Congestion Trends in the City of Toronto (2011-2014)

September 15, 2015

Funded by City of Toronto [20002856]

McMASTER INSTITUTE FOR TRANSPORTATION & LOGISTICS

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September 15, 2015

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Acknowledgements

Errors and omissions are solely the responsibilities of the study authors. MITL would like to acknowledge both the financial support of the City of Toronto Transportation Services Division and the regular input and ideas generated by Steven Buckley, Scott Fraser, and the City of Toronto Transportation Services Division. Thanks also goes out to Bronson Bullivant's contributions as a research assistant while at MITL.

Executive Summary

This study estimates metrics of transportation system performance in 2011, 2013, and 2014 for Toronto arterials, Toronto freeways, and the downtown core. Archived probe data purchased from Inrix, Inc. is used to explore annual variations, monthly variations, day-to-day variations, and hourly variations in several categories of performance measures, including speed, delay, and unreliability. Analyses, such as this one, using large datasets which are continuously being generated (but not necessarily collected) and repurposing them for business analytics has emerged as a potentially fruitful means of better managing policymaking and program management. Results from this study indicate that traffic congestion materially grew between 2011 and 2014 (but was lower in 2013), but that this growth was uneven. Delay increased and speeds decreased much faster over time on the city-wide arterial system and in the downtown core than on the freeways (city-owned and 400-series). Moreover, while travel unreliability is generally lower (reliably slow) in the downtown, unreliability grew much faster in the core than in the city as a whole.

This study illustrates how probe data can be leveraged for better transportation performance monitoring. Archived probe data from Inrix, Inc. are purchased for portions of 2011 and 2013 and all of 2014 purchased from Inrix, Inc. These probe data cover 88.7% of individual freeway links and 48.0% of all arterial links, on average, during any given 15-minute interval within the traffic network between 5am and 10pm. When coupled with a four-step travel demand model (TRAFFIC), City of Toronto count data, and Ontario Ministry of Transportation count data, this speed data is used to monitor road performance characteristics. In cases where the level of granularity may introduce sampling bias into metrics, multiple methods are employed, including conventional descriptive statistics, multilevel modeling, and simulation.

Results from this study are intuitive and demonstrate how Big Data can be leveraged for performance monitoring. However there are four critical challenges in how Big Data can be deployed to guide policy decisions. First, results must be intuitive, credible, and sufficiently interpretable to be easily understood by decision-makers with a range of expertise. While temporal and geographic granularity of a Big Data program should be able to assess, interpret, and inform rapid changes for certain applications, its core capabilities should not function at such a fine granularity across the board as to lead to "information overload." Second, if pairing multiple sources of data which are dynamically collected, this can enable explicit assessments of policy trade-offs to be made and judged by policymakers. In this study, traffic volumes and road capacities are largely static and variations in performance are primarily driven by speed data. Third, even to reasonably use static volume estimates and dynamic speed estimates, as in this study, the secondary data collection and management tasks rely on combining multiple sources of data which cover very different temporal and spatial extents. Inter-agency coordination to improve the comparison of different data sources should be encouraged. Finally, a path towards integrating Big Data into performance monitoring should be prepared to discover, explain, and leverage newly generalizable information on unique system attributes. Probe data, such as those purchased from Inrix, Inc., provide sufficient coverage to explore link-specific dynamics in speed, travel times, and unreliability which can be merged with link-specific policymaking characteristics from other data sources (e.g. on street parking policies and prices, changes in off-street parking supply/demand, lane configurations, bicycle facilities, sidewalk characteristics, or on-street transit services). Thus, unique user experience and volume-speed dynamics can be assessed not just by generalized functions, but based on context-specific characteristics.

A critical caveat in this study is that within the task of policymaking, value judgments lying therein remain critical and the granularity of new Big Data analyses does not eliminate the need for program managers and policymakers to prioritize some objectives over others. Results from this study indicate that understanding congestion's many dimensions even within a single city is complex and that the fundamental task of identifying those key performance indicators which shape policymaking inherently shapes the extent to which different policy solutions may be warranted. If we best understand travel times, road speeds, travel unreliability, traffic volumes, transit reliability, transit travel times, or any other single performance metric, we will be best equipped to exercise policymaking to improve that particular attribute of transportation system performance. There are many possible system outputs which are worthy of monitoring and policy action, so highlighting the potential trade-offs between each of these will be critical for better managing the transportation system.

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Introduction

Among North American regions, Greater Toronto Area traffic congestion is among the worst (TomTom, 2014). Both in Toronto and across most urban regions, traffic congestion enters dinner conversations, bridges social ties to enable common commiseration, and enables powerful public discourse about shortcomings, successes, and potential futures for our surface transportation system. But inherent in our understandings of congestion at the regional level are normative values: the sometimes unspoken perspective that congestion is a sign of failure. Regionally-scaled congestion studies can provide an order of magnitude estimate of gridlock's inconvenience to transportation system users and others whose livelihoods depend on the function of Canadian cities. But such studies can also be interpreted to obfuscate the meaning of congestion to the diverse range of transportation system users and their heterogeneous needs in Canadian urban ecosystems and may even mislead the public.

This study paints a detailed portrait of congestion's intensity, temporal extent, and spatial patterns using metrics developed by the study team using Inrix, Inc. data for the City of Toronto in 2011, 2013, and

2014. This study focuses on the City of Toronto as a whole and its arterials and freeways, while also honing in on the unique characteristics of the downtown core (the arterials bounded by Bloor, Bathurst, Lake Ontario, and Jarvis). Results from this study indicate that understanding congestion's many dimensions even within a single city is complex and that the fundamental task of identifying those key performance indicators which shape policymaking inherently shapes the extent to which different policy solutions may be warranted.

1.1 The Need

This study does not depict a simple picture of congestion in Toronto. Most regional or national studies of congestion estimate single sets of metrics for each region to generalize typical levels of gridlock. Such studies, including HDR (2008) in the Toronto region or Schrank, Eisele, and Lomax (Schrank, Eisele, & Lomax, 2012) in the United States, are important for the purposes of identifying the relative magnitude of congestion across regions. They do not, however, reflect the heterogeneity of user experiences across different spaces and at different times and on different assets within the system. Employing single regionally-scoped metrics of congestion are useful to identify the order of congestion's magnitude, but is not useful for policymaking or improving user experiences because it does not reflect the local and spatially-fixed nature of transportation policy interventions or congestion. Measuring regional congestion as uniformly burdensome motivates system users and tax payers to fund transportation programs. But users are diverse, so unduly simplifying reality may generate dissonance among those with significantly different experiences – generating questions about whether the transportation policies justified on the basis of congestion alleviation may or may not actually benefit them. Different users have different needs, so it is critical to identify the multiple dimensions of congestion to focus policy interventions on the most important issues in the transportation system.

Big Data has entered the public conversation as a new trend in the rational decision-making model of planning, whereby the increased availability of near real-time data being collected most frequently for other reasons is re-purposed and analyzed using high-performance computing capabilities for a specific reason. For the purposes of this study, the trend towards Big Data is defined as the proliferation of new information on transportation flow, speeds, and trip information from probe data, global positioning data, and Bluetooth technology in near-real time and in such volumes as to make conventional computing methods unable to manage the challenge. Big Data approaches and methods hold much promise in better understanding traffic congestion by focusing on user experiences, highlighting its temporal variations across different system components, and identifying regionally-scoped magnitudes. This study adds new dimensions to conventional traffic congestion studies: it employs empirical measures of road performance to follow congestion between 2011 and 2014 for the City of Toronto.

1.2 The Study Organization and Purpose

While many have measured congestion, new data is becoming available with which we can better study congestion, measure it, estimate its implications, identify its causes, and explore policy solutions. The key task of exploring both regional and localized congestion patterns at different time periods is critical to better managing traffic congestion's impact on transportation system performance and the function of cities. Although most studies focus on broad regional trends, highlighting potential localized hotspots or critical infrastructure assets is important to targeting policy intervention to system components with the most need. To that end, we introduce congestion and its causes in Chapter 2, introduce the research design of this report in Chapter 3, and introduce results in Chapter 4, before concluding with final thoughts which could be used to shape policymaking in Chapter 5.

The purposes of his study is not to overcomplicate the topic of congestion. Public discourse over congestion can motivate public support for expensive transportation policies and programs and therefore congestion study results generally provide seemingly large single cost estimates to stimulate regional support. Our point here is not to disagree with the magnitude of congestion's problem, but to better identify the extent, intensity, and changes over time, while striving to improve empirical estimates. Better focusing on the local and complex spatial changes in transportation system performance can enable congestion studies to better inform policymaking and target scarce resources to potentially fruitful areas of intervention and management. A more nuanced portrait is needed which has the capacity to focus on tangible, local elements of the system with potential to improve user experience.

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About Congestion

Congestion is a powerful cultural construct which has informed transportation policymaking since before the days of Julius Caesar. Engineers would define congestion as occurring when road volumes exceed road capacity (Bertini, 2005). Economists would define congestion as occurring when incremental road use disproportionately impacts others (Ozbay, Bartin, & Berechman, 2002). Sociologists would define congestion as a cultural construct which varies from place to place based on normative perspectives (Weinstein, 2006). But underlying each perspective is the normative view that congestion is (or at least that it can be) a problem which can and should be alleviated. All three perspectives provide different guidance on identifying how policy should manage traffic congestion.

Understanding congestion is culture-dependent: what might be deemed as acceptable in downtown Toronto, Vancouver, or Montreal might be viewed as a significant burden in rural Canadian communities. Much previous research has documented how congestion is measured, but linking measures with more fundamental social and environmental outcomes has been challenging. While public discourse frames congestion as "bad," relatively less research has focused on the conditions under which it is worse or better for more fundamental social and environmental outcomes. At the heart of the task of better measuring congestion is identifying how our transportation systems does function relative to how it could or should function. While all commuters are experts of their own congestion experiences, better managing congestion depends on evidence-based estimates of congestion's burden and the outlook for policy success. This study focuses exclusively on the task of generating a more nuanced portrait of measuring traffic congestion.

2.1 What Causes Congestion?

Although there are many definitions of traffic congestion, most definitions of congestion center around the conditions under which high traffic volumes relative to capacity impede transportation services. Transportation system supply and travel demand are central concepts which inform when, why, and where one might expect traffic congestion. Broadly, there are two types of congestion: *recurring* and *non-recurring* congestion (Bertini, 2005). Recurring congestion (henceforth referred to simply as *congestion*), refers to traffic congestion which is a result of regular demand fluctuations relative to road supply which slow road performance. In contrast, non-recurring congestion stems from irregular occurrences, such as collisions, poor weather, or special events. Although recurring congestion may make a transportation system more vulnerable to non-recurring congestion, the difference between the two is important for policymaking. While managing non-recurring congestion is often the focus of safety policies or incident management policies, managing recurring congestion is likewise challenging because it involves shaping travel demand by changing people's behavior, altering transportation prices, or increasing road capacity – the topics of this chapter. Fundamentally, changing any of these three chief causes of traffic congestion are often expensive, politically challenging, or socially undesirable.

2.2 Travel Demand

Travel demand refers to the aggregate desire to consume travel services by a broad population. It differs from travel behavior in that demand is an aggregate concept, while behavior reflects individual decisions which cumulatively shape travel demand (Small, 2005). The magnitude of travel demand depends on the actions of multiple individuals, reflecting aggregate travel as a function of trade-offs, choices, and responses to public policy made by system users on a daily basis. The discussion of travel demand here is constrained to auto users, but a full discussion would include other modes as well.

Vehicular travel demand depends significantly on the characteristics of people – the potential system users; the price of road use; land use patterns; the temporal aspects of demand; and the spatially-fixed attributes of demand. Critically, each of these forces conspire to make cities and urban regions pre-programmed for gridlock. Cities have dense populations, affluent households, many vehicles, high potential economic benefits from travel and activity participation, low prices for auto use which vary little by time or area, temporally constrained workdays and activity schedules, spatially fixed job destinations, and absolute constraints on adding road capacity. Given the outlook for high urban travel demand relative to scarce road space, cities and their inhabitants are left to the tasks of managing traffic, adapting, or slowing growth rates whereby congestion-sensitive industries and system users locate elsewhere (Sweet, 2014). There is much at stake.

2.2.1 People

All cultures, societies, and individuals have their own transportation habits which are formed and shape their daily lives (Van Exel & Rietveld, 2009; Walker & Li, 2007; Verplanken, Aarts, & Van Knippenberg, 1997; Aarts & Dijksterhuis, 2000). But significant patterns have emerged in how socioeconomic and cultural characteristics of individuals shape travel demand. Travel is generally a normal good: more affluent households travel more using most modes (Crotte, Noland, & Graham, 2009), particularly by vehicle, (Gidlow, Johnston, Crone, Ellis, & James, 2006). Working individuals and households which own vehicles (which is in itself an endogenous choice based on a household's expected travel demand) generally travel more than non-working individuals without automobiles (Van Acker & Witlox, 2010). Thus, populous urban regions with high concentrations of affluent individuals already have very high travel demand both on a per person basis and in aggregate – regardless of transportation supply characteristics or other aspects of travel demand. Different ethnic and cultural groups also travel differently: recent immigrants are more likely to use transit than auto relative to others (Blumenberg, 2009).

But while demographic and personal characteristics shape travel demand, shaping demography remains largely outside of the policy realm (Taylor & Fink, 2013). Although preference shaping information campaigns have been launched in various contexts, policy cannot easily change cultural definitions of "normal" travel behavior or normative aspects of how travel should happen (Zhao, 2009; Zhao, 2010). For example, while some, have argued that the newer generations' proclivity to use automobiles less than previously (Florida, 2012; Metz, 2010), there remains some disagreement on whether such changes are because of changing cultural norms or primarily because of the underemployment of younger generations and millennials (Blumenberg, Taylor, & Smart, 2012).

2.2.2 Prices

Travel demand is impacted by the marginal price of auto travel – much of which is unseen by road users when they travel (Ozbay, Bartin, & Berechman, 2002; Lindsey, 2012). The price of auto ownership, maintenance, insurance, parking, and gasoline all contribute to average auto use costs (Schweitzer & Taylor, 2008). Of transportation funding mechanisms, users appear to be particularly sensitive to the perceived burden of marginal user fees and tolls (Schade & Baum, 2007), as these are viewed as large losses when paid incrementally for system use (Schweitzer & Taylor, 2008). Thus, while average auto travel costs are significant and the marginal costs auto users impose on others – for example due to congestion – are high (Ozbay, Bartin, & Berechman, 2002), marginal perceived monetary prices to use automobiles are low, leaving few economic incentives for individuals to avoid or create less congestion. In short, once somebody decides to own a car, there are few incentives to use it less because of the high benefits of getting places and doing things.

Users make travel decisions based on their own perceived experiences of travel costs and benefits, when in reality the incremental burdens inflicted upon others is much higher because road use leading to congestion affects not just the individual but all other road users. While additional road users incur delay on others, price incentives reflect experienced delay and costs (average costs) and do not reflect incremental social costs (delay incurred by individuals to themselves and to others). The decision for individuals to travel is based on their own calculus of whether benefits exceed costs. If citizens expect higher benefits, they will continue traveling on a roadway even with very high average travel costs and these effects are even stronger in cities with very high expected benefits from travelling to access destinations. Therefore, realigning the incremental travel costs to reflect the congestion-inducing burden placed upon others is viewed as the single necessary precondition for long-term sustained long-term congestion alleviation (Sorensen, et al., 2008; Taylor, 2004). In fact, research has found immense capacities individuals to ration travel and adjust travel behavior in response to relatively modest road price signals (Eliasson, 2008), which have led to sustainable transportation funding and to congestion alleviation in contexts such as Stockholm (Borjesson, Eliasson, Hugosson, & Brundell-Freij, 2012).

2.2.3 Land Use Patterns

The spatial arrangement and characteristics of potential trip destinations shape travel demand. Policies designed to curb urban sprawl and manage growth have been partly justified on the basis of decreasing congestion and travel demand (Anas & Rhee, 2007; Anas & Xu, 1999; Anas, Arnott, & Small, 1998). But the link between land use, travel demand, and congestion is complex. Behaviorally, land use patterns are expected to influence travel behavior by shaping the quantity of travel necessary to access destinations, the quality of the travel experience, and the price of traveling (Crane, 1996; Chatman, 2008). Simultaneously, the characteristics of potential trip origins and destinations shape the willingness of travelers to overcome great distances to engage in activities. Thus, while potential destinations in compact cities may be closer, the individual benefits from accessing a somewhat further but more beneficial activity can outstrip the convenience of closer alternatives. Thus, the extent to which land use patterns are linked with travel demand or congestion depends on the trade-offs between quantity, quality, and price of travel relative to the travel-inducing force of unique big-city amenities.

Travel Quantity - Although sprawling suburban land use patterns are associated with higher levels of automobile use and dependence, it is unlikely that travel demand is higher than in built environments with walkable streets and amenities. According to Taylor (2002), one would expect gross travel demand to be higher in compact and dense urbanized areas than in sprawling suburbs most fundamentally because travel demand per person declines more slowly than increases in population or land use density. This translates into higher travel demand per unit area or per unit of transportation infrastructure. Thus, while one may need to travel further to reach destinations in more sprawling regions, fewer individuals compete for road space or for land, making aggregate travel demand comparatively lower.

Travel Quality – Travel demand depends likewise both on the quality of potential trip destinations and the quality of travel experiences (Crane, 1996). Travel demand is lower to destinations which are relatively less unique, are of equal relative value, or do not confer significant user benefits. For example, patrons are willing to travel further to participate in unique professional sporting events or exceptional nightlife than they are willing to travel to a more conventional activity, such as a chain restaurant or convenience store. In contrast, demand and willingness to travel to reach more unique destinations is significantly higher. But the uniqueness of destinations does not just depend on providing a novel destination for many individuals to access, but for individuals to access destinations which are uniquely valuable to themselves. The difference between traveling 15 and 30 kilometers may be the difference between accessing a perfectly decent job and accessing one's dream job – or conversely the difference between living in a perfectly decent home and living in one's dream home. Because cities also have higher proportions of regionally-scaled and unique attractions and because the significantly benefits of accessing uniquely desirable destinations for individuals, travel demand is even higher in urbanized areas. Likewise, land use patterns influence the quality of the travel experience – providing desirable scenery, visual stimulation, and enjoyment (Isaacs, 2001) – which, in turn, are one link which spurs travel which is not strictly derived through destination access (Mokhtarian & Salomon, 2001; Mokhtarian, Salomon, & Redmond, 2001). Thus, insofar that some regions foster both qualitatively more desirable activities and more enjoyable travel experiences, one would expect travel demand to go up.

Travel Price – Finally, land use patterns impact the price of travel by inducing priced parking (perhaps a function of high-cost real estate) or by creating traffic congestion. Some have found evidence that while land use patterns impact other attributes of the travel experience, fundamentally shifting the price and burden of auto travel may be the chief means through which land uses impact travel (Chatman, 2008; Crane, 1996). Thus, insofar that congestion increases the price of travel, increasing the price of travel moderates incremental demand, and moderating incremental demand attenuates congestion growth - traffic congestion has traits of self-management in retaining equilibrium conditions.

2.2.4 Space and Time

There are also both spatial and temporal attributes of travel demand which make cities designed for gridlock. The benefits to system users of accessing spatially-fixed destinations at set time periods are significant. Interacting, working together, sharing information and experiences, and capitalizing on city benefits all depend on being spatially proximate to others at set time periods, such as working hours. Agglomeration benefits refer to the synergies of many individuals sharing knowledge, resources, or competitive drive and they depend on individuals or firms being proximate and interacting (Glaeser, Kallal, Scheinkman, & Shleifer, 1992). Thus, regardless of other aspects of travel demand, travel demand to access job-rich or activity-rich urban centers at set time periods (usually working hours) are significant (Safirova, 2002). But while the special and temporal attributes of demand are present in all places, these forces are even stronger in big cities because of the even higher potential agglomeration benefits through knowledge or resource sharing and competition (Graham, 2007).

2.3 Congestion and Managing Travel Demand– the Track Record

Based on the causes of travel demand, big cities are pre-programmed for traffic congestion. Cities are major cultural and economic centers which house affluent individuals with high levels of auto ownership who travel a great deal to take part in high-value activities. Cities contain exclusive local neighborhoods and housing stock with unique potential trip destinations: global financial centers, high-tech hubs, sporting and artistic events, and intensely developed real estate. Job locations continue to be clustered in space and the advantages of physical interaction in the workplace continue to outweigh the congestion-inducing drag of simultaneously traveling during peak periods.

While demand-side interventions can shift some of these factors and enable better use of the existing system, the underlying demand-side forces which create congestion remain. Telecommuting and flex-time have become more popular, firms have suburbanized and residents (in the cases of some regions) have moved back into the center cities, but such traffic-reducing effects are overshadowed by the latent demand to conduct activities in the urban context (Metz, 2008). Policies can encourage demand management, including carpooling (Ferguson, 1997; Habib, Tian, & Zaman, 2011), telecommuting (Garrison & Deakin, 1988; Mokhtarian, Collantes, & Gertz, 2004), more balanced land uses (Cervero & Duncan, 2006), and flex-time (Lucas & Heady, 2002). Demand management policies can even place driving restrictions in a bid to reduce congestion, but such measures have been unsuccessful because people do not like to follow rules about where they can go and when (Wang, Xu, & Qin, 2014). Moreover, policy plays a very limited role in managing the characteristics of people and their own needs; and at best, there appears to be limited evidence that policies designed to provide information about travel alternatives may marginally shape behavior (Zhao, 2009).

Of the causes of travel demand, shifting the price of road use has been documented as a policy tool with significant promise to alleviate congestion. Road pricing provides economic incentives which rebalances the current lower marginal financial price (which remains stable at the incremental cost of maintenance and gas) relative to the high marginal cost of road use (delay incurred by other motorists). Under congested conditions, users currently "pay" for congestion in terms of travel time and delay, but increasing the financial price of road use gives users choices about when and whether to pay to avoid congestion - either paying financially for road use during peak periods or paying in terms of adjusting the trip timing and mode of travel to avoid financial payment. But pricing designed to incentivize more economic decision-making by the public, allowing the price of road use to vary by demand and time of day, remains politically unpalatable with some exceptions (Noordegraaf, Annema, & van Wee, 2014; King, Manville, & Shoup, 2007; Hensher & Bliemer, 2014; Hensher & Li, 2013).

2.3.1 Transportation Supply

While travel demand is one attribute of congestion, the relative supply of transportation systems also shapes congestion levels. One of the fundamental principles of transportation economics is that infrastructure supply can reduce the cost of travel, inducing the potential for users to reduce costs, become more productive, and invest savings in other economically productive or valuable endeavors. But while the cost-reducing and productivity-enhancing effects of infrastructure supply consistently are validated (Apogee Research, Inc. and Greenhorne & O'Mara, 1998; Bell & McGuire, 1997; Boarnet & Haughwout, 2000), the relative magnitude of investment-induced travel time savings has diminished over time partly because of the relative ubiquity of roads (Banister & Berechman, 2000) and partly because new roads become congested over time (Boarnet, 1997; Hymel, 2009; Sweet, 2014). Understanding the availability and potential to shift system capacity is critical to estimating traffic congestion levels (Hartgen & Fields, 2006). As recurrent congestion stems most fundamentally from the relationship between travel volumes and system capacity, exploring the limits and potential of capacity-side interventions to shift congestion is important.

There are three fundamental attributes of travel supply: physical assets, operations, and intelligent transportation systems (ITS). For the road system, physical assets include freeways, arterials, local streets, bridges, parking lots or garages, and the vehicles themselves (Sussman J. , 2000). For the transit system, assets include the transit fleet (buses, trains, etc.), travel ways, transit stops and stations, maintenance or storage facilities, centralized control systems, and power-generation systems (Vuchic, 2007). Each of these influences roadway capacity: the width of travel lanes, the size of vehicles, the spatial arrangements of maintenance or storage facilities, and the locations and sizes of parking facilities.

Operations influence how physical assets are used and managed and are relatively easier to change than the task of building new assets and from the perspective of some should be the core focus of efforts to expand capacity (Sussman J. M., 2005). Examples of common elements of operations include traffic signal timing, signal coordination, ramp meters, signing and striping, parking restrictions, high-occupancy vehicle services, express transit, transit route and stop planning, transit service frequency and amenities, and services provided at transit stations. In contrast with building new assets, operations are usually lower-cost and can be adjusted in reasonable timeframes in response to changing conditions.

Intelligent transportation systems, provide a novel real-time element in better linking vehicles with infrastructure using technology (Sussman J. M., 2005). ITS can employ available physical capacity to overcome less time-responsive elements of operations in order to more closely link supply and demand based on rapidly changing conditions (Collins & Mineta, 2000). The sub-tasks of ITS extend to various parts of the transportation system, shaping both capacity and demand. Advanced Traveler Information Systems (ATIS) provides traveler information, leading to two chief outcomes: marginally shifts system use by some users to other modes, alternate routes, or alternate times (Kenyon & Lyons, 2003; Bottom, Masroor, & Lappin, 2002; Lappin & Bottom, 2001), and reducing stress by informing users what they should expect (Vipre, 2006; Coernet, 2005; Lyons, 2006). Advanced Traffic Management Systems (ATMS) manage traffic through video monitoring using trained staff and adaptive control systems which "learn" and respond to patterns in travel demand to surgically enhance capacity on key systems (Abdulhai, Pringle, & Karakoulas, 2003). Better control of auto and transit vehicles through Advanced Vehicle Control Systems (AVCS) and Advanced Public Transportation Systems (APTS) make travel safer (Vahidi & Eskandarian, 2003) and reducing the role of human error (Sussman J. , 2000; Gietelink, Ploeg, De Schutter, & Verhaegen, 2009), eventually leading towards driverless vehicles (Xiao & Gao, 2010; Guo, Hu, Li, & Wang, 2012).

2.3.2 Capacity Building and Congestion Alleviation – the Track Record

Transportation capacity building – historically focused on road building, but more recently focused on transit – has been a fundamental tenant of modern North American transportation programs and has long been the preferred policy response to traffic congestion (Giuliano & Wachs, 1992). But the extent to which the "predict and provide" policy responses and cultures can alleviate congestion using supply-side responses has long been questioned (Gifford, 2005; Winston & Langer, 2006). Much of this shift in thinking has stemmed from a better understanding of traffic volumes and system capacities as not being independent and instead mutually causing one another. High travel demand induces capacity building (Baum-Snow, 2007), while capacity building induces higher travel demand (Cervero, 2002; Fulton, Noland, Meszler, & Thomas, 2000; Noland, 2001).

Thus, although supply-side solutions continue to be implemented in response to urban congestion, most cities' right-of-ways cannot accommodate additional capacity expansion within the existing constraints of public coffers - leaving road capacity expansion as the historically preferred but unfeasible current solution to traffic congestion (Taylor, 2000). Based both on the capital bias of transportation finance and on the sheer political attractiveness of building physical assets, there has been a bias towards capital funding and against operations, ITS, and maintenance (Boarnet, 2014; Sussman J. M., 2005; Taylor, 2004). Regardless of whether capacity expansion should be or could be a solution to traffic congestion, physical limits preclude road capacity programs. Instead, many transportation programs rely on public transit capacity expansion, travel demand management, and operational improvements as a potential solution to traffic congestion. However, like road capacity building, alternative policies are implemented in environments with limited physical resources, finite public coffers, and the same simultaneous supply-demand adjustments whereby capacity expansion does not necessarily improve congestion due to induced demand – particularly over the long term (Duranton & Turner, 2011).

2.4 How Much Congestion Should There Be?

Normative perspectives on how much congestion there ought to be has enormous implications for estimating and communicating the magnitude and conditions under which congestion is a "problem" and identifying how we should respond to it in policymaking. To illustrate why this may be the case, four normative policy objective cases are defined and the "optimal" level of congestion is discussed in the context of each. These normative policy objective introduce four separate concepts or performance metrics which could inform traffic congestion management practices: speeds, volumes, prices, and downstream social impacts. In practice, no single objective is sufficient to guide congestion management practices under all circumstances, so these (and other potential objectives) may inform policy in different contexts.

Objective: retain design or free-flow speeds – if retaining high-speed road performance were the chief policy objective of managing congestion, any incremental volume which slows speeds would be viewed as excess congestion. Significant supply-side or demand-side interventions would be needed to accomplish such a policy objective. Constructing sufficiently high road capacity to meet this objective would likely be politically, socially, and fiscally infeasible in most cities. Alternatively, demand-side changes would be needed – whereby system users would need to significantly alter how they travel, together colluding to optimize system performance. However, behavioral economic theory posits that individuals act to maximize their own utility and do not benevolently act to maximize gross utility of the system, so such collusion and broad travel behavior shifts are not expected. Alternately, the politically-challenging decision would be necessary to increase the price of road use to reduce transportation volumes, particularly during peak periods. Perhaps most critically, as a policy objective, the objective of retaining free-flow travel speeds provides relatively little guidance on how roads should function, as once free-flow speeds are retained, the public cost and role of volumes, prices, and downstream social and environmental implications are completely ignored.

Objective: maximize flow – if maximizing traffic flow given fixed physical infrastructure constraints were the primary policy objective, estimates of congestion would consider both a) at what point incremental travel demand reduces the throughput of the road system and b) what transportation services or modes accommodate the most throughput. For roads, maximum throughput is achieved at a facility-specific speed and flow rate (the inflection point of the conventional speed-flow-density diagram). But it is unclear for how long the flow-maximizing level of road service could be sustained. Such flow-maximizing conditions would be challenging to monitor and maintain on the road system, likely requiring very sensitive pricing mechanisms, abilities to adjust road capacity on the fly through ITS, and abilities to manage other attributes of demand in real time. Alternatively, interpreting flow maximization objectives to extend beyond the road system would lead one to build out and developing transit demand and ridership in a scaled fashion to maximize total system capacity, allocate scarce road resources to the most high-capacity uses, and retain flow-maximizing road speeds. But while flow-maximizing policies appear desirable for maximizing the amount of work completed by the transportation system, such policy objective ignore both the cost of system management and the relative downstream value of activity participation and economic activity afforded through travel. Just because travel occurs does not mean it is the most valuable allocation of time and financial resources.

Objective: eliminate the congestion externality. In contrast to the previous two engineering-based policy objectives, eliminating the congestion externality is an economic understanding of congestion's causes and of optimal system function. By shifting the price of travel to the marginal price of road use (and given user responses to such changes), one would incentivize more rational decision-making precluding congestion on the transportation system. System users would compare the expected financial price of road use with the expected value of their benefits of traveling and accessing destinations. However, as the additional value of accessing destinations varies based on regional and individual circumstances, one would expect both the marginal price and marginal benefit of system use to vary substantially within and between regions and highly-sensitive pricing mechanisms to be needed. As an additional benefit, by pricing road use in proportion with marginal social impact, a traffic flow rate very close to maximum flow may be retained – enabling not just high-quality services but also services which cater to as many people as possible. Nevertheless, such services would be very challenging to implement for two reasons. First, few politicians are willing to propose and support road tolling (Noordegraaf, Annema, & van Wee, 2014; Hensher & Li, 2013; Hensher & Bliemer, 2014). Secondly, as the relationships between marginal social cost and incremental traffic flow changes (e.g. as the system becomes more congested over time), the incremental price of road travel changes while responsive road pricing regimes are challenging to implement.

Objective: maximize social and environmental benefits – Finally, and perhaps most challengingly, to manage traffic congestion in a way to maximize social benefit, it would be necessary to consider a host of transportation system-related and downstream social and environmental outcomes. Thus, multiple costs and benefits to system users would be considered, including environmental implications of travel and congestion due to emissions (Bigazzi & Figliozzi, 2012), user benefits of participating in additional activities (Sweet, 2014) or different types of activity-travel experiences (Jakobsson Bergstad, et al., 2011; Jakobsson Bergstad, et al., 2012), economic benefits of productivity changes or shifts in development patterns (Boarnet, 1997; Boarnet & Haughwout, 2000; Hymel, 2009; Sweet, 2014; Sweet, 2014), quality of life differences according to alternate policy environments (Abou-Zeid & Ben-Akiva, 2014; Ettema, et al., 2011; Ettema, Gaerling, Olsson, & Friman, 2010; Jakobsson Bergstad, et al., 2011), and the magnitude and distribution of paying for transportation programs and infrastructure (Transportation Research Board, 2011; Schofer, et al., 2011; Taylor, 2004). Different users and economic systems have varying sensitivity to congestion, so identifying the conditions under which traffic changes firm or individual behavior and lead to net reductions in urban function and environmental quality is critical. Moreover, it is unclear how much congestion would foster a socially-maximizing outcomes – particularly given that some policy objectives may be at odds with one another. For example, while increasing the flow of goods or people may advance social or economic objectives (Melo, Graham, & Canavan, 2012), higher road traffic volumes (all else being equal) translate into higher greenhouse gas emissions and environmental consequences (Bigazzi & Figliozzi, 2012). Managing or alleviating congestion entails costs (Winston & Langer, 2006), so to maximize social and environmental benefits, the preferred action may or may not be to not intervene in the transportation system in any given case. There is much uncertainty in identifying and forecasting congestion management tools which maximize social and environmental outcomes, so prioritizing within these broad categories of objectives could lead to a much more nuanced approach.

2.5 Approaches to Studying Congestion

The shift towards Big Data has much potential to change how travel services are delivered and used. *For the purposes of this study, the trend towards Big Data is defined as the collection, analysis, and use of new travel data, e.g. transportation flow, speeds, and trip information, from technology in near-real time and in such volumes as to make conventional computing methods irrelevant.* But to explore how such data may shape transportation service delivery, four of the chief approaches to measuring and assessing congestion are introduced, illustrating why gridlock continues to be badly understood. Which approach is "better" depends on the core objectives of estimating congestion, but choosing entails trade-offs between generalizing or focusing on unique user experiences and facility conditions, and between observing conditions or inferring conditions to simulate policy alternatives. A weakness underlying each of the four approaches is that much of what practitioners and researchers know about traffic congestion is based on deeply established methods - most notably, the Bureau of Public Roads function (also called Davidson Equation) describing the relationships between speed, flow, and density - which overly simply trade-offs between different transportation service objectives. New data holds much promise in better understanding these trade-offs and understanding the uniqueness of facilities and user experiences.

There are many definitions and approaches to studying congestion, but four key techniques for studying congestion include *travel demand modeling*, *real-time traffic monitoring*, *facility-specific traffic studies*, and *empirical regionally-scaled congestion studies*. Each of these methods has its own advantages and disadvantages, but they differ across two conceptual dimensions: whether they generalize (travel demand models and empirical regionally-scaled congestion studies) or identify the uniqueness of congestion experiences (facility-specific traffic studies and real-time traffic monitoring), and whether they are based on observed speed data (empirical regionally-scaled congestion studies or real-time traffic monitoring) or based on inferred speeds using other inputs (facility-specific traffic studies and travel demand modeling). In sum, empirical data on transportation system performance is becoming increasingly available, reducing the need to infer based on established (but highly-generalized) speed-flow functions. As in this study, such data is expected to permeate congestion studies at all scales: regional, local, corridor or facility-specific, and user-specific.

The broad availability of traffic speed data across vast shares of the transportation system in near real-time is changing the realm of what is possible in studying congestion. Of the four congestion study approaches discussed, the success of two has been driven by the increased power to leverage new sources of traffic data to monitor system performance: real-time traffic monitoring and empirical regionally-scaled congestion studies. Meanwhile, travel demand modeling and facility-specific traffic studies have improved over time in non-trivial manners and have been core traffic engineering methods employed to support and justify transportation policymaking for more than half a century. But these later two have not yet capitalized on the new capacities for streaming empirical data of multiple types to inform policymaking in very close to real-time.

2.5.1 Travel Demand Models

Travel demand models were pioneered in the 1950s and include the use of computers, survey data, and models to explore user travel experiences and how they are likely to travel under different policy alternatives. Generalization enables studies to explore the broad range of user experiences as a consequence of the travel conditions. As such, generalization is designed to not only to estimate user experience and infrastructure performance at unique locations, but to extrapolate these experiences to reflect on the function of the entire system. The Chicago Area Transportation Study (CATS) of 1955 was among the first and most important travel demand models (Weiner, 1997) in which the four-step process of travel demand modeling was pioneered (Johnston, 2004). Accordingly trips are generated, distributed across space, modes are chosen, and routes are assigned to estimate user travel experiences, mode share, and changes in behavior due to alternative policies. While early models assumed very static behavioral decisions by individuals and businesses, others have updated travel demand models to reflect the complexity of urban systems whereby land uses and travel behavior influence one another and system users change behavior in response to system performance (Farooq & Miller, 2012). Nevertheless, such models have been critiqued on the basis of becoming more complex without fundamentally capturing the innate motivations of individuals to maximize utility (not minimize travel) (Scott, Kanaroglou, & Anderson, 1997), to retain relatively stable travel time budgets on aggregate (Mokhtarian & Chen, 2004; Zahavi, 1974), and to adjust location decisions and travel behavior dynamically and over time in unpredictable or unexplained ways (Habib, Swait, & Salem, 2012). Others have broadly critiqued the use of travel demand modeling on the basis of misunderstanding the relationships between traffic volumes and speeds (Hall, 1987) – leaving estimates of traffic congestion in question. In fact, according to Handy (2008), these limitations of travel demand modeling has led many of the largest U.S. Metropolitan Planning Organizations to de-emphasize travel demand model results in favor of empirical estimates of change in a wide variety of performance metrics over time.

2.5.2 Regionally-Scaled Congestion Studies

Regionally-scaled congestion studies are generalized performance monitoring tools to reflect broader congestion experiences, but unlike travel demand modeling, they use observed road speed data and do not explicitly test links between congestion, policy, and other outcomes. These studies aggregate travel and road service data to estimate typical user experiences at different times of the day within a large geographic region. The Texas Transportation Institute`s Urban Mobility Report (UMR) series began in the 1980s, is federally funded in the United States, and is perhaps among the best-known such congestion study. But with the exception of recent congestion reports generated by private companies such as Inrix, Inc. (Inrix, Inc., 2014) and TomTom (TomTom, 2014), few equivalent regionally-scaled congestion studies consistently track change over sustained durations of time. Regionally-scaled congestion studies assess the state of congestion, one of many potential performance metrics, but leave to others the task of linking congestion estimates with changes in policy outcomes, background characteristics, or social outcomes[1].

In the case of the UMR, the report has long been both the standard for congestion studies and a lightning rod for critique (Gordon & Richardson, 1994; Boarnet, Kim, & Parkany, 1998). Many have critiqued the use in the past of volume and capacity data to infer speeds (Gordon & Richardson, 1994), but the direct application of speed data from Inrix, Inc. beginning with the 2010 UMR has reduced the need to infer speeds using volume-capacity information. While travel demand models continue to rely on inferred speeds, the state of practice in regionally-scaled congestion studies makes such inferences, which lead to systematic error, unnecessary – enabling a more complete picture of observed changes in system function over time. The power of measuring speeds directly has greatly improved the potential to monitor speeds and performance over time without leaving one vulnerable to underlying assumptions.

2.5.3 Facility-Specific Traffic Studies

Facility-specific traffic studies have been a core skill of traffic engineers and are designed to use volume, capacity, and operating conditions information to identify how to improve the speed and efficiency of traffic flow on specific facilities. The Highway Capacity Manual (Transportation Research Board, 2010) establishes the relationships between operating conditions (signalization, striping, and external factors) user conditions (volumes, movement, vehicle types, driver types), physical conditions (roadway geometry, design, sight distances, and roadway alignment), and roadway performance. Such analyses assume given relationships between operating conditions and volumes, enabling traffic engineers to simulate alternate volume scenarios or operating conditions and identify current and future traffic conditions at intersections, arterial links, freeway links, merging sections, and weaving sections. Some

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[1] *For examples of deploying UMR results to identify predictors of congestion alleviation or links between congestion and economic outcomes, see Winston and Langer (2006), Melo, Graham, and Canavan (2012), Hymel (2009), Sweet (2014) or Sarzynski et. al. (2006).*

localized traffic study augment volume-capacity information with speed estimates with which the relationships between volumes, capacity, and speeds can be better calibrated, but legal practices have encouraged little deviation from universally-assumed relationships between volumes, capacities, and speeds on select facilities which establish the basis of analysis. Thus, while the previous means of studying congestion focus on general user experiences across the region, facility-specific traffic studies focus exclusively on specific facilities. As such, they are rooted in a relatively clear set of potential policy levers (improving operations or capacity) but ignore the dynamic nature of travel conditions – whereby users adjust to other routes, modes, destinations, and times of day. In fact, the dependence on volume-capacity relationships to estimates speeds and congestion on specific facilities is a critical assumption and weakness of the method (Hall, 1987) – stripping engineers of the potential to increase volumes while retaining speeds.

2.5.4 Real-time traffic monitoring systems

Real-time traffic monitoring systems are being deployed by both the public and private sectors and have emerged as a newer means of studying and disseminating traffic information which independently collects different system performance data (e.g. speeds, volumes, travel times). When implemented, Advanced Traveler Information Systems (ATIS) inform users and lead them to adjust their expectations (Vipre, 2006; Coernet, 2005; Lyons, 2006) or change their travel behavior (Kenyon & Lyons, 2003; Bottom, Masroor, & Lappin, 2002; Lappin & Bottom, 2001). ATIS have become attractive for sub-markets of transportation system users (Kenyon & Lyons, 2003) to search online traffic updates from their computers, listen to radio traffic reports, employ smart phone mapping applications, or sign up for real-time information on specific links to get information on current traffic conditions (Campbell, Havlicek, Stevenson, & Barnes, 2012). Real-time traffic monitoring could thus shape not only service supply – insofar that public entities may employ real-time information to change operations, but also travel demand – insofar that users use and respond to ATIS. Real-time traffic monitoring is common in public and private applications (Campbell, Havlicek, Stevenson, & Barnes, 2012), but users' consumption of information through ATIS is relatively slower (Seebauer & Berger, 2010; Adler & Blue, 1998). Thus, real-time traffic monitoring and communication through ATIS remains largely descriptive and behavioral change en masse remains elusive (Kenyon & Lyons, 2003). But unlike other methods of studying congestion, real-time traffic monitoring focuses on users' own unique potential needs by describing the conditions on select routes on select days using streamed empirical traffic data (Gandy & Meitner, 2008; Zografos, Androutsopoulos, & Nelson, 2010). Real-time traffic monitoring is highly-localized, relies on empirical data, and is not designed to forecast future conditions for policymaking (Transit Cooperative Research Program, 2003). In short, while information from real-time traffic monitoring systems and ATIS are still penetrating the market of transportation system users, they can inform the public of transportation conditions and can better link real-time conditions with both capacity (the domain of service providers) and demand (the collective actions of system users).

2.5.5 Will New Data Meaningfully Change Congestion Management?

New data holds much promise in better understanding trade-offs between different transportation output objectives (e.g. flow, speed, reliability) and understanding the uniqueness of facilities and user experiences. With the exception of four-step travel demand models, we might expect the proliferation of probe data to significantly change how each of the other three types of congestion study can be conducted. Real-time monitoring and information provision can be significantly improved and both regional and localized facility-specific congestion studies can be conducted more regularly with direct comparisons between areas and over time.

The outlook for new data to change congestion studies and transportation program management hinges on four critical challenges. First, if tools leveraged by new data sources establish <u>credibility and sufficiently informative and interpretable information</u> to drive decision-making, the actions of both the traveling public and program managers could be influenced by tools and products generated using new Big Data sources and analyses. In this context, the efficacy of Big Data in improving policymaking rests on measuring the right thing. In contrast, for transportation system users who are already exposed to a host of competing sources of information - many of which already come from "Big Data" sources - one would expect new data-driven products to compete directly with known products which are evaluated on the basis of elements such as reliability, ease of use, and utility.

Second, if pairing multiple sources of data which are dynamically collected, this can enable explicit assessments of policy trade-offs to be made and judged by transportation program managers. This varies from previous studies in that it does not rely on generalized engineering functions (e.g. speed-volume) and focuses on multiple performance indicators. In this study, traffic volumes and road capacities are largely static and variations in performance are primarily driven by speed data from Inrix, Inc. To assess a more complete range of potential policy outputs or outcomes, Big Data-driven analyses can improve how policy trade-offs are made - including those between vehicular speeds, vehicular volumes, user travel times, user volumes, among others.

Third, even to reasonably use static volume estimates and dynamic speed estimates, as in this study, the secondary data collection and management tasks rely on combining multiple sources of data. Inter-agency coordination to relate and use different data sources should be encouraged. This analysis relies on City count locations, MTO count locations, and four-step travel demand estimates estimated by MITL using TRAFFIC. Although each of these datasets are coupled, improving analyses from using historic archived speed data to using streamed incoming data of multiple types requires data-driven (and not only professional relationship-driven) means of gathering and using the requisite inputs.

Finally, to either generalize system performance or assess the uniqueness of specific assets, newer data sources can provide new insight into transportation system function which are unavailable when relying on generalized engineering functions. This is a significant departure from the state of practice. Capacity, speed-flow dynamics, and user expectations vary from facility to facility and from time of day to time of day, so insofar that the proliferation of probe data can enable better metrics of how the transportation system should or does function in different circumstances can better hone traffic management to specific contexts. As found by other Big Data users researching other topics, including Hsu's study of building energy efficiency in New York City (Hsu, 2014), Big Data analyses often find that each unit of analysis (in the case of this study, road segments) is sufficiently unique that policies or predictors of performance have very different outcomes in different circumstances.

Research Design

Integrating Big Data into transportation performance monitoring relies on combining various sources and types of data, validating results, and streamlining analyses for reproduction. This study employs two basic types of data inputs: link-specific and time-specific speed estimates (from Inrix, Inc.) and link-specific and time-specific volume estimates (from four-step travel demand modeling output, City of Toronto count data, and Ontario Ministry of Transportation count data). Several sets of count estimates based on different assumptions are employed to scale up the speed data to reflect experiences of road users. As traffic counts are not continuously collected at all locations at all times, assumptions are necessary to estimate seasonal, weekly, and hourly fluctuations in traffic volumes. First, the method for estimating traffic volumes is described using TRAFFIC, the MITL four-step travel demand model, City of Toronto traffic count data, and Ministry of Ontario traffic count data. Second, methods are discussed for using speed data in combination with volume estimates for extracting performance indicators for system components.

3.1 Traffic Volumes

Traffic volumes are important inputs into most transportation system performance measures, including those developed as part of this study. Traffic volumes are critical for this work because they enable road speed data to be interpreted in light of how many users are likely impacted. As such, metrics can be estimated on a per user basis and aggregated to the level of the transportation system and its sub-components.

To estimate traffic volumes on the study area roadways, three traffic volume estimates are generated sequentially based on results from the four-step model. These estimates are adjusted based on empirical traffic volume estimates from the Gardiner Expressway (managed by the City of Toronto) and several of the 400-series freeways (managed by MTO).

3.1.1 TRAFFIC – the four-step Travel Demand Model

First, the MITL four-step travel demand model, TRAFFIC, is estimated using the 2006 Transportation Tomorrow Survey. Trip generation, attraction, distribution, mode choice, and route assignment are each performed according to conventional industry standards. Traffic volumes are estimated for specific links on the TMC network and matched with the TMC links for which other sources of data, principally Inrix, Inc. speed estimates. Traffic volume estimates are converted to estimates of vehicle-kilometers of travel (the sum of volume and link length) to illustrate the intensity of travel across the day based on TRAFFIC model output, as shown in Figure 1.

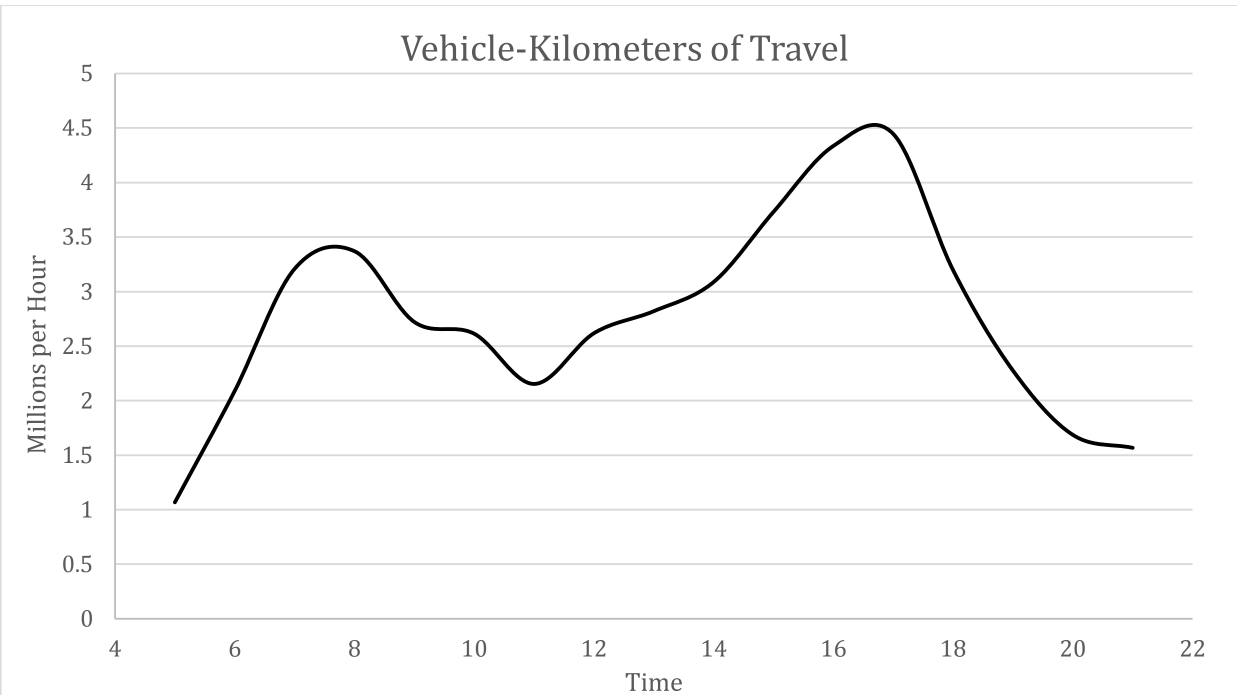

Figure 1. TRAFFIC Four-Step Model Output: Estimates of Hourly Vehicle-Kilometers of Travel

Second, traffic volumes estimated using the four-step model are compared with volume estimates from the City of Toronto Transportation Services Division's ongoing traffic count program. Traffic count locations from 2011 which are located along Inrix, Inc. links are mapped in Figure 2 and illustrate that even when simply dividing the year in two (January-June vs. July-December), relatively few count locations are continuous throughout the year – providing challenges in estimating unbiased point adjustments and seasonal adjustment factors.

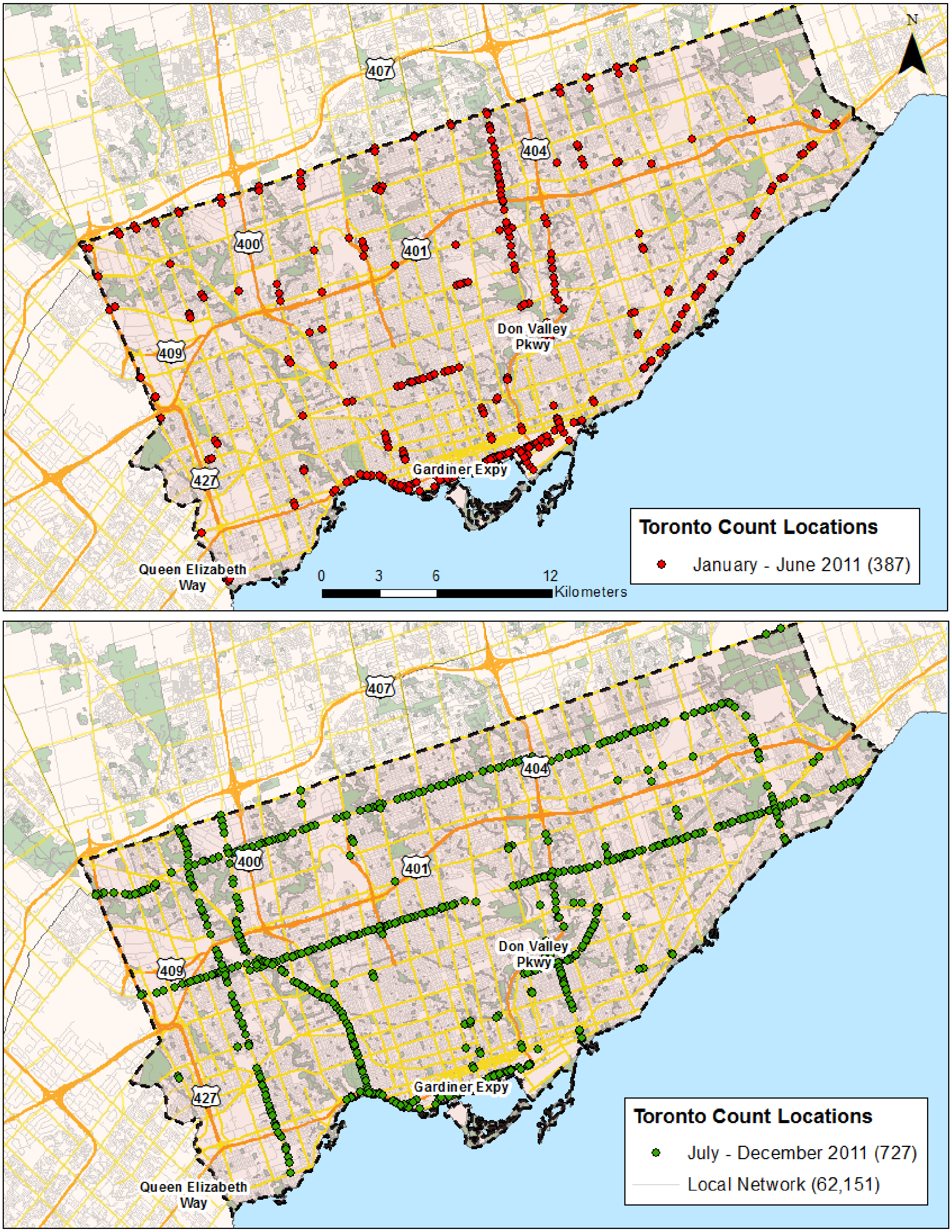

Figure 2. City of Toronto Traffic Count Locations on Inrix, Inc. Links (2011)

Although counts are provided for all links within the City of Toronto, only the Gardiner Expressway volumes from 2011 are used to compare with TRAFFIC model output. Gardiner volume counts are collected regularly throughout the year, as shown in Figure 2, providing insight on the seasonal, weekly, and daily variations in traffic volumes which are not reflected in the TRAFFIC model output. As such, continuous count locations on the Gardiner in 2011 are used to adjust TRAFFIC model output for 2011, 2013, and 2014.

Count data for 2011 is employed in lieu of 2013 or 2014 for two reasons. First, 2011 is one of the two years (in addition to 2014) for which full-year Inrix, Inc. data is available. Second, although 2014 traffic count data is also available from the City, extensive closures and maintenance on the Gardiner began in late April 2014 – making the seasonal volume adjustments invalid when expanded to the rest of the road system.

Using the adjustment factors relating volume estimates from the four-step model and City of Toronto count data for 2011, seasonal, weekly, and hourly adjustments are used to adjust 2011, 2013, and 2014 TRAFFIC model output. Adjustment factors are estimated using regression in which month-specific and weekday-hour-specific adjustment factors are estimated. First, adjustments are estimated assuming that each of the seven days of the week have distinct hourly profiles (shown in Figure 3), according to which early mornings and mid-day volumes are systematically upward biased in the TRAFFIC model output, while morning peak period volumes are systematically downward biased in TRAFFIC compared to observed counts on weekdays (but not on weekends) and evening volume estimates from TRAFFIC after 4pm are underestimated compared to observed counts.

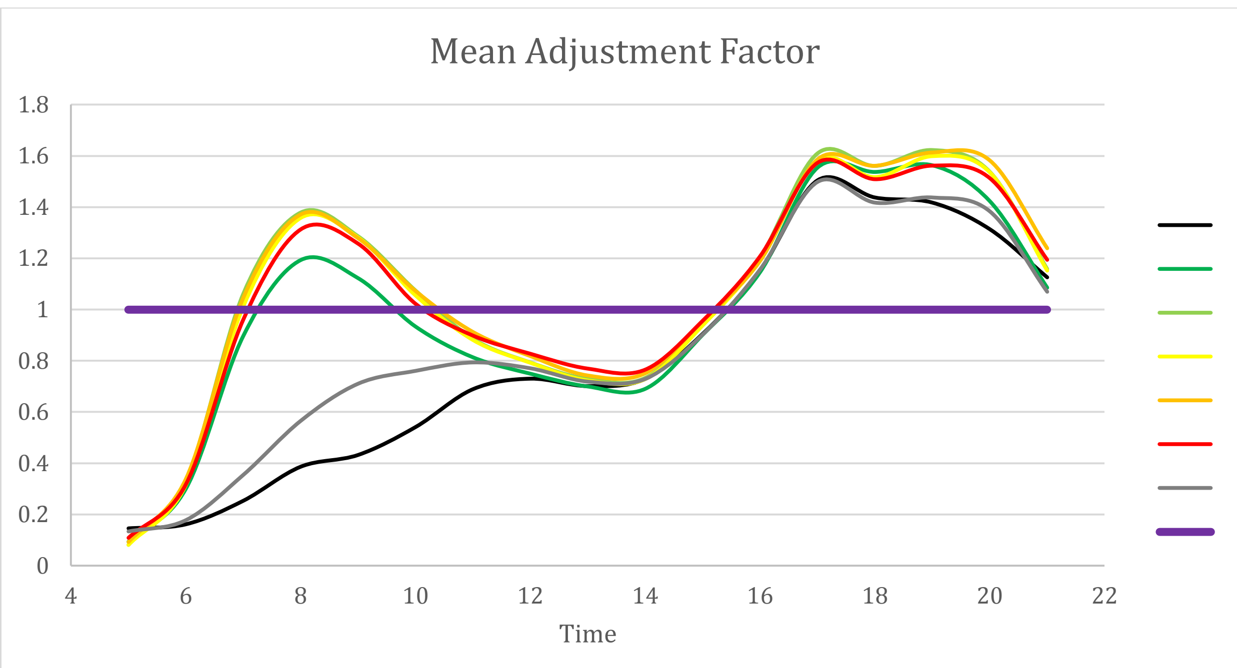

Figure 3. Estimated Mean Weekday Adjustment Factors relative to TRAFFIC

However, based on the relative lack of variation between each of the five weekdays and the two weekend days, each of these are combined to estimate a simpler adjustment scheme which is adopted, whereby month-specific adjustment factors are used and hour-specific adjustments are used for weekdays (combining Monday through Friday) or Weekends (Saturday and Sunday).

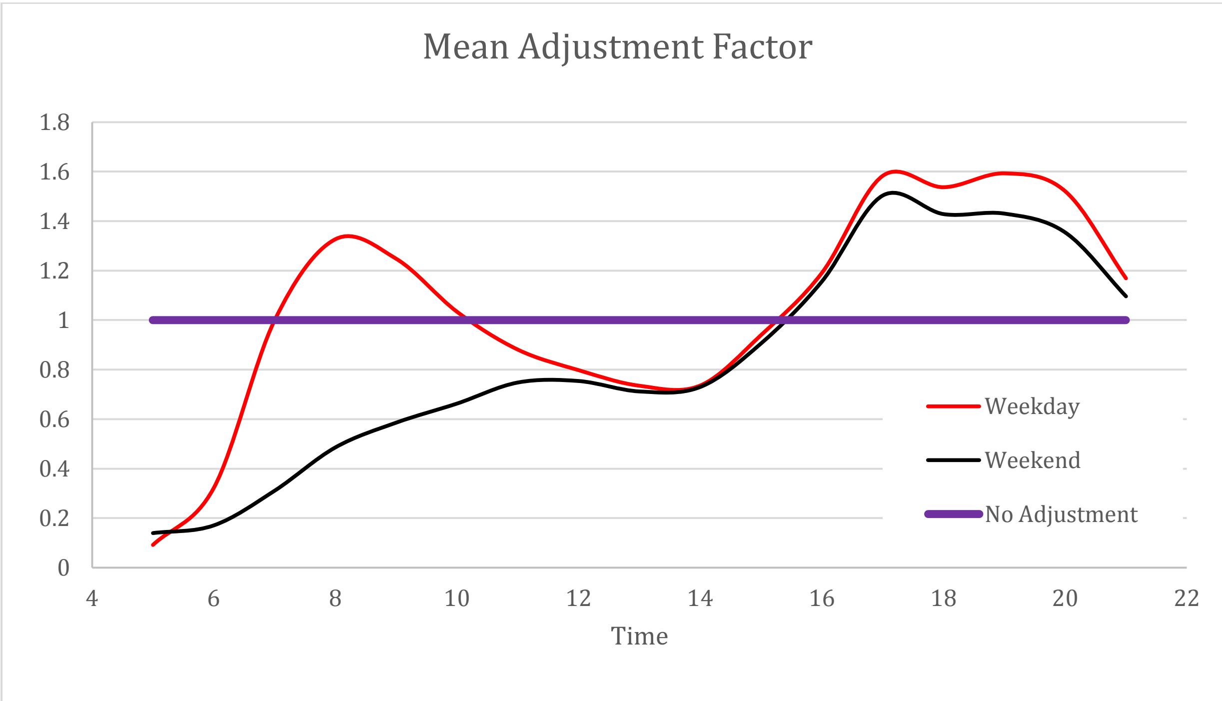

Figure 4. Final Estimated Mean Adjustment Factors relative to TRAFFIC

To interpret the precise meaning of the final adjustments (Figure 4), the mean hourly adjustments are applied to the TRAFFIC model output for weekdays and weekends and shown in Figure 5 and the corresponding mean seasonal adjustment factors are estimated and shown in Figure 5.

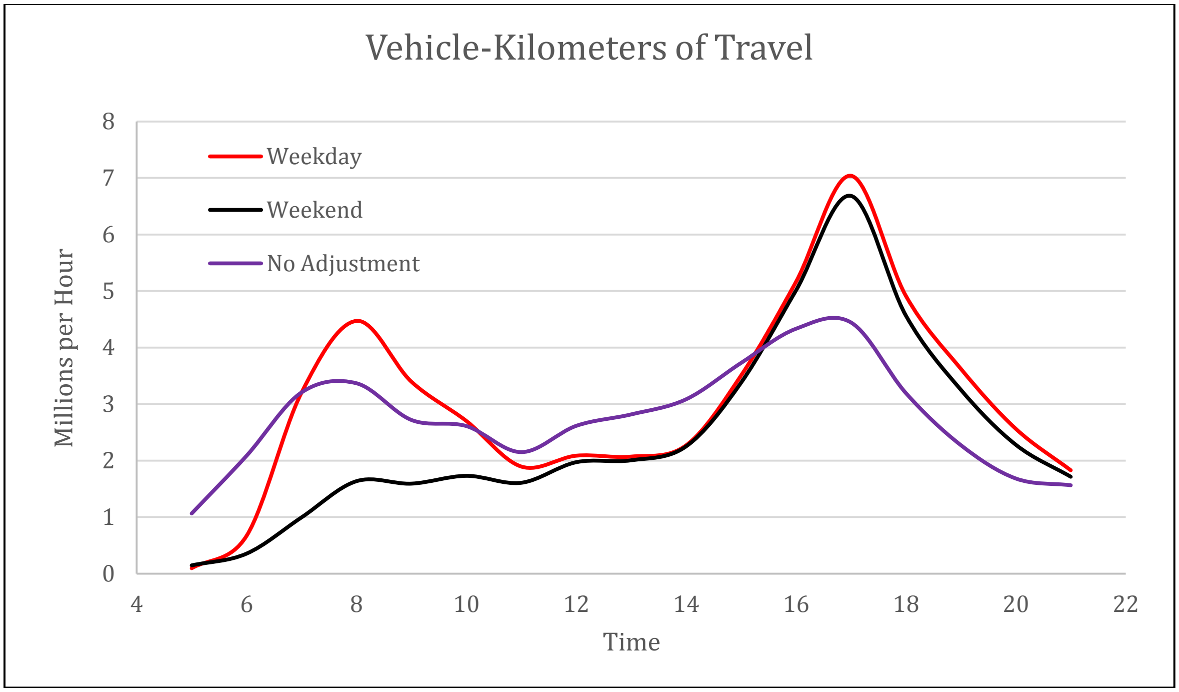

Figure 5. TRAFFIC Output and Weekday/Weekend VKT Estimates Based on Final Adjustments

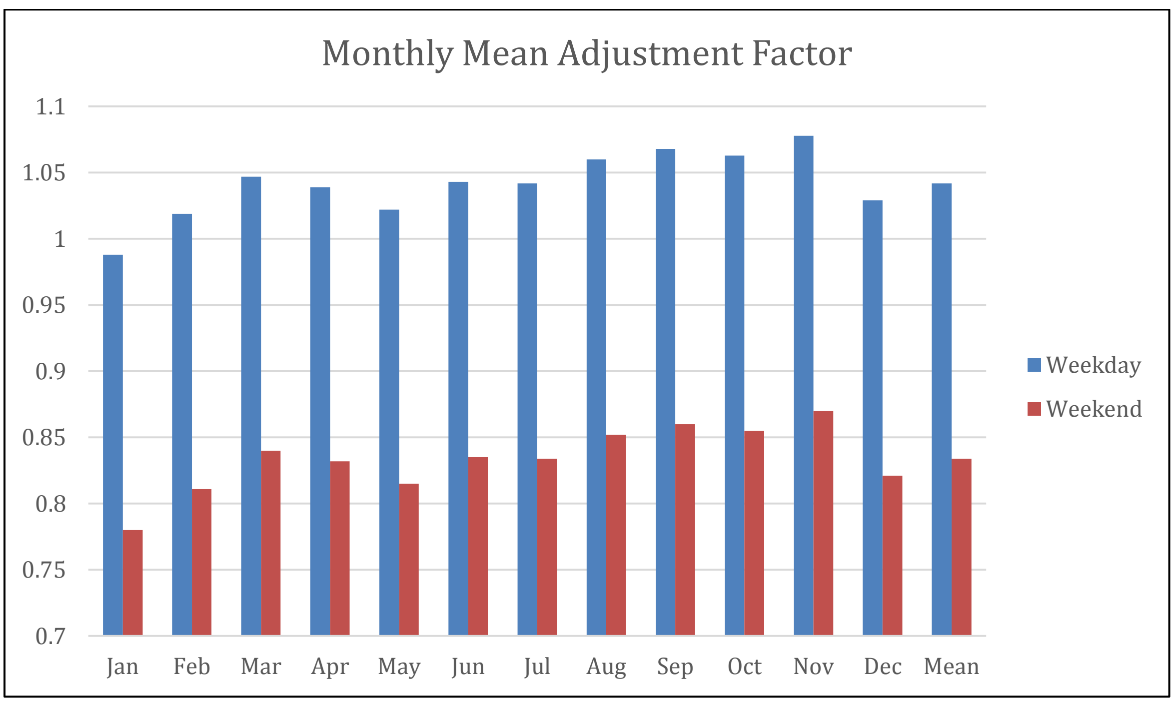

Figure 6. Final Estimated Mean Adjustment Factors relative to TRAFFIC

Finally, traffic volume estimates are further adjusted using cross-sectional data from the Ministry of Transportation for the 400-series freeways. Because 400-series freeway volumes are such a critical component of overall traffic flow, the precision of seasonally-adjusted TRAFFIC model output with daily and seasonal adjustments are tested. As such, a regression model is estimated in which the city count-adjusted hour and day-specific counts are used to predict the observed hourly traffic counts collected by the Ontario Ministry of Transportation along 400-series highways. Corridor-specific adjustment factors are estimated, such that if the existing count estimates overestimate volumes on one freeway but not another, these differences are accounted for. Beyond corridor-specific adjustment factors, other 400-series links which are badly represented by the count locations below (e.g. the 427 between the Gardiner and the 401) are adjusted using a regression model of the pooled adjustment factor (with no corridor-level differentiation). Adjustment factors only applied to 400-series freeways.

1. ON-427 north of the 401
2. ON-400 north of the 401 but south of Finch
3. ON-404 north of Sheppard but south of Finch
4. ON-409 between Martin Grove Road and the 427
5. ON-401 between the 427 and Martin Grove Road/Dixon Road
6. ON-401 between Weston Road and the 400
7. ON-401 between the 400 and Keele Street
8. ON-401 between Yonge Street and Bayview Avenue
9. ON-401 between Victoria Park Avenue and Warden Avenue
10. ON-401 between Neilson Road and Morningside Avenue

3.2 Speed Estimates

To estimate road system performance, road speed data are purchased from Inrix, Inc. Data are provided using Traffic Message Channel (TMC) links as the unit of observation and cover parts of 2011 (August 8 - December 31), 2013 (July 1 - December 31), and all of 2014 (January 1 - December 31). There are 1,911 TMCs included in the full City of Toronto network, on which Inrix, Inc. traffic data is collected by numerous types of floating probe vehicles, many of which represent heavy vehicle operators.

While the variations in transportation system performance reflect both spatial and temporal variations in performance among the sampled users, the sample reflects the acceleration and deceleration patterns of the vehicles comprising the Inrix, Inc. vehicle probe fleet,. Based on the differences between vehicles comprising the Inrix, Inc. probe dataset and general road users, one would expect the potential issues of lack of representativeness and sampling bias. First, many Inrix, Inc. probe vehicles are both heavier and slower than the general user fleet. Moreover, during stop-start conditions (e.g. during congestion or on heavily signalized roadways) acceleration patterns of heavy vehicles would further slow Inrix, Inc. probe vehicles down. These would lead Inrix, Inc. speed estimates to be slower on arterials and comparatively slower on freeways under congested conditions.

Second, insofar that the travel patterns of Inrix probes and heavy vehicles do not reflect broader travel patterns by the general motoring public, there is additional sampling bias. For example, while freight system users are more likely to travel by freeway over longer distances, trips by members of the general public are not as long and freeway travel does not feature as prominently in comparison. As a result, one would expect freeways to be oversampled relative to arterials. Without adjusting for these sources of oversampling, metrics would be expected to overstate the role of freeways in reflecting broader transportation service conditions.

CIMA (2012) compared several data sources used to estimate traffic speeds, including Bluetooth technology, TomTom, and Inrix, Inc. Despite the above two potential sources of sampling error, CIMA (2012) concluded that the three data sources studied were largely indistinguishable in terms of accuracy or validity. Instead, the chief differentiating factor among the data sources was the geographic coverage within the network. Among the three, Inrix, Inc. had wider geographical coverage than the other sources. The full Inrix, Inc. dataset purchased for this study includes 1,911 links comprising 2,021 link-kilometers of roadways, of which 383 link-kilometers (19%) are freeways. These links represent freeway mainlines and major arterials within the network but in no way reflect the entire road system (which would also include local streets and collectors upon which very few of the freight vehicles comprising Inrix, Inc.'s probe fleet regularly travel.

3.3 Methods

Although the Inrix, Inc. data is available to depict link-specific speeds during specific seconds during the day, to generalize performance metrics, data are aggregated - as needed - to reflect typical speeds for 15-minute intervals (on each individual day) or to reflect speeds for specific 15-minute intervals or hours during the typical weekdays, months, or years. As such, the core methodological challenge is to appropriately adjust data to eliminate sampling bias. In short, the finer the data is sliced, the larger the potential for sampling bias to significantly bias results. Specific methods fall into three categories:

3.3.1 Descriptive Statistics

To extract performance measures in their most basic form, raw data are first extracted and preprocessed for use in specific analyses. Two types of preprocessed data are extracted: 1. data which is specific for 15-minute intervals between 5am and 10pm for each specific link on each specific day for which data is collected and 2. data which captures average speeds for each pair of 15-minute intervals (17 hours * 4 15-minute intervals = 68 intervals), weekdays (7 days of the week), and months (12 months in the year) for each of the study time periods: August - December 2011, July - December 2013, and January - December 2014.

To further extract descriptive statistics, pre-processed data are used to estimate specific performance metrics for specific time periods. The following equation is designed to extract speed and travel time index performance measures for a specific year and not to compare between different years.

Equation 1. Simplified Weighted Descriptive Statistics

$$\bar{x}_{gdmt} = \frac{\sum_{i=1}^{n} P_{igdmt} * V_{igdmt}}{\sum_{i=1}^{n} V_{igdmt}},$$

where x_{gdmt} represents the mean performance measure (either speed or travel time index) for a specific geography and time period denoted as follows:

> g represents a specific geographic unit (e.g. the city, the downtown, or a specific corridor),
>
> d represents the specific day of interest (one of the seven weekdays, or a typical weekday or weekend),
>
> m represents the specific season of interest (either one of the seven months, the entire year, or a three month period - e.g. September through November),
>
> t represents a specific time period of interest (either one of the 64 15-minute intervals or one of the 17 hours studied in the course of the day),

P_{igdmt} represents a mean performance measure (e.g. speed or travel time index) for a specific link (i) which is part of a geographic unit (g), day (d), season (m), time (t), and

V_{igdmt} represents the volume estimate for a specific link (i) which is part of a geographic unit (g), day (d), season (m), and time (t).

When estimating speed or travel time index-based performance measures, differences between days of the week, months, and time periods are restricted to two full dimensions at a time when extracting results: e.g. all seven weekdays for all time periods, but for a typical year (not based on seasonal variations) or all months of the year for all time periods, but only for a typical weekday.

Next, aggregate delay-based measures are calculated similarly to above:

$$d_{gdmt} = \sum_{i=1}^{n} O_{igdmt} * V_{igdmt} - \sum_{i=1}^{n} F_{igdmt} * V_{igdmt}$$

where d_{gdmt} represents the delay for geographic unit g, day d, season m, and time t; O_{igdmt} represents the observed travel time for link i which is observed for geography g, day d, season m, and time t; V_{igdmt} represents the volume (in vehicle-kilometers of travel); and F_{igdmt} represents the free-flow travel time. All delay-based measures are further adjusted to estimate average delay for a typical one-hour period which is denoted by *dmt*.

3.3.2 Multilevel Modeling

For analyses requiring more than three full dimensions (weekday by month by time of day), multilevel modeling is employed to ensure that sampling bias is not a source of error. Multilevel modeling is primarily employed when year-over-year differences (the additional data dimension) are estimated in order to ensure that year-over-year differences do not stem from differences in sampling density and rather are differences in the underlying phenomenon. Speed-based measures are described below but these can easily be expanded to reflect delay or travel time indices by post-processing. The following example is specifically for exploring day-to-day differences, but the dimension of interest (different days, different years, different weekdays, different hours) can be defined as needed (but with some estimation and computational constraints). In the following example which could be used to estimate annual differences in 2014 for the freeway system (398 links), annual differences are the key dimension of interest. The model would be of the following functional form:

Equation 2. Day-Variant Model

$$y_{itd} = \beta_{0y} + \beta_{1itd} + \varepsilon_{itdy},$$

where y_{itdy} represents the observed speed for a given link (*i*) during a time period (each denoted *t*) for either a weekday or a weekend (denoted *d*) during a specified year (denoted *y*) for each of the 17 hours in the day, β_{0y} represents the intercept for each of the three specific years, β_{1itd} represents the intercept for each link at each time period on either a weekday or a weekend in each of the three years; and ε_{itdy} represents the error term specific to observation *i* at time *t* on day *d* in year *y*.

Thus, three coefficients are being estimated for β_{0y}, each representing the mean unbiased freeway speeds in the network in each of the three years, and (in this example) more than 13,532 unique coefficients are estimated for β_{1itd} (398 unique links * 17 hours in the day * 2 types of weekdays: either weekend or weekday). In this example, the coefficient estimates for β_{1itd} are only of secondary interest and are designed to establish an expectation from which the mean daily congestion levels can vary. As such, even if a given day only has sampled speeds on less congested links at off-peak time periods while another has sampled speeds for more congested speeds during peak time periods, the speeds on each of these sets of links and time periods are compared to the expected means for those links to establish whether the daily mean is higher or lower than expected. Models are estimated using the lme4 package with the software R.

3.3.3 Simulation and Sampling

Beyond conventional descriptive statistics and multilevel modeling, sampling is employed as a method for extracting travel time unreliability measures. While one might be tempted to extract unreliability measures similarly to conventional descriptive statistics and aggregating link-level performance up to the system, this ignores that transportation system users' perceptions of unreliability relies on their trip experiences which are made up of several road links. Thus, while there may be atypically slow travel conditions on a given link, adjacent or proximate links which could make up a trip may have different characteristics at any given point in time. As such, understanding the unreliability of trips (as opposed to specific links) rests on considering the joint distributions of travel speeds on a simulated set of links which could comprise a trip.

Potential trips of set lengths (5 kilometers, 10 kilometers, 15 kilometers, and 20 kilometers) are sampled to simulate the distribution of travel speeds associated with trips of approximately these lengths. The volume-adjusted mean link length is approximately 1.25 kilometers, so four links are selected for five-kilometer trips, eight links are selected for ten-kilometer trips, 12 for 15-kilometer trips, and 16 for 20-kilometer trips. Links are sampled using the probability of traveling on a specific link based on its length and volume such that the sum of the probabilities of selecting each link add up to one. While each simulated trip is not precisely the mean trip length, on average, the mean trip length (five, 10, 15, or 20 kilometers) is retained and the mean speeds for each simulated trips are used to estimate unreliability metrics. At least 10,000 simulated trips are used to estimate the distributions of travel speeds for simulated trips - from which both typical and atypical performance indicators can be generated to explore unreliability.

4

Results

Results from this study indicate the importance of selecting appropriate methods to study transportation system performance and indicate that road transportation system performance is a highly-dynamic and complex process across the City of Toronto's arterial and freeway systems and in the downtown core. Substantive findings are discussed first before exploring conclusions about methods, future directions, and the potential for Big Data analytics to inform transportation program management.

Transportation system performance estimates are performed for two geographies: the City of Toronto as a whole and Downtown Toronto (arterials only), bounded by Lake Ontario, Jarvis Street, Bloor Street, and Bathurst Street. Results from each are discussed simultaneously to explore transportation system performance across six broad dimensions: change over time, hourly variations within the day, monthly variations, daily variations within the week, unreliability, and specific corridors.

4.1 Peak-Hour Changes in System Performance

Using multilevel modeling, changes in transportation system performance are estimated between 2011, 2013, and 2014. To increase comparability, only data for September, October, and November are used to estimate differences between the three years. This restriction is preferred for three reasons: first, 2011 (August 8-December 31) and 2013 (July 1 - December 31) only have partial data and second, the month of December contains many severe weather events which significantly impact weather-induced differences in congestion which are not strictly functions of annual differences in recurring congestion. Thus, September through November are preferred to improve comparability between the years.

4.1.1 City-Wide Annual Changes

Differences between each of the years are first estimated for the entire city as a whole (see Figure 7). Four core performance measures are estimated: two which reflect recurring congestion (speed and delay) and two which reflect the unreliability of the system (planning time index and buffer time index). City-wide delay is estimated using both the 85th percentile fastest travel speeds and the mean night speeds (between 11pm and 5am), illustrating the importance of the free-flow speed as a reference point. Each metric indicates that congestion decreased (or remained flat) between 2011 and 2013 but that it grew in 2014 - particularly on the arterial system. The largest shifts in recurring congestion occurred during the PM peak hour (5pm - 6pm) and the largest increases in congestion occurred on the arterial system (on average, 7kph slower during the evening hour). Results indicate that delay on the arterial system increased by between 6,453 and 6,721 hours (using night speeds as free-flow) or 7,236 or 7,398 hours of delay per hour (using 85th percentile speeds as free-flow) during the morning and evening peak hours. Both speed-based measures of congestion and delay-based measures indicate that changes on the arterial system between 2011 and 2014 are more severe than on the freeway system. An increase of approximately 7,000 hours of delay per peak hour translates into approximately (52*5*7000 + 52*5*7000) = 3.64 million hours of delay annually during the morning and evening peak periods alone.

Figure 7. Study Area Roadways within City of Toronto (Red and Orange)

Measures of unreliability similarly indicate that city-wide travel conditions become less reliable over time - in this case for a simulated 5-km trip during the 5pm hour. Unreliability is measured using two indices: the planning time index (PTI), which represents the ratio of the 95th percentile slowest travel times to the free-flow travel times, and the buffer time index (BTI), which represents the ratio of the 95th percentile slowest travel times to the average time-specific travel times. While PTI reflects unreliability relative to free-flow expectations, BTI reflects unreliability relative to mean time-specific expectations - which also change.

Results are only shown for the PM peak hour and indicate that PTI increases by 0.4 units between 2011 and 2014. For a hypothetical ten-minute trip, this would indicate that for one to arrive on-time 95% of the time in 2011, one would need to allow 21.9 minutes in 2011 but 25.9 minutes in 2014 - an additional four minutes. Changes in buffer time index are much more modest: buffer time index increases only by 0.16 units between 2011 and 2014. Thus, changes in buffer time index must be interpreted relative to changes in background speeds (which are decreasing). As such, a 0.16-unit increase in BTI between 2011 and 2014 means that the 95th percentile longest travel times increase 16% faster than the increase in mean travel times for simulated 5-kilometer trips during the evening peak period.

Table 1. City of Toronto Changes in Congestion (2011-2014)

Key Performance Indicators		2011		2013		2014		Change (2011-2014)	
		Arterials	Freeways	Arterials	Freeways	Arterials	Freeways	Arterials	Freeways
Speed (km/h)	AM Peak	42	75	43	75	37	73	- 5	- 2
	PM Peak	42	72	42	74	35	70	- 7	- 3
Delay Hours (ff = 85 pct.)	AM Peak	4,761	9,066	3,872	10,129	11,997	11,791	+7,236	+2,725
	PM Peak	4,346	9,776	3,994	9,522	11,744	11,838	+7,398	+2,062
Delay Hours (ff = night)	AM Peak	4,919	8,036	4,324	9,139	11,371	10,779	+ 6,453	+ 2,743
	PM Peak	4,352	8,786	4,193	8,583	11,073	10,857	+ 6,721	+ 2,071
Planning Time Index		2.19		2.11		2.59		+ 0.40	
Buffer Time Index		1.6		1.6		1.76		+ 0.16	

4.1.2 Downtown Annual Changes

The downtown study area (see Figure 8) reflects all arterials covered by Inrix, Inc. data between Jarvis, Bathurst, Bloor, and Lake Ontario. Although the Gardiner Expressway crosses through this study area, it is not included as part of the downtown core because, as a freeway, its function is significantly different from the downtown arterials. Similarly to annual changes in road system performance city-wide, downtown congestion increased significantly between 2011 and 2014, while congestion drops slightly or remains stable between 2011 and 2013. Downtown delay is estimated exclusively using 85th percentile speeds as free-flow speeds (and not using night speeds) because night speeds in the downtown core are already very slow -yielding unreasonably low estimates of travel delay.

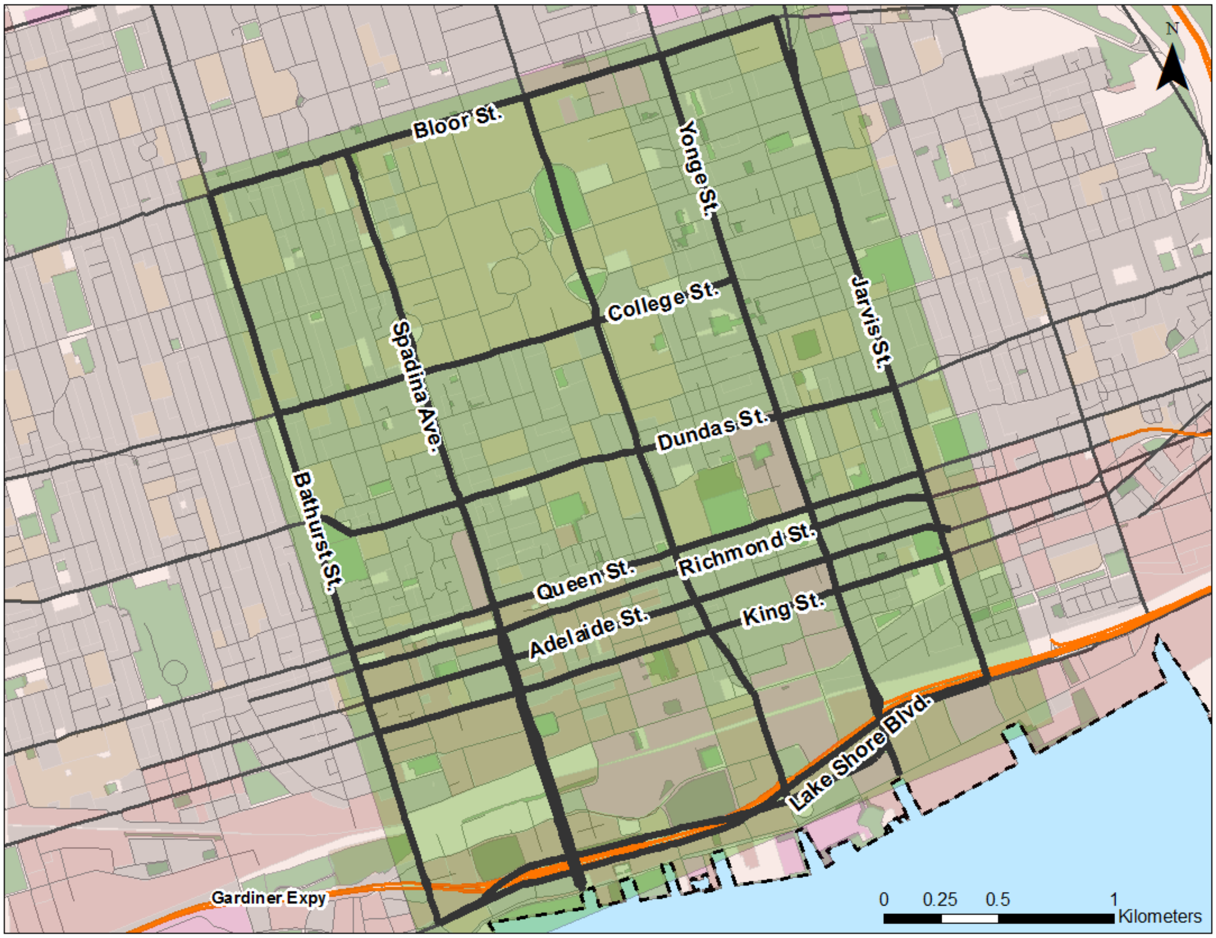

Figure 8. Downtown Toronto Study Area and Roadways (Green)

Changes in mean downtown vehicle speeds are similar to those for the City of Toronto: four and seven kilometers per hour slower in the morning and evening peak hours. However, as the mean base speeds in 2011 are approximately 10 kph slower in the downtown in 2011 than in Toronto as a whole, this represents a larger proportional decrease in speeds in the downtown core. In contrast to the city as a whole, travel conditions during the PM peak hour are somewhat more reliable (reliably slow) during both 2011 and 2014, but the planning time index increases by 0.64 units between 2011 and 2014 while the PTI for the city as a whole increased by 0.4 units. As discussed above, the 0.4-unit increase in PTI translates into an additional 4 minutes of time between 2011 and 2014 to arrive on time 95% of the time for a 10-minute trip under free-flow conditions. The 0.64-unit increase in PTI in the downtown unreliability translates into an additional 14 minutes of time between 2011 and 2014 to arrive on time 95% of the time. Thus, while unreliability remains higher in the City as a whole and reliably slower in the downtown, the changes in unreliability between 2011 and 2014 have the highest implications for downtown travel experiences.

Table 2. Downtown Toronto Changes in Congestion (2011-2014)

Key Performance Indicators		2011	2013	2014	Change (2011-2014)
Speed (km/hr)	AM Peak	31	32	27	- 4
	PM Peak	28	28	21	- 7
Delay Hours	AM Peak	183	172	605	+ 422
	PM Peak	353	332	1035	+ 682
Planning Time Index		1.51	1.50	2.15	+ 0.64
Buffer Time Index		1.15	1.15	1.21	+ 0.06

4.2 Hourly Variations and Changes Over Time

Hourly variations in transportation system performance within a typical day in 2014 are shown for both the city as a whole and the downtown. Results indicate significant morning and evening peak periods on the freeway system, but both the city-wide arterials and the downtown arterials have peaks which have spread so much as to make peak/off-peak differences challenging to interpret.

4.2.1 City-Wide Hourly Variations

While speeds increase and delay increases across the city between 2011 and 2014, the changes on the arterial system are most pronounced. First, focusing on the metric of travel speeds during typical weekdays, hour-specific differences between 2011, 2013, and 2014 illustrate when changes in system performance occurred. For the freeway system, see Figure 9, speeds in 2014 are lower at all times of day while 2013 speeds are somewhat higher than those in 2011 - particularly after approximately 10 am. Likewise, 2014 speeds on the full city arterial system are significantly lower at all times but particularly in the afternoon. In fact, while the morning and evening peak periods are very clear on the freeway system, the speeds on the arterial system never increase in the course of the day to their levels before the morning rush until after 9pm. In short, peak spreading is evident on both systems, but the significant drop in arterial speeds between 2011 and 2014 make distinguishing peak from off-peak arterial conditions challenging.

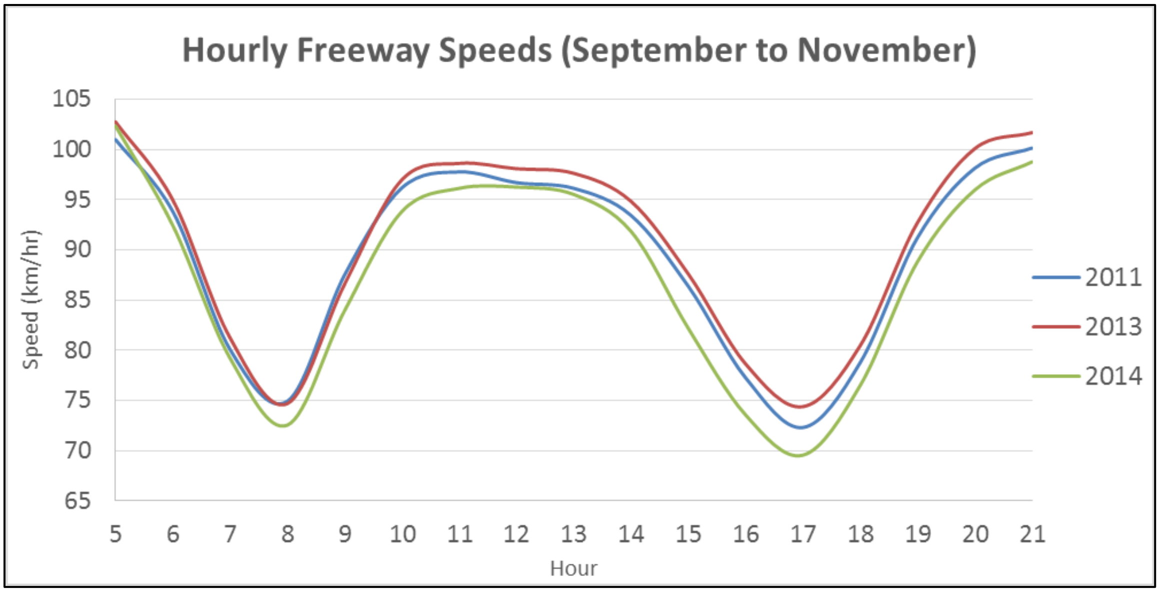

Figure 9. City-wide Hourly Mean Freeway Speeds (2011, 2013, and 2014)

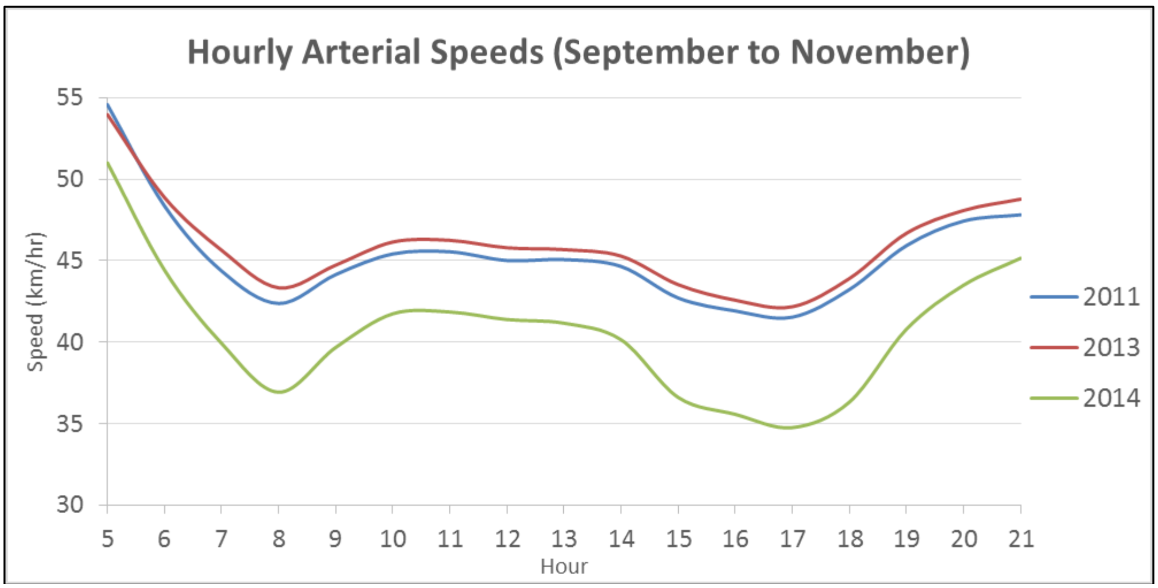

Figure 10. City-wide Hourly Mean Arterial Speeds (2011, 2013, and 2014)

Next, when focusing exclusively on vehicular delay during 2014, the hourly delay profiles of the arterial system demonstrate that while the freeway system hosts approximately equal delay to the arterial system during peak periods, arterial delay significantly outweighs freeway delay during all afternoon periods. In fact, as shown in Figure 11, the notion of congestion as a problem which is exclusive (or most pronounced) during the peak commuting periods only applies to the freeway system; whereas hourly delay on the arterials system remains high throughout much of the day.

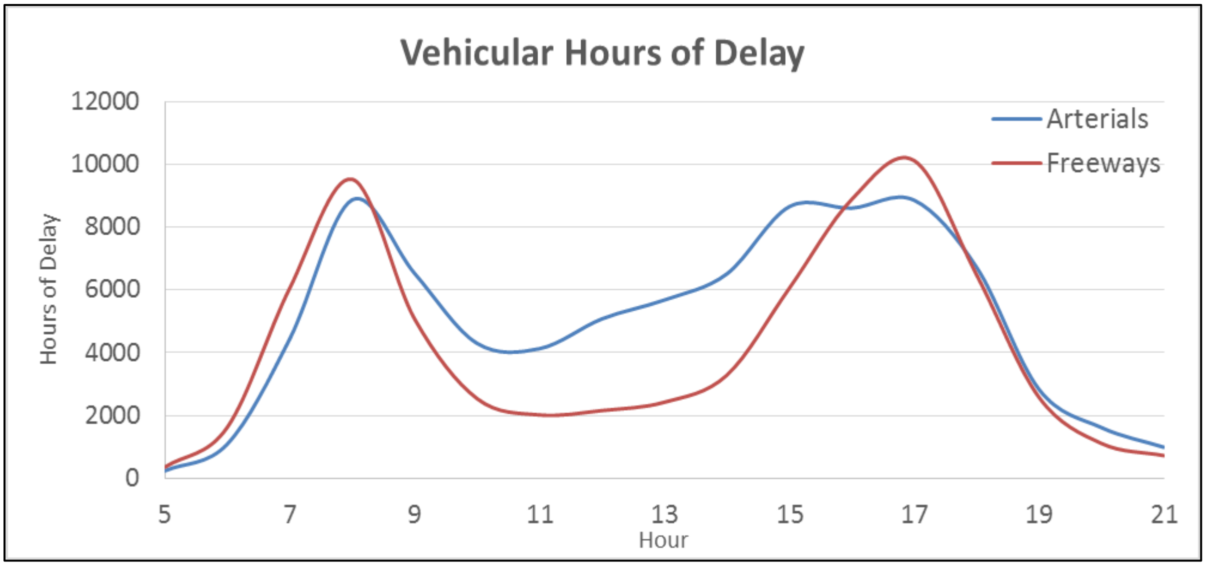

Figure 11. City-wide Hourly Travel Delay Profile

Finally, when focusing on differences between typical weekdays and weekends on freeways and arterials in the City of Toronto, results confirm weekday arterial and freeway trends, but illustrate that weekend speeds are much more static: speeds generally decrease in the course of the day, reaching their lowest in the late afternoon. As such, while congestion significantly contributes to travel experiences on some links at some times on weekends, at the scale of the entire city, the magnitude of the weekend congestion "problem" is small in comparison with weekdays.

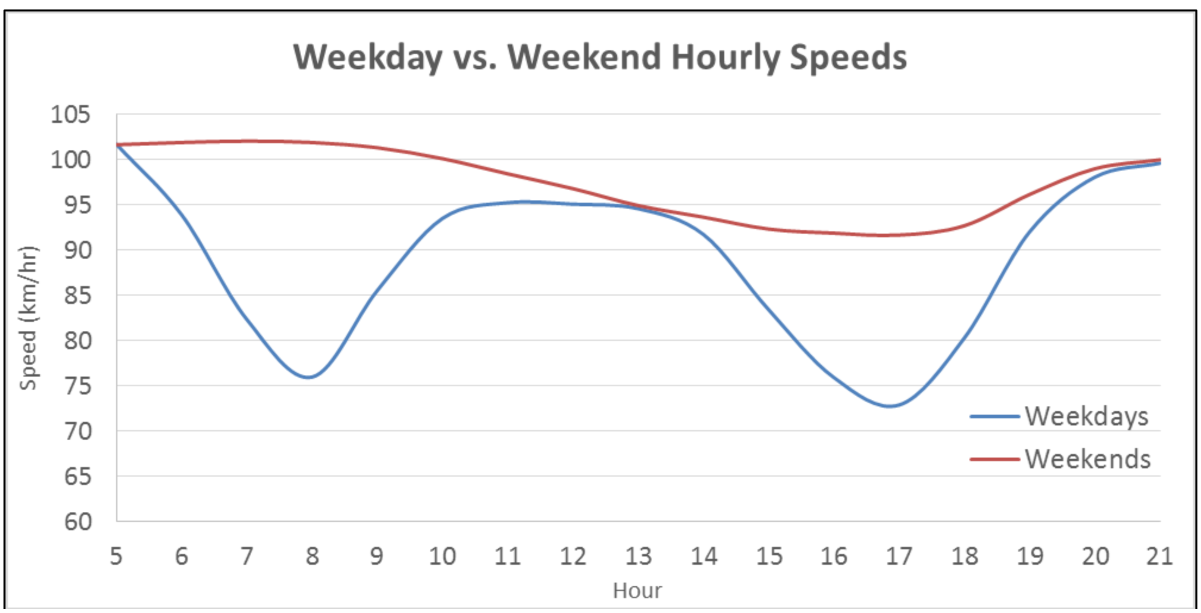

Figure 12. City-wide Mean Freeway Speeds for Typical Weekday and Weekend (2014)

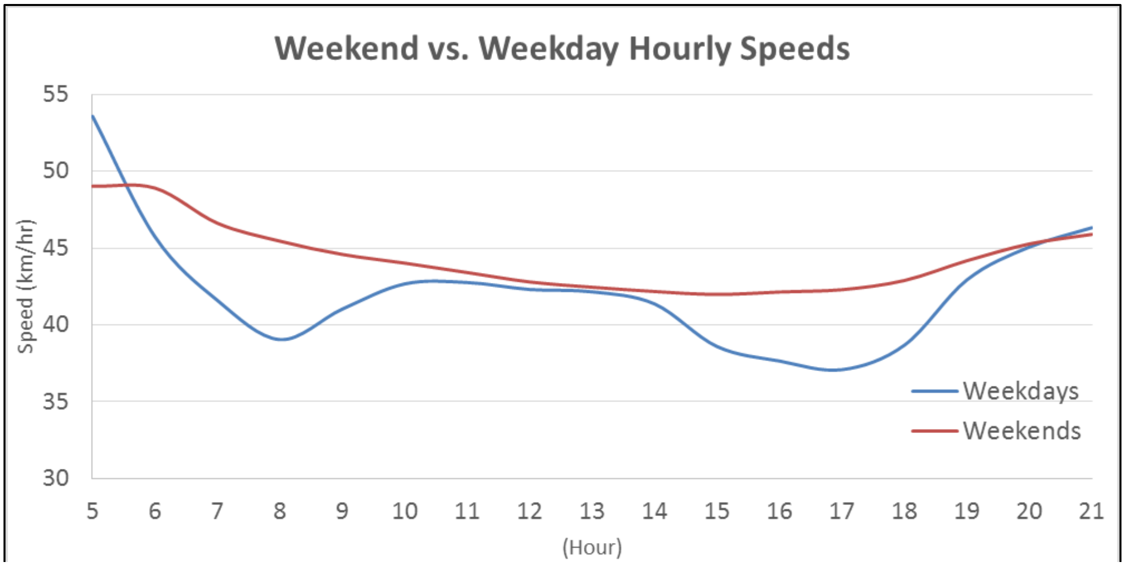

Figure 13. City-wide Mean Arterial Speeds for Typical Weekday and Weekend (2014)

4.2.2 Downtown Hourly Variations

While analyses of city-wide freeways indicate significant peaks, hourly variations in transportation system performance exclusively for arterials within the downtown core suggest a very different daily congestion pattern. As shown in

Figure 14, vehicle speeds decrease in the course of the day, reaching their lowest levels during the evening peak period. Although speeds during the morning peak period are somewhat lower (particularly during the 8 o'clock hour in 2014), the trend of decreasing speeds in the course of the day is much stronger than the impacts of the morning rush hour. Speeds are significantly slower at all times of day in 2014 and the evening peak period with the lowest speeds lasts longer than in 2011 or 2013.

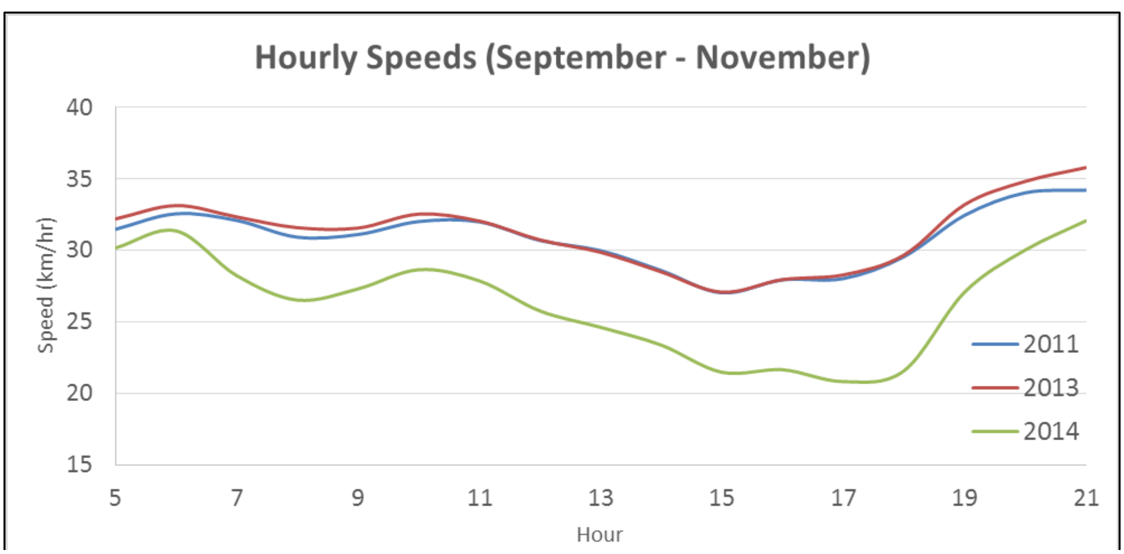

Figure 14. Downtown Hourly Mean Speeds for Arterials (2011, 2013, and 2014)

The hourly variations in downtown road system performance can be further explored by focusing on delay as an alternate metric. As shown in Figure 15, while differences in speed during the morning peak hour are relatively smaller, morning peak period delay is significantly higher because traffic volumes are also much higher. However, by 1pm, hourly delay on the downtown system already exceeds morning peak period delay - leading delay in the afternoon and evening peak periods to comprise the majority of all travel delay). Although congestion is typically portrayed as a "peak-period problem," travel delay in downtown Toronto does not exhibit clear peaks; instead, there is significant travel delay throughout the day which becomes more pronounced as a typical weekday progresses.

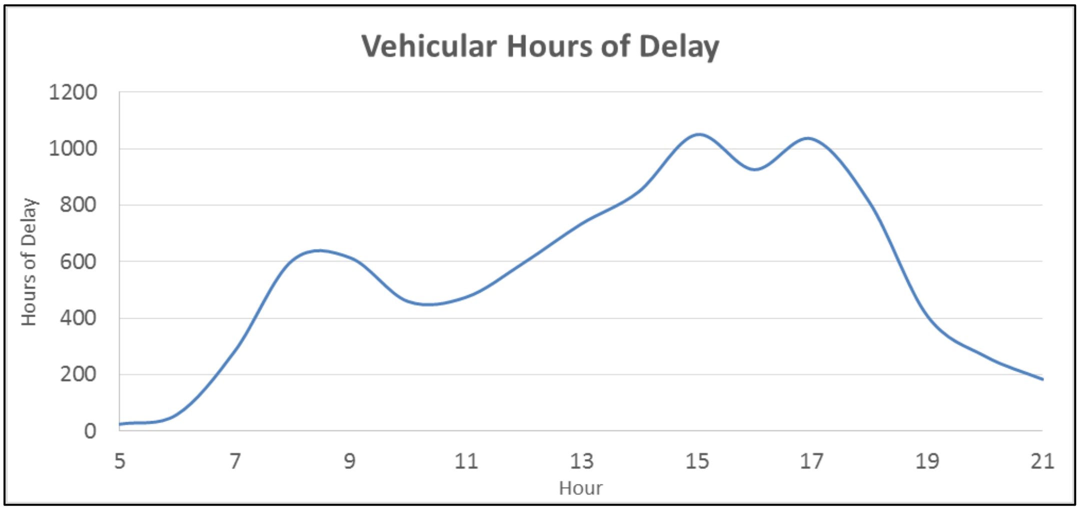

Figure 15. Downtown Toronto Hourly Travel Delay Profile (2014)

Finally, when focusing on differences between a typical weekday and typical weekend in the downtown in 2014, results indicate that road speeds on downtown arterials are only moderately higher on weekends than during weekdays. During both weekdays and weekends, speeds decrease in the course of the day, but while they reach their lowest levels during the 3pm-7pm peak period on weekdays, road speeds already begin to increase by the 6pm hour on weekends. Differences between weekends and weekdays are at most 5kph (during the evening period), indicating that - in contrast to the city as a whole (and particularly on freeways) - downtown roadways face congestion challenges during all days of the week.

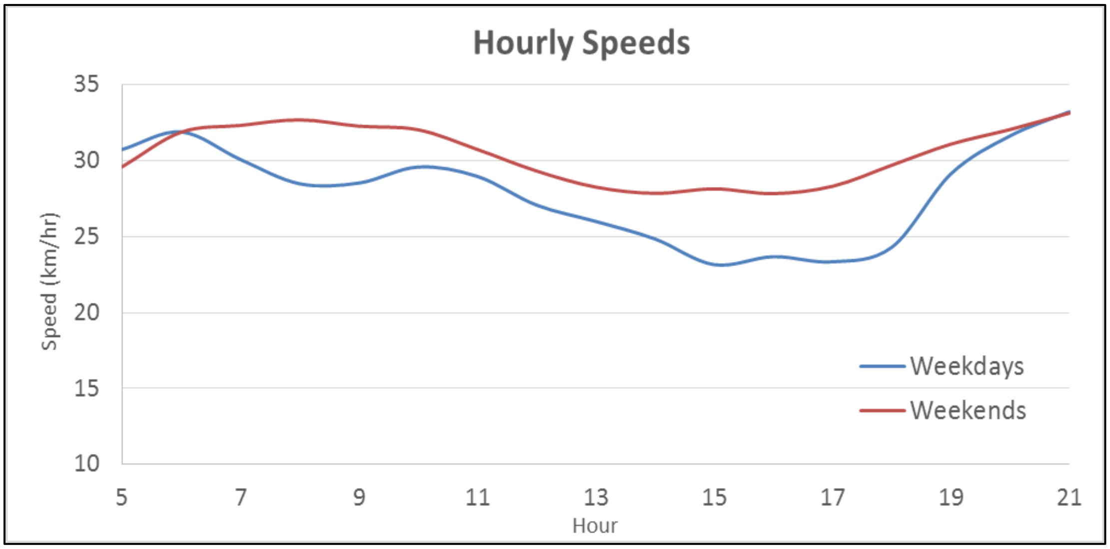

Figure 16. Downtown Mean Speeds for Typical Weekday and Weekend (2014)

4.3 Monthly Variations

Next, monthly variations in road system performance are explored for city-wide freeways and arterials and for the arterials in the downtown core for 2014. While the magnitude of seasonal differences in road system performance vary between the different levels of geography and between the arterial and freeway systems, all results indicate that road speeds declined in the course of the year, reaching their lowest points in November of 2014.

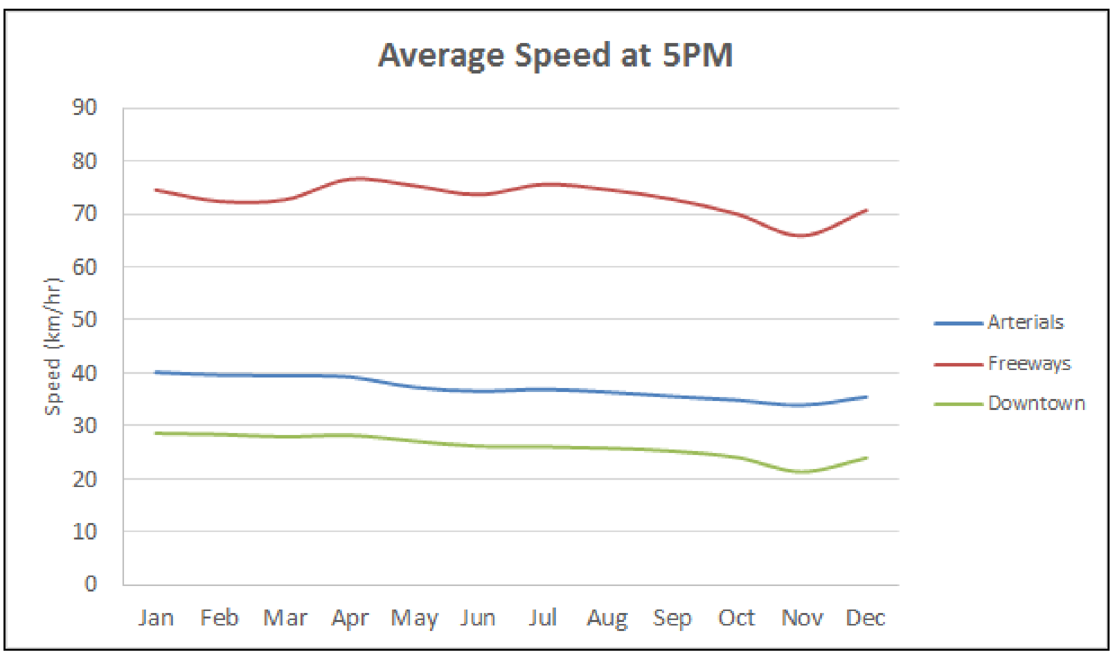

Figure 17. City-wide Monthly Variations in Mean PM Peak Travel Speed for Arterials and Freeways and Downtown (2014)

4.4 Daily Variations

Although transportation system users both shape and take into consideration the day-to-day variations in traffic congestion, results from this study indicate that the slowest speeds are Thursdays, the single slowest day, and Fridays. In fact, for the 5pm hour, day-to-day variations in road system performance are clearest for the freeway system, whereby weekend speeds are highest (of which Sunday has the single highest speeds) and speeds decline between Monday and Thursday before increasing modestly on Friday. As shown in Figure 20, day-to-day variations in travel speeds within the downtown core mirror the city as a whole - both in terms of evening peak period speeds and average daily speeds.

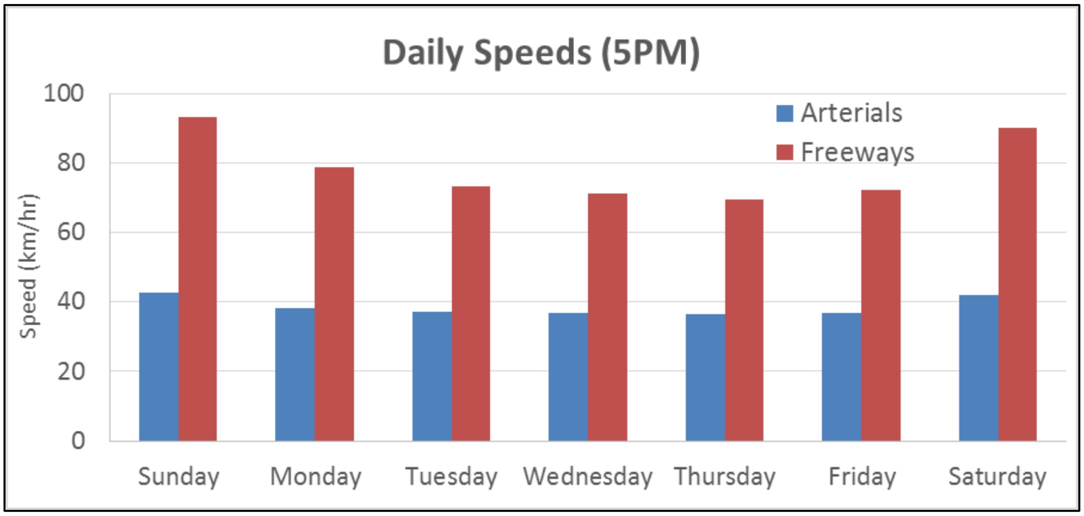

Figure 18. City-wide Variations in Peak-Hour Speeds for Days of the Week (2014)

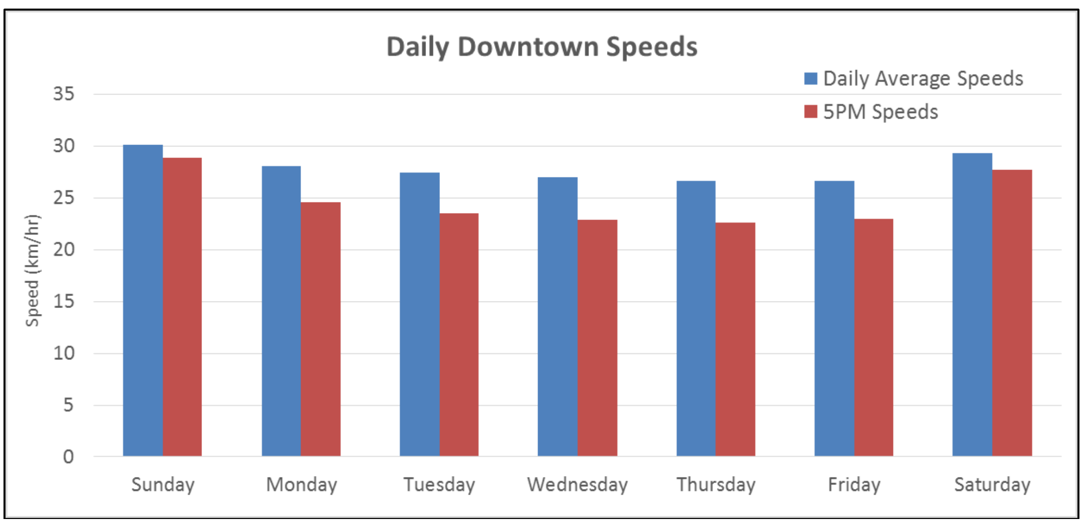

Figure 19. Downtown Core Variations in Peak-Hour Speeds for Days of the Week (2014)

4.5 Unreliability

While the previous analyses depict transportation system performance measures using single point estimates of "typical" congested conditions, analyses of travel unreliability explore generalized patterns in the variability of road performance at particular times of the day. However, as the experiences of road system users hinges on traversing multiple road links, the metrics of travel time unreliability are estimated for different trip distances for illustrative purposes: 5, 10, 15, and 20-kilometer trips.

4.5.1 City-wide

First, the range of travel experiences are shown for trips of each of the four lengths for a typical weekday in 2014 across the city. As shown in Figure 20, the uncongested travel time to travel each of the trip distances is shown in blue. For example, a 5-kilometer trip would take approximately five minutes under free-flow conditions - implying a simulated free-flow speed of approximately 60 kilometers per hour. Incrementally, under average congested conditions in the 5pm hour, the red in Figure 20 indicates the incremental travel time needed between free-flow and typical congested conditions. Beyond typical congestion, the green shaded area represents the incremental time between "typical congestion" and the 5th percentile slowest speeds, "severe congestion," meaning the incremental time beyond free-flow conditions one would need to schedule to arrive "on-time" 95% of the time for each typical trip length. When looking at variations in travel time unreliability by trip length, there are two important implications. First, as trips get longer, one must allow for more time in the absolute sense to ensure on-time arrival. Second, and less clear from the Figure 20, as trips become longer, both buffer time index and planning time index decrease (the ratio of the travel times under severe congestion to travel times under either typical congestion or uncongested conditions). In short, for shorter trips, congestion on any given link can increase travel times significantly in terms of percentage, while the absolute difference in travel time is much less.

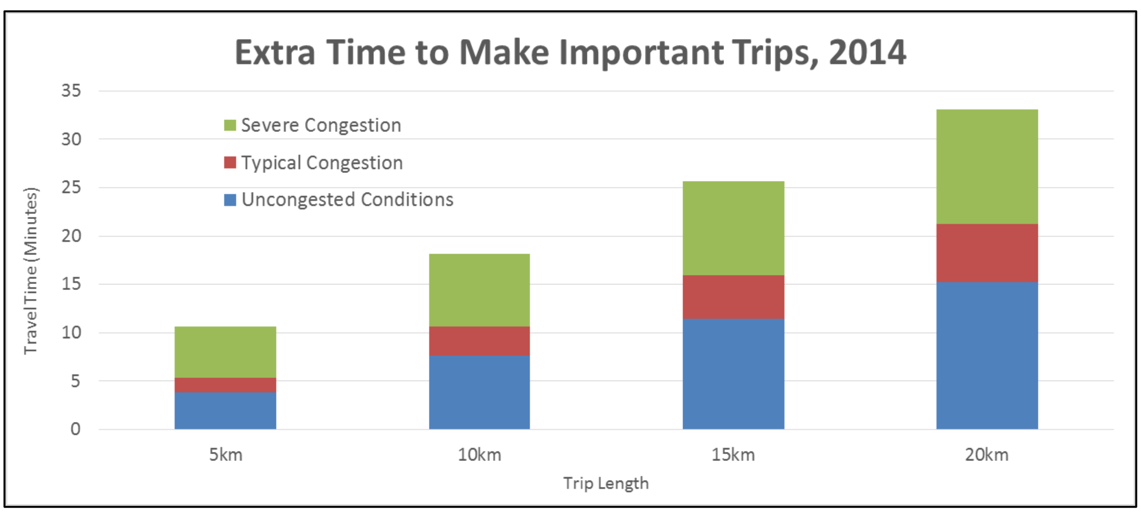

Figure 20. City-wide Evening Peak Hour Travel Unreliability for Typical Weekday Trip Distances (2014)

Weekday differences in travel time unreliability for the evening peak hour are further estimated for different weekdays. In order, the most to least reliable days are Monday, Tuesday, Friday, Wednesday, and Thursday. These results closely mirror findings on congestion's intensity.

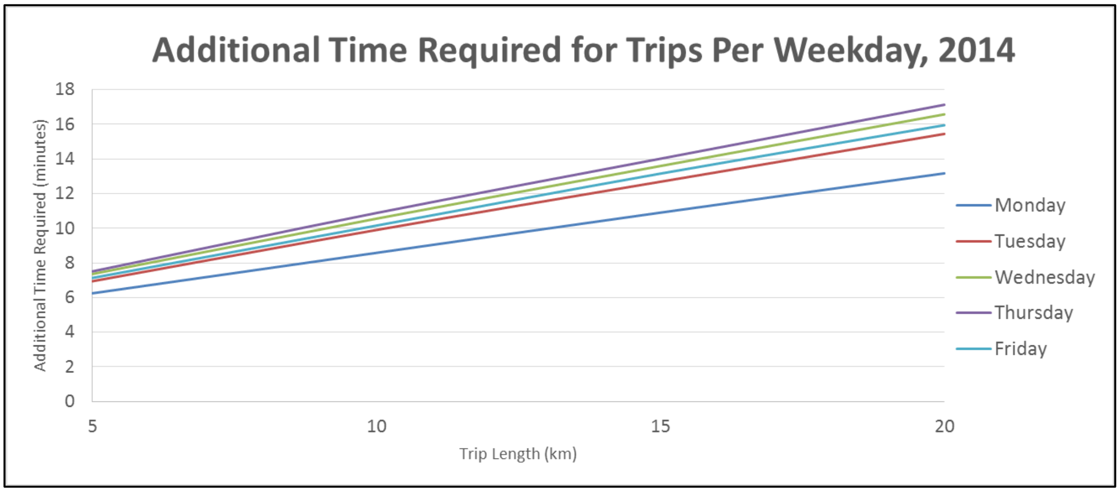

Figure 21. City-wide Evening Peak Hour Travel Unreliability for Different Days and Trip Distances (2014)

Finally, month-to-month variations in unreliability are estimated and illustrated in Figure 22. But while both estimates of unreliability and the intensity of congestion (previously discussed) indicate the highest congestion levels in the fall, metrics of unreliability (in contrast to congestion's intensity) show much more pronounced seasonal variations in transportation system performance. Travel conditions become less reliable between January and March before becoming more reliable in the summer and significantly less reliable in the fall, peaking in October. Thus, while the most intense congestion occurs in November, the least reliable peak period road travel conditions occur in October.

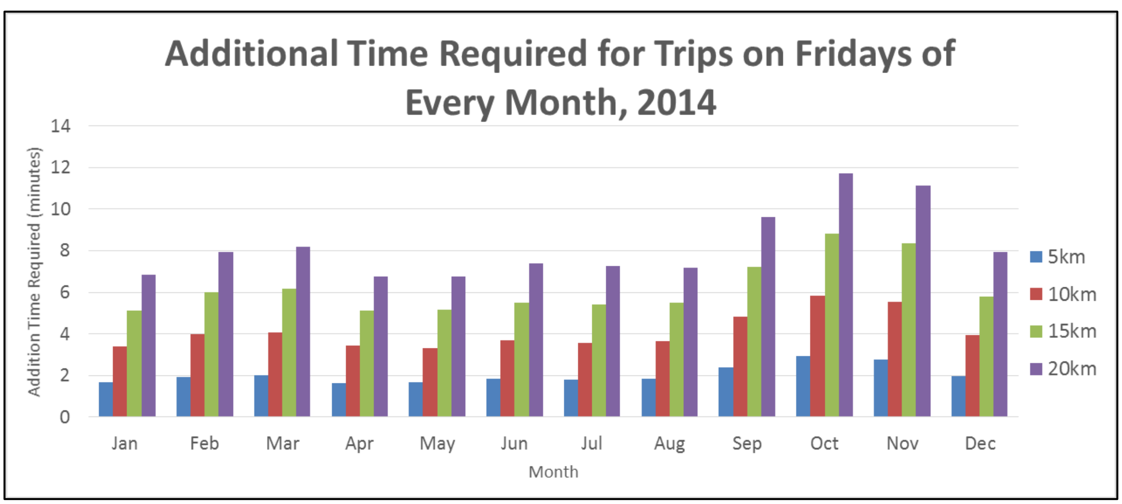

Figure 22. City-wide Monthly Variations in Travel Time Unreliability by Trip Length (2014)

4.5.2 Downtown

Unreliability metrics are also estimated for the Toronto downtown, indicating similar patterns as across the city with several minor differences. Unreliability is only estimated for a hypothetical five-kilometer trip due to the size of the study area. First, when comparing free-flow, congested, and severe (95th percentile slowest) travel conditions between 2011, 2013, and 2014, metrics of downtown unreliability indicate little change between 2011 and 2013 but an increase in unreliability in 2014 (see Figure 23).

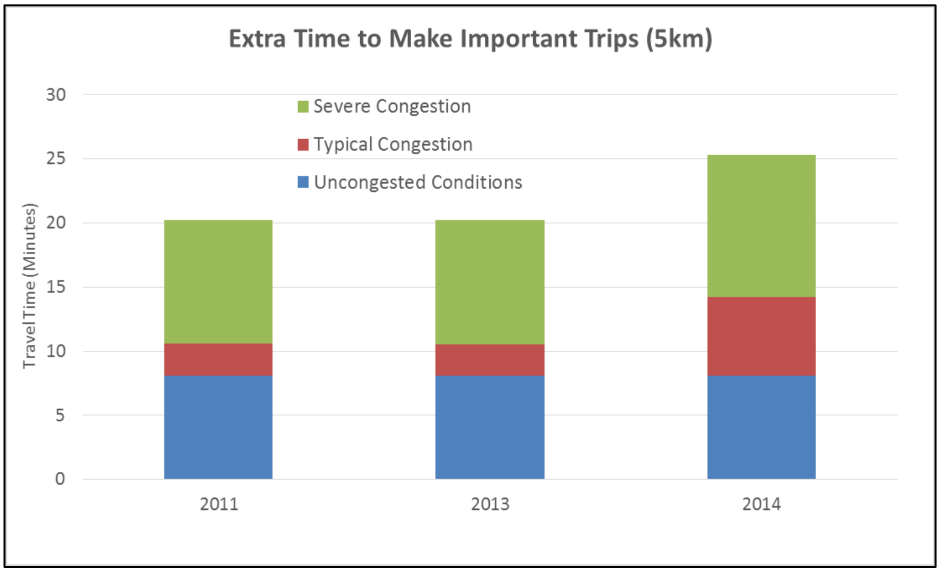

Figure 23. Downtown Toronto Travel Unreliability in 2011, 2013, and 2014

Daily variations in unreliability in downtown Toronto closely mirror those across the city. The rank order of least reliable (Thursday) to most reliable weekday (Monday) is the same in both the downtown (see Figure 24) and across the city (see Figure 21).

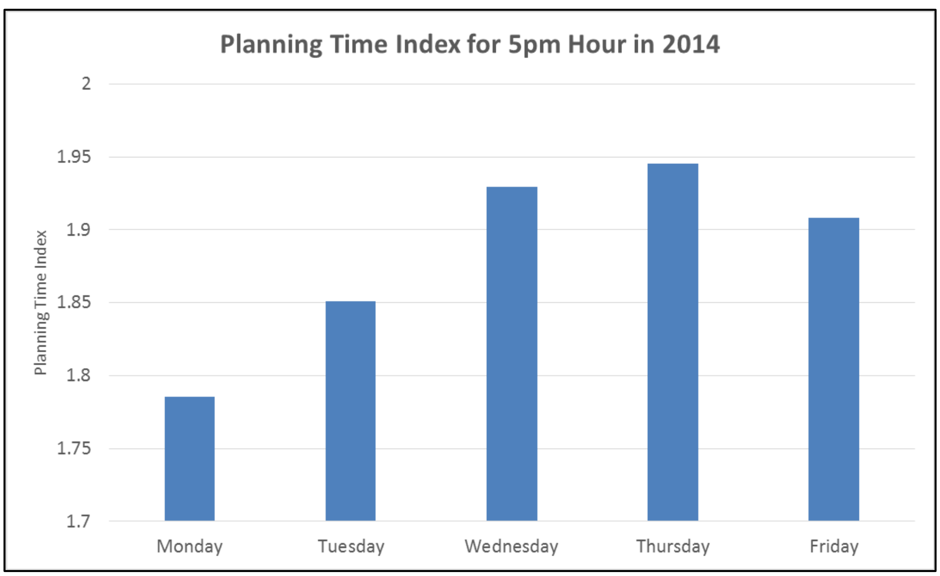

Figure 24. Downtown Toronto Weekday Variations in Travel Unreliability (2014)

Finally, when comparing seasonal variations in unreliability in downtown Toronto with those across the city, there appear to be seasonal differences (see Figure 25). While city-wide seasonal patterns in unreliability indicate that unreliability peaked in October and that summer travel is more reliable than both spring and fall (see Figure 22), patterns in downtown unreliability indicate that November was the least reliable month, while unreliability generally increased throughout the year - even in the summer.

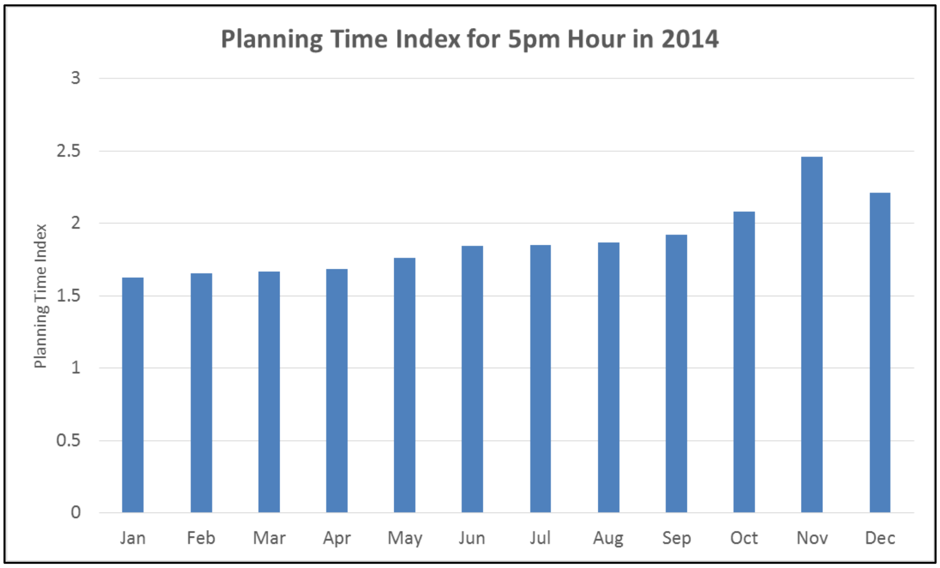

Figure 25. Downtown Toronto Seasonal Variations in Unreliability in 2014

4.6 Corridors

Finally, while all previous metrics of road transportation system performance reflect typical conditions for the city-wide arterial or freeway system or the downtown arterials, corridor performance metrics are also estimated to illustrate those corridors with the most intense congestion. Travel time index indicate the ratio of 85th percentile slowest travel times to the mean travel times experienced during the peak periods of analysis (the 8am and 5pm hours).

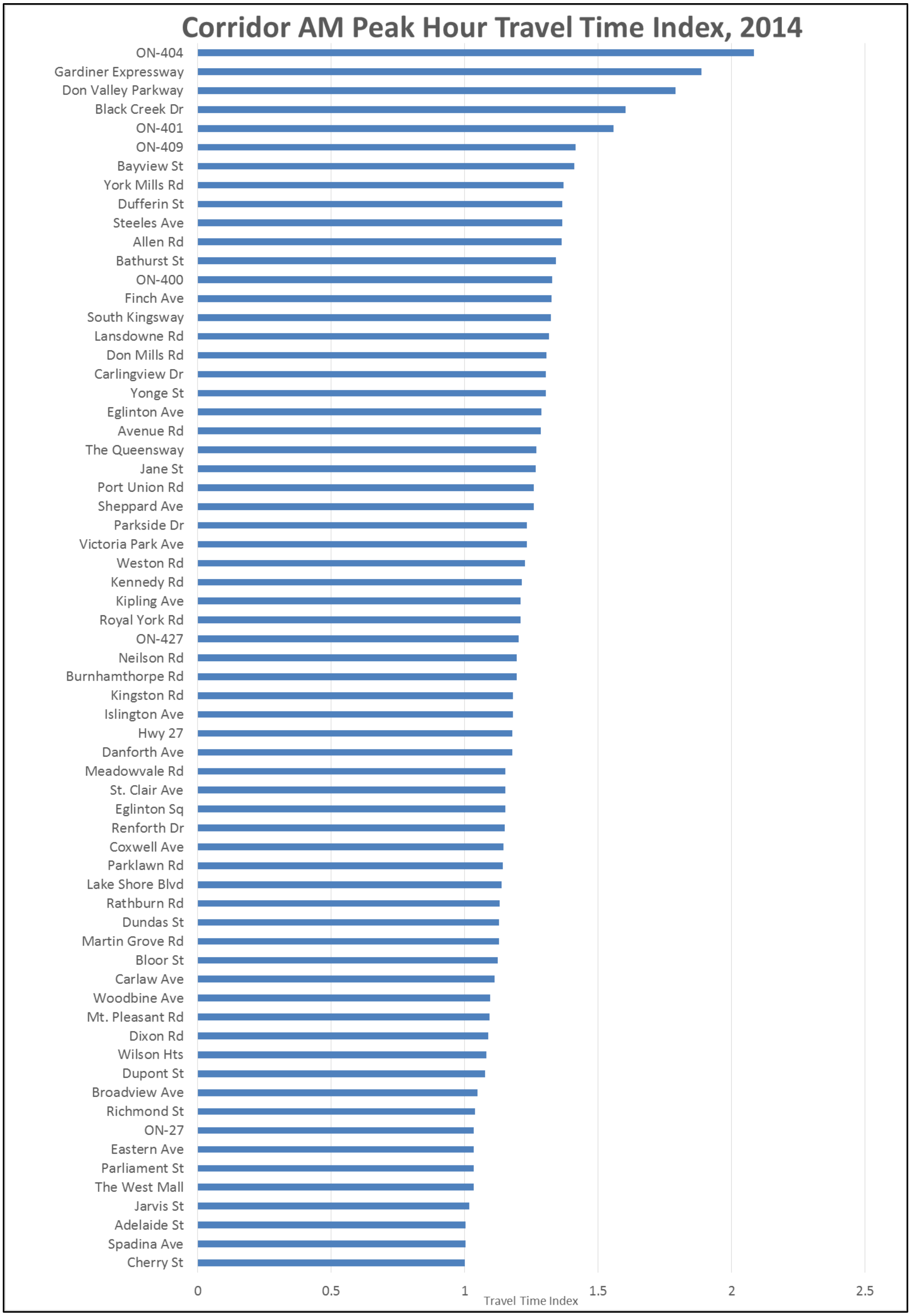

Figure 26. Corridor AM Peak Hour Travel Time Index (2014)

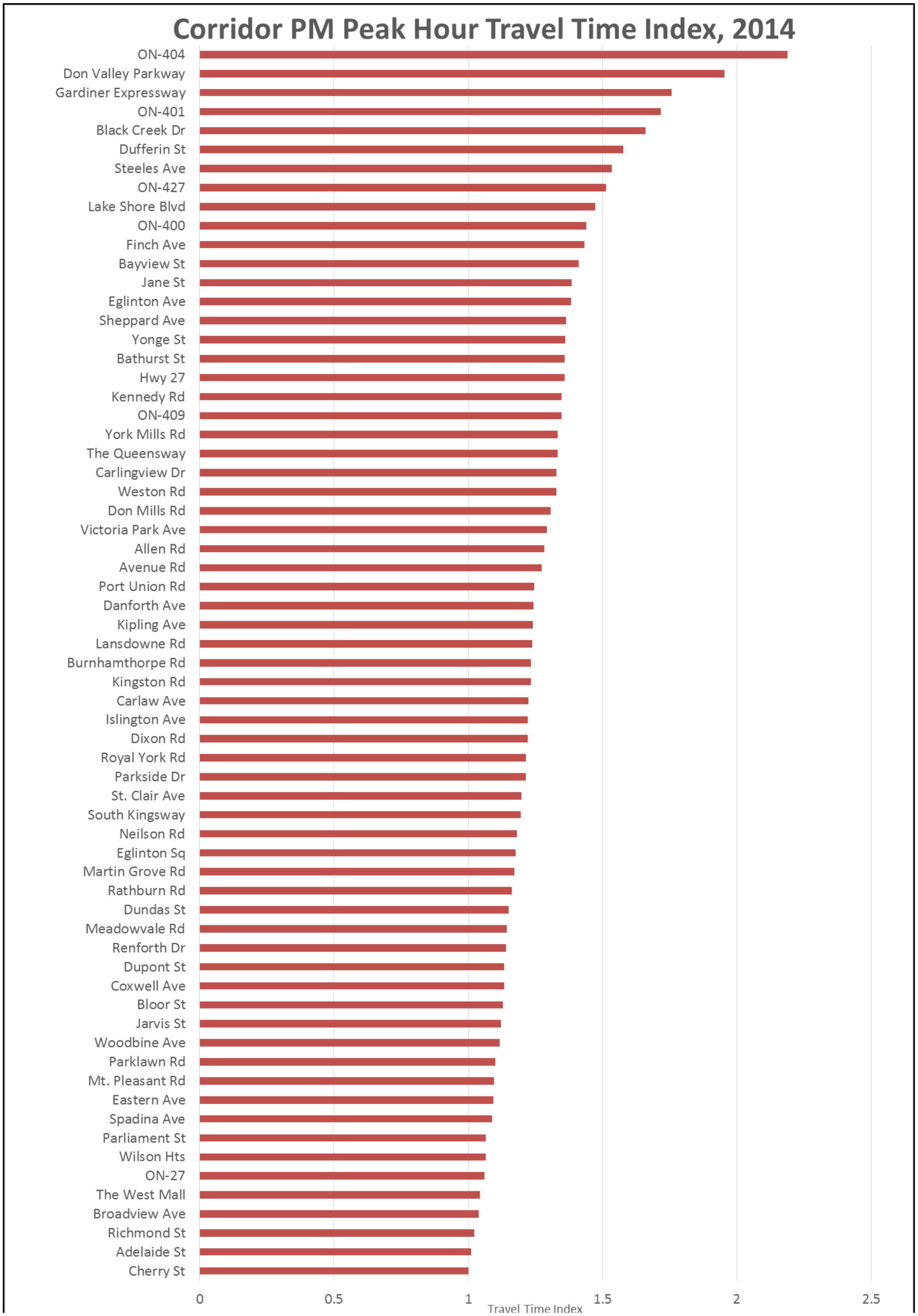

Figure 27. Corridor PM Peak Hour Travel Time Index (2014)

4.6.2 Asset-Specific Delay in 2014

The share of asset-specific road system travel delay is illustrated at representative times of day: average across the day, 8am, and 5pm in 2014. On average, as shown in Figure 28, the arterial system comprises 57% of all travel delay, while the 401 (21%), Gardiner Expressway (8%), and DVP (4%) are the three freeways with the single largest shares of total daily delay. But in comparison with the average across the day, the arterials comprise a lower proportion of delay during peak hours. For example, arterials comprise 49% of delay during the 8am morning peak hour (see
Figure 29) and 46% of delay during the 5pm evening peak hour (see
Figure 29). As illustrated above in Figure 11, arterial delay significantly outweighs freeway delay during off-peak periods, leading arterials to comprise a majority of all delay in the course of the day but less than half of all delay during peak hours.

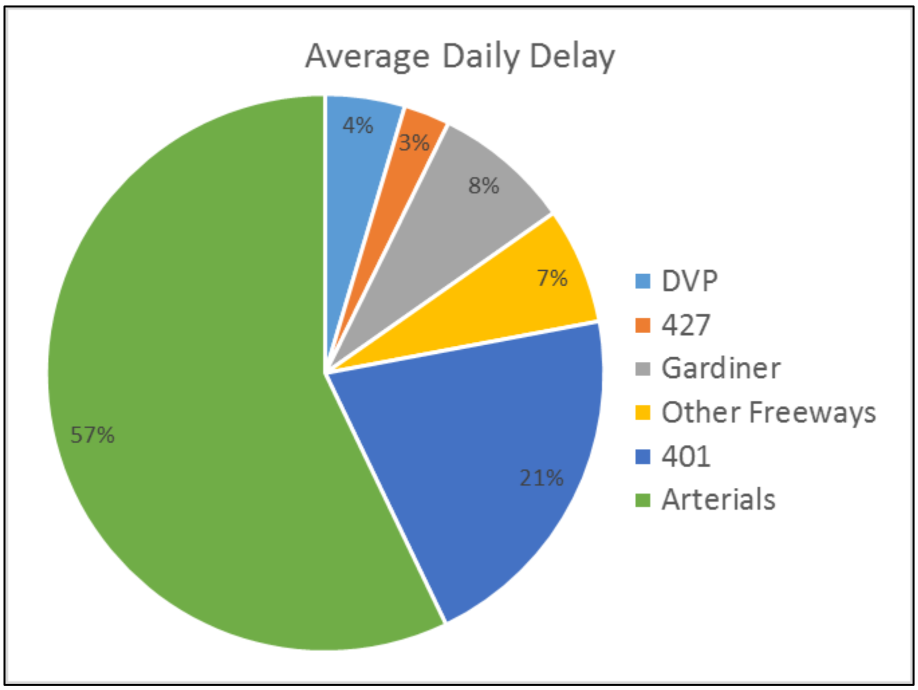

Figure 28. Average Weekday Asset-specific Share of Road System Delay (2014)

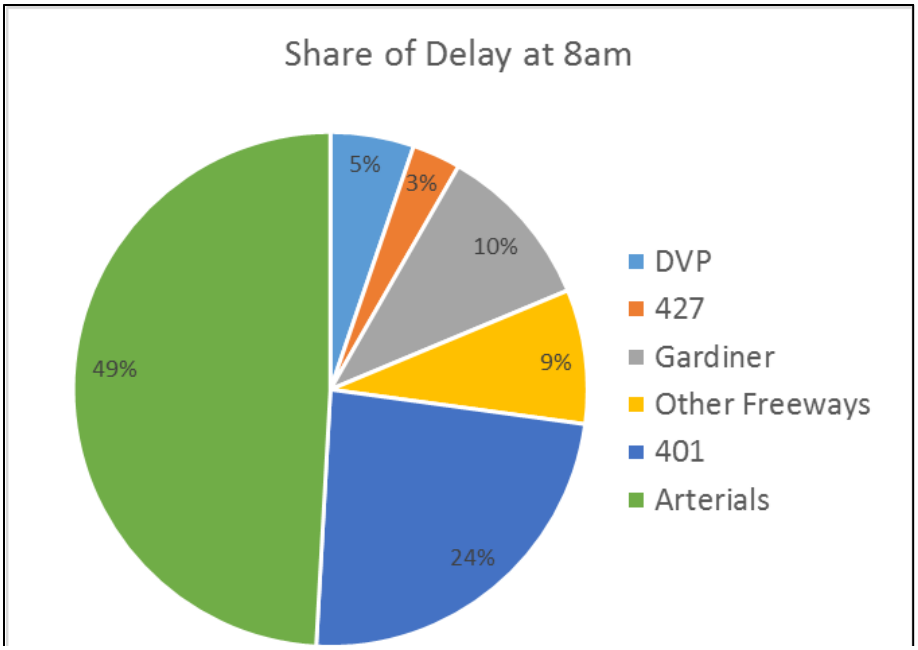

Figure 29. Asset-specific Share of Road System Delay at 8am (2014)

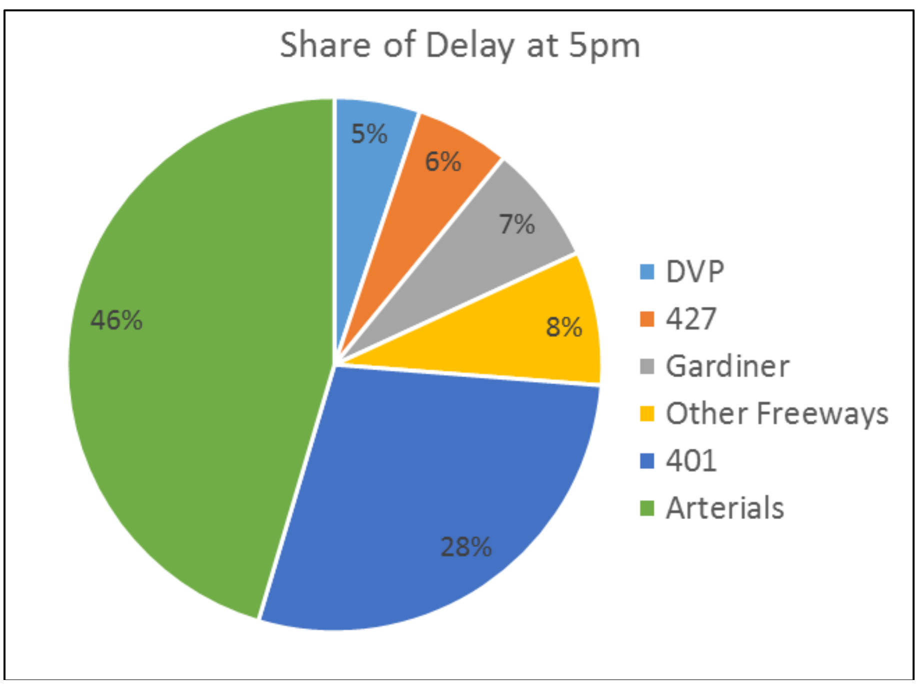

Figure 30. Asset-specific Share of Road System Delay at 5pm (2014)

5

Conclusions

This study illustrates how new sources of data can be employed to monitor road system performance over time in the City of Toronto. While multiple methods are employed, including descriptive statistics, multilevel modeling, and simulation, results can be reproduced for regular use in performance monitoring. Conclusions from this study address two issues: 1) the substantive topical findings of this study and 2) how such methods could be used in the future for program management.

5.1 Substantive Findings and Implications

Congestion grew significantly between 2011 and 2014, but remained stable between 2011 and 2013. Increases in congestion were not equal across the road system. Congestion on the arterial system grew much faster than freeways both in terms of typical intensity and transportation system unreliability. Road speeds on city-wide and downtown arterials decreased by 7kph during the peak period, while freeway speeds in the PM peak decreased by 3kph. Typical unreliability grew by 0.4 planning time index (PTI) units across the city (meaning that 95th percentile slowest speeds were 40% slower relative to free-flow speeds in 2014 compared to 2011), unreliability in the downtown core grew by 0.64 PTI units. Given the difference in base speeds, this increase in unreliability is large: approximately 14 additional minutes needed to arrive on-time 95% of the time in the downtown for a typical 10-minute trip, while only 4 additional minutes are needed between 2011 and 2014 for the city as a whole.

Although freeway congestion is consistent with a "peak-period" problem, city-wide arterials and downtown arterials are congested throughout much of the weekday. Results indicate significant peak spreading and gross decreases in vehicular speeds between 2011 and 2014. While the freeway system exhibits conventional morning and peak periods of vehicular delay, both the city-wide and downtown arterial systems have congestion throughout the day in which speeds generally decline as the day continues. These findings suggest very different policy measures for each of the system components. Managing peak periods of travel demand on the freeway system may yield high benefits (e.g. through road pricing). But the high arterial congestion throughout the day - particularly in the downtown - suggest that demand so dramatically outstrips capacity that retaining or improving travel speeds may be hampered by the potential for induced demand. The high levels of arterial congestion throughout the day and not just during peak periods suggests that managing congestion as a peak-period problem may be less fruitful than managing congestion as a mode-agnostic capacity problem which inhibits user volumes and the potential for more people to engage in their daily lives.

5.2 Implications for Program Management

Using probe data for transportation system performance monitoring holds much promise for better managing the use of scarce transportation system resources. However there are four critical challenges in how Big Data can be deployed to guide policy decisions. First, results must be intuitive, credible, and sufficiently interpretable to be easily understood by decision-makers with a range of expertise. While temporal and geographic granularity of a Big Data program should be able to assess, interpret, and inform rapid changes for certain applications, its core capabilities should not function at such a fine granularity across the board as to lead to "information overload." Second, if pairing multiple sources of data which are dynamically collected, this can enable explicit assessments of policy trade-offs to be made and judged by policymakers. In this study, traffic volumes and road capacities are largely static and variations in performance are primarily driven by speed data. Third, even to reasonably use static volume estimates and dynamic speed estimates, as in this study, the secondary data collection and management tasks rely on combining multiple sources of data which cover very different temporal and spatial extents. Inter-agency coordination to improve the comparison of different data sources should be encouraged. Finally, a path towards integrating Big Data into performance monitoring should be prepared to discover, explain, and leverage newly generalizable information on unique system attributes. Probe data, such as those purchased from Inrix, Inc., provide sufficient coverage to explore link-specific dynamics in speed, travel times, and unreliability which can be merged with link-specific policymaking characteristics from other data sources (e.g. on street parking policies and prices, changes in off-street parking supply/demand, lane configurations, bicycle facilities, sidewalk characteristics, or on-street transit services). Thus, unique user experience and volume-speed dynamics can be assessed not just by generalized functions, but based on context-specific characteristics.

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