Case Studies on Transport Policy 11 (2023) 100932

Contents lists available at ScienceDirect

Case Studies on Transport Policy

journal homepage: www.elsevier.com/locate/cstp

Regional transport accessibility and residential property values: The case study of the Greater Toronto and Hamilton area

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A R T I C L E I N F O

Keywords:
Regional transport accessibility
Residential property values
The Greater Toronto and Hamilton Area
Spatial panel

A B S T R A C T

There has been a growing interest in land value capture as a means of funding investments in transport infrastructure (TI), as reported in a vast literature analyzing the relationship between property values and accessibility provided by TI in general and transit specifically. There has, however, been limited research on the role of network-level regional transport accessibility and the intra-regional spatial heterogeneity of the price effects. Furthermore, studies usually focus on one transport mode, disregarding the multi-modal competition, and are mostly (pooled) cross-sectional analyses which do not reflect the dynamic nature of developments in TI and housing markets. To address these gaps, this paper empirically investigates the roles of local and regional transport accessibility by car and transit on the evolution of sales prices of single-family homes from 2001 to 2016, across different geographical contexts while controlling for various determinants in the Greater Toronto and Hamilton Area (GTHA). The spatial panel models' results confirm that regional transport accessibility does indeed play a significant role in property values over and above the local proximity to TI, with variations between transit and car and over the spectrum of low–high density areas, which needs to be accounted for in land value capture policies.

1. Introduction

There has always been a strong interest in the relationship between land and property values, most often represented by sales prices, and transport infrastructure (TI) in general and transit infrastructure and services specifically. This relationship lies at the core of expected transport – land use interactions, in which it is assumed the accessibility provided by the transport system will influence both land development patterns and the location choices of households and firms (Wegener and Fürst, 2004; Meyer and Miller, 2001).

A vast literature investigates the possibility and extent of the capitalization of improved accessibility provided by TI, especially transit, into land and property values in its vicinity (for reviews and meta-analyses, see for example Bartholomew and Ewing, 2011; Cervero, 2004; Debrezion et al., 2007; Mohammad et al., 2013; Ryan, 1999). The premise of this relationship is derived from the bid-rent theory (Alonso, 1964), which posits that properties near new or improved TI become more attractive due to travel cost savings. Thus, the demand for these locations rises, resulting in the bidding up of property values (O'Sullivan, 2003). The relationship between property value and TI is of critical importance to both transport and urban policy. Key policy questions of relevance to this relationship include: i) the potential to "capture" increases in property values resulting from TI investment (Levinson and Istrate, 2011); ii) the need to include property value impacts of TI investments, among other urban form impacts such as reductions in greenhouse gas emissions and congestion, in the calculation of the total benefits accruing from such investments (Ustaoglu and Williams, 2020); iii) the desire to reduce urban auto dependency and associated auto-related urban sprawl by inducing more "transit-oriented" and active transport-oriented urban forms (Cervero, 2004); iv) an increasing concern in many major urban areas about the affordability of housing for lower- and even middle-income households and the fear of transit-induced gentrification due to transit accessibility improvements (Grube-Cavers and Patterson, 2015); v) the concern about distorted land markets in rapidly growing urban regions where TI investment fails to keep pace with population and employment growth, and the resulting

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https://doi.org/10.1016/j.cstp.2022.100932
Received 24 December 2021; Received in revised form 5 July 2022; Accepted 29 November 2022
Available online 5 December 2022

spatial distribution of households and firms competing for increasingly scarce activity/travel accessibility (Lin and Yang, 2019).

Thus, understanding the role of property values within the two-way land use – transport interaction is critical to urban transport policy analysis and investment planning. Property value is also a strong "proxy" for a wide range of other attributes of policy interest, such as urban form, equity and sustainability, and travel demand. This paper focuses on the temporal and spatial evolution of property values, as captured in housing sale prices, in response to changes in transport accessibility.

Despite the importance of this issue and the size of the associated literature, there has been limited research on the role of network-level regional transport accessibility and the intra-regional spatial heterogeneity of the price effects (He, 2020). These are important because transport accessibility has a network impact that goes beyond the catchment areas of transit stations or highway buffers. Prices are also found to vary significantly based on the spatial context. Furthermore, studies usually focus on one transport mode, disregarding the influence of competition between different modes (e.g., car vs transit) on property values (Mohammad et al., 2013). Finally, many studies on the relationship between transport accessibility and property values use (pooled) cross-sectional data and do not reflect the dynamic nature of developments in TI and housing markets. This could lead to a biased estimation of the marginal impacts of changes in accessibility (Iacono and Levinson, 2017).

To address the above gaps, this paper empirically investigates the relationship between local and regional transport accessibility by car and transit, and the evolution of property values in the case of single-family home sales prices from 2001 to 2016. The analysis covers different geographical contexts in the Greater Toronto and Hamilton Area (GTHA) –the largest and fastest growing urban region of Canada which serves as its commercial and financial capital. Single-family homes is a major dwelling type in the region, making up the lion's share of the GTHA's housing in the first half of our analysis period (around 60–70 %) and a significant share of dwellings in the second half (around 40–45 %) (Table 2). Transit accessibility at the regional level is operationalized by gravity-based measures of accessibility derived from a multi-modal transit network including the commuter rail, metro rail, the bus and the streetcar networks. Transit accessibility at the local level is proxied by distances to commuter and metro rail stations. Here, streetcar/bus stops are excluded as their influence on sales prices is shown to be generally less than heavy rail systems (Debrezion et al., 2007). The sales prices of around 1.3 million single-family homes are aggregated at the level of around 6000 dissemination areas (DA, with an average size of approximately-one km^2), fused with built environment and socio-economic zonal attributes, plus transport accessibility measures to provide a unique longitudinal data base that is analyzed by spatial panel models. The results of this empirical analysis provide insight into the role of regional transport accessibility by auto and transit on property values and its spatial heterogeneity across various markets.

2. Operationalizing the relationship between transport accessibility and property values

Several studies have established that improved access to TI results in value gains for properties along road corridors or close to rail transit stations. Table 1 outlines select literature and their findings with a focus on works investigating the relationship between transit systems, especially commuter rail and metro rail, and residential land and property values (henceforth simply referred to as property values). As can be seen from the table there is no general consensus on the sign and magnitude of TI effects on property values. The observed premiums vary significantly, ranging from a 19 % decrease (Bowes and Ihlanfeldt, 2001) to a 75 % increase (Banister and Thurstain-Goodwin, 2011). This substantial variation is attributed to various factors including the type of TI and its

Table 1
Authors' compilation of international academic studies on transit systems, especially commuter rail and metro rail, and residential property values.

Author(s), Year	Location	Transit system type and name	Dependent variable	Result
Bajic (1983)	Toronto, Canada	Metro rail, Spadina subway extension	Private family house sales price	A proximity premium of $2,237 for an average house in the Spadina area
Gatzlaff & Smith (1993)	Miami, USA	Metro rail	Single-family home sales price	Sales prices not significantly influenced by the announcement of the new rail system or distance to station
Baum-snow & Kahn (2000)	Boston, Atlanta, Chicago, Portland & Washington D.C., USA	Various rail transit systems	House value	A decrease in distance to transit line from 3 to 1 km increases housing values by $4972
Haider & Miller (2000)	Toronto, Canada	Metro rail, TTC	Freehold sales price	Proximity to subway and highway do not improve the model performance but are significant. Average house price within 1.5 km of the subway is higher by $4,000
Bowes & Ihlanfeldt (2001)	Atlanta, USA	Metro rail, MARTA	Single-family home sales price	A proximity premium from −19 % to 3.5 % for properties within 1/4 mile from a station, and within 1 to 3 miles from the station, respectively
Debrezion, et al. (2011)	Amsterdam, Rotterdam & Enschede, The Netherlands	Commuter rail	House sales price	Transit distance elasticity for the most frequently chosen station: Amsterdam = -0.012; Rotterdam = insignificant; Enschede = -0.025
Banister & Thurstain-Goodwin (2011)	London, UK	Metro rail, Jubilee line extension (JLE)	House value	A proximity premium of up to 75 %, but overall, smaller effect than anticipated
Brandt & Maennig (2012)	Hamburg, Germany	Various rail transit systems	Condominium listing price	Relation between condo price and distance to station: insignificant within 250; maximum premium of 4.6 % for 250–750 *m*

(*continued on next page*)

Table 1 (*continued*)

Author(s), Year	Location	Transit system type and name	Dependent variable	Result
Shyr et al. (2013)	Hong Kong Taipei & Kaohsiung, Taiwan	Various rail transit systems	House (sales) price	Transit distance elasticity: Hong Kong = -0.016; Taipei = -0.044; Kaohsiung = -0.072
Dubé et al. (2013)	Montreal, Canada	Commuter rail, South Shore CRT	Single-family home sales price	A premium of 11 % and 2.6 % on mean house price for the houses located in the stations' vicinity and the entire South Shore, respectively
McIntosh et al. (2014)	Perth, Australia	Metro Rail	Residential land value	A substantial premium (up to 40 %) even in car dependent corridors and poorly integrated station locations
Bohman & Nilsson (2016)	Scania region, Sweden	Commuter rail	Single-family home sales price	Distance to a train station has a negative impact on price, but this effect is most important in the lower price segments of the housing market
Diao et al. (2017)	Singapore	MRT, Circle line (CCL)	Non-landed private house sales price	A proximity premium of 8.6 % for houses within 600 m of a station
Mohammad et al. (2017)	Dubai, UAE	Metro rail	Residential property sales price	A proximity premium of 1.2 % for properties within 1.5 km of a station; negative effect for properties<500 m from a station and a maximum premium of 13 % for 701–900 m
He (2020)	Hong Kong	MTR (Mass Transit Railway) network	Apartment sales price	Elasticity for MTR access improvement from 2001 to 2011 varies across different submarkets from 0.03 to 0.95

life cycle maturity, the method used, the definition of transport accessibility, the delineation of study area, and contextual determinants such as land use controls and economic growth (Knight and Trygg, 1977; Mohammad et al., 2013; Ryan, 1999).

The rest of this section focuses on the operationalization of the relationship between TI and property values while highlighting four key factors that can affect the assessment of this relationship: the definition of transport accessibility indicators and impact area, as well as the considered transport mode(s) and impact period.

2.1. Transport accessibility indicators

The operational definition of transport accessibility can significantly influence the estimated capitalization of improved accessibility into property values (He, 2020; Ryan, 1999). A host of indicators have been used to measure transport accessibility, for the most part focusing on simple continuous variables of distance or travel time to transit stops/ highway exits and dichotomous variables representing the presence of a transit station within certain distance bands (see e.g., McIntosh et al., 2014; Ryan, 1999 for a compilation of accessibility measures commonly used).

However, TI's impact on land use has network effects. This means that a change in a specific part of a transport network not only changes the accessibility of that link or node and the land use in its direct vicinity, but also has consequences for network-level accessibility and could induce land-use changes in other locations (Giuliano, 2004). A transit station or a highway exit is not a destination in itself. Thus, not only is the proximity to a particular station or exit important, but also its location within the regional transport networks that provide access to jobs and amenities –and the corresponding time and monetary costs– play a critical role. Ryan (1999) contends that distance measures of transport accessibility may not accurately reflect the travel cost reduction and its beneficiaries. Her review of around 30 transport-property value studies concludes that those using travel time measures are more consistent in demonstrating the bid-rent theoretical relationship. This finding is corroborated by other studies arguing that more complex network-level accessibility measures better capture the impact of transport infrastructure on land use changes in general (Kasraian et al., 2020) and property values specifically (Ahlfeldt, 2013; He, 2020; Mitra and Saphores, 2016). In short, simple measures of proximity to transport facilities, which are often used in the literature, do not reflect travel cost savings and network-level accessibility changes, and cannot capture adequately the evolution of TI network over time.

2.2. Impact area

The operationalization of transport accessibility goes hand in hand with the delineation of the impact area. Most studies investigate the impact of TI confined to the level of a single city and within different buffers of TI's catchment areas, while few studies have examined the regional or system-wide impact of transport accessibility on property values (Bohman and Nilsson, 2016; Debrezion et al., 2011). However, the impact of TI, because of its network effects, goes farther than its direct vicinity. In a notable regional investigation, He (2020) confirms that the capitalization effect of rail lines exceeds the local catchment areas and calls for a re-evaluation of land value capture policies. Thus, a regional perspective is needed to understand the full extent of TI's impact (Saxe and Kasraian, 2020).

2.3. Transport mode

Depending on the time period and study context, most studies have focused on the impact of a single transport mode. Examples include the first (1950s and 1960s) and second (1970s and 1980s) generation US highway studies, and the first (1970s and 1980s) and second generation (1990 onwards) US transit studies focusing on heavy and light rail, respectively (Ryan, 1999). More recently, due to an increasing interest in (re)investments in sustainable transport modes and their growing market, a series of studies have emerged focusing on the land value uplift caused by pedestrian and transit-oriented developments (TOD) around the world (Bartholomew and Ewing, 2011).

Studies focusing on one transport mode overlook the competition between different modes on property values. To identify the impact of a specific transport mode like transit, competing modes should also be included (Debrezion et al., 2011). The presence of an alternative competitive transport mode, such as car versus transit, is argued to be contributing to the diversity of findings. For instance, the reason behind transit's non-existent or negative impact on property values in certain areas could be the failure of transit to provide a viable alternative to the residents and users of these areas compared to other modes, such as cars (Mohammad et al., 2013).

2.4. Impact period

The longitudinal relationship between transport accessibility and property values has not received as much attention as the cross-sectional relationship. A large number of studies use (pooled) cross-sectional data and demonstrate lower property value changes compared to studies with panel or time series data (Mohammad et al., 2013). However, in locations that are already developed and enjoy high levels of accessibility, cross-sectional findings tend to over-predict the impact of transport projects or improvements (Iacono and Levinson, 2017).

Panel data can capture changes over time, which is needed for assessing the impacts of a dynamic TI system. It is argued that variations found in the results of previous studies can be due to the time period during which the TI's impact is measured in relation to its life cycle maturity (Mohammad et al., 2013; Ryan, 1999). There are different justifications for the varying impacts of TI on property values depending on the study period. Giuliano (1989) argues that the marginal increases in accessibility due to the American interstate highway construction were initially strong enough to cause changes in land use patterns and property values but reduced over time. Landis et al. (1995) suggest that the variations in property values follow the degree to which land markets have adjusted to the travel cost savings caused by new or improved TI. Thus, property value growth follows a logistic curve, where prices in the vicinity of new TI are initially low, then appreciate and eventually become inelastic to further TI investments. On the other hand, it is also shown that property values can rise at the time of announcement of new TI and in anticipation of its arrival (Golub et al., 2012; Knaap et al., 2001; McDonald and Osuji, 1995), and that the initial perceived gains at the announcement time are usually higher than the actual benefit achieved after the stabilization of the rail system (Bae et al., 2003). The development of property values over time also depends on how the competition between different transport modes unfolds. For instance, a new rail station may initially fail to provide a car-dependent neighborhood with significant accessibility gains. Over time, however, and with the increase of disincentives for car use (e.g., congestion and/or penalizing policies), it may become a viable car competitor, attract passengers and hence influence property values. All in all, it can be concluded that the true impact of TI investments on property values can only be studied longitudinally. Furthermore, panel data estimators are also likely to produce more accurate estimates, as they control for unobserved heterogeneity, which are often assumed to be time-invariant (Hsiao, 2003). Finally, longitudinal land use-transit models can help predict land value increments over a period for the purpose of value capture financing (Smith & Gihring, 2006).

2.5. Current study in context

In conclusion, the role of network-level transport accessibility and intra-regional spatial heterogeneity on property values have been underresearched in the existing literature. Furthermore, recent literature focuses for the most part on the land/property value uplift of transit improvements. However, comparing transit with car over time will reveal the extent of competition between the two modes and its development as both networks expand over the years. Finally, more longitudinal research is needed to capture the impact of TI network expansions on property values over time.

Considering the gaps in the existing literature, our paper's contribution is threefold. First, it takes the network-level regional accessibility into account. Second, it investigates the relationship between transport accessibility and property values while controlling for both car and transit accessibility rather than focusing on one mode. Third, it measures this relationship over time and across space, while testing various potential determinants.

3. Data

3.1. The GTHA

The GTHA houses a population of around seven million (2016 Census) and consists of the Cities of Toronto and Hamilton and regional municipalities of Durham, Halton, Peel and York (Fig. 1). The GTHA has for some time been consistently the most rapidly growing urban region in North America. As a result of this growth, like other successful global urban regions, the GTHA has experienced rapid and sustained increases in housing prices (Fig. 2), creating challenges with respect to housing affordability, especially for younger and lower-income households. At the same time, transport (particularly transit) infrastructure investment has not kept pace with the region's population and economic growth, resulting in increasing congestion on both its road and transit networks. Thus, the region is becoming increasingly costly to live in and difficult to move around, threatening its potential for continued growth and prosperity in the long run.

The GTHA is served by a multimodal transport system, consisting of an extensive road network and transit systems ranging from buses, streetcars, bus rapid transit, light rail and subway to commuter rail. While Toronto's subway system caters to intra-city transit demand through its two main north–south and east–west lines, the Government of Ontario (GO) Transit's commuter rail provides inter-regional connectivity to the downtown core of Toronto from the outer suburbs as well as from the City of Hamilton. Property values in the GTHA have been increasingly rising in recent years in line with the growth in population and demand for housing (Table 2).

3.2. The dependent variable

This study models median sales prices of single-family homes at the DA level as the dependent variable. Out of 9182 DAs in the GTHA as per the 2016 Census, 6319 DAs have been included in the final database, as DAs without transaction records in one or more time points were excluded, resulting in a total of 101,104 observations over the 16-year time period. The sales prices at the DA level are based on a sample of 694,111 single-family home plots, responsible for approximately 1.3 million sales transactions, between the years 2001 to 2016, which is considered a large sample compared to similar studies (see Bartholomew and Ewing (2011) for a number of comparable studies and their number of observations). The data on sales transaction values were extracted from Teranet's property sales dataset. The property sales records, maintained and updated annually by Teranet Inc., include information on Property Information Number (PIN), date of sale, sales price, address and geographic coordinates of the parcel centroid, since the early 1800 s to 2017 for the Province of Ontario. However, the records lack structural characteristics of the building and land plot as such data were not available free of charge. Dwelling typology was identified by joining the geo-coded parcels with detailed land use datasets for the Greater Toronto Area (sourced from an academic field survey completed between 2011 and 2013 by the Department of Geography and Planning students at the University of Toronto) and the City of Hamilton's open data portal. The data cleaning and joining process is explained in detail in Appendix B. Both average and median sales prices at the DA level were considered for the dependent variable in the model. Ultimately, the median sale price was chosen to be the dependent variable as it produced better model performances and has the advantage of being insensitive to outliers. All sales prices are inflated to 2018 Canadian Dollars (CAD).

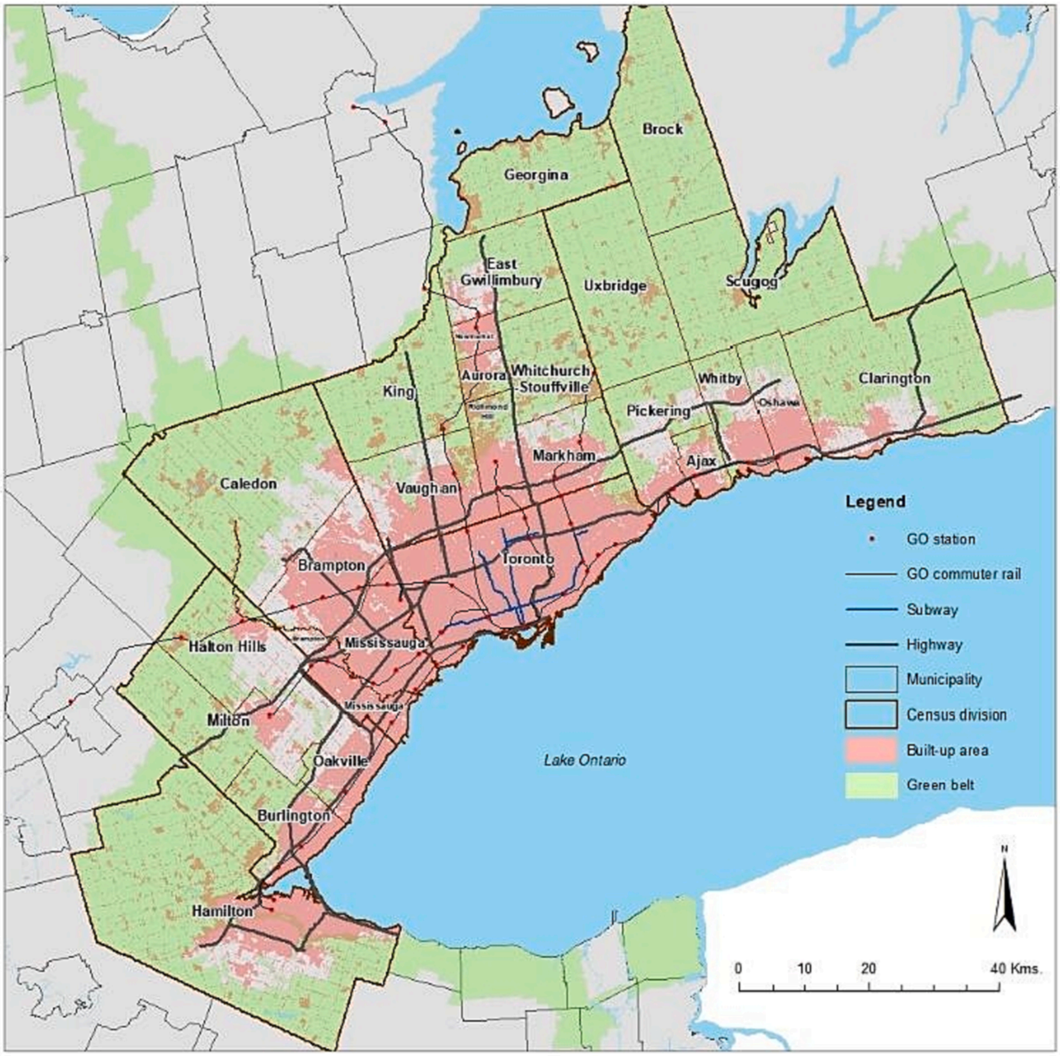

Fig. 1. The GTHA and its transport infrastructure networks in 2016.

Fig. 2 shows the annual trends of single-family home sales transaction count in the final dataset and average sales price of single-family homes in the GTHA, where the effects of the 2008 financial crises are clearly seen. Interestingly, despite the significant growth in GTHA population and housing stock, the number of transactions of single-family home sales has remained relatively stable and even declined over the study period. This is due to the decreasing share of single-family homes in the region over the years (Table 2) as other types of dwelling, i.e., attached houses and especially condominium – apartments, have become more preferred and affordable for (especially first time) buyers. The geographic distribution of DA-level median sales prices for single-family homes for year 2016 are shown in Fig. 4.e.

3.3. *The tested and chosen independent variables*

This section outlines the different independent variables that were tested and highlights the final set of chosen variables used in the models under the three sub-categories of built environment, socio-economic, and transport accessibility indicators. The procedure for the selection of the final set of variables is explained in Section 4.2. *The choice of variables*. Sales prices are modelled as a function of built environment, socio-economic, and transport accessibility characteristics of the DA which houses the property. Thus, a DA-level longitudinal geo-coded data on the three categories was collected (see Appendix A for the variable definitions and their sources). Data available at different spatial units (e.g., varying census boundaries of different time points, data at the traffic analysis zone (TAZ) level) were made consistent over time using the 2016 DA boundaries as the spatial analysis unit, through an areal-weighted interpolation in ArcGIS. Data sourced from Statistics Canada Censuses and TTS (household travel survey of the GTHA, managed by the Data Management Group (DMG) at the University of Toronto Transportation Research Institute) exist at every-five-year interval – 2001, 2006, 2011 and 2016. Census year data were applied to non-Census years at five-year mid-blocks to generate a continuous database for the 2001–2016 time period (e.g., Census data for 2006 has been applied to years 2004–2008, inclusive).

- Built environment indicators: In the absence of structural property variables (property characteristics such as number of bed/bathrooms, garages and property condition were not available free of charge), we have used neighborhood (DA) averages for dwelling related variables provided by Census. These include DA averages for dwelling typology, condition and age, as well other variables like population density. DAs' distance to the central business district (CBD), access to various public amenities, and the share of different land uses were calculated in ArcGIS based on the Enhanced Points of Interest (EPOI) shapefiles (DMTI Spatial, 2013) and land use data (DMTI Spatial, 2014).

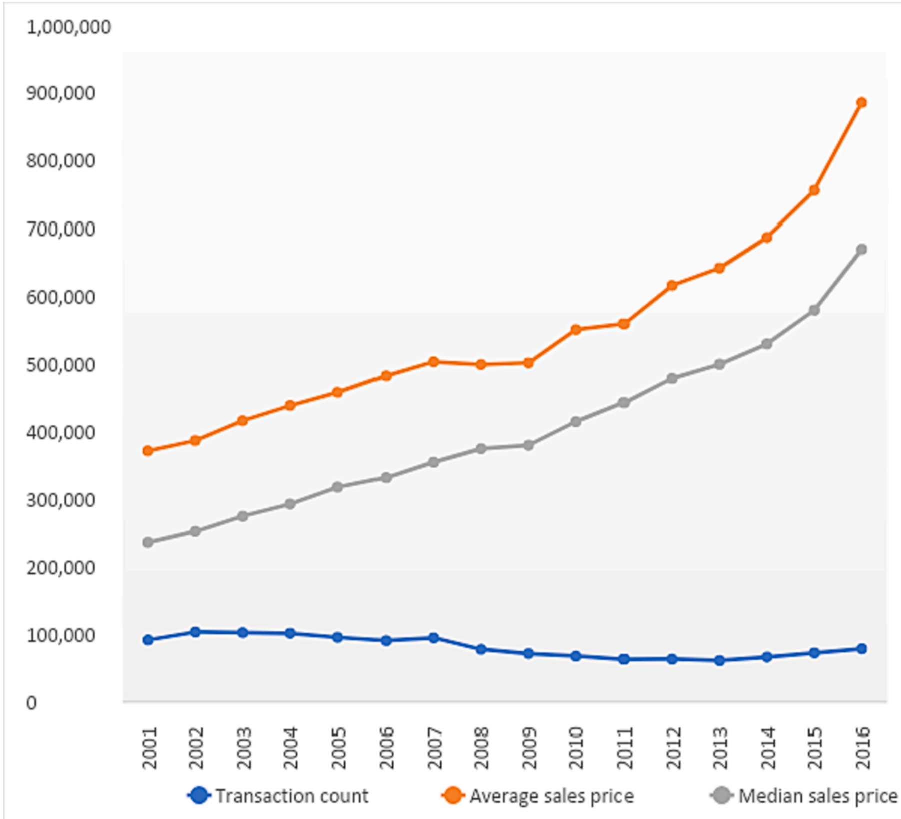

Fig. 2. Trends of average and median annual sales prices ($) and transaction counts for single-family homes in the GTHA (2018 CAD).

Dwelling density was used to capture the variation in the level of urbanity across the study area rather than administrative units. Here, terciles of dwelling density (including all dwelling types in a DA) were used as proxies for high-, medium- and low-density areas, which roughly correspond with arears with urban, suburban and rural characteristics respectively. The result is groups of areas that are not necessarily contiguous but have the same density (Fig. 3).

The final chosen built environment variables were the DAs' *population density*, *percentage of single-family homes* and *percentage of dwellings with structure age over 45 years*.

- Socio-economic indicators: These include age cohorts, marital and immigration status, ethnicity, household characteristics, income, education, employment, place of work and commuting mode, share of rented and owned dwellings, and shelter costs sourced from the Census and school rankings from the Fraser Institute (Cowley & Macleod, 2019). Other socio-economic variables such as job density, household-level full-time workers and auto ownership data were derived from the TTS. Macroscopic supply and demand fundamentals were factored in as explanatory variables for house price appreciation by including municipal population growth rate, the municipal unemployment rate, annual Bank of Canada prime lending rate and regional-level percent change in annual single-family dwelling starts (an economic indicator that reflects the number of privately owned new houses) and annual violent crime severity index.

The final socio-economic variables included in the models were DAs' *average household size* and *unemployment rate*.

- Transport accessibility indicators: Local accessibility is measured by straight-line and network distance to the nearest GO/subway station from a DA's centroid, the number of rail transit stations in one-km buffer of a DA centroid and binary variables indicating the distance to the nearest rail transit station as being within 0 m – 800 m, 800 m – 1600 m, 1600 m – 3200 m, or greater than 3200 m.

Regional accessibility indicators include average potential travel times between zones by auto/transit (Fig. 4.a&c), and regional potential accessibility by auto/transit (Fig. 4.b&d). The travel times were calculated using auto and transit origin–destination (O-D) travel times from TTS. Year-specific road and transit network models were used for calculating network travel times and distances to capture the effects of road congestion and changes in road and transit supply as a behaviorally relevant proxy for accessibility between zones (Hess et al. 2007). Road and rail transit networks, incorporating rail station opening dates were extracted from Equilibre Multimodal/ Multimodal Equilibrium (EMME) networks developed by the University of Toronto Transportation Research Institute's Travel Modelling Group (TMG) for each time point. Travel demand for years 2001, 2006, 2011 and 2016 was used to calculate congested network travel times under peak AM traffic conditions from each TAZ to every other TAZ on EMME using the deterministic user equilibrium (DUE) assignment method. The modeled transit network also includes the bus and streetcar networks and their corresponding routes and schedules for the analyzed time points. Thus, their presence for the first mile access to transit is taken into account. Bicycle access to transit was negligible in GTHA during the study period (Xi et al., 2016). Park & ride is an important access mode for GO Rail. This is captured to first order by the "Distance to nearest GO transit station" variable. EMME transit assignment procedure calculates transit paths between O-D zones, based on multi-modal transit network and service schedules, including link frequencies and travel times.

The calculated auto and transit times were used to generate gravity-based measures of accessibility to population and jobs as proxies for available opportunities. These network-level variables indicate regional potential accessibility by auto and transit (henceforth referred to as

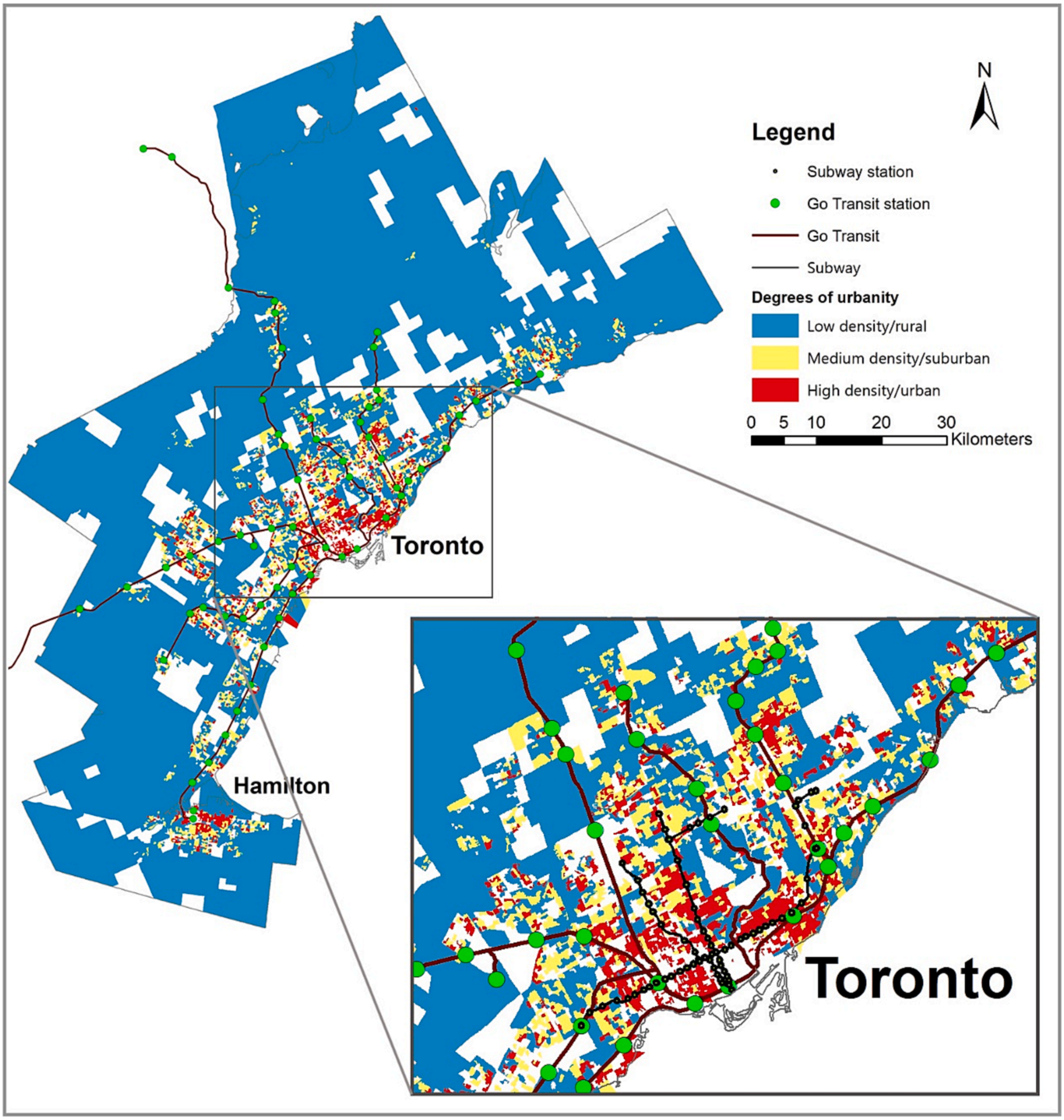

Fig. 3. Degrees of urbanity proxied by dwelling density. The white areas are the DAs without transaction records in one or more time points which were excluded from the analysis.

regional auto/transit accessibility). They combine a positive function of destination size (amount of population/jobs) with an inverse function of travel cost (travel time) to all destinations (see Appendix C for more detail on the construction of these variables).

During the initial exploratory analysis of the dataset, auto and transit accessibility were found to be highly correlated. However, in order to investigate the competition between the two modes, both accessibility variables should ideally be included in the models. This problem of multicollinearity was addressed by creating variables which measure the change in local and regional auto and transit accessibility from our baseline year (2001).

The finally chosen local accessibility indicators were *change in distance to nearest highway exit* and *change in distance to nearest GO transit station* (changes in travel times to exits and transit stations behaved similarly). *Change in regional transit accessibility* and the *change in regional auto accessibility* made it to the final model as well (gravity based variables of access to jobs were also tested and had a similar performance). The descriptive statistics of the key variables are shown in Table 3.

4. Methods

The standard economic tool for estimating sales price determinants is hedonic price (HP) modelling, formalized by Rosen (1974). This is a revealed preference method which derives the implicit price of various attributes for composite goods like a house. By separating the attributes of a housing unit into homogenous attributes, the implicit price of each attribute can then be used to estimate its market value. In general, the hedonic price model can be expressed as:

$P = f(\mathrm{S, N, E})$ where P is sales price, S are the structural characteristics of the house itself (e.g., floor area, number of rooms, etc.), N are the attributes of its neighbourhood (e.g., socio-economic characteristics) and E are the environmental characteristics (e.g., proximity to amenities). Typically, the implicit price of each characteristic is estimated using multiple regression analysis, with various functional forms. The

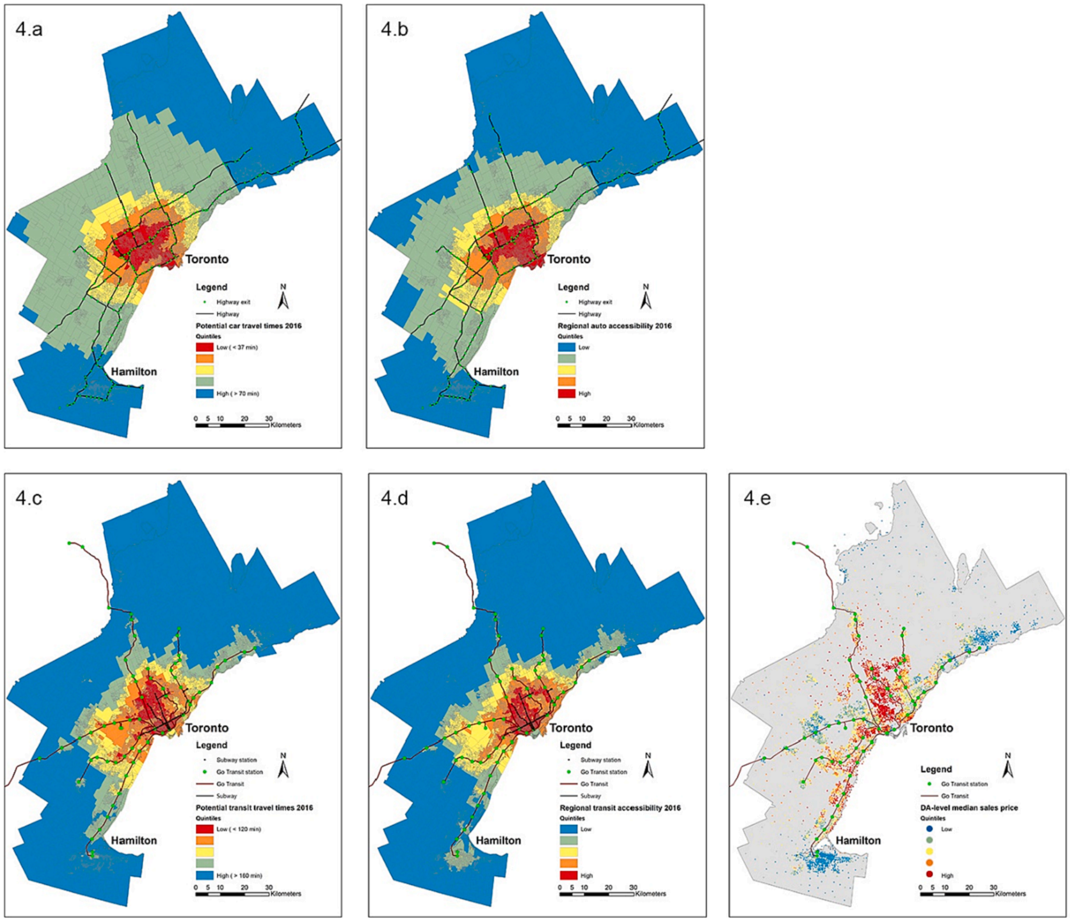

Fig. 4. Average potential auto travel times (4.a); regional auto accessibility (4.b); average potential transit travel times (4.c); regional transit accessibility (4.d); DA-level median sales prices of single-family homes (4.e); all indicators are in quintiles and for year 2016.

most common specification used in the literature are the semi-log and log–log forms, which have the advantage of correcting for heteroscedasticity and capturing non-linear relationships (Andersson et al., 2010; Helbich et al., 2014).

4.1. The choice of model

Sales prices have been shown to cluster geographically and capitalization of accessibility is shown to vary across different submarkets. Since the price of a dwelling is partly determined by its surrounding features, housing sales prices inherently exhibit spatial effects (Dubin, 1992; Pace et al., 1998). More specifically, the issues of spatial heterogeneity, which refers to the variation of regression coefficients across space, and spatial autocorrelation, which suggests there is interdependence between observations that are geographically close to one another, must be addressed when modelling housing sales prices. Thus, there is a need for a temporally and spatially sensitive model that can account for i) the panel structure of the data, ii) spatial autocorrelation, and iii) spatial heterogeneity across different submarkets. The above requirements were addressed by applying:

- Panel models that control for the data's longitudinal nature.
- Spatial models to account for the spatial autocorrelation (further explained below).
- Separate models for different submarkets (low, medium and high density areas) to control for spatial heterogeneity.

Several specifications have been proposed to account for the spatial effects in hedonic price models, all of which can be easily extended to panel datasets as parameters are assumed to be fixed across time periods. Appendix D provides a brief overview of the most common spatial panel models which were tested here; for a more in-depth explanation of spatial models, refer to LeSage and Pace (2009) and Elhorst (2010).

The DAs were separated into low, medium and high density areas (as described in Section 3.3. *The tested and chosen independent variables*) and three corresponding spatial weight matrices were generated to create the spatially lagged variables used in our models. A first-order binary contiguity-based weight was used to represent the neighboring structure of observations as an $N \times N$ matrix, where the spatial weight w_{ij} is 1 if DA i and j share a common edge or vertex (i.e., queen contiguity), and zero otherwise. The resulting matrix is symmetric, and the diagonals of the matrix are set to zero to exclude the influence of a DA on itself. It is common practice to normalize spatial weights to remove the effects of scale factors, thus the matrix was row normalized such that the weights in each row have a sum of one. Doing so allows the weights to be interpreted as the fraction of all spatial effects on i attributed to j. An inverse-distance matrix was also tested, but the resulting model did not perform according to theory, thus suggesting that it is not the correct specification given our dataset and model structure.

A variety of spatial model specifications were tested, including the spatial autoregressive model (SAR), spatial error model (SEM), the spatial lag of X model (SLX) and the spatial Durbin model (SDM) (see Appendix D for definitions of these models). All of the spatial panel models were estimated using Stata 13 and the xsmle package, which uses a quasi-maximum likelihood method to fit the model (Belotti et al., 2017). The SDM was ultimately excluded from our study as the model did not converge. Time-invariant specific effects (denoted by α in Equations D.1, D.2, D.4, and D.5 in Appendix D) are included in panel

Table 2
Growth in population, housing stock, share of single-family homes and median sales price, per regional municipality and the GTHA.

	2001	2006	2011	2016
Halton				
Population[1]	375	439	502	548
Total housing stock[1,2]	133	157	179	193
% Single-family homes	79	83	60	58
Median annual sales price of single-family homes[3]	387,415	507,598	605,205	896,627
Hamilton				
Population	490	503	520	537
Total housing stock	188	193	204	212
% Single-family homes	65	68	58	57
Median annual sales price of single-family homes	232,546	282,102	306,237	452,262
Durham				
Population	506	561	608	646
Total housing stock	171	194	213	228
% Single-family homes	80	82	67	67
Median annual sales price of single-family homes	266,597	326,807	357,334	550,585
York				
Population	729	892	1,032	1,110
Total housing stock	223	275	323	357
% Single-family homes	86	88	67	64
Median annual sales price of single-family homes	408,312	535,133	657,262	1,108,546
Toronto				
Population	2,479	2,492	2,615	2,732
Total housing stock	937	969	1,046	1,113
% Single-family homes	51	55	26	24
Median annual sales price of single-family homes	427,627	558,844	669,849	1,052,359
Peel				
Population	988	1,158	1,297	1,382
Total housing stock	308	356	403	430
% Single-family homes	74	78	46	46
Median annual sales price of single-family homes	407,791	466,593	547,954	771,026
Total				
Population	5,566	6,045	6,574	6,954
Total housing stock	1,961	2,143	2,369	2,533
% Single-family homes	64	69	44	43
Median annual sales price of single-family homes	236,000	332,000	443,000	670,000

Notes: [1] In thousands; [2] sum of single-family and attached houses and apartment units; [3] in 2018 CAD;

models to control for individual heterogeneity and account for unobservable differences at the DA level. These effects can either be treated as fixed parameters, resulting in a fixed effects (FE) model, or as a random variable that follows a probabilistic distribution (e.g., normal), otherwise known as a random effects (RE) model. The choice between FE and RE model in panel data analysis is determined using the Hausman's test, which evaluates whether unique errors are correlated with the explanatory variables. If there is no correlation between the regressors and the group-level effects, an RE model is an efficient and consistent estimator of the true parameters (Hsiao, 2003). Here, the null hypothesis of the Hausman test was rejected, thus suggesting that FE is more appropriate for our model specification. Including DA-specific effects that are constant over time controls for bias due to omitted variables in our model (Hsiao, 2003). Finally, a dynamic model specification containing a lagged (in time) dependent variable was also estimated using the generalized method of moments; however, the lagged dependent variable was found to be insignificant.

Table 3
Descriptive statistics of variables over the study period in the sample at the DA level.

Variable	2001	2006	2011	2016
(1) Median price [2018 CAD]				
Mean	367,421	477,149	555,942	873,081
Std. Dev.	202,928	266,341	279,676	497,161
(2) Population density [people/ km^2]				
Mean	3,824	4,028	4,179	4,191
Std. Dev.	2,976	2,925	3,142	3,240
(3) % Single-family homes				
Mean	72.82	72.32	68.45	67.52
Std. Dev.	28.11	26.42	28.79	29.00
(4) % Dwellings with structure age over 45 years				
Mean	21.27	31.50	37.20	42.70
Std. Dev.	25.64	33.82	34.49	37.38
(5) Average household size [person]				
Mean	3.04	2.98	2.95	2.93
Std. Dev.	0.51	0.50	0.53	0.52
(6) Unemployment rate				
Mean	5.77	6.51	8.51	7.56
Std. Dev.	1.24	1.12	1.15	1.03
(7) Distance to nearest highway exit [m]				
Mean	3,459	3,416	3,363	3,118
Std. Dev.	4,347	4,354	4,252	3,484
(8) Distance to nearest GO transit station [m]				
Mean	4,605	4,487	4,442	4,415
Std. Dev.	4,958	4,926	4,827	4,815
(9) Regional auto accessibility				
Mean	945,685	1,071,930	1,095,262	1,110,604
Std. Dev.	427,816	459,094	489,810	512,638
(10) Regional transit accessibility				
Mean	102,389	107,594	126,066	120,113
Std. Dev.	79,946	82,770	90,388	85,344

Each model specification was evaluated based on the significance of independent variables, as well as its information criterion and log-likelihood (see Appendix E). The SLX results were discarded as several accessibility variables did not comply with theoretical expectations (i.e., their main effects turned out non-significant while they had high correlations with the outcome variables and behaved consistently across other (non) spatial models). Ultimately, the SEM model was selected as the best model over a similarly performing SAR model. Although the SEM is unable to measure the effects of spillovers and only provides information about the direct effects of determinants, the global spillover effect obtained from the SAR model (which means that a change in an independent variable at any DA affects the median sales price in all other DAs, regardless of their location) is hard to justify (Elhorst and Vega, 2013; Gibbons and Overman, 2012).

Three different SEMs were estimated, one for each submarket (low, medium, and high density areas). Although not all of the explanatory variables were significant across the three models, the same specification was kept to allow for comparison between the models. Finally, interaction of independent variables with time were included to measure changes in their shares in sales prices over time but were found to be insignificant and were removed from the models.

4.2. The choice of variables

The sales price in DA *i* at time *t* is estimated by its built-environment, socio-economic and transport accessibility characteristics. The choice of a suitable subset of variables that best explain variations in sales price was based on a systematic process. First, correlations between the independent and dependent variables were computed for each of the three variable groups (i.e., built environment, socio-economic and transport accessibility variables). Second, univariate and then multivariate models with different combinations of variables having high correlation with the dependent variable were estimated. Here, variables emphasized by and in line with theory were included.

Multicollinearity was controlled for by testing the correlation between pairs of variables as well as the models' mean collinearity indicated by the variance inflation factor (VIF) indicator. The final choice of variables was based on theoretical expectations, while controlling for collinearity between variables, and assessing various model performance statistics such as the VIF and log-likelihood. Only the statistically significant and theoretically sound variables were selected from the extensive pool of independent variables for estimating the models. The final choice of variables includes 3 built environment variables (i.e., DA's population density, share of single-family homes and share of dwellings with structures age over 45 years), 2 socio-economic variables (DA's average household size and unemployment rate) and 4 transport accessibility variables (changes in distance to nearest highway exit/GO transit station and changes in regional auto/transit accessibility).

The same procedure was repeated for choosing the most suitable functional form for the models including linear, semi-log and log–log formulations. A double-log function was chosen where a constant elasticity is assumed for all variables as it resulted in the best model fit. Thus, all continuous variables are log transformed because, as previous research suggests, the dependent and independent variables are likely to have a non-linear relationship. This logarithmic transformation also reduces the risk of heteroscedasticity. Finally, the log–log formulation allows for the estimated parameters can be interpreted as elasticities.

5. Results

Table 4 shows the results of the three SEM models estimating median sales prices at the DA level, by a combination of built environment, socio-economic and transport accessibility variables. To correctly interpret the coefficients of spatial models, the partial derivatives of each explanatory variable *K* must be calculated. For a SEM with a row normalized spatial weight matrix, the calculation simplifies such that β_k coefficients can be instantly interpreted as direct effects (Golgher and Voss, 2016). For example, the direct effect of average household size in the low density model is 0.160, meaning that a 10 % increase in average household size within a specific DA will result in a 1.6 % increase in median sale price for that DA, *ceteris paribus*.

The built environment and socio-economic variables behave as expected and more or less similarly, with variations across the low–high density spectrum. Higher population density of a DA is related to its higher sales prices in the low and medium density areas. In the high density areas, however, this relationship is not significant. This can be explained by the fact that higher population density in low and medium density areas is a proxy for the presence of amenities and job opportunities which are relatively lacking, and thus favored in these areas. In the high density areas, however, high population density is likely associated with negative externalities of density (e.g., congestion, air and noise pollution, lack of privacy and/or access to green spaces) that are not favored by home buyers in general and single-family home buyers in specific. A higher percentage of single-family homes in a DA relates to a higher sales price in high density areas. This low density typology is more favored by the market especially in the high density areas and is also an indication of higher wealth of the DA residents in general. As expected, the percentage of old housing stock (over 45 years) has a negative impact.

A larger average household size in a given DA is associated with a higher sales price. This indicator is a proxy for the average property size in the DA and behaves as expected as larger households probably occupy larger houses that in turn are likely to cost more. The positive coefficient of household size for sales price is larger in medium density and especially in low density areas. This is probably because there is a stronger relationship between household size and dwelling size in these areas compared to high density areas. On the other hand, the negative association of municipal unemployment rate with sales price is highest in the high density areas (these areas also show a higher unemployment rate on average).

The accessibility variables show the change in the local and regional auto and transit accessibility from the base year 2001. For example, change in distance (d) to nearest highway exit for year t is calculated as

Table 4
SEM models estimating median sales prices of single-family homes at the DA level.

	SEM		
	(1) Low density	(2) Medium density	(3) High density
Built environment			
Population density	0.030***	0.047***	0.003
% Single-family homes	0.015	0.009	0.009*
% Dwellings with structure age over 45 years	−0.009***	−0.003*	−0.008***
Socio-economic			
Average household size	0.160***	0.096***	0.082**
Unemployment rate	−0.062**	−0.172***	−0.356***
Transport accessibility			
Change in distance to nearest highway exit	0.008*	0.021**	0.546***
Change in distance to nearest GO transit station	0.023**	0.006*	0.126**
Change in regional auto accessibility	0.052***	0.093***	0.011
Change in regional transit accessibility	0.107***	0.032*	0.010*
Time Dummies			
2002	0.045***	0.059***	0.055***
2003	0.115***	0.115***	0.115***
2004	0.154***	0.118***	0.205***
2005	0.207***	0.158***	0.233***
2006	0.248***	0.197***	0.277***
2007	0.282***	0.231***	0.325***
2008	0.301***	0.240***	0.331***
2009	0.301***	0.270***	0.427***
2010	0.374***	0.349***	0.502***
2011	0.396***	0.378***	0.532***
2012	0.473***	0.455***	0.608***
2013	0.509***	0.500***	0.660***
2014	0.571***	0.551***	0.691***
2015	0.664***	0.647***	0.785***
2016	0.820***	0.811***	0.929***
lambda	0.139***	0.138***	0.095***
sigma2_e	0.032***	0.024***	0.030***
Log-likelihood	9846.38	14767.54	11199.9
AIC	−19640.8	−29483.1	−22347.8
BIC	−19421.7	−29264	−22128.8
Observations	33,712	33,696	33,696

Notes: All variables are ln transformed and all models include year dummies; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

$(d_t - d_{2001})$. Here, a negative value at year t represents a smaller distance to the highway exit compared to the base year 2001, which means the distance has been shortened due to the addition of a new highway exit. The interpretation of the "change in distance to nearest highway exit/ GO transit station" variable $(d_t - d_{2001})$ is the same as the "distance to nearest highway exit/GO transit station" variable (d_t), as the first is a linear transformation of the latter.

The network-level regional transport accessibility indicators are confirmed to generally have an effect on sales prices, although the size and significance of their impact vary across the three submarkets and differ between the two modes. These variables measure a zone's overall connectivity to all possible destinations in the region and capture the effects of road congestion and changes in road and transit supply over time in combination with access to population centers across the region. Car regional accessibility is shown to play a more important role in the medium density areas. Interestingly, the results suggest that low/medium density areas can potentially see higher percent gains in sales prices due to improved regional transit than in high density areas. The insignificant and negligible contributions of car and transit regional accessibility to high density areas is possibly because both road and transit accessibility are already high in these areas and their marginal improvements have limited value (see the final section for a detailed discussion on the role of regional transport accessibility and its policy implications).

The models also show that proximity to a highway exit has a negative effect on sales prices, particularly in high density areas where the effect size is seen to be the largest and most significant. Other studies have also observed similar findings; for example, Carey and Semmens (2003) found that while being located near the Superstition Freeway (US-60) had a positive effect on multi-unit dwellings and commercial properties, it produced an adverse impact on the property values of single-family homes. One possible explanation for this could be that while highway developments improve the accessibility of an area, they also induce an increase in noise and air pollution as well as traffic intensity levels. Another possible explanation could be that highways act as barriers that sever communities and have detrimental impacts on their social cohesion and people's fluid mobility. The distance to a highway also produces a negative impact in medium density/suburban areas, albeit the effect size is notably smaller. This could be because these areas are located near commercial hubs. Many retail strips or big box stores are located near suburban highway ramps, and correlations show that proximity (800 m buffer) to supermarkets and malls has a negative impact on single-family home prices. Lastly, the distance to a highway exit in low density areas was found to have the smallest negative impact on sales prices, which is likely attributed to the fact that pollution and traffic congestion is less of a problem in low density/rural areas. This confirms earlier findings indicating that the negative effect of motorways on housing values is less pronounced in rural areas compared to urban areas (Paliska and Drobne, 2020).

Additionally, the impact of local transit accessibility was analyzed in the models by similarly including a variable which measured the proximity of a DA to the nearest GO Transit station. Based on the positive and statistically significant coefficients in all three models, it is observed that the proximity to a GO Transit station has a negative effect on sales prices. Although this may seem counterintuitive as being near a transit station would improve accessibility, it is important to clarify that the negative effects are specific to being near a GO Transit station; the proximity to a subway station was found to have a positive relation with sales prices, though it was statistically insignificant. Some previous studies have shown that areas close to the (heavy) rail stations have a "disamenity zone", where negative externalities like noise, pollution, vibrations, crime, or unsightliness, offset the accessibility benefits and decrease property values (Bowes and Ihlanfeldt, 2001; Bartholomew and Ewing, 2011; Seo et al., 2014). Due to the GO Transit's aboveground stations and rail tracks, the positive impacts of being near transit are very likely to be undercut by these negative externalities.

Furthermore, being close to a GO station has the largest effect on sales prices in high density areas and the smallest effect in medium density areas. This is probably because people living in high density areas are less likely to find a commuter rail service to be beneficial, whereas on the other hand, there is greater perceived value of being near a GO Transit station in the suburbs as they connect residents to the downtown core. In summary, while proximity to GO Transit stations seem to reduce the sales prices of single-family homes generally across the GTHA, houses in low and medium density areas seem to experience a slower decline in sales prices with distance from GO stations than houses in high density areas.

Trends in the time fixed effects (year dummies) show that controlling for socio-economic, built environment and transport access variables, sales prices have been significantly and steadily increasing over the study period compared to the base year of 2001 in all three submarkets (Fig. 5). As expected, the prices show the highest growth in the high density/urban segment. Interestingly, prices in the low density/rural segment show a slightly higher increase than the medium density/suburban one. This could be attributed to the presence of relatively larger homes and higher income communities in these areas.

6. Conclusion, discussion and policy implications

This work presents a long-term empirical investigation of the role transport accessibility on single-family home sales prices from 2001 to 2016 in the Greater Toronto and Hamilton Areas (GTHA). It measures the price gains from the development in both auto and transit networks, at the local and regional levels, and over different submarkets (low, medium and high density areas), while testing various potential determinants and spatial effects.

It is important to note the main caveat of this study, namely the absence of structural variables for single-family homes (data not available free of charge) and the consequent need for the aggregation of indicators at the DA level. However, the investigated longitudinal dataset has a relatively large number of observations (around 100.000 observations over a 16-year time period) and reveals aggregate sales price patterns across a metropolitan region with different development types while focusing on the role of regional transport accessibility. This paper makes several contributions to the accessibility and sales price research field.

First, our results confirm the significant relationship of certain socio-economic and built environment indicators (i.e., population density, percentage of single-family/over 45-year-old dwellings, average household size, unemployment rate) with sales prices, with variations observed over the low–high density spectrum. It is interesting to observe that, with macro-economic and region-wide trends like population growth and unemployment rate in the background, certain areas have become more attractive to home buyers and have witnessed increasing sales prices. The time-fixed effects show that, while controlling for socioeconomic, built environment and transport access changes, sales prices have increased in all three submarkets (increases are led by the high density, then the low density and finally the medium density areas) over the study period, except for short halts around the 2007 to 2009 period coinciding with the economic recession. The statistical insignificance of interaction of independent variables with time show that the determinants' shares in sales prices have been fairly stable over the study period.

Second, while our results confirm that access to GO transit positively influences sales prices when considering regional accessibility, an inverse relationship is found at the local level. It is important to note that the negative relation has been found with GO transit which is an above ground heavy rail system, thus with more nuisance for its direct surroundings in terms of noise, vibrations, and unsightliness. GO stations are also often located in pre-existing rail corridors that are often less attractive for development. This relationship could be explained by the negative externalities of the aboveground GO stations and rail tracks and

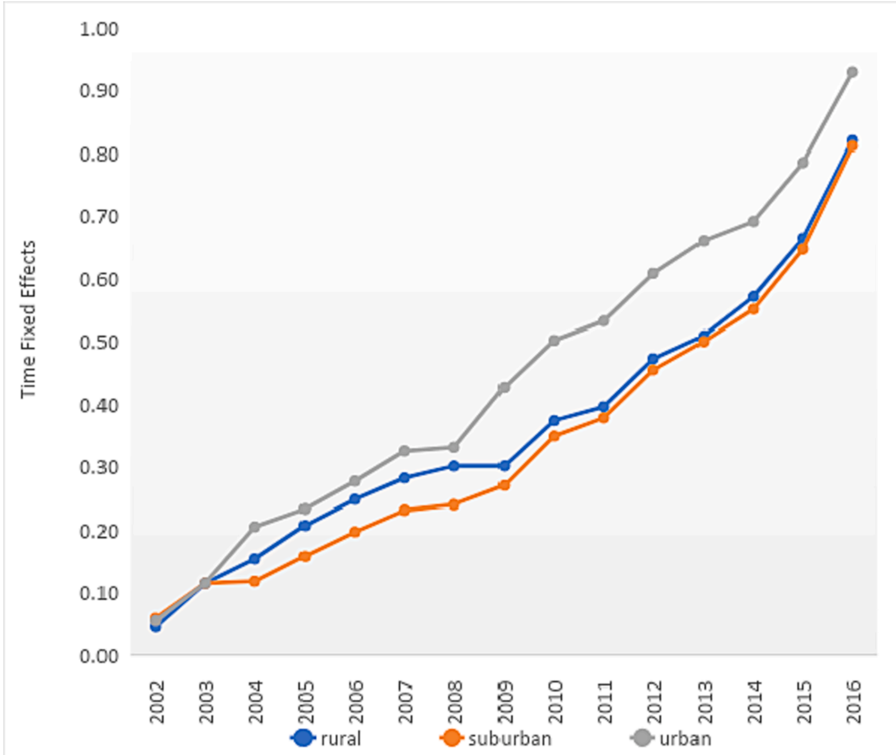

Fig. 5. Time fixed effects' trends per area.

is most influential in high density areas where residents are less likely to benefit from commuter rail. Furthermore, our focus on single family homes is likely to play a role in the identified negative relationship. As this segment aims for a more private and quite residential typology, it is potentially more sensitive to dis-amenities of such transit stations. Future works could expand the analysis to other dwelling types, potentially identifying different relationships between sales prices and local/regional transport accessibility. Similarly, proximity to highway exits plays a negative role in single-family homes' sales price in both medium and high density areas, which is likely due to negative highway externalities (higher noise/air pollution/proximity of big box stores/community severance) in these areas.

Third, and most importantly for this paper's primary hypothesis, the findings confirm that regional potential accessibility does indeed play a significant role in sales prices, over and above local proximity to TI. The regional potential accessibility used is a gravity-based measure of a zone's accessibility to population centers (proxy for opportunities) across the region, and it captures the effects of road congestion and changes in road and transit supply over time. This finding is very significant from a policy analysis perspective in that it clearly shows that TI improvements have not just local "near-field" impacts (e.g., immediately around a transit station or immediately along a BRT or LRT corridor) but also region/network-wide "far field" impacts. These reflect the fundamental fact that the transport system is a network. Any change in one component of the network potentially affects the connectivity/accessibility of many (and often a very large number of) points across the region. This fact, however, is more often than not ignored in even large planning/investment studies, in which only local impacts (positive and/or negative) are considered. In such cases, important benefits and costs are almost inevitably ignored, often leading to sub-optimal and possibly unwanted outcomes.

Fourth, it is also very important to note that the contribution of regional accessibility varies by mode and across space. Specifically, regional accessibility by car plays an important role in the medium density areas, while regional transit accessibility is more impactful in the low density areas. The numerically low and statistically insignificant contributions of regional transport accessibility (by transit and car, respectively) to sales prices in high density areas can be argued to be based on the TI's life cycle maturity in these areas. Land markets have seemingly adjusted to the accessibility gains due to improvements in the car and transit networks in high density areas and are no longer susceptible to change.

Interestingly, sales price gains related to transit accessibility improvements are strongest in low density/rural areas. This seemingly counter-intuitive finding is also corroborated by Shyr et al. (2013) and is economically justifiable. High density areas are more likely to be already benefiting from a viable transit system with a high regional network coverage. Hence the marginal increase in transit accessibility is not likely to increase price premiums. In transit-poor areas, however, access to transit can make a significant contribution and hence is capitalized in sales prices.

It should be noted that sales price gains related to transit accessibility improvements in low and medium density areas do not necessarily mean that their residents are using transit. While our study has not included ridership changes in the analysis, there is evidence elsewhere that higher GO rail ridership is associated with favorable TOD characteristics near GO stations, which are mainly located in low-medium density areas (Akbari et al., 2018). Moreover, in terms of local context, while Toronto is a polycentric metropolis, the downtown/central area is a very dominant regional center that attracts workers and other trip-makers from throughout the GTHA. As a result, auto access to the central area is very congested (by North American standards). Thus, suburban rail access to the central area is highly valued. In short, while not all who live near suburban stations will use transit to commute downtown, those who do, find it a very attractive place to live.

It is also useful to mention that the pronounced role of regional transit accessibility in sales prices in low and medium density areas could likely be due to a major regional transport policy introduced in 2008 to provide an integrated regional transit network (The Big Move - Metrolinx, 2008). This policy highlighted GO stations as focal points of urban development in combination with operation of high frequency services. The majority of these stations are located in areas with low and medium densities (Fig. 3). While it is still "early days" in terms of assessing the impacts of "Big Move" policies, it is arguable that some effects are being seen from this policy, at least as captured in housing price changes in low and medium density areas. Fig. 6 specifically illustrates low density areas that have witnessed the highest increase in regional transit accessibility as well as the highest price gains during the 2001–2016 period (top terciles in both cases). It can be observed that most of the high-increase areas are relatively close to rail lines, especially when good local transit and auto access to these lines is accounted for. The two notable exceptions are in north Whitby in Durham Region to the east of the City of Toronto, which has excellent highway connections, and in Caledon in Peel Region to the west of Toronto, which is an attractive development site for high-end estate housing.

In short, the results indicate that regional network-level travel time savings resulting from TI investments are capitalized in areas beyond the direct vicinity of transit and highway infrastructure and this needs to be accounted for in urban and transport policy assessments, including, but not limited to, land value capture schemes.

From a policy perspective, our results indicate that low and medium density areas that have relatively high regional accessibility can potentially benefit from TOD as:

1. The highest gains in transit accessibility improvements and their impact on sales prices can be expected in low and medium density areas. Thus, transit investments in these areas, in combination with planned densification (to provide the demand to support transit) can be beneficial. The linkage between accessibility and property values is critical in this equation, since it is the induced increase in property values that makes denser development financially feasible.

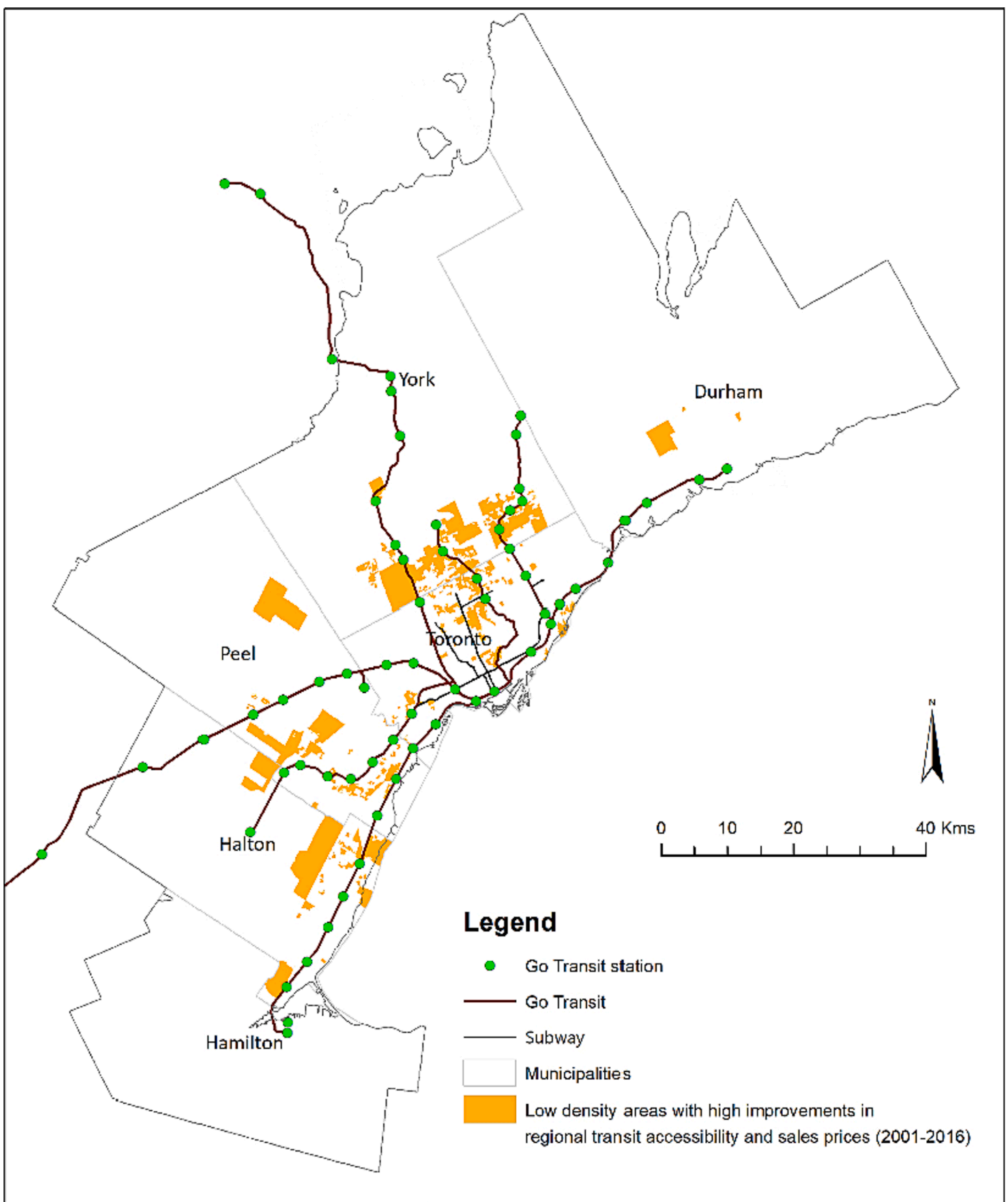

Fig. 6. Low density areas with highest increase in regional transit accessibility and highest gains in sales prices from 2001 to 2016 (top terciles in both cases).

2. Proximity to transit stations in these areas has a much lower negative impact on sales prices compared to high density areas, so the stations' disamenity and the subsequent loss of housing value are much smaller here.

Furthermore, it is shown that land development stimulated by increased transit network accessibility is more likely to happen in non-urban areas, which have more developable land and less restrictions and change-resisting land uses compared to the GTHA's urban areas (Kasraian et al., 2020). Finally, this is in line with calls for improving transit accessibility levels in the suburbs to discourage the increasing rise in suburbanization of poverty (Allen and Farber, 2021).

However, complementary policies are needed to ensure that those who live in these areas are transit users and that the increase in premia in these areas due to increase in regional accessibility does not price-out low- and moderate-income people. Such a transit-induced gentrification can nullify the impact of transit for this target group who can obtain the most marginal benefit from it. This has been the case in Toronto and Montreal where census tracks that are exposed to rail transit stations are shown to have a higher likelihood of undergoing gentrification (Grube-Cavers and Patterson, 2015). Thus, integrated land use and transportation measures are needed that provide and protect affordable public housing in the rural and suburban transit station areas. Examples of such measures are local inclusionary zoning programs that award density bonuses to developers who provide affordable housing, and rent control regulations.

To conclude, both road and transit infrastructure investments have region-wide, not just local, impacts on housing prices and, hence, on a wide range of urban policy issues, including urban growth, housing affordability and the overall social, economic and environmental sustainability of urban regions. These network-wide effects must be understood and accounted for in transport investment and other major policy analyses if these investments are to be maximally effective in moving urban regions towards a more sustainable future. Our findings can be relevant for other comparable fast-growing North American metropolitan regions with a variety of low–high density development types where transit infrastructure, while increasing, is still lagging behind regional needs and tailored land value capture policies may be one useful tool to help finance further transit investments.

CRediT authorship contribution statement

Dena Kasraian: Conceptualization, Methodology, Data curation, Visualization, Formal analysis, Writing – original draft, Writing – review & editing. **Lisa Li:** Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Shivani Raghav:** Methodology, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Amer Shalaby:** Writing – review & editing. **Eric J. Miller:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The research reported in this paper was supported by an Ontario Research Fund Research Excellence Round 7 grant, and a Natural Sciences and Engineering Research Council Discovery grant.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cstp.2022.100932.

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