2008; Zorn, Sall and Wu 2012), with the model re-calibrated in coordination with those enhancements, but its basic structure has remained consistent. It has been the topic of dozens of publications and national conference presentations, providing opportunities for external review. Over this period, it has been used for virtually every project (https://www.sfcta.org/delivering-transportation-projects) and study (https://www.sfcta.org/completed-projects-and-studies) undertaken by the San Francisco County Transportation Authority. These have spanned the time periods before, during and after the 2008-2011 recession, providing some indication that the structural relationships built into the model are not merely a function of conditions during an anomalous time period. It is worth keeping in mind a few aspects of this research design and results. First, any uncontrolled factors must be different between 2010 and 2016. Second, the estimation results as reported in **Table 5** Fixed-effects panel estimation results with TNC variables show that congestion is growing more than expected specifically on the links and in time periods with high levels of TNC activity. While it is possible the growth in another confounding factor is concentrated on those same links at those same times, the result further limits what those factors may be. Third, the magnitude of the results is large. Even if there is an important confounding factor that has been missed that serves to increase the growth in background traffic, it is likely that the effect would be to reduce the magnitude of the reported TNC effect rather than change its direction.

Also, as evidenced by the results of this section detailed later, these outer city vehicles potentially are sources of fractional increase of each PCE associated with their total numbers. This data do not provide a direct observation of what TNC users otherwise would have done, so they cannot speak directly to modal substitution. The data do allow us to infer the pick-up and drop-off locations and associate those locations with specific directional roadways. Given the prevalence of TNCs activity outside San Francisco city boundaries, one would expect drivers starting outside the city to get a pickup request outside the city and not have to deadhead into the city. On the other hand, That a driver may commute into the city is merely a comment on one of multiple possibility of how deadhead miles *may* accrue within the city network. Given the enhanced earning potential, even for significantly shorter trips, for a driver within the city boundaries due to high TNC demand within the city, it is more probable that a driver commute to the city looking for rides. Being matched to a trip originating outside the boundaries of the study area will, in that case, merely be an added opportunity for the driver, rather than being a conscious choice around which he/she plans her commute to the city.

A.4 Addressing Potential Limitations

It should be noted that deadheading is not limited to TNCs. Both TNCs and taxis are vehicles that deadhead. When any other type of vehicles deadhead, they contribute to congestion as well. For this analysis, it matters what this (increased) amount of deadheading is, and whether this quantity is expected to change between 2010 and 2016 in an accountable way. These details have been considered for each of the vehicle types identified. Taxis are about 1% of vehicle trips within San Francisco and deadheading accounts for 40-50% of taxi VMT (TNCs Today SFCTA 2017). Taxis are represented in SF-CHAMP, although it does not explicitly account for out-of-service taxi travel. It is expected that taxi travel reduced in 2016 from 2010 due to some taxi trips converting to TNC trips.

Public transit vehicles are about 1% of vehicle trips within San Francisco (TNCs Today SFCTA 2017) (although they are a much larger share of person trips). SF-CHAMP also accounts for the congestion effect of in-service bus trips. It does not explicitly account for out-of-service bus trips, although this is expected to be a small share of the total bus trips since bus service routes are planned in a way that explicitly seeks to minimize deadheading. Nevertheless, according to SF-CHAMP, bus service miles are 13% higher in 2016 than in 2010. Private car trips are 83% of vehicle trips within San Francisco (TNCs Today SFCTA 2017). Escort trips, such as dropping kids at school or taking a friend to the airport are included in SF-CHAMP within the "other" trip purpose. In the state of the art experience working with household travel surveys, it is found that the vast majority of escort trips are to escort children. Neither Uber nor Lyft allow children under the age of 18 to ride without being accompanied by an adult. No knowledge has been found that escort travel or the associated deadhead traffic has changed substantially between 2010 and 2016 beyond what has already been accounted for in the analysis. When considering the net effect of TNCs on congestion, what matters is a comparison of what happens versus what otherwise would have happened. If a person otherwise would have driven end-to-end in a private car, the VMT generated by a TNC would be greater for that same trip because there is some associated deadheading. It is worth noting that the TNC trip would result in less demand for parking at the destination, which is a benefit to using a TNC, but does not affect congestion.

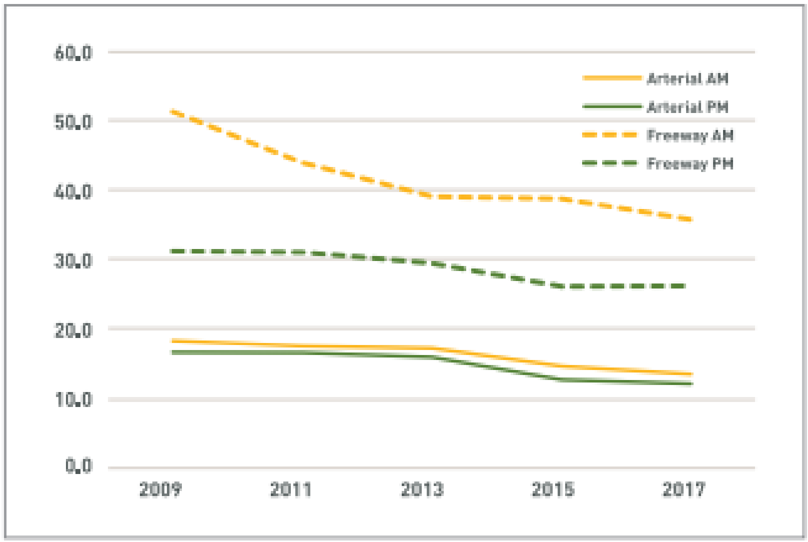


Figure A 2 San Francisco Arterial and Freeway Speeds (2009-2017). Source: TNCs and Congestion, SFCTA (Collaborated work)

APPENDIX B: Supplemental Data

The data and scripts used in this research are being archived as follows:

1. The following data files are included with supplementary materials associated the publication of Erhardt, Roy et al (2019). Please check the associated materials from *Science Advances* when the article is released.
    - Supporting data for **Figure 6**.
    - Supporting data for **Figure 7**.
    - Model estimation files for the empirical models presented in Chapter 2.
    - Model application results for the empirical models presented in Chapter 2.
2. The following data files are included with supplementary materials associated the publication of Roy et al (in-review). Please check the associated materials when the article is released.
    - Shape files of loaded road networks for each of the six model scenarios.
    - Shape file of the Traffic Analysis Zone (TAZ) layer.
    - Trip tables of TAZ to TAZ TNC trips in origin-destination format.
3. The following data files were released with the publication of *TNCs & Congestion*, and are available at: https://www.sfcta.org/emerging-mobility/tncs-and-congestion
    - ESTFILE_2010.csv – model estimation file with 2010 data for the empirical models presented in Chapter 2.
    - ESTFILE_2016.csv – model estimation file with 2010 data for the empirical models presented in Chapter 2.

4. An interactive data visualization of the results presented in Chapter 4 is available at: http://tncsandcongestion.sfcta.org/

Additional working scripts were written primarily in python, and are stored in a GitHub repository. Please contact the authors with any requests for additional information or scripts.

APPENDIX C: Media Coverage

This research, specifically the *TNCs & Congestion* report, has been featured in the following media articles.

Saval, Nikil. "Uber and the Ongoing Erasure of Public Life," *The New Yorker*, February 18, 2019.

Said, Carolyn. "Uber, Lyft Cars Clog SF Streets, Study Says." *San Francisco Chronicle*, October 16, 2018, Front Page.

Fitzgerald Rodriguez, Joe. "Study: Half of SF's Increase in Traffic Congestion Due to Uber, Lyft." *The San Francisco Examiner,* Top News, October 16, 2018.

Brekke, Dan. "City Analysis: Uber, Lyft Are Biggest Contributors to Slowdown in S.F. Traffic." *KQED News*, October 16, 2018, Top News.

Chronicle Editorial Board. "Editorial: Uber, Lyft Must Work with City to Ease Traffic Congestion." *San Francisco Chronicle*, October 21, 2018.

Asperin, Alexa Mae. "Uber and Lyft Are Being Blamed for Most of the Traffic in San Francisco." *KRON*, October 16, 2018.

Baldassari, Erin. "Uber, Lyft Responsible for Half of Growth in SF Traffic, Study Says." *San Jose Mercury News*, October 16, 2018.

Bay City News Service. "Report Links Increased Traffic Congestion To Uber, Lyft." *SFGate,* October 17, 2018.

Brinklow, Adam. "City Blames Half of New Congestion on Lyft, Uber." *Curbed SF*, October 16, 2018.

California News Wire Services. "Uber, Lyft To Blame For SF Traffic Congestion: Report." *Patch*, October 17, 2018.

CBS SF. "Report Links Increased San Francisco Traffic Congestion To Uber, Lyft." *KPIX*, October 16, 2018.

Christien Kafton. “Uber-Lyft Dispute They’re to Blame for San Francisco’s Traffic Congestion.” *KTVU*, October 16, 2018.

Cory Doctorow. “Study Blames Uber/Lyft for San Francisco Traffic, Uber/Lyft Blames Amazon, Propose Surge Pricing.” *Boing*, October 16, 2018.

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Gibson, Eleanor. “Uber and Lyft Blamed for San Francisco’s Congested Streets.” *Dezeen*, October 18, 2018.

Hammerl, Teresa. “Uber, Lyft Main Reason for Increased Traffic Congestion in SF, Study Finds.” *Hoodline*, October 16, 2018.

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Mojadad, Ida. “New Report Confirms Uber, Lyft Make S.F. Traffic Miserable.” *SF Weekly*, October 16, 2018.

Rudick, Roger. “Data Confirms Uber and Lyft Jam up San Francisco.” *Streetsblog*, October 17, 2018.

Said, Carolyn. “CA: Uber, Lyft Cars Clog SF Streets, Study Says.” *Mass Transit Magazine*, October 16, 2018.

Said, Carolyn. “County Study Blames Uber, Lyft for Much of SF’s Congestion Woes.” Government Technology, October 16, 2018.

Sze, Kristen. “Study Says Uber, Lyft Making San Francisco Traffic Worse, but Drivers Disagree.” *ABC7,* October 17, 2018.

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Young, Eric, Kel Hahn, and Lindsey Piercy. “Uber, Lyft Contributing to Congestion in Major US City, According to UK Researcher.” *UKNow,* October 18, 2018.

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VITA

- Place of Birth: Patna, India
- Educational Institutions Attended:
  - Birla Institute of Technology, Mesra – Bachelors in Civil Engineering, First Class with Distinction
  - Iowa State University, Ames IA – Masters in Science in Civil Engineering, 3.7/4.0
  - University of Kentucky, Lexington KY – Pursuing PhD in Civil Engineering, 3.8/4.0
- Professional Positions Held:
  - Publicis.Sapient – Technology Trainee, Software Engineering
  - Institute of Transportation, Iowa State University – Graduate Student Researcher
  - Transport Lab, University of Kentucky – Graduate Student Researcher
  - Iowa Department of Transportation – Summer Research Intern
  - San Francisco County Transportation Authority – Technology, Data and Analysis Intern
  - Cambridge Systematics – Senior Professional
- Scholastic and Professional Honors:
  - Graduate Professional Certificate in Applied Statistics
  - Kentucky Section Institute of Transportation Engineers Spotlight Student and Scholarship recipient for the year 2018
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- Professional Publications:
  - Roy, S., Cooper, D., Mucci, R.A., Sana, B., Chen, M., Castiglione, J., Erhardt, G.D. (in-review) "Why is Traffic Congestion Getting Worse? A Decomposition of the Contributors to Growing Congestion in San Francisco", in review by *Transportation Research Part A: Policy and Practice*.
  - Erhardt, G.D., Roy, S., Cooper, D., Sana, B., Chen, M., Castiglione, J. (2019) "Do Transportation Network Companies Decrease or Increase Congestion?" accepted for publication by *Science Advances*.
  - Castiglione, J., Roy, S., Cooper, D., Sana, B., Chen, M., Erhardt, G.D. (2019) "The Effect of Transportation Network Companies (TNCs) on Congestion in San Francisco", Proceedings of the *98th Transportation Research Board Annual Meeting*, Washington, D.C.
  - San Francisco County Transportation Authority (2018) *TNCs & Congestion*, San Francisco, CA.
  - We have presented portions of this research in the following forums:
    - Roy, S., "Exploring the relationship between the emergence of Transportation Network Companies (TNCs) and growing congestion in San Francisco", presented by Sneha Roy at the Workshop on Doctoral Research in Transportation Modeling, *98th Transportation Research Board Annual Meeting*, Washington, D.C., January 2019.
    - Erhardt, G.D., Castiglione, J. "Empirical Evidence from San Francisco", speakers and panelist at interactive session on "Do TNCs Increase or Decrease

Congestion", *98th Transportation Research Board Annual Meeting*, Washington, D.C., January 2019.

    - San Francisco County Transportation Authority "TNCs & Congestion", presentation to the Board of Transportation Commissioners on the findings of the *TNCs & Congestion* report by Joe Castiglione, San Francisco, CA.
    - Roy, S., Mucci, A., Brashear, J., Cooper, D., Sana, B., Tischler, D., Castiglione, J., Erhardt, G., "Exploring the Relationship between the Emergence of Transportation Network Companies (TNCs) and Growing Congestion in San Francisco," presented by Sneha Roy at the *7th International Conference on Innovations in Travel Modeling (ITM2018)*, Atlanta, Georgia, June 2018.
    - Roy, S., Cooper, D., Sana, B., Chen, M., Castiglione, J., Erhardt, G.D. "Quantifying the Impact of Transportation Network Companies on Traffic Congestion in San Francisco using Big Data", poster presented by Sneha Roy at the *Commonwealth Computational Summit*, Lexington, Kentucky, June 2018. 3rd Place in Student Poster Competition.

- My research has been featured in a number of media publications, as listed in Appendix C.

SNEHA ROY