GROWING VALUE: DESCRIBING THE NATURE OF THE RELATIONSHIP BETWEEN STREET-LEVEL GREENERY AND HOUSING PRICES IN TORONTO

By

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A thesis

presented to Ryerson University

in partial fulfillment of the

requirements for the degree of

Master of Science in Management

in the program of

Master of Science in Management

Toronto, Ontario, Canada, 2019

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Growing Value: Describing The Nature Of The Relationship Between Street-Level Greenery And Housing Prices In Toronto by Spencer Bridgwater, MScM, Ryerson University, 2019.

Abstract

The role of urban forestry has become increasingly important in the context of sustainability, both from an environmental context, and from a developmental context. Greenery in an urban environment has demonstrable implications for health, air quality, aesthetics, and land value, as described broadly across the literature.

Until recently, studies on green urban canopies and housing prices have been limited in their methodology by using aerial-perspective data. The MIT Senseable City Lab in 2015 developed the Treepedia project, which uses Google Street View images to quantify greenery levels in urban environments. Using the green view index (GVI) data from the Treepedia project, street-level greenery densities were compared against housing prices across Toronto. Models for different property types, accounting for characteristic, locational, and demographic variables, were estimated. It was determined that a statistically significant relationship between street-level greenery and housing prices exists in Toronto for detached homes, semi-detached homes, row/townhouse units, condo apartments, and condo townhouses.

Acknowledgements

I would like to express my sincere gratitude to my supervisor and mentor on this project, Dr. Murtaza Haider. Thank you for having confidence in me, and for providing the guidance, knowledge, patience, motivation, and enthusiasm necessary for me to grow into a better researcher.

I would also like to thank everyone at the Senseable City Lab at MIT for graciously providing the Treepedia dataset. This research would not be possible without it.

Thanks to Mike Wieczorek, for his seemingly endless advice on a countless number of subjects. Thank you for your questionable insight, wealth of knowledge, and absurd humour.

Thank you to Liam Donaldson, for all the advice and direction, and for helping me to understand basic statistics. I think with a bit more practice I may be able wrap my head around normality.

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1. Introduction

Housing prices are a function of dwelling characteristics, locational amenities, and neighbourhood demographics. What a buyer is willing to pay for a property is contingent on the value they place on these attributes in relation to their needs. Desirable attributes generally incur a price premium compared to non-desirable attributes. Greenery is an attribute often desired by residents. In the past, greenery at the neighbourhood level has been observed to have an impact on housing prices, in terms of canopy density and coverage across an urban area. Proximity to street trees and open green spaces has been cited to generate positive amenity value for housing units across a variety of settings (Morancho, 2003; Luttik, 2000; Siriwardena, Boyle, Holmes, & Wiseman, 2016).

The City of Toronto also claims that street trees benefit property owners through providing shade, reducing heating and cooling costs, and increasing property values (City of Toronto, 2017a). However, though efforts in the literature have used hedonic modelling techniques to give an approximation of the asset value of greenery on nearby housing prices, the models themselves consider the urban *canopy*, which constitutes an aerial view of coverage. This perspective cannot be appreciated by buyers or sellers, who primarily view street greenery from ground level as they walk down an avenue. However, recent work by Li et al. (2015) developed a method by which street-level greenery can be quantified in urban environments. The resulting *Treepedia* project has successfully compiled greenery data for many cities around the globe, and allows for a more robust valuation approach.

Past work in the literature has shown that neighbourhood choice is largely driven by income (Hedman, van Ham, and Manley, 2011). However, a high variability in income and an increasing degree of high-density development may confound neighbourhood choices of new urban dwellers. Further, a greater amount of space staked for urban development (especially high-density development) limits the amount of space available for street-level canopy coverage, making the presence of greenery in a given neighbourhood all the more valuable.

An externality of increasing urban density is systemic environmental decline, which has implications for health, climate change, and ecological development. Urban canopy coverage contributes to lowering urban temperatures by blocking shortwave radiation and increasing water evaporation (Lafortezza et al., 2009). Creating more comfortable microclimates, trees also mitigate air pollution caused by everyday urban activities (Lawrence, 1995; Jim and Chen, 2008). Cities around the world are recognizing this and many are developing strategies to increase green canopy coverage.

In a suburban context, lower density is likely to be more conducive to a less-disrupted environment. Larger housing lots have more room for trees and other greenery, which in turn are able to sequester more pollutants compared to a bustling downtown neighbourhood (Holcombe, 1999). However, while the draw of these areas lies in their affordability (with suburban land being generally less expensive than property within a city center), the cost is their accessibility. Suburban residents must drive to wherever they wish to go, as the majority of adjacent development is residential. Conversely, urban centers offer a wider breadth of amenities and services through their highly accessible nature, either through foot or bicycle travel, by car, or by transit, at the cost of individual living space.

Despite these reductions in personal space due to cost, urban income can be highly variable. In a research report by the Urban Institute (2008), it was found that family (but not *individual*) incomes in urban centers have been increasing in volatility for a 30 year period between 1972 and 2003 (Nichols and Zimmerman, 2008). The authors postulate that different emerging patterns of work (more households with two earners) and higher rates of household formation and dissolution are underlying factors (Nichols and Zimmerman, 2008). In any case, the reduction of individual space in an urban context suggests intensification, whose protocol is often at odds with environmental sustainability—but this does not have to be the case. Careful consideration of the value of urban greenery reveals a high degree of social and economic value.

Trees provide many benefits in urban settings. From cleaning the air and reducing stormwater runoff, to providing habitats for birds and other wildlife, to beautifying an urban area in general, street-level greenery is an essential component of the city's landscape. In brief, the objective of this thesis is to describe the impact of street-facing green space on adjacent housing prices. This paper seeks to address whether or not differences exist in pricing due to green space not only at the individual home level, but across comparable neighbourhoods as well. Regardless of outcome, this analysis in turn drives new questions: what neighbourhood features are shared by comparably "green" areas? How much responsibility lies with the individual, the neighbourhood, and the City to maintain such areas, and who receives what level of benefit?

2. Background

In its current state, Toronto has a tree canopy cover of roughly 27% (Beacon Environmental Limited, 2016). This is below the city's target coverage of 40%, which the city plans to achieve through implementing policies, bylaws, or other programs relating to tree preservation and establishment (Beacon Environmental Limited, 2016). These programs are grounded by work through academic and corporate institutions, whose research quantifies the degree of benefit offered by the greenery within the city. Ideally, investment toward specific policies or programs would be predicated on their predicted social and economic return, but the starting point for any consideration is awareness of what is at stake—the value of Toronto's canopy as not only an amenity, but as an asset.

Research into the area of the environmental role in urban development is an important contribution to a sustainable future. Urban development with disregard for the local urban ecology has implications for health, both physical and mental, throughout a city's inhabitants. However, accurately measuring the level of ecological development across an entire city is challenging. Recent data collection and visualization work by Li et al. (2015) and Seiferling et al. (2017) has provided a novel and robust means by which street-level canopy coverage can be assessed for a number of urban centres, including Toronto. This work is a valuable asset in the context of urban forestry because it provides a direct proxy to an individual's view of street greenery at ground level, rather than the semblance of how green an area is (visually) based on top-down canopy views—such as through satellite images.

The research described herein aims to generate both knowledge for explanation and knowledge for action. From an explanatory point of view, research into the nature of a relationship between street-level canopy coverage and urban development statistics and housing metrics can provide insight as to what constitutes a desirable neighbourhood (*neighbourhood choice*). Land valuation for development staking and acquisition can consider Treepedia's green view index (GVI) values as a contributing variable to pricing and return. From an action point of view, an identifiable relationship can be used to help public and private developers in their consideration of methods and protocols for sustainable urban development in the context of the local ecology, which is becoming increasingly relevant as downtown density rises. Further, identifying areas that are underserved in terms of public greenery may be achieved through these data—especially in areas where households are economically disadvantaged such that the costs of maintaining green spaces are comparatively high.

The elucidation of the nature of a relationship between street-level canopy coverage and housing/development can be used as a consideration model for current and next-generational city planners.

Using space to maximal benefit in an increasingly dense city such as Toronto is crucial, and planners must balance infrastructural needs with ecological needs.

3. Literature Review

In this paper, a foundation for the relationship between street-level canopy coverage and housing prices will be established. In order to assess the urban environment holistically, current housing and development strategies and processes (with a focus on Toronto), ecological impacts of urban development, and the role of canopy coverage in new developments are assessed in tandem. Housing pricing trends, family size, and family incomes in Toronto are also described.

3.1 Density

Toronto is a rapidly growing urban centre from both population and development standpoints. Statistics Canada reported from its 2016 Census that the Toronto CMA (Census metropolitan area) housed just under 6 million people, up 6.2% since 2011 (Statistics Canada, 2017a). The Census goes further to report that in the same year, there were just over 2.1 million private dwellings occupied in the same area, and increase of 7.3% from 2011 (Statistics Canada, 2017a). The Ministry of Finance also predicts that the Greater Toronto Area (the fastest growing region in Ontario) will see its population increase by 42.3 percent by 2041, with a strong emphasis on international migration (Ministry of Finance, 2017). While the population density of Toronto (roughly 4,457 people/km^2) is not as high as other major cities such as London (11,000 people/km^2) or New York (14,796 people/km^2), the sustainability of current growth rates will depend on adequate infrastructure (Filipowicz, 2018).

The need for adequate housing in a rapidly growing city such as Toronto cannot be understated. However, in order to enjoy the amenities offered by the city proper, Toronto's new and future citizens are finding individual space diminishing in terms of availability—especially given the shift towards single-person dwellings. Indeed, the percentage of one-person households in Canada grew from 16.8% in 1976 to 28.2% in 2016, according to the 2016 Census (Statistics Canada, 2017a). Between 1996 and 2011, the number of houses and low-rises built in Toronto grew 6.1%, whereas the number of townhouses built grew 30.6%, and apartments above 5 stories 29.6% (City of Toronto, 2015). Condos and other similar style multi-unit housings the primary means by which migration growth rates can be sustained, as there is simply a lack of room for new detached homes within the city proper. The market for these condos has been meeting the demand at a significant pace. In the Toronto region, over 87% of condos in all stages of development have been sold—the highest market absorption rate in history (Kalinowski, 2016). These developments constitute the majority of new "urban" development.

3.1.1 Urban Density

In their report on density in Canadian cities, the Fraser Institute (2018) notes that many density measurements capture the entirety of a census metropolitan area, which can often include vast non-urban or rural areas such as national/provincial parks, undeveloped land, and other dissemination areas (Filipowicz, 2018). The author proposes a modified method of calculating density which removes these non-urban areas from consideration (Filipowicz, 2018). Nevertheless, "urban areas" are defined by Statistics Canada as areas with populations of at least 1,000 and a density of 400 or more people per square kilometer (Filipowicz, 2018). This paper refers to density with respect to the 2016 Census definition.

Overall, Toronto has 4,457 inhabitants per square kilometer, based on an urban land area of 613 km^2. (Filipowicz, 2018). However, certain downtown neighbourhoods exhibit densities well above the city average. North St. James Town and the Church/Yonge Corridor have densities above 18,600 and 31,300 people per square kilometer, respectively (City of Toronto, 2016a). Indeed, of the 10 highest-density neighbourhoods in Canada, 7 exist within Toronto (Cain, 2017). For some of these high-density areas, poverty is systemic. For St. James Town, the incidence rate of low income is considerably above that of Toronto as a whole, and is more than double that of Toronto in general for families (Perkins and Zizys, 2005). Average yearly income in the neighbourhood is $26,000, far lower than the provincial average of just over $42,000 (Statistics Canada, 2011). However, Rosedale, an adjacent low-density neighbourhood reports average yearly family income to between 140% and 830% of Toronto CMA's average of $50,479 (Monsebraaten, 2017). While these differences in density and income across two nearby areas are staggering, significant variation of income exists throughout the downtown urban core, where density is most prominent.

3.1.2 Household Type & Size

Toronto's household type changes over time have been considerable. In the past 20 years, the growth rate of non-family households has outpaced that of family households (City of Toronto, 2015). In the period between 1996 and 2011, 54% of Toronto's net household growth came about from increases in non-family households (City of Toronto, 2015). This accounts for roughly 78,500 households, or a growth of 25% overall, and a share increase of total households from 34.6% to 37.3% (City of Toronto, 2015). Statistics Canada reports that this is change is a subset of the total historical trend in Canada over time (***Figure 1***). Indeed, families without children and lone-parent families increased 16% and 20%, respectively, between 1996 and 2011 (City of Toronto, 2015).

A 2017 report by the Ryerson City Building Institute purported that the average number of persons per household in Toronto was 2.46 in 2011, down from 2.60 in 1996 (Ryerson City Building Institute, 2017). Toronto subsequently added 146,000 dwelling units (housing 345,000 people), an average of 2.36 people per unit, between 2011 and 2016 (Ryerson City Building Institute).

Currently, low-rise apartments and houses provide the primary type of housing for families with children, while non-families dominate the high-rise apartment market. This follows the trend towards smaller individual housing as a result of increased urban density. Accessibility to work and surrounding amenities also play a major role in this trend, but they are not the only factors. Lower fertility, greater life expectancy, changing social structures and constructs, and high rates of divorce and separation all contribute to the incidence of smaller households being the norm (Statistics Canada, 2014). Nevertheless, there has been a recent shift into high-rise apartments, particularly in downtown Toronto, among families with children younger than 5 years (City of Toronto, 2015).

Despite this, these families will likely face housing challenges due to the recent shortfall of large-size units and the decrease in size of these units overall. Indeed, the average size of resale condo apartments in Toronto between 1996 and 2014 has fallen significantly (***Figure 2***).

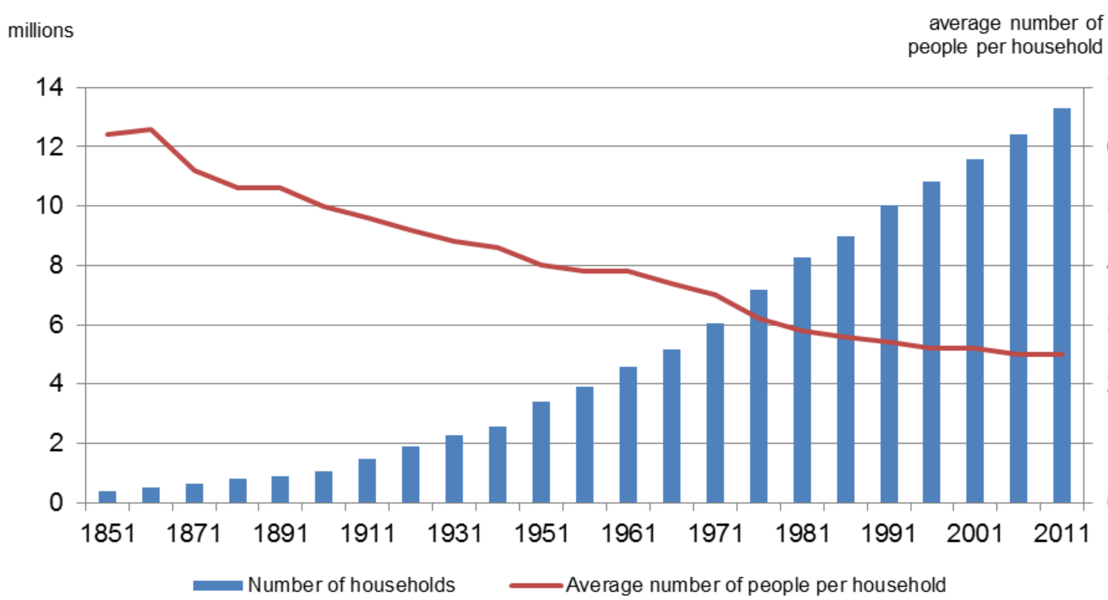

Figure 1: Canadian households and average number of people per household over time (From Statistics Canada, 2014. Image from https://www150.statcan.gc.ca/n1/pub/11-630-x/11-630-x2015008-eng.htm).

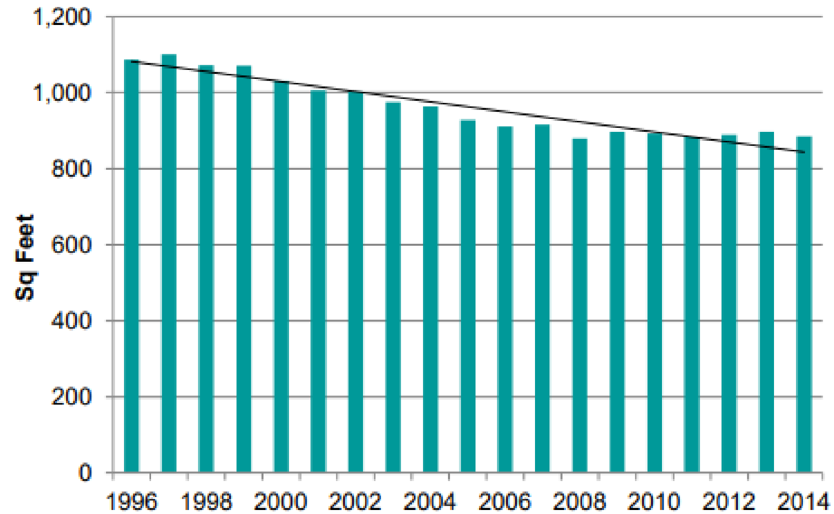

Figure 2: Average size of resale condominium apartments in Toronto, 1996-2014 (City of Toronto, 2015; image from https://www.toronto.ca/legdocs/mmis/2015/pg/bgrd/backgroundfile-84816.pdf)

In recent years, the average size of family households in ground-related dwellings has declined. This trend has also been observed for recently-built high-rise apartment units in Toronto, while in older high-rise apartment units average family size has instead increased (City of Toronto, 2015). The observation of older (*i.e.* generally larger) apartments increasing in *average* family size is due in significant part to a general progression in social attitudes. In recent years, young adults are delaying marriage, having fewer children, and taking longer to live independently (City of Toronto, 2015). Further, as many households in the 45 to 64 year cohort approach retirement, the needs of their inhabitants change, which also may contribute to current movements in housing trends in general.

Given the nature of the relationship between household size and unit size, it is reasonable to purport that smaller households in general may *require* smaller dwellings, and larger households may *require* larger dwellings. As such, this trend towards smaller households in the same (or comparable) area creates demand for multiunit structures. For Toronto, 78% of all housing units completed in the past 18 years have been either low or high-rise condominium units which have become smaller over time (City of Toronto, 2015). As more and more people move into the downtown Toronto area, this trend will continue in this fashion for at least the foreseeable future.

3.1.3 Suburban Density

While downtown urban centres are necessarily dense from both residential and commercial aspects, suburban sprawls are categorically more residential-oriented, with detached and semi-detached homes comprising the majority of dwellings. Income inequality is generally less striking, with most suburban resident families earning around the median or above-median amounts for yearly income, with exceptions for a few key areas (Monsebraaten, 2017). As neighbourhoods in suburban areas exhibit less variability in terms of density and income compared to more central urban areas in Toronto, they allow for insight into factors about neighbourhood choice and immigration. However, for the purposes of this research (in the context of urban-environmental development), suburban regions will be mostly disregarded due to data limitations (see *Data and Methods*).

3.2 Household Income

The median total income of Canadian households rose from $63,457 in 2005 to $70,336 in 2015, a 10.8% increase (Statistics Canada, 2017b). This is compared with a 9.2% growth in the previous decade, and a decline of 1.8% the decade before that, with the growths in general being led by resource-rich provinces (Statistics Canada, 2017b). For the period between 2005 and 2015, this accounts to a real wage growth of slightly more than one per cent per year. For perspective, average rent for available units in the same period for Toronto has been rising at more than 3% per year, effectively outpacing income growth (Ryerson City Building Institute, 2017).

Toronto's median total household income in Toronto for 2015 was $65,829 (City of Toronto, 2016b). The difference from the median total Canadian household income can be partly explained by the increased presence of single person households in Toronto. Further, differences across census regions (and neighbourhoods in general) in household income exist. For Toronto, the highest median incomes are found roughly in the centre of the city, above the downtown core (***Figure 3***). As aforementioned, Toronto exhibits a high degree of income variability among its urban neighbourhoods. Indeed, household income in Toronto is highly variable at the inter-neighbourhood level, even (often commonly) for adjacent neighbourhoods.

There are several externalities that arise from income challenges for households. In Canada, low household income has consistently been associated with poor health, particularly in metropolitan areas (McLeod et al., 2003). Despite this finding, there was little evidence to suggest that *income inequality* is associated with lower levels of health status in Canada (McLeod et al., 2003). Nevertheless, the authors note that income inequality is a possible proxy for underlying conditions that may influence health status (McLeod et al., 2003). Additionally, findings by Astell-Burt et al. (2014) suggested that inequitable distribution of green spaces could exacerbate health inequalities of people with lower incomes, who are already at a greater risk of preventable diseases, due to poorer access (Astell-Burt, Feng, Mavoa, Badland, & Giles-Corti, 2014).

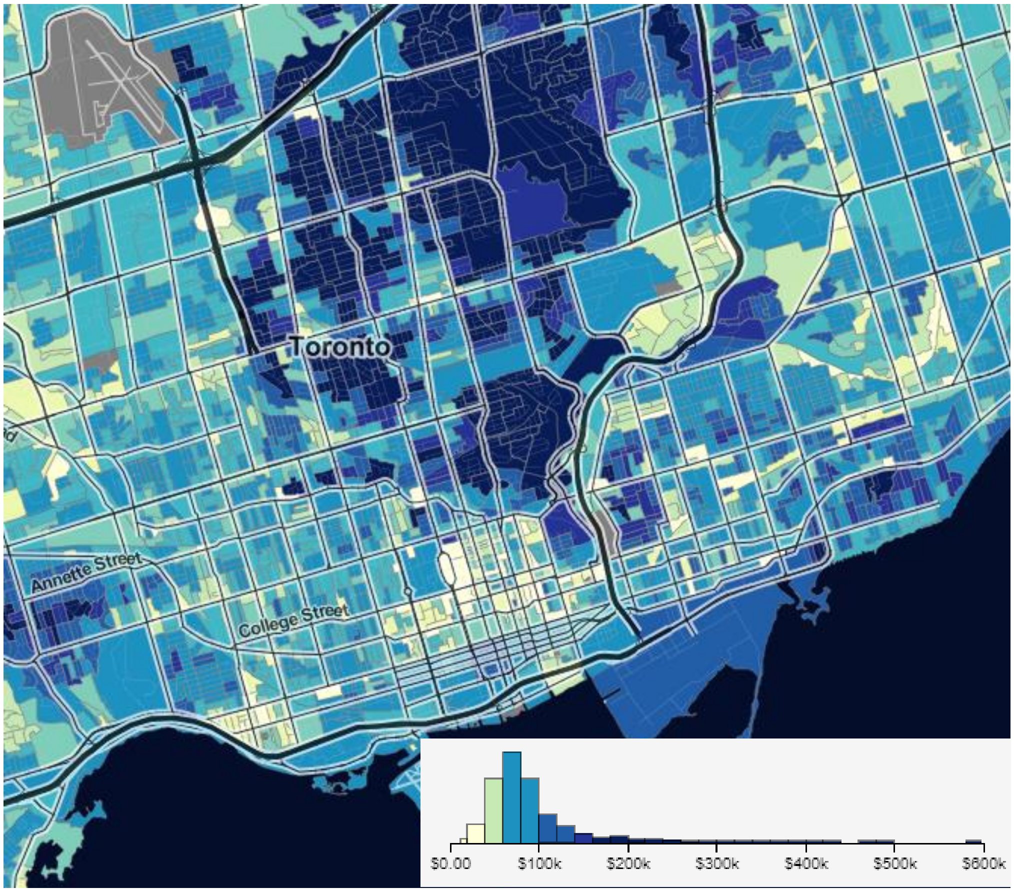

Figure 3: Median household income by census region in Toronto. From the 2016 Census, the City of Toronto's median household total income was $65,829. Generated from Census Mapper: https://censusmapper.ca/maps/838?index=3#12/43.6947/-79.4020

The authors of this study used the "parkland" GIS Meshblock as their basis for green space analysis from the Australian Bureau of Statistics. In their research, the authors determined that green space accessibility inequity varied significantly across the cities studied, with a maximum discrepancy of 8 percentage points between the highest and lowest income earners (Astell-Burt, et al., 2014). However, while the use (and an individual's perceived value) of public open space is sensitive to distance, many public green spaces cannot be modified in size in the same way that they can be modified in *attractiveness*[1].

[1] Previous work by Giles-Corti & Donovan (2003) showed the impact of *attractiveness* for public green space use was significantly less than the impact of either distance or size (Giles-Corti & Donovan, 2003). Despite this,

3.2.1 Demographics

Toronto is a diverse cultural center consisting of people and communities from a wide variety of backgrounds. After English, both mother tongue and home languages spoken in the Toronto Census subdivision (CSD, referred to herein simply as Toronto) are dominated by Mandarin/Cantonese, Tagalog, Spanish, Italian, Portuguese, Tamil, and several others (City of Toronto, 2016c). According to the 2016 Census, 51.5 percent of individuals in Toronto belong to a visible minority, up from 47 percent in 2011, compared to 22.3 percent for Canada overall (Whalen, J., 2017). In the downtown area, demographics are more variable depending on neighbourhood, with some areas having visible minorities consisting of between 5-25%, and others between 60-78% (City of Toronto, 2016c).

Within Toronto, the highest median incomes are found at the centre of the city, bounded roughly by Bloor St, Wilson Avenue, Bathurst St and Leslie Avenue, with additional high income pockets around Royal York Road and the Bloor St West area (City of Toronto, 2017b). These areas consist of lower proportions of visible minority populations overall. The downtown core conversely exhibits both trends of lower median income and higher proportion of visible minority populations (City of Toronto, 2017b).

3.2.2 The Cost of Owning a Home

Buying a home is one of the most significant purchases an individual or family can make in their entire lives. However, due to differences in purchasing power and costs of living across different areas of the country, a buyer's location will be a major determining factor for cost (either rental or ownership costs), as well as income purchasing power. A $500,000 home in Moncton, New Brunswick will be significantly different in terms of characteristics and cost burden based on expenses and income than an equivalently-priced home in Vancouver, British Columbia. Alternatively, a detached 4-bedroom home in downtown Moncton will sell for less than a comparable home (in terms of physical characteristics) in downtown Vancouver because the demand to live in downtown Vancouver is higher. This is due to many reasons, but it is primarily relevant that Vancouver has a significant number and density of higher-paying jobs than Moncton, and that the number of people already living in Vancouver is higher than that of Moncton, which makes the demand for space and employment accessibility greater. It is therefore not enough to simply use housing prices in the context of home affordability—income relative to housing prices must also be considered.

Perhaps one of the most widely-used metrics for calculating "affordability" for a home is the proportion of individual (or household) income to costs (by means of mortgage payments in the case of

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attractiveness is the most easily changed parameter for green space, as one cannot simply build a park bigger or closer to them easily. As such, promoting the use of public green space is based on the feasibility of increased *attractiveness* for that area.

purchase). The RBC Housing Affordability Measures show the "proportion of median pre-tax household income that would be required to service the cost of mortgage payments (principal and interest), property taxes, and utilities based on the average market price for single-family detached homes and condo apartments, as well as for an overall aggregate of all housing types in a given market" (RBC Economics Research, 2018, p. 7).

The metric is based on a 25% down payment, a 25-year mortgage loan at a five-year fixed rate, and is estimated on a quarterly basis for 14 major urban markets in Canada, as well as an overall average (RBC Economics Research, 2018). In RBC's case, the measure uses household income rather than family income in order to account for the growing number of unattached individuals in the housing market (RBC Economics Research, 2018). In general, the higher the measure, the more difficult it is to afford a home. For example, an affordability measure of 50% means that home ownership costs, including mortgage payments, utilities, and property taxes take up 50% of a typical household's pre-tax income.

In the case of Toronto, home ownership costs as a percentage of median household income have been rising steadily since the mid-1990s, and significantly for the past 5 years (***Figure 4***, from RBC Economics Research). As of the end of 2017, Toronto's measure sits at roughly 50%, second only to the Vancouver area at 59.3% (aggregate as of 1985; RBC Economics Research, 2018).

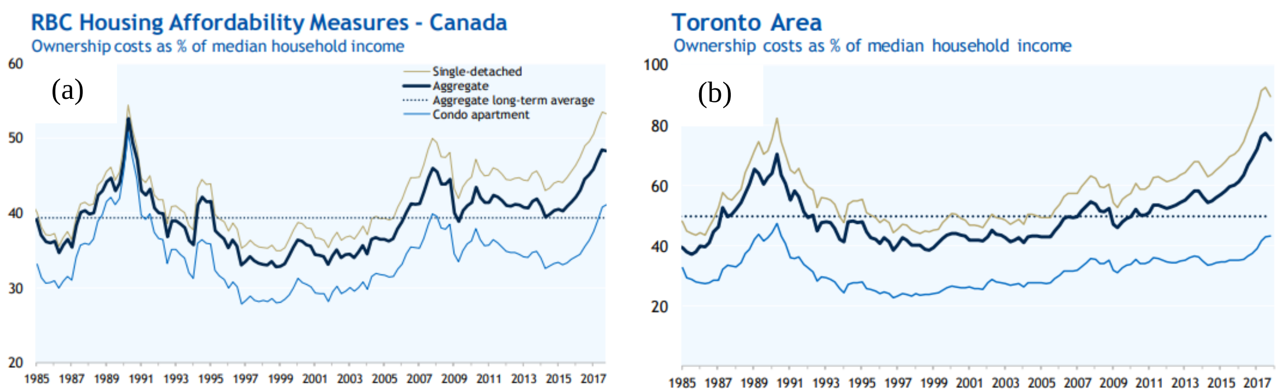


Figure 4: Historical home ownership costs as a percentage of median household income in (a) Canada, and (b) Toronto, 1985-2017. Canada's aggregate long-term average sits at just below 40%, driven primarily by dominating markets such as Toronto, Vancouver, and Montreal (From RBC Economics Research).

For comparison, Canada's long-term aggregate measure is approximately 40%. However, these values pale in comparison to recent developments in both the Vancouver and Toronto areas, with Q4 2017 measures reaching 85.2% and 75.1%, respectively (RBC Economics Research, 2018). When broken down into housing type, single-family detached homes in the Vancouver area by the end of 2017 reached an affordability measure of 116.5% (89.6% for Toronto). For Vancouver, this implies that the costs of owning a home exceed that home's total pre-tax income, which is inherently unsustainable.

For Toronto, housing prices have increased significantly over time, and in particular since the financial crisis of 2008. ***Figure 5*** depicts the average monthly house price in Toronto since January 2009.

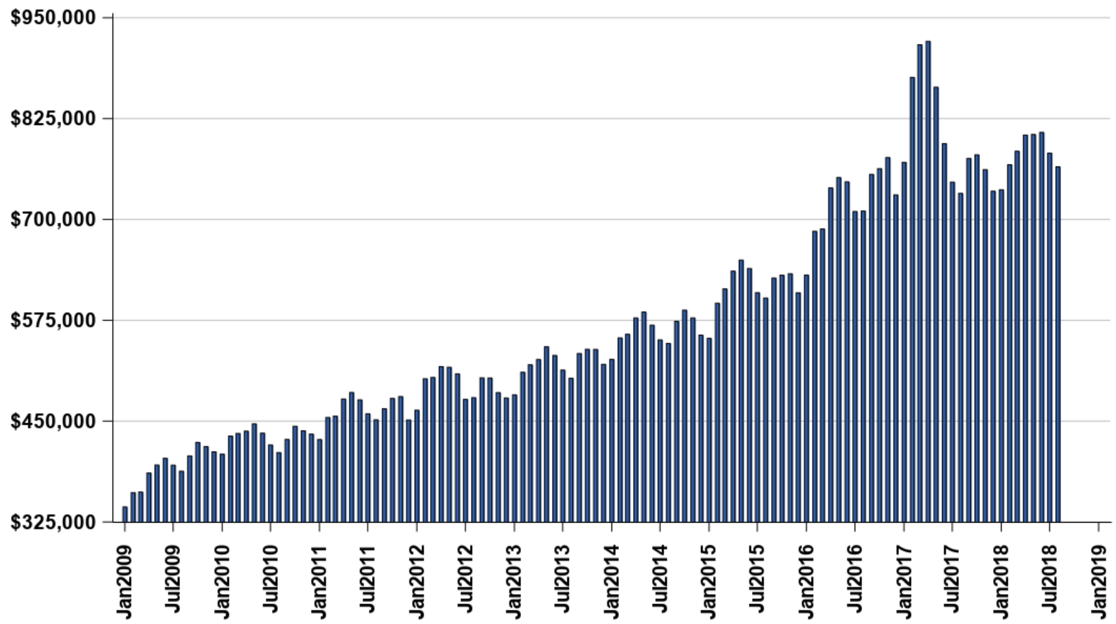


Figure 5: Housing prices in Toronto have been increasing steadily and at a significant rate since early 2009. In just under 10 years, the average house price in Toronto has gone up nearly 150%.

These increases over time are due to a variety of factors. At a basic level, the laws of supply and demand dictate that as more and more people move into Toronto, and in particular the downtown core, more housing is required. If the rate of supply cannot keep pace with the rate of demand, then prices will shift upwards. This upward trend has significant implications for employment, public policy and spending, resource management, and quality-of-life measurements.

3.3 Urban Green Space

3.3.1 Description

Jorgensen's (1974) classification of urban forestry referred to it as specialized in its objectives, with the capacity to contribute to the physiological, sociological, and economic well-being of urban society. He notes specifically that "these contributions include the over-all ameliorating effect of trees on their environment, as well as their recreational and general amenity value" (Jorgensen, 1974).

Urban green space in general in similar to urban forestry, but includes a few key nuances. Urban forestry may be classified as a subset of urban green space, which in turn encompasses the urban canopy as it exists holistically. This may be further be divided into green spaces that are either private (such as with a backyard) or public (such as with street medians). In general, while private green spaces are maintained primarily by residents and business owners, public green spaces are maintained by the City. Both front yard trees and street trees are visually accessible to the public, although property owners have a specific investment and responsibility for front yard trees, whereas the responsibility for street trees lies with the City. Thus, in some instances, street trees may indeed be more highly valued by residents as they provide amenity services without incurring significant private costs (Pandit, et al., 2013). Nevertheless, both types play a role in adding value to the urban environment, and indeed to different and varying extent.

3.3.2 Health Benefits

Numerous health benefits of green spaces to individuals are purported in the literature. Mass et al. (2006) determined that the percentage of green space inside a 1 km and 3 km radius had a significant relation to perceived general health—a relationship generally present at all levels of urbanity. The authors of the study also found that the overall relationship is stronger for lower socioeconomic groups, and that elderly, youth, and secondary educated people ostensibly benefit more from proximity to green areas in their living environment compared to other groups within large cities (Mass, et al., 2006).

More recently, a systematic review of epidemiological studies in 2015 found an association between living in greener or lusher environments and better mental health and lower all-cause mortality (van den Berg, et al., 2015). The authors of the review also note that the suggestion that a proportionately greater benefit of green space can be achieved for lower socioeconomic status groups is important due to underlying differences in health in general between high and low socioeconomic status groups (van den Berg, et al., 2015). A different study on cause-specific mortality in urban New Zealand found no significant association between assessed mortality and green space, but was limited in that it could not account for individual-level factors such as diet or alcohol consumption (Richardson, et al., 2010). The authors of the study note that the relationship between green space and health likely varies according to locational, societal, or environmental context, and that New Zealand in general has an abundance of green space with less social and spatial variation compared to other geographical areas (Richardson, et al., 2010).

3.3.3 Environmental Effects

The trees providing urban canopy coverage contribute to critical natural functions, including maintaining air quality, providing shade, controlling water flow during downpours, and absorbing airborne pollutants. These effects have historically been observed over the past several centuries, though perhaps not empirically supported until rather recently. Dr. Benjamin Rush, one of the signatories of the U.S. Declaration of Independence, insisted that deforestation across Pennsylvania in the 18th century had increased the prevalence of diseases and fevers (Rush, 1789). However, as Thompson (1978) points out, while clearing a land of its natural forest can be detrimental, Rush's position was more complicated, instead fixating on the *cultivation* of land as the source of healthful benefit through means of destroying weeds, draining swamps, and planting healthy crops and grasses (Thompson, 1978).

Indeed, the World Health Organization noted generally in a 1989 report on the health principles of housing that "The planting of vegetation in housing areas-trees along the streets, patches of greenery or woodlands-helps to improve climatic conditions in the community by absorbing dust, regulating humidity, reducing excessive exposure to sun and wind, and recharging the ground-water, and adds a touch of beauty to the environment." (World Health Organization [WHO], 1989, p. 17).

Positive externalities relating to green coverage are not limited to environmental contexts. Green spaces have also proven to act as ameliorating factors of climatic features relating to heat stress (Lafortezza et al., 2009). Frequent visits to green spaces are linked with significant improvements to well-being and reduction in heat stress episodes among urban individuals (Lafortezza et al., 2009). Further, increasing green canopy coverage has been shown to reduce stormwater runoff (through the absorptive capacities of soil), with retention ranging from 35 percent to 100 percent (Zhang et al, 2015). This reduction has significant implications for problems such as flooding, soil acidity, and water-based structural damages.

Though technical solutions to air pollution are becoming increasingly relevant in the literature, urban vegetation plays a significant role in reducing certain air pollutant levels (Jim and Chen, 2008). Work by Jim and Chen (2008) demonstrated significant and proportional reductions to SO_2 and NO_2 levels in South Chinese cities based on tree cover over time. Green space management is becoming increasingly important in the context of urban development due to the development precluding higher rates of pollution overall.

3.3.4 Ecological Benefits

Urban green spaces provide a wealth of ecological benefits to cities, ranging from the promotion of biodiversity to regulation of climate within the urban environment. Further, urban areas experience significant differences in solar input, rainfall patterns and temperature. Due to the dense built-up environment in a city centre, air temperatures, wind speeds, and relative humidity often vary significantly. Further, large areas of heat absorbing surfaces contribute to what is known as the *urban heat island effect*. In combination with high energy use in cities, urban heat island effect can increase urban temperatures by 5˚C (Haq, 2011). However, an abundance of well-distributed green space within an urban environment can offset this increase significantly (Haq, 2011).

In addition, well-designed urban green spaces play a role in maintaining urban biodiversity. Research by Byrne and Sipe (2010) proposed that green spaces with a high degree of connectivity may function as 'wildlife corridors' within an urban forest. These corridors can maintain viable populations of species that would otherwise disappear from built environments (Byrne and Sipe, 2010).

3.3.5 Toronto's Green Space

In 2013, the release of Toronto City Council's Parks Plan laid out a five-year plan covering four areas of priority: communicate and connect with users, preserve and promote nature, maintain quality parks, and strengthen system planning (City of Toronto, 2017c). On November 9, 2017, Toronto City Council adopted the Parks and Recreation Facilities Master Plan for 2019 – 2038, with an implementation plan to be submitted to Council in 2019 (City of Toronto, 2017c). However, while the Master Plan addresses parks and recreational areas in general, it does not remark on street-level forestry, which falls under the joint responsibility of the City of Toronto and homeowners. The City's responsibility lies with the portion of land between roadways and private property, known as the *public road allowance* (City of Toronto, 2017a). This distance is generally a minimum of 66 feet (20 metres) for historic reasons, but can be wider in suburban areas (Ontario Ministry of Natural Resources, 2007).

As aforementioned, Toronto has a tree canopy cover of roughly 27%, which is below the city's target coverage of 40% (Beacon Environmental Limited, 2016). The City plans to achieve this target through implementing policies, bylaws, or other programs relating to tree preservation and establishment (Beacon Environmental Limited, 2016). The city recognizes the benefits of increased canopy coverage, although individual compliance at the corporate and institutional level is variable.

3.3.6 Methods of Creating Green Space

The process of creating new green space in a dense urban environment is challenging. Many competing factors, such as areas staked for residential or commercial development, zoning restrictions, and other limiting development policies over specific areas throughout the city forces a creative approach to the layout and design of green spaces. For example, the Toronto and Region Conservation Authority (TRCA) announced in April 2018 that 16 kilometers of hydro corridor is planned to be transformed into a linear urban park (Toronto and Region Conservation Authority [TRCA], 2018). Named “The Meadoway”, this stretch of green space extends from the Don River ravine in downtown Toronto to Rouge National Urban Park, connecting 34 neighbourhoods across 200 hectares together through accessible green space (TRCA, 2018).

On an individual level, Toronto city residents can request a tree be planted on the road allowance in front of their homes. The variety of flora available is fairly broad[2], with different soil types and sunlight allowances considered. Due to site line issues with adjacent roadways, the City prohibits the planting of coniferous trees on City-owned road allowances. These issues surrounding these tree types are related to a lack of tolerance for road salt and difficulty of pruning (City of Toronto, 2018).

3.4 Measuring Green Space

Several methods for quantifying how “green” a space is are given in the literature. At a most basic level, the qualitative value estimate by an individual (such as a city appraiser) may take into account the degree of visual field coverage at street level, but the process is generally neither rigourous nor robust. A more holistic (and comparatively more accurate) description of the urban environment can be achieved through top-down imagery, such as by photograph or satellite image. In one study on property prices and their relationship to urban forests in Finland, Tyrväinen and Meittinen (2000) generated an inventory of urban forest areas using both the town plans and black and white aerial photographs from 1987, which they compile with housing sale data across the same geographic area (Tyrväinen & Meittinen, 2000). A more precise but exhaustive approach by Donovan and Butry (2010) in Portland, Oregon went so far as to physically travel to the study’s sites and count the individual trees, recording their width and height in addition to number (Donovan & Butry, 2010).

In general, there is an inclination in the literature towards using geospatial techniques to assess how green an area is (more specifically, how an area’s canopy is defined). Early methods for the analysis

[2] Available at https://www.toronto.ca/services-payments/water-environment/trees/tree-planting

of natural resources in cities through vegetation mapping led to the development of the i-Tree method (Rogers, et al., 1988). After extensive work and refinement, and through collaboration with the USDA Forest Service, the horticulture and arboriculture industry, a web app for the project was released in 2006 (Hotte, et al., 2015)[3]. The i-Tree tool functions by randomly laying points onto Google Earth imagery and then has the user classify what cover class each point falls upon. The accuracy of the analysis depends on the ability of the user to correctly classify each point into its correct class, and the precision of the estimate increases as the number of points selected increases. The i-Tree method has been used in the literature to describe street tree density as well as overall coverage (McPherson, van Doorn, and de Goede, 2016).

Many standardized literature methods involve using high-resolution GIS layer data and are interpreted automatically by software, often in conjunction with land-use zoning maps for defining boundaries. Pandit et al. (2013) use a similar method in their research on street trees and their effect on property value in Perth, Western Australia (Pandit, et al. 2013). Such a process also facilitates post hoc analyses of data such as calculating distances to key areas (central business district distance, distance to the closest transit stop, etc.), as most GIS software typically features a variety of calculation tools. In general, most papers on urban tree research focus on mathematical derivations rather than programs such as i-Tree for their methodology. A meta-analysis by Roy, Byrne and Pickering (2012) determined that of 115 original, peer reviewed research papers on urban trees, roughly 79% used mathematical derivations, while only 14% used i-Tree (Roy, Byrne & Pickering, 2012).

While the current literature methods are generally accurate and robust in quantifying the degree of canopy coverage across a city using geospatial images, they are limited in that they address green spaces (namely green canopies) that are not specifically visible to individuals living within the studied areas. As such, they are at best a proxy to the visual aspect of the urban environment—what an individual actually sees when they walk down a street.

3.5 Treepedia

Developed in 2015 at the Senseable City Lab at MIT in partnership with World Economic Forum's Global Agenda Council on the Future of Cities and its Global Shapers Community, Treepedia is an urban analytics project that maps the street-level greenery coverage within cities. The project aims to

[3] Available at www.itreetools.org, concept by David J. Nowak, Jeffrey T. Walton, and Eric J. Greenfield (USDA Forest Service). Current version adapted and developed by David Ellingsworth, Mike Binkley, and Scott Maco (The Davey Tree Expert Company)

raise a proactive awareness of urban vegetation improvement, using computer vision techniques based on Google Street View images (MIT Senseable City Lab, 2015). Treepedia maps city streets and indexes "green" values based on the amount of foliage that is visible to pedestrians at the ground level, but it does not map things like parks, forests, or other open green areas such as golf courses. This ground-level perspective is relevant to this research presented herein because the mapped values represent what individuals walking down a street can actually see, as opposed to a proxy for visible greenery (*i.e.* the green *canopy*).

Treepedia allows city dwellers to view the location and size of tree coverage within their communities and to submit input to help tag, track, and advocate for more such trees in their cities. Cities such as Boston, London, Paris, Oslo, and Toronto have already been indexed to a comparable extent, with more being added as data is collected (***Figure 6***). Specific methods for Treepedia's use and application are discussed in ***Methodology***.

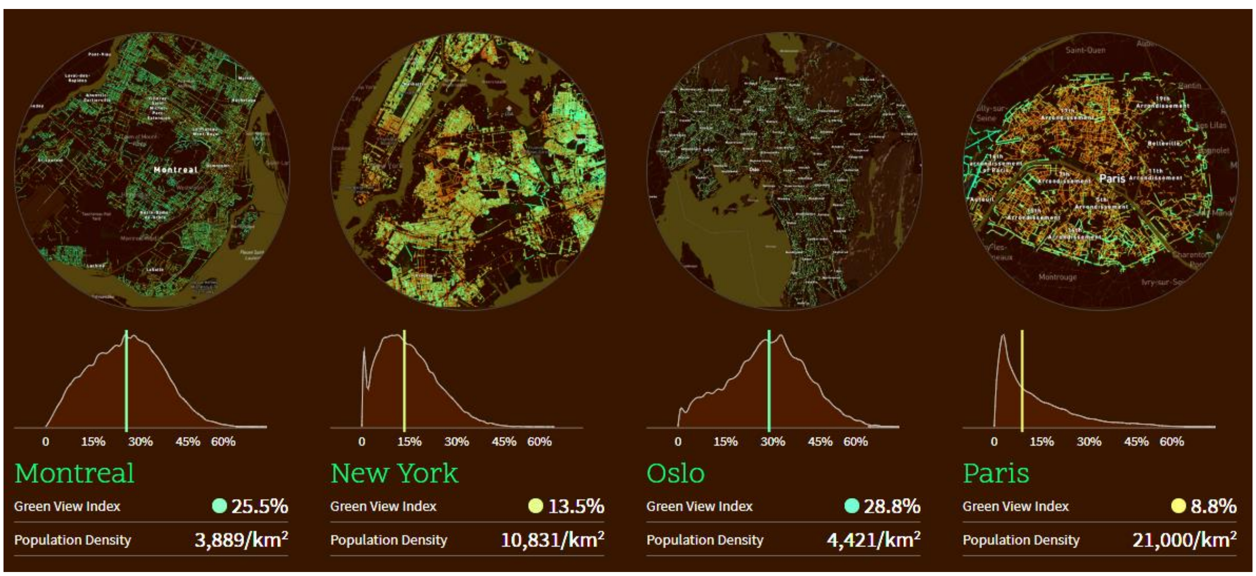


Figure 6: A selection of city green view indices collected by the Treepedia project researchers. GVI distribution and average values are shown in comparison to population density (From http://senseable.mit.edu/treepedia)

3.6 Street-Level Greenery

Work by Li et al. (2015) and Seiferling et al. (2017) developed a scalable and robust method of quantifying street-level canopy coverage in major urban areas by algorithmically analyzing the amount of green perceived while walking down the street (Li et al., 2015; Seiferling et al., 2017). Of the cities studied, Toronto ranked fifth in terms of street-level canopy coverage, at 19.5% overall—ahead of Los Angeles, New York and London, but behind Vancouver at 25.9% coverage (Seiferling et al., 2017). Compared to an estimated canopy coverage of 27%, Toronto's street-level coverage (and indeed all cities' street-level coverage) is lower, but more precise when quantifying the degree of individual visibility throughout its urban environment.

3.6.1 Urban Greenery & Household Income

There are several modern studies in the literature that address the nature of income inequality as it relates to canopy coverage. Research by Iverson and Cook (2000) found that both household income and household density and strongly related to land covers (particularly those with tree cover and urbanized land) in the Chicago region (Iverson & Cook, 2000). The authors note that both ends of the relationship scale are highly apparent, with the poorest areas being strongly correlated to urban land and a lack of greenery, most likely within housing projects in the city centre, and the greatest tree cover within the city exists where income is three to four times higher than the regional average (Iverson & Cook, 2000). The authors also note that for these wealthier urban areas, the properties have proportionately more manicured grassland compared to tree cover, and also that there is a higher degree of income variability for middle-income earners (Iverson & Cook, 2000).

Later work by Heynen and Lindsey (2003) reported no such relationship between tree canopy coverage and median household income for homes in Indiana (Heynen & Lindsey, 2003). However, the authors used county-level data, such that certain variables exhibited particularly large value ranges. Population density, for instance, ranged from 80 persons per square kilometer to nearly 2,050 persons per square kilometer, which may not accurately capture the essence of an "urban" environment. Work by Schwarz et al. (2015) also determined a positive correlation between urban tree canopy (UTC) cover and median household income across several US cities (Schwarz et al., 2015). However, the methods outlined by this work used high spatial resolution imagery from satellite ("bird's-eye view") perspectives, as opposed to street-level coverage, such as would be seen from an individual on their front lawn. Nevertheless, the authors report a positive correlation with income across all cities studied, with the strongest correlations existing in more arid cities (Schwarz, et al., 2015). This may be due to the higher cost of maintaining a green space in climate regions that are dryer or hotter, especially in areas that are prone to drought such as in California.

Recent work by Greene, Robinson, and Millward (2018) examined the nature of Toronto's household incomes as they relate to canopy coverage, both realized and potential (Greene, et al., 2018). In their work, the authors report a measureable inequality of access to the urban tree canopy according to median household income (Greene, et al., 2018). In terms of rectifying this inequality, further development of green space (especially in low-income areas) is essential. Greene et al. (2018) points out that areas with a significant proportion of high-median-income earners are generally older—they exhibit lower degrees of new construction and are *stable* in terms of socio-demographic characteristics, contributing to the generation and maintenance of a more extensive tree canopy over a long time period (Greene et al., 2018). As such, a case for examining the impact of street-level greenery on property values is further supported. Additionally, the authors note that this level of inequality is exacerbated by the notion that spatial clusters of simultaneously both low-income households and low realized and potential tree canopy cover are the most restricted for increasing green space (Greene et al., 2018). This is due to lower individual and public investment, a lack of light from building shadows, space constraints for growth, and a lack of soil volume (Greene, et al., 2018).

3.7 The Value of Green Space

Urban green space has demonstrable value in several different contexts. The health, environmental, and ecological benefits have been described above, and research into these topics is extensive. However, the monetary value of street-level greenery to properties and neighbourhoods has been studied in the literature to a lesser extent. Nevertheless, evaluation of the monetary value of urban forests includes not only forest functional characteristics, but also amenity benefits. This evaluation requires careful consideration from planners and managers during the land use proposal and city-building process (Vandermeulen et al., 2011). Indeed, urban forest protection and management is most effectively promoted when the key financial components involved are able to be compared with other city infrastructure during budget analysis (Hotte, et al., 2015).

The evaluation of trees in an urban environment has seen a number of approaches in the literature. Historically, trees have been appraised based on their compensatory value in the case of damages and loss. In North America, the precedent for assessing compensatory value of trees was developed by the Council of Tree and Landscape Appraisers in 1992 (Nowak, Crane, & Dwyer, 2002). These values can and have been used to estimate actual or potential loss caused by catastrophe such as major storms, fire, and earthquakes (Nowak, et al., 2002). Using this appraisal method, the value of the Toronto urban forest is over $16 billion, based on an average value of $700 per tree (Farr, 2004). Further, a report issued by TD Economics highlighted that for every dollar spent on annual maintenance, Toronto's urban forest returns between $1.35 and $3.20 worth of benefits and cost savings each year (Alexander & McDonald, 2014).

Distance to public green space has been cited in the literature as a contributor to neighbourhood property valuation increases. Morancho (2003) found an inverse relationship between the selling price of a dwelling and its distance from a green urban area in a study in Spain (Morancho, 2003). However, the author of this study also notes that housing size was the most relevant variable with regards to price in their model (Morancho, 2003). Findings by Morancho (2003) were also found to be in agreement with those of a 2000 paper on homes in Portland, Oregon, which explored the relationship between housing prices and proximity to open space (Bolitzer & Netusil, 2000). Though a statistically significant relationship was found, the paper has several drawbacks of addressing open space as a general concept. For instance, the originally-studied Portland Metro area consists of approximately 8% publically-owned open spaces, with more than half of which existing in a single park. With a total study area of roughly 3,700 hectares, the sheer width of a single open space can separate vastly different neighbourhoods in the context of income and plot size. Indeed this issue is also relevant for other large open green spaces such as golf courses or ravines, which can sprawl in different directions and make comparisons between adjacent neighbourhoods more susceptible to confounding variables.

Nevertheless, numerous reports in the literature that highlight the spatial variation in amenity values for both quantity and quality of green open space in the housing market exist. One study in the Netherlands demonstrated an increase in housing sale prices of up to 28% due to environmental factors (Luttik, 2000). The author of the study found that within the set of homes studies (N = ~3,000), price increases were found for homes built in proximity to bodies of water (8-10%), or open space (6-12%), with attractive landscape types shown to attract a premium of 5-12% over less desirable sites (Luttik, 2000). For consistency in data, the author noted that the dataset of houses included only transactions for units built after 1970 (to roughly control for maintenance levels) and sold between 1989 and 1992, a particular period characterized by price stability in the region (to minimize the impact of inflation)(Luttik, 2000).

More recently, Cho et al. (2008) showed that differences in green space attractiveness exist across urban areas and semi-urban/rural areas. In general, the authors determined that natural forest edges and a diverse landscape was more highly valued in rural contexts, and smoothly-trimmed and man-made forest patch boundaries were more highly valued in urban core areas (Cho et al., 2008). In this sense, a dense urban area likely requires more efficient use of open space in the context of greenery, as space and layout of greenery is restricted to a far greater extent compared to rural areas.

In the context of providing asset value to property, urban trees have been shown to play a small but significant role. A study by Donovan and Butry (2010) determined that street trees in Portland, Oregon added US$8,870 on average to the sales price of homes (roughly 3.0% of median sales price). In their analysis, the authors determined that the majority of tree variables collected were not significant, with only number of trees and crown area within 100 ft of the house being significant (Donovan & Butry, 2010). Earlier work on homes close to forested areas in Finland found that an increase of 1 km from a forested area reduced sales price by 5.9%, and properties with a direct view onto a forest increased sales price by 4.9% (Tyrväinen & Miettinen, 2000).

A 2016 meta-analysis on hedonic property values demonstrated a positive and significant relationship between property values and proximal tree canopy coverage in the U.S. (Siriwardena, Boyle, Holmes, & Wiseman, 2016). Interestingly, the authors of the studied also showed that squared (quadratic) regression terms surrounding tree canopy coverage produced a negative coefficient, indicating that there are diminishing returns to greenery and indeed an inflection threshold at which point additional greenery near a property may detrimentally impact its value (Siriwardena, et al., 2016). As the authors point out, this may be the case for several reasons:

- Shade is desirable, but too much shade may block wanted sunlight
- Green coverage provides privacy, but may obscure otherwise attractive views
- Trees provide aesthetic value for homes, but require maintenance and care
- Trees attract wildlife, but an excess of foliage may attract undesirable wildlife
- Trees provide cover from weather, but may act as a hazard in extreme situations

(Siniwardena, et al., 2016)

3.8 On Hedonic Models in the Literature

Although house pricing models that incorporate environmental variables have been tackled in the literature for many years, a focus towards the effect of proximity to green space on housing prices and perceived neighbourhood attractiveness have only in the last two decades become more prominent. Work of this nature generally captures hedonic variables and modelling techniques. In the context of asset pricing, a hedonic regression analysis estimates the relationship between the price of an asset and all of its characteristics, *i.e.* independent variables (Boardman et al., 2004). More rigorously, hedonic prices are defined as "the implicit prices of attributes and are revealed to economic agents from observed prices of differentiated products and the specific amounts of characteristics associated with them" (Rosen, 1974, p. 34).

In general, the method measures the value of a non-market good by utilizing the value of a market good (or group of market goods). The hedonic pricing method also estimates the willingness to pay function of consumers, accounting for individual incomes and tastes. For example, the willingness to pay for a park is expressed in terms of how much property owners would pay for a view of or access to the park (Tajima, 2016). However, there are many other factors influencing the value of the park that are not accounted for, which limits the efficacy of such a pricing model.

Boardman et al. (2004) notes that several caveats with hedonic models exist. The model assumes perfect information and knowledge exists of all relevant characteristics to the consumer, requires correctly measured variables (as opposed to proxy variables), assumes linearity (which is almost never the case in the real world), requires the availability of many different “comparable” assets in the market, and assumes market prices adjust immediately to characteristic changes (Boardman et al., 2004). In a study by Luttik (2000) on housing prices adjacent to open spaces in the Netherlands, the author notes that caution must be exercised when applying hedonic models based on specific datasets to novel areas (Luttik, 2000). The premium in each case is relative; it applies to a group of houses in relation to a specified group of other houses. As such, the value of a specific attribute can only be tested if suitable situations with and without can be found (Luttik, 2000). This follows the “comparable” assets requirement that Boardman et al. points out.

Despite these drawbacks, the hedonic model has been used throughout modern literature on the valuation of green areas in urban environments. The vast majority of these studies explore urban green areas as parks, public gardens, or other open green spaces near to housing units. Boardman et al. (2004) also describes several other valuation methods, each of which have their own advantages and disadvantages. The travel cost method, suited more for valuation of recreational sites, considers the differences in total costs incurred by individuals depending on proximity to an amenity, but incurs the challenge of estimating opportunity costs (Boardman et al., 2004). The defensive expenditures method on the other hand describes an amount spent to mitigate the effect of a negative externality, which is more applicable in a case which considers some production process—Boardman uses the example of hiring someone to clean windows in a smoggy city, where the cost incurred is dependent on the pollution level (Boardman et al., 2004).

3.8.1 Other Models

Tajima (2016) discusses the usage of a contingent valuation method for evaluating a public good by directed asking a group of people how much they are willing to pay for a given good, such as for different hypothetical scenarios (Tajima, 2016). Fuguitt & Wilcox (1999) note that as there are no observed economic activities for imaginary scenarios, contingent valuations must be based on a survey (Fuguitt & Wilcox, 1999). While contingent valuation offers the benefit of evaluating goods and functions by informing people about the goods through the survey, it has several shortcomings. Namely, the notion that people are often unable to express an exact value, and may provide a wide range based on different levels of personal perceived value of a given good. Further, when survey respondents know that they are not actually required to pay for the good in question, their responses may be based on inflated valuations (Tajima, 2016).

4. Problem Statement

Asset valuation of street-facing greenery has in the literature been derived from physical perspectives (satellite imagery or zoning maps) that are fundamentally restrictive to the models generated from them. In order to accurately assess the utility of street-facing greenery on measures such as housing prices, the data and analysis must come from street-level data. This data represents the green space that is directly visible to individuals within an urban environment.

4.1 Hypothesis

Based on review of the available literature, it is hypothesized that there will be a positive correlation between street-level canopy coverage and housing prices. This relationship is predicted to be most applicable to low-rise housing such as detached or semi-detached homes, and a lower impact is expected for high-rise units such as condominiums. The reasoning behind this thinking is that trees require space, and dense urban environments such as Toronto command a high value on individual space, increasing towards the downtown core. As such, the utility offered by a downtown location likely far outweighs the value added by increasing nearby green space. Additionally, it is reasonable to believe that an individual or family living on the 30^{th} floor of a condominium in downtown Toronto will not strictly consider how lush the street-level canopy is in regards to the cost of their unit.

5. Methodology & Data

5.1 Green View Index Data

Work by Li et al. (2015) established a novel data set using modified Google Street View (GSV) images (Li et al., 2015). The GSV images display 360^o horizontal coverage and 180^o vertical coverage, providing a panoramic view that is stitched together to formulate images that comprise the entirety of a given street section. The green vegetation captured in these images was allocated appropriately into the dataset by comparing light reflectance values (Li et al., 2015). Green vegetation has a high reflectance at the green band and comparatively low reflectance at both red and blue bands. Using this criterion, the collected images were appointed “green view” value compositions based on the pixel values of the green band (provided that the green band pixel values are larger than the red band values in the same image; Li, et al., 2015). Finally, 6 horizontal images and 3 vertical images (***Figure 7***) were considered at each direction for each image, giving green value indices calculated as per:

$$Green\ View = \frac{\sum_{i=1}^{6}\sum_{j=1}^{3} Area_{g\_ij}}{\sum_{i=1}^{6}\sum_{j=1}^{3} Area_{t\_ij}} \times 100\%$$

Where $Area_{g\_ij}$ is the number of green pixels captures in one of these images for all captured directions, and $Area_{g\_ij}$ is the total pixel number for each of the GSV images (Li et al., 2015). Accuracy assessment of the authors’ automatic classification results was conducted using 33 randomly selected GSV images. The authors report an R^2 value of 0.96 (root mean square error of 2.9) for the relationship between the modified GVI values calculated using their proposed method and the corresponding values calculated based on the reference data delineated manually using Photoshop (***Figure 8***, Li et al., 2015).

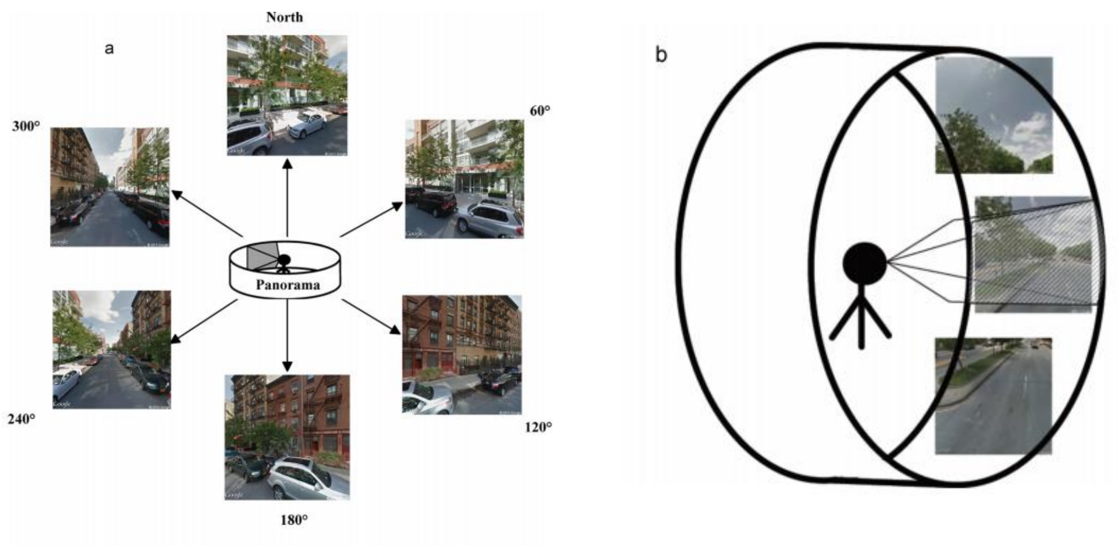


Figure 7: GSV images captured in six directions at a sample site in the study area (a) and GSV images captures at three vertical view angles at a sample site (b) (From Li et al., 2015).

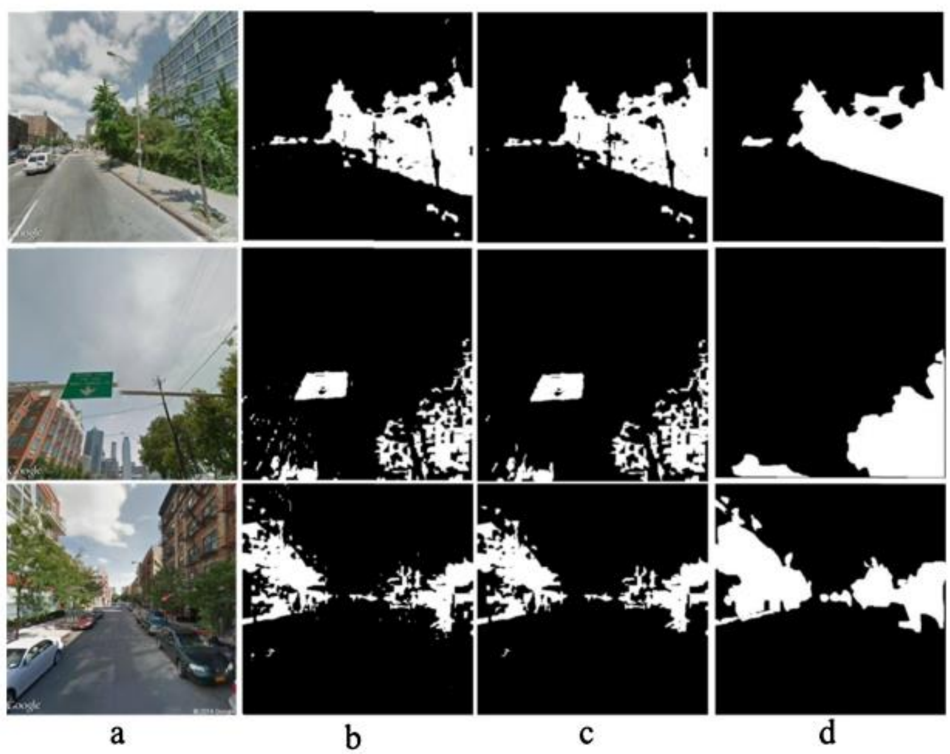


Figure 8: GVI generation and reference images: (a) original GSV images, (b) initial classification results, (c) refined classification results, and (d) manually extracted green vegetation (From Li et al., 2015).

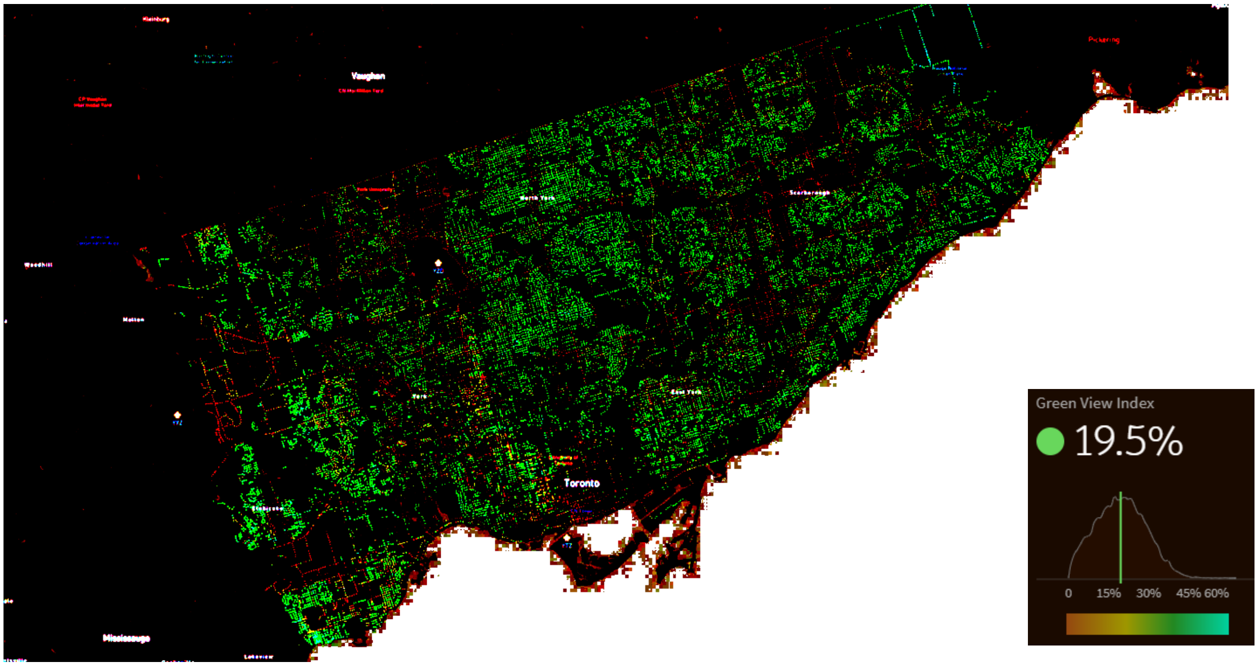


Figure 9: Overview of Toronto's Green View Index profile. Data points that are more "green" or lush are more bright green in colour, and low-GVI areas are coloured in yellow to red (From Li et al., 2015, retrieved from the Treepedia website at http://senseable.mit.edu/treepedia/cities/toronto).

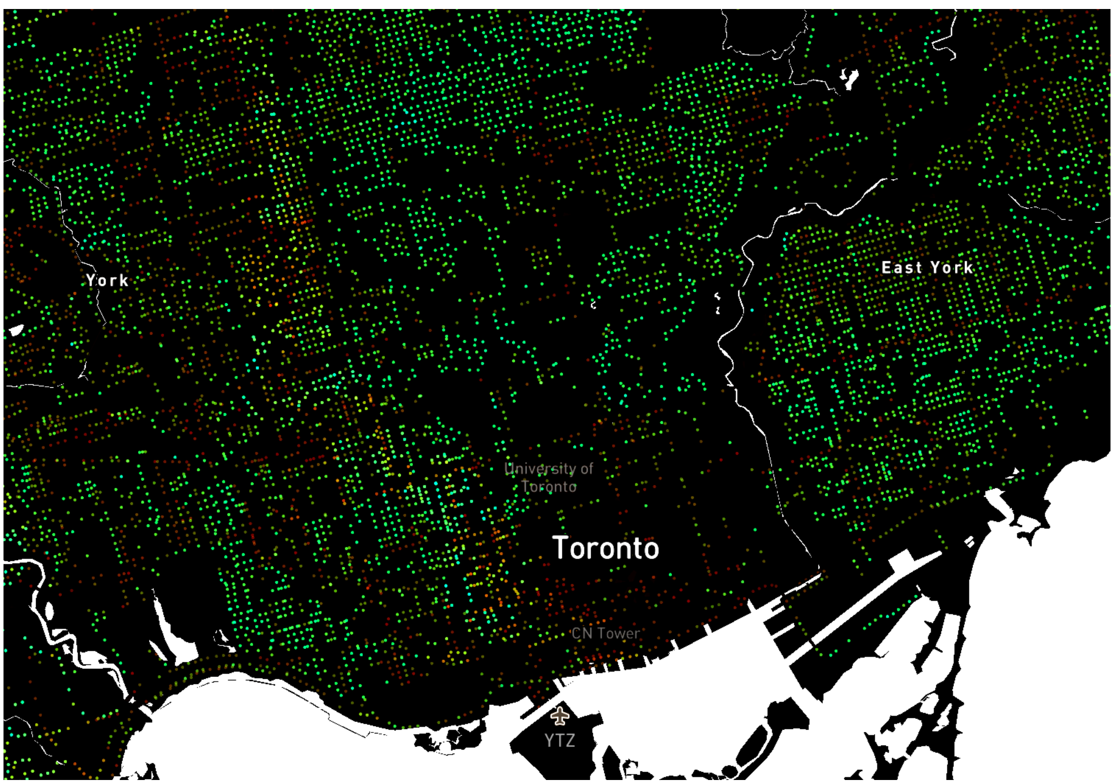


Figure 10: A closer look at downtown Toronto's Green View Index profile. Data points that are more "green" or lush are more bright green in colour, and low-GVI areas are coloured in yellow to red (From Li et al., 2015, retrieved from the Treepedia website at http://senseable.mit.edu/treepedia/cities/toronto).

5.1.1 Temporal Differences in Data

The authors of the Treepedia study note that at the time of data collected the Google Street View Image API was not able to deliver multi-temporal GSV images for one location (Li et al., 2015). Further, the authors manually filtered a handful of GSV images taken in the winter months when street-level greenery was less apparent. As such, temporal changes in variables studied against the GVI data are not able to be measured.

However, a different approach may be used to assess the effect of greenery at street level being visible and accessible to individuals. Separating housing sales data into two temporal categories (treated vs. untreated) that consider the individual ability to view "green view indices" allows for a comparison during the regression modelling process. For the untreated subset (*i.e.* for homes sold during winter months), the buyers/sellers are unable to directly appreciate the potential intangible value offered by the proximal greenery, whereas those in the treated subset directly experience the hypothetical benefits of greenery (as it is "visible").

5.2 Housing Data

The original housing data file (a .csv file) contained 79,586 records of homes sold in the Toronto Census subdivision area between January 2016 and January 2018. The data were merged with the green index data file on the basis of longitudinal and latitudinal coordinates. Because coordinates for both files were not able to be matched identically, a buffer was created around green view index coordinates. In general, the minimum distance between two GVI values is 20 metres. Thus, while a GVI value may not geographically line up exactly with the positioning of a given property, the corresponding greenery is within a short visual distance of its purported value. Qualitative examples are given in *Discussion*.

Data in the form of comma-separated values was imported into R for filtering and analysis. Non-applicable variables (those where sold price was not included) were removed from the R data file, and the remaining variables were cleaned and sorted, resulting in a total of 79,557 records. It was hypothesized that the effect of greenery on a property type such as a high-rise condo would be different than that for a detached house. As aforementioned, it is expected that an individual or family living on the 30th floor (for example) of a condominium is less likely to find direct asset value of street-level greenery than someone who can see the proximal greenery from their living room. As Li et al. (2015) points out, there may indeed be discrepancies between land cover maps and GVI values, as pedestrians' viewing scope on streets may be blocked by buildings or be otherwise obscured (Li, et al., 2015). As such, in order to properly assess the effect of greenery on property values, the data set was subset by property type. The property types and their relative makeup are as follows:

```
                             Overall
n                            79557
Property Type (%)
   Condo Apt                 40263 (50.8)
   Detached                  22767 (28.7)
   Semi-Detached              6811 ( 8.6)
   Condo Townhouse            5188 ( 6.5)
   Att/Row/Twnhouse           2547 ( 3.2)
   Common Element Condo       1315 ( 1.7)
   Multiplex                   356 ( 0.4)
   NA                          310 ( 0.4)
```

The appropriate variables to be used for each model depend on the property type. For instance, characteristic amenities such as ‘hydro included’, ‘parking included’, and ‘ensuitSe laundry’ apply only to condominiums and condo townhouses, and not to detached or semi-detached homes. Variables such as number of bedrooms or washrooms apply to all types. Summary statistics for applicable variables are given in the Appendix [see ***Data Tables***].

Housing price was also separated by property type. For illustration of the reasoning behind this separation, as per ***Table 1***, the mean sale price of homes with the property type of condo apartment is significantly less than the sale price for detached homes—roughly $500,000 compared to $1.3 million, respectively, with a slightly upward skew compared to the median values for each type due to a number of high-priced properties. In order for accurate comparison and modeling with respect to street-level greenery, it is critical for property types to be assessed separately.

For each property type, housing prices below $50,000 were deemed ineligible due to likely being entry errors, and were accordingly filtered from the dataset. Properties with values greater than $8,000,000 were also excluded as they are considered luxury outliers. The filtered summary statistics for sale price by property type are shown in ***Table 1***.

Table 1: Summary statistics of sale price by property type, filtered

Property Type	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Detached	$360,000	$756,000	$1,000,000	$1,308,408	$1,560,000	$8,000,000
Semi-Detached	$310,000	$670,000	$820,000	$925,112	$1,050,000	$7,100,000
Att/Row/Twnhouse	$362,000	$650,000	$795,000	$882,116	$1,000,000	$5,600,000
Multiplex	$420,000	$996,000	$1,310,000	$1,456,567	$1,699,250	$5,850,000
Condo Apt	$52,000	$345,000	$432,890	$495,117	$560,000	$7,000,000
Condo Townhouse	$85,000	$425,000	$525,000	$578,171	$650,000	$5,550,000
Common Element Condo	$72,000	$315,000	$405,000	$450,089	$525,000	$2,600,000

Due to the existence of several property sales with substantially high values, the mean sale price for each property type is skewed upwards. This is illustrated in ***Figure 11***. In general, high-rise-type units (condo, condo townhouse, and common element condo) sold for lower prices than low-rise-type units (detached, semi-detached, townhouses, and multiplexes), and also had lower degrees of price variability. It is worth noting that most of the property types have positive skews that reflect a strong degree of high-value sales. Taking the natural logarithm of sale price results in an improvement towards normality, but is also done for comparative reporting purposes (***Figure 12***).

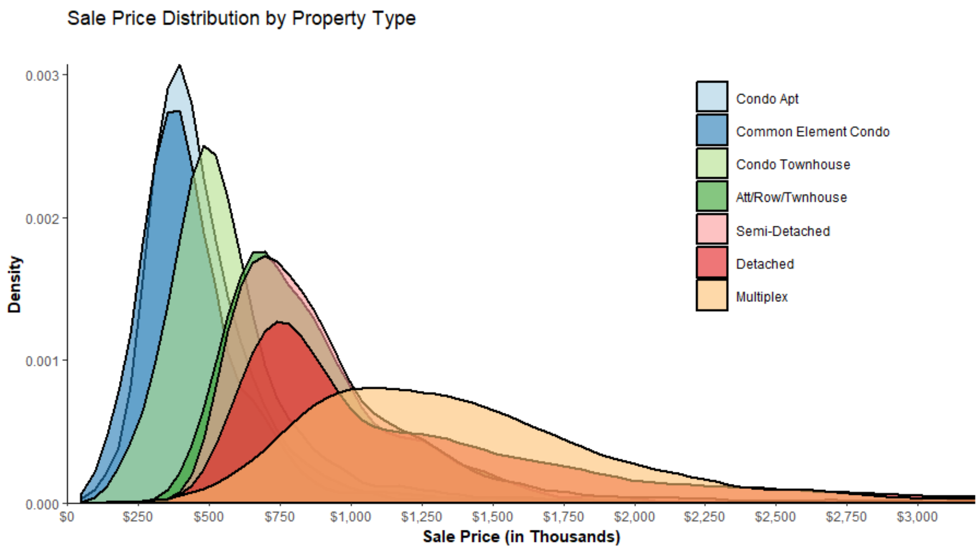


Figure 11: Value density distribution for sale price (in thousands of CAD) according to property type. High-rise housing types (condo and related) show in general a lower sale price and a lower degree of variability compared to low-rise types (detached, semi, etc.). Units with sale prices greater than $3 million are truncated for visualization purposes.

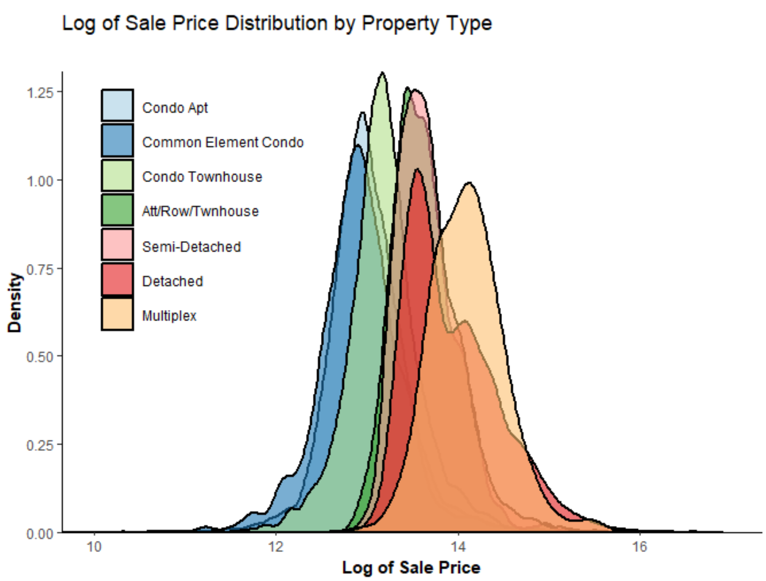


Figure 12: Value density distribution for natural logarithm of sale price according to property type. Note that while pricing distributions are generally more comparable across housing types compared to simply using sale price, that the distributions themselves are not completely normal, in particular for detached homes.

In particular relevance to condos and related property types, unit square footage is also reported (***Table 2***). The data show that across the different varieties of condo-related property types, condo townhouses on average had the largest square footage, with a mean of 1,327 sqft, followed by condo apartments and common element condos, at 869 sqft and 839 sqft, respectively. However, condo apartments were skewed upwards by the inclusion of very large units (approx. 5,000 sqft), which account for units such as penthouse apartments and other high-value spaces. For low-rise type properties (detached, semi-detached, row/townhouse, multiplex), square footage is generally higher by 2-fold or 3-fold, depending on specific type.

Table 2: Summary statistics of square footage by property type

Property Type	Min.	1st Qu.	Median	Mean	3rd Qu.	Max
Condo Apt	500	650	750	868	1,100	5,000
Condo Townhouse	500	1,100	1,300	1,327	1,500	4,250
Common Element Condo	500	650	750	839	950	3,375
Detached	700	1,750	2,250	2,477	3,250	5,000
Semi-Detached	700	1,300	1,750	1,845	2,250	5,000
Att/Row/Townhouse	900	1,750	1,750	1,924	2,250	5,000
Multiplex	1,300	2,250	2,750	3,031	4,000	5,000

For detached and related property types, square footage ranges are also reported, but are missing in over 70% of the data, significantly reducing the number of model observations. For the largest low-rise category property type (detached houses), this reduction leaves 6,220 observations. Although this reduction is significant in proportion to the total dataset size, it is deemed necessary to include property size (range in square feet) in this paper, as the metric is of primary importance in a real estate context and is reported in hedonic pricing models throughout the literature (Zabel, 2015; Mok, Chan, and Cho, 1995; Meese and Wallace, 1991; Donovan and Butry, 2010; Tyrväinen & Miettinen, 2000; Pandit, et al., 2013[4]).

In order to assess if this subset of data involving recorded square footage values is statistically applicable, we compared the mean of the subset for low-rise homes that report living area to the mean for low-rise homes that do not report. For the low-rise housing data in which square footage is reported, the mean value of the natural logarithm of sale price is 13.798, and for the data subset where square footage is unreported, the mean value of the natural logarithm of sale price is 14.023. Because n is fairly large for these data, we run into the issue of encountering a significant statistical difference when comparing the

[4] Pandit et al. reports land area (lot area) in their model. A handful of papers report both land area and living area, most report only living area.

means *via* parametric testing, even though the actual means are reasonably similar. Further, an examination of the comparison between the two subsets for low-rise housing (***Figure 13***) show a reasonably consistent distribution across price, in a psuedo-bimodal fashion.

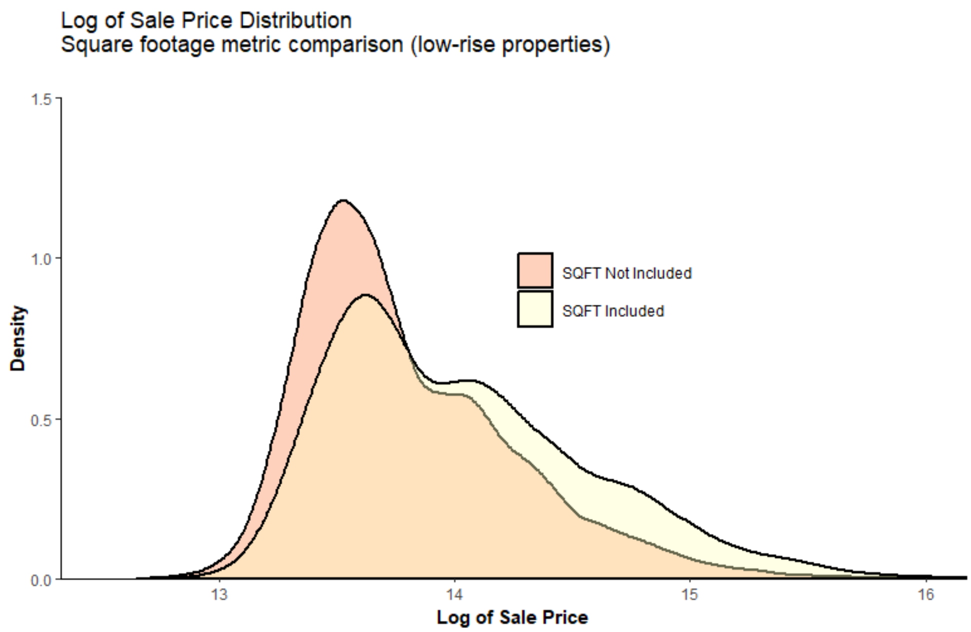


Figure 13: Value density distribution for the natural logarithm of sale price for low-rise properties, comparing where square footage is reported and where it is not. Although relative distributions show similarities across the curves, properties where square footage was reported are skewed slightly towards higher sale prices.

Thus, we limit our low-rise data to only include properties that have square footage reported, such that a more holistic asset description can be achieved.

5.2.1 Property Type Descriptions

Detached homes are permanent dwellings which house a single family, and are physically separate from adjacent housing units. Semi-detached homes are attached on one side, with each unit typically housing a single family. Row houses and townhouses are terraced homes that have shared side walls. Multiplex homes (duplex, triplex, etc.) are buildings that are divided into multiple units. Each household has its own entrance and is responsible for its own unit. It is common for multiplex units to be rented out by a primary building owner in order to offset mortgage payments and provide a continuous revenue stream. Condominiums are property types where the buyer owns the unit, but not the land on which it is built or any common space outside of the unit itself. Condos are generally found in apartment buildings, but townhouse condos and common element condos (where certain amenities are shared among the unit owners) are also common.

5.3 Housing Regression Models

Regression analysis (ordinary least-squares, OLS) is performed herein to describe the nature of a potential relationship, using Green View Index values as predictors for development and demographic data. In general, regression analysis allows for the description of the relationship between a dependent variable and its explanatory variables. The general equation for such a relationship is as follows:

$$y_i = \alpha + \beta_1 X_i + \cdots + \beta_n X_i + \varepsilon_i \qquad \textbf{Eq. 1}$$

Where y is the value of the dependent variable (e.g. house sale price), α is a constant, X_i represents an explanatory variable at observation i, and ε is an error term (the *random* component). For each explanatory variable, the magnitude of the term's impact on y is denoted by β (the slope). In a theoretical context, each term acts purely independently of the other terms, describing only its own impact unto the dependent variable. In real world examples, this is often not the case; confounds often exist between the explanatory variables. In the context of hedonic price modeling for housing markets, Tajima (2016) gives the example:

$$\ln P_{ij} = \alpha + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2j} + \beta_3 \ln X_{3j} + \varepsilon_{ij} \qquad \textbf{Eq. 2}$$

Where i indexes a condominium unit, j indexes the condominium building, P is the assessed value of each unit, X_1 is a vector representing physical characteristics of each condo unit, X_2 is a vector of location attributes of the buildings (such as distance to subway stops, etc.), X_3 is a vector of community attributes (dummy variables for zip codes), β_i is a vector of price elasticity with respect to each estimator, and ε_{ij} is an error term (Tajima, 2016). Logarithmically transforming variables in a regression model is a technique that may be employed to deal with scenarios where a non-linear relationship exists between the independent and dependent variables (Benoit, 2011). More specifically, these transformations are convenient for turning a highly skewed variable into one that is more approximately normal. This is important because multiple linear regression requires that the associated residuals are normally distributed. A *log-normal* distribution is one whose logarithm is normally distributed but whose untransformed scale is skewed (Benoit, 2011).

Different model types exist for different response variables and expressions of the dependent variable Y. For a purely linear model, the equation follows as in ***Equation 1*** (above). In many cases however, transformations of an independent variable is necessary. A *linear-log* model may be interpreted such that a one-unit increase in log$X$ will produce an expected increase in Y of β units (Benoit, 2011), such that:

$$y_i = \alpha + \beta \log X_i + \varepsilon_i \quad \textbf{Eq. 3}$$

More generally, we have that the expected change in Y associated with a p% increase in X may be calculated as β * log([100 + p]/100). For small p, the numerator within the logarithm approximates to p/100, such that for p = 1, we see that β/100 can be interpreted roughly as the expected increase in Y from a 1% increase in X (Benoit, 2011).

For a *log-linear* model, we interpret that a 1-unit increase in X multiplies the expected value of Y by e^{β}, as per the equation (Benoit, 2011):

$$\log Y_i = \alpha + \beta X_i + \varepsilon_i \quad \textbf{Eq. 4}$$

For a *log-log* model (***Equation 5***), we have both the dependent and independent variable(s) being log-transformed. For a p percent increase in X, the proportional change in Y followed from first calculating a = log([100 + p]/100) and use $e^{a\beta}$ (Benoit, 2011).

$$\log Y_i = \alpha + \beta \log X_i + \varepsilon_i \quad \textbf{Eq. 5}$$

In the case of the hedonic model, variable coefficients are expected to have positive values for which a larger value is desirable, such as with lot size, number of bedrooms, and distance to a highway. Conversely, negative coefficients are expected for variables for which a smaller value is desirable, such as age of buildings or distances to subway stations or green open spaces (DiPasquale & Wheaton, 1996).

Using the indexed data from previous research by Li et al. (2015) and Seiferling et al. (2017) (from the Treepedia project), correlation analysis is performed in order to assess if a relationship exists between GVI (green view index) values and housing prices, controlling for other relevant factors. Housing characteristic and locational data is applied through GIS mapping across the Toronto area and compared to GVI values.

5.3.1 Variable Types

A regression model was estimated for each subset property type, and explanatory variables were explored and used as appropriate for each type. For both major functional property type categories (low vs. high rise), there are three comprising predictor categories: characteristic variables, locational variables, and demographic variables.

5.3.2 Characteristic Variables

Characteristic variables encompass the physical attributes of the property in question. These types of predictors are most commonly used in everyday valuations of properties and homes, and are generally the most intuitive set of descriptors for comparison by realtors and homebuyers. For condo apartments, condo townhouses, and common element condos, the characteristic explanatory variables chosen were green view index, square footage, building age range, number of above-ground bedrooms, number of washrooms, indicators for family room, hydro included, parking included, heat included, and locker included. These characteristics were chosen to represent one of the most significant factors considered when purchasing a home: space and how it relates to amenity value. For instance, for condos and related property types, it is anticipated that an increase in square footage will have a positive impact on sale price. Further, it is expected that newer buildings will sell for higher prices than older buildings, and it is expected that the magnitude of the effect of street-level green index values on condo unit sale prices will be low or insignificant.

For detached homes, semi-detached homes, attached/row/townhouse homes, and multiplexes, the selected characteristic variables were green view index, number of above-ground bedrooms, square footage, number of washrooms, type of parking available, and an indicator variable for family room. Housing size (square footage) is expected to correlate positively with sale price, for reasons similar to those above. For detached homes, space is generally seen as a more important feature than location, compared to condos, and also relates closely with household lifestyle. For instance, individuals who live in a detached (or similar) home outside of the city centre but commute downtown to work are likely to drive if they are not near to a subway. This precludes a higher likelihood of, say, owning a car, and as such a higher likelihood of desiring private parking options. These options (such as a drive way or separate garage) necessarily remove space that could otherwise be covered by greenery, but in return provide a different type of utility, namely parking (asset *storage*).

5.3.3 Locational Variables

Locational variables involve proximities to nearby amenities or potential *dis*-amenities and how they influence value. The impacts of these variables are more complex and less tangible than characteristic variables. For instance, it is easier to grasp the direct value of another washroom in a detached home versus moving that home an additional 500 metres from a highway, even though there is a clear benefit of moving further away from the highway (less noise, less traffic, better neighbourhood aesthetic, etc.).

The locational variables chosen are identical for both property type categories. They include distance to central business district (CBD, in this case the intersection of King St and Yonge St), distance to a subway, distance to a highway, and distance to a mall. Another more specific variable included is an indicator variable for homes within 250 m of Lake Ontario (*i.e.* with a view of the water). Lastly, adjacent road speed is included in order to describe the relative amount of traffic (and to a lesser extent, traffic noise) passing by the property.

5.3.4 Demographic Variables

Demographic variables describe neighbourhood factors that contribute to the underlying socioeconomic and socio-geographic conditions for the area. The demographic variables chosen are also identical for both property type categories and are reported at the Census Tract level. As such, they are not a direct expression of household demographics *per se*, but rather a general descriptor for the relevant area in which the property was sold. While there is of course a degree of variability for criteria such as median household income for a given tract, these differences are expected to be relatively consistent across neighbourhoods. These variables include after-tax income, population density, and proportion of immigrant population.

6. Results

For comparative purposes, low-rise property types (detached, semi-detached, row/townhouse, multiplex) are shown together (**Table 3**), and high-rise (generally) property types (condo apartment, condo townhouse, common element condo) are shown together (**Table 4**), though each property type has its own regression model.

Table 3: Low Rise Housing Types - Regression Models

	Dependent variable: Log of Sale Price			
	Detached (1)	Semi-Detached (2)	Att/Row/Townhouse (3)	Multiplex (4)
green_new	0.0055***	0.0025***	0.0047***	-0.0032
	(0.0005)	(0.0008)	(0.0010)	(0.0042)
month.soldFebruary	0.0149	0.0123	-0.0598*	0.2714*
	(0.0164)	(0.0324)	(0.0338)	(0.1506)
month.soldMarch	0.0339**	0.0669**	0.0236	0.1603
	(0.0156)	(0.0304)	(0.0312)	(0.1517)
month.soldApril	0.0386**	0.0901***	-0.0189	0.1416
	(0.0154)	(0.0300)	(0.0311)	(0.1409)
month.soldMay	0.0614***	0.0475	0.0061	-0.0987
	(0.0216)	(0.0372)	(0.0402)	(0.1980)
month.soldJune	0.0415*	0.0425	0.0360	0.0913
	(0.0216)	(0.0378)	(0.0408)	(0.1883)
month.soldJuly	0.0273	0.0020	0.0086	0.0788
	(0.0226)	(0.0385)	(0.0421)	(0.2519)
month.soldAugust	0.0548**	0.0240	-0.0180	0.0585
	(0.0229)	(0.0399)	(0.0416)	(0.2025)
month.soldSeptember	0.0697***	0.0512	0.0305	0.0345
	(0.0221)	(0.0377)	(0.0418)	(0.2060)
month.soldOctober	0.0255	0.0612**	0.0026	0.1563
	(0.0164)	(0.0310)	(0.0325)	(0.1557)
month.soldNovember	0.0177	0.0527*	0.0295	0.0896
	(0.0164)	(0.0316)	(0.0320)	(0.1364)
month.soldDecember	0.0281	0.0252	0.0348	0.3551**
	(0.0188)	(0.0344)	(0.0413)	(0.1496)
bedrooms.ag	0.0006	0.0079	-0.0132	0.0169
	(0.0043)	(0.0069)	(0.0099)	(0.0222)
washrooms	0.0729***	0.0738***	0.0462***	0.0298***
	(0.0031)	(0.0059)	(0.0078)	(0.0094)
f.family.room1	0.0108	0.0325***	-0.0159	0.0171
	(0.0075)	(0.0111)	(0.0125)	(0.0708)
log(square.feet.int)	0.4105***	0.3443***	0.4632***	0.5213***
	(0.0126)	(0.0238)	(0.0310)	(0.1191)
f.parking.typeAttached	0.0636***	-0.0047	-0.0276	0.0933
	(0.0095)	(0.0199)	(0.0241)	(0.1272)
f.parking.typeBuilt-In	0.0939***	-0.0018	-0.0217	-0.1901
	(0.0105)	(0.0167)	(0.0217)	(0.1472)
f.parking.typeDetached	0.0458***	0.0373***	0.0193	-0.0458
	(0.0096)	(0.0128)	(0.0247)	(0.0709)
f.parking.typeOther	0.0490***	0.0400	-0.0351	0.1416
	(0.0176)	(0.0276)	(0.0418)	(0.1340)
dist_cbd_km	-0.0048***	-0.0151***	-0.0148***	-0.0152
	(0.0013)	(0.0024)	(0.0026)	(0.0166)
dist_hway_km	-0.0113***	-0.0038	0.0028	-0.0214
	(0.0022)	(0.0043)	(0.0051)	(0.0234)
dist_mall_km	0.0042**	-0.0172***	-0.0201***	-0.0003
	(0.0018)	(0.0037)	(0.0040)	(0.0200)
dist_stn_km	-0.0420***	0.0034	-0.0016	-0.0180
	(0.0019)	(0.0039)	(0.0040)	(0.0295)
within_250m_lake1	0.1908***	0.0830	-0.0134	0.2310

	(0.0260)	(0.0696)	(0.0532)	(0.2313)
f.speed_kmh50	-0.0497**	-0.0164	0.0229	0.0310
	(0.0245)	(0.0221)	(0.0270)	(0.1234)
f.speed_kmh60	-0.1031***	-0.1353***	-0.0386*	-0.2303**
	(0.0148)	(0.0241)	(0.0199)	(0.0885)
f.speed_kmh100	-0.1645			
	(0.2213)			
immigrants_per	0.0065***	0.0006	0.0055***	0.0032
	(0.0003)	(0.0007)	(0.0008)	(0.0049)
log(aftertax_inc)	0.5531***	0.4790***	0.5516***	0.3468***
	(0.0105)	(0.0209)	(0.0265)	(0.1244)
log(pop_dens)	0.0406***	0.0699***	0.0666***	0.1284
	(0.0061)	(0.0094)	(0.0095)	(0.0831)
green_new:month.in.green.rangeTreated	-0.0017**	-0.0004	-0.0023	0.0096
	(0.0007)	(0.0012)	(0.0015)	(0.0066)
Constant	4.1322***	5.3704***	3.6630***	4.9335**
	(0.1586)	(0.2956)	(0.3482)	(2.0318)
Observations	6,220	1,529	1,062	107
R2	0.8403	0.7834	0.7376	0.7424
Residual Std. Error	0.2208 (df = 6187)	0.1923 (df = 1497)	0.1907 (df = 1030)	0.2567 (df = 75)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Condo & Related Housing Type Regression Models

	Dependent variable:		
		Log of Sale Price	
	Condo Apt	Condo Townhouse	Common Element Condo
	(1)	(2)	(3)
green_new	0.0013***	0.0049***	0.0020
	(0.0003)	(0.0009)	(0.0013)
month.soldFebruary	-0.0494***	-0.0342	-0.0305
	(0.0082)	(0.0262)	(0.0425)
month.soldMarch	0.0056	-0.0282	-0.0235
	(0.0078)	(0.0249)	(0.0393)
month.soldApril	0.0085	0.0220	-0.0176
	(0.0078)	(0.0246)	(0.0406)
month.soldMay	0.0005	0.0382	-0.0081
	(0.0090)	(0.0305)	(0.0495)
month.soldJune	-0.0106	0.0096	-0.0056
	(0.0091)	(0.0312)	(0.0493)
month.soldJuly	-0.0190**	0.0059	0.0286
	(0.0093)	(0.0320)	(0.0475)
month.soldAugust	-0.0050	0.0110	-0.0074
	(0.0092)	(0.0319)	(0.0484)
month.soldSeptember	0.0184**	0.0237	-0.0041
	(0.0093)	(0.0315)	(0.0510)
month.soldOctober	0.0143*	0.0167	0.0237
	(0.0081)	(0.0254)	(0.0427)
month.soldNovember	0.0399***	0.0163	0.0659
	(0.0082)	(0.0263)	(0.0433)
month.soldDecember	0.0398***	0.0452	-0.0084
	(0.0089)	(0.0305)	(0.0483)
f.age.range6-15	-0.0590***	-0.0930***	-0.0526**
	(0.0039)	(0.0122)	(0.0220)
f.age.range16-30	-0.2377***	-0.1196***	-0.2302***
	(0.0071)	(0.0184)	(0.0397)
f.age.range31-50	-0.3974***	-0.1930***	-0.3776***
	(0.0089)	(0.0173)	(0.0420)
f.age.range51-99	-0.2884***	-0.2424***	-0.3079***
	(0.0300)	(0.0557)	(0.0504)
f.age.range100+	0.0446	0.0890	0.2435**
	(0.0455)	(0.0777)	(0.1227)
bedrooms.ag	-0.0250***	-0.0296***	0.0415*

	(0.0043)	(0.0104)	(0.0235)
washrooms	0.0850***	0.0577***	0.0832***
	(0.0047)	(0.0101)	(0.0245)
f.family.room1	0.0363***	0.0483***	0.0593***
	(0.0060)	(0.0125)	(0.0228)
log(square.feet.int)	0.8124***	0.7130***	0.7096***
	(0.0094)	(0.0287)	(0.0553)
f.parking.includedIncluded	0.0546***	-0.0035	0.0209
	(0.0043)	(0.0223)	(0.0218)
hydro.included1	-0.0530***	-0.0647**	-0.0520*
	(0.0054)	(0.0269)	(0.0267)
f.heat.includedIncluded	-0.0286***	-0.0591***	0.0313
	(0.0040)	(0.0176)	(0.0231)
f.lockerNo Locker	-0.0358***	-0.0232**	-0.0315
	(0.0035)	(0.0108)	(0.0199)
f.ensuite.laundryIncluded	0.0879***	0.0118	0.1052***
	(0.0110)	(0.0258)	(0.0382)
f.exposureEw	-0.0571**	0.0300	-0.0428
	(0.0285)	(0.0228)	(0.1066)
f.exposureN	-0.0131**	-0.0100	-0.0196
	(0.0056)	(0.0168)	(0.0321)
f.exposureNe	-0.0008	0.0320	0.0051
	(0.0064)	(0.0292)	(0.0362)
f.exposureNs	0.0437	0.0429**	0.1459
	(0.0285)	(0.0218)	(0.1483)
f.exposureNw	0.0068	0.0286	-0.0044
	(0.0066)	(0.0277)	(0.0339)
f.exposureS	-0.0066	0.0212	-0.0116
	(0.0054)	(0.0156)	(0.0313)
f.exposureSe	0.0087	0.0515*	-0.0076
	(0.0060)	(0.0287)	(0.0346)
f.exposureSw	0.0090	0.0452*	-0.0213
	(0.0059)	(0.0269)	(0.0341)
f.exposureW	-0.0056	0.0028	-0.0007
	(0.0055)	(0.0160)	(0.0317)
dist_cbd_km	-0.0219***	-0.0177***	-0.0189***
	(0.0006)	(0.0019)	(0.0036)
dist_hway_km	0.0341***	-0.0064	0.0167*
	(0.0016)	(0.0045)	(0.0087)
dist_mall_km	-0.0107***	-0.0108***	-0.0105**
	(0.0010)	(0.0029)	(0.0051)
dist_stn_km	-0.0322***	-0.0161***	-0.0146**
	(0.0011)	(0.0032)	(0.0059)
within_250m_lake1	0.0304***	0.0442	-0.0045
	(0.0063)	(0.0326)	(0.0333)
f.speed_kmh40	0.0559		
	(0.1434)		
f.speed_kmh50	0.0551	0.0510**	0.1348***
	(0.1435)	(0.0222)	(0.0399)
f.speed_kmh60	0.0608	-0.0274**	-0.0073
	(0.1434)	(0.0125)	(0.0184)
f.speed_kmh90	0.0303	-0.0001	0.1510
	(0.1527)	(0.0753)	(0.1278)
f.speed_kmh100	0.0341		
	(0.1585)		
immigrants_per	0.0042***	0.0015**	0.0024*
	(0.0002)	(0.0006)	(0.0013)
log(aftertax_inc)	0.2979***	0.2516***	0.2402***
	(0.0069)	(0.0183)	(0.0398)
log(pop_dens)	0.0157***	0.0347***	0.0333***
	(0.0021)	(0.0076)	(0.0117)
green_new:month.in.green.rangeTreated	-0.0002	-0.0019	-0.0018
	(0.0004)	(0.0012)	(0.0019)
Constant	4.1327***	5.3983***	5.2502***
	(0.1719)	(0.2642)	(0.5659)
Observations	18,686	1,765	668
R2	0.7551	0.7895	0.7757
Residual Std. Error	0.2022 (df = 18636)	0.1997 (df = 1717)	0.1992 (df = 620)
Note:			*p<0.1; **p<0.05; ***p<0.01

For the low-rise housing type regression models, there are a total of 8,918 observations. Roughly 70% of these are from detached homes, 17% from semi-detached homes, 12% from row houses/townhouses, and a little over 1% of the observations are from multiplex houses. For the detached house model, the highest correlation coefficient was returned, at approximately 0.84. This indicates that roughly 84% of the variance in the logarithm of sale price can be explained by the variance of the predictors used. The lowest correlation coefficient for low-rise type properties is for attached/row/townhouse units, at 0.74. For condo and related units, the highest R^2 was determined to be 0.79 for condo townhouses, and the lowest was 0.76 for condo apartments.

The predictor variables used in this model are comprised of three types: characteristic variables, locational variables, and demographic variables. Their impacts within the model follow:

6.1 Characteristic Variables

6.1.1 Green View

The green view index value (*green_new*) corresponds to the visible level of street greenery near the property. In the case of detached homes, the value of 0.0055 indicates that a one percentage point (one unit) increase in green view for detached homes, holding all other predictors constant, will equate to a change in house price of exp(0.0055) = 1.0045, or a 0.552% increase in sale price, significant at the 0.01 level. Accordingly, a 5-percentage point increase in green view for detached homes has a 2.79% impact on housing price, or the equivalent of roughly $13,900 on a $500,000 property.

For semi-detached, attached/row/townhouse, and multiplex property types, the impact of green view is lower, but still significant in the case of semi-detached and row houses. For semi-detached and row houses, a one percentage point increase in green view equates to a sale price increase of 0.25% and 0.47%, respectively (both at the 0.01 confidence level). A 5-percentage point increase in GVI values for these property types equates to a 1.26% and 2.38% price increase, respectively. This translates to an additional $6,290 and $11,890 to sale price for semi-detached and row houses, respectively. For multiplex housing, there was no significant impact of green view index on housing price, and the magnitude of the effect measured was negative, and close to 0.

For condo-type units, condo apartments had a statistically significant but low-magnitude effect of 0.0013 log units per 1 percentage point increase of green view index. Common element condo units experienced a similar magnitude of effect, but were not found to be statistically significant. Interestingly, the impact of green view on condo townhouse units was positive and statistically significant at the 0.01 level. For condo townhouses, a one percentage point increase in green view index equated to a exp(0.0049) = 0.49% increase in sale price, nearly as high as detached homes. Thus, for a 5-percentage point increase in GVI for condo townhouses, a sale price premium of roughly $12,400 is effected on a $500,000 unit.

The distribution of green view index values for each property type is given in ***Figure 14***. It is worth noting that in general, the condo and related property type homes have lower green view index means compared to low-rise property types such as detached homes and multiplexes.

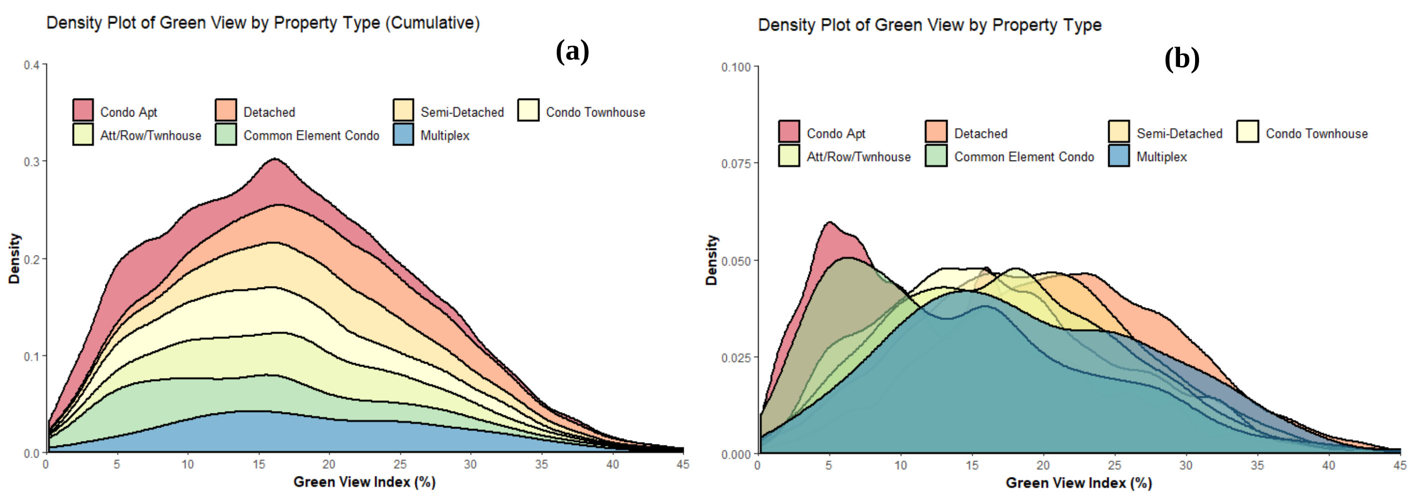


Figure 14: (a) Cumulative and (b) individual green view index (GVI) distribution for all housing property types.

From a temporal standpoint, the green view index applies generally only for a subset of the year, namely when greenery exists on trees and other foliage (*i.e.* late spring and summer). For properties listed and sold during winter months, the buyers in general cannot explicitly appreciate or consider value potentially offered by a lush street or neighbourhood, as the majority of trees are barren. As such, the data was categorized into *treated* and *untreated* bins based on “exposure” to the green view in front of the property. The interaction variable *green_new:month.in.green.range* describes the difference of green view index impacts on sale price between treated months (May through September) and untreated months (October through April). Examples of this difference are illustrated in ***Figure 15*** and ***Figure 16***, which show the relative impact for detached homes and condo apartments, respectively.

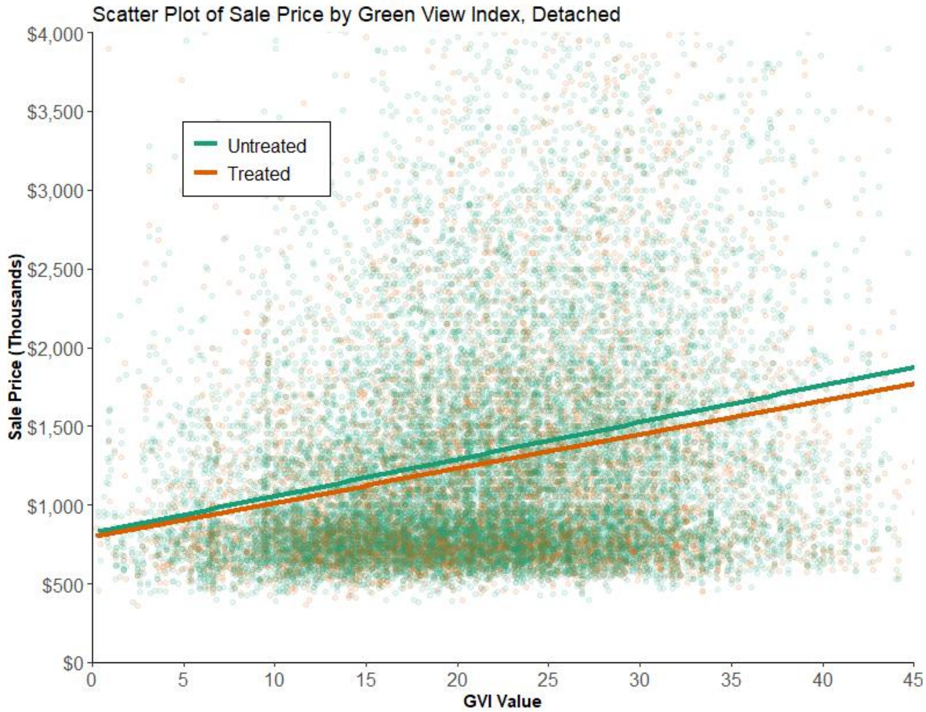


Figure 15: Illustrating the impact of GVI value increases on sale price, untreated and treated detached units

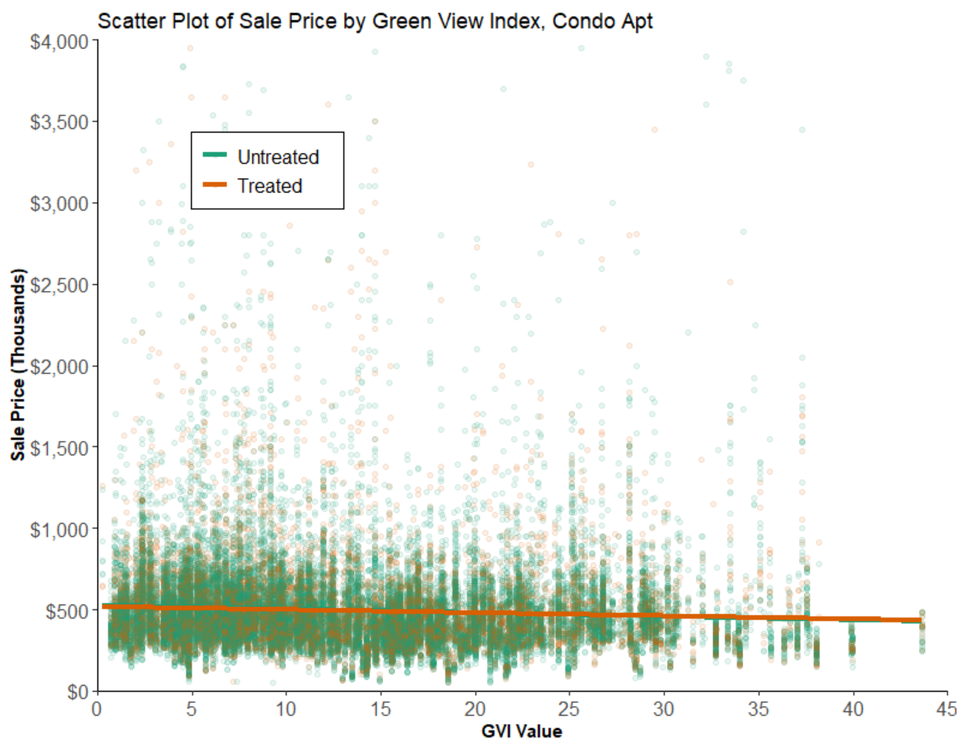


Figure 16: Illustrating the impact of GVI value increases on sale price, untreated and treated condo units

In all property type cases (except for multiplexes), the impact of untreated homes—those sold during the late fall and winter months—on sale price contingent on GVI value is higher compared to that of treated homes. However, only detached homes were found to be statistically significant, at the 0.05 level, with a magnitude of -0.0017. This implies that detached housing prices are sold for roughly 0.2% less for each 1 percentage point increase in GVI during treated months (late spring through summer) compared to untreated months (fall through winter).

However, Toronto experienced significant housing price increases in 2017 in particular, which may have skewed this interpretation overall. A closer examination of treated versus untreated sales in 2016 show that sale prices differences for each property type are similar for both temporal categories, with a slight upward skew toward treated home sales (***Table 5***). Conversely, 2017 sales in general show a heavier skew towards sale prices of homes sold during untreated months (***Table 6***).

Table 5: Treated and Untreated Home Sales by Property Type, 2016

Property Type	Untreated (Oct-Apr) Sales	Treated (May-Sept) Sales
Condo Apartment	$443,620	$451,650
Detached	$1,242,400	$1,250,550
Semi-Detached	$860,330	$875,330
Condo Townhouse	$541,570	$555,390
Attached/Row/Townhouse	$815,630	$836,720
Common Element Condo	$393,530	$414,880
Multiplex	$1,362,360	$1,352,820

Table 6: Treated and Untreated Home Sales by Property Type, 2017

Property Type	Untreated (Oct-Apr) Sales	Treated (May-Sept) Sales
Condo Apartment	$554,910	$543,570
Detached	$1,409,190	$1,312,400
Semi-Detached	$986,700	$959,500
Condo Townhouse	$621,100	$626,450
Attached/Row/Townhouse	$979,400	$924,450
Common Element Condo	$498,120	$475,620
Multiplex	$1,636,340	$1,589,460

Using the values from ***Table 5*** and ***Table 6***, two observations are present. First, housing prices for all property types were greater in 2017 compared to 2016. Second, the relative increase in sale prices from 2016 to 2017 for untreated homes was greater for all property types compared to treated homes, with price premiums for untreated home sales ranging between 2% and 10% compared to treated home sales.

6.1.2 Living Area Size

Housing unit size (in square feet) was found to be a significant impact variable on housing price overall, and was statistically significant at the 0.01 confidence level for all property types. For detached homes, a one percentage increase in square footage resulted in a 0.41% increase in housing price. Accordingly for detached homes, a 10% increase in square footage while holding other factors constant results in an increase in sale price by 4.00%. For semi-detached homes, a 10% increase in square footage results in a 3.34% increase in sale price. For row housing, a 10% increase in square footage results in a 4.51% increase in sale price. . For multiplexes, a 10% increase in square footage results in a 5.09% increase in sale price.

Condo apartments saw the largest impact from square footage overall, with a 10% increase in living space equating to a 8.05% increase in sale price. Condo townhouses and common element condos followed suit to a similar extent, with 7.03% and 7.00% increases in sale price from a 10% increase in living space, respectively.

6.1.3 Number of Bedrooms

For detached, semi-detached, row/townhouse, and multiplex homes, the number of above-ground bedrooms was not found to be statistically significant in relation to housing price. Conversely, condo apartments and condo townhouses both had negative correlations with housing price, both at the 0.01 confidence level, and both incurring a roughly 2.5% price penalty with each bedroom added (keeping square footage constant). Common element condos had a positive relationship between house price and number of above-ground bedrooms, significant at the 0.10 level.

6.1.4 Number of Washrooms

The number of dwelling washrooms was found to correlate positively and significantly for all housing types. For detached homes, an additional washroom added 7.3% to sale price, keeping all other factors constant. For semi-detached, row/townhouse, and multiplex homes, an additional washroom added 7.4%, 4.6%, and 3.0% to sale price, respectively.

For condo apartments, an additional washroom incurred a sale price premium of 8.5%. For condo townhouses and common element condos, an additional washroom added 5.8% and 8.3% to sale price, respectively. For the relationship between number of washrooms and sale price, all property types were statistically significant at the 0.01 confidence level.

6.1.5 Family Room

For low-rise homes, the inclusion of a family room within the housing unit was only found to correlate significantly sale price for semi-detached homes (at the 0.01 level). The impact of including a family room in semi-detached homes commands a premium on sale price of roughly 3.25%.

For condos, the inclusion of a family room was found to be statistically significant for all types, at the 0.01 level. Condo apartments had a sale price premium for inclusion of 3.63%, condo townhouses 4.94%, and common element condos 6.11%.

6.1.6 Parking Type

Parking type was included for only non-condo type residences. Detached homes benefited significantly from all types of parking compared to no parking, and all at the 0.01 level of significance. Compared to no parking, attached parking incurred a sale price premium of 6.57%; built-in parking 9.85%; detached 4.89%; and other 5.02%. The only significant correlation for parking type for a property type other than detached was semi-detached, which commanded a sale price premium of 3.80% for detached parking.

6.1.7 Age Range

Due to a high degree of missing values for low-rise type housing, the age range variable is limited to condo and related housing types, and was indeed found to be statistically significant at nearly all levels. In general, compared to newly built units, condo apartments, townhouses, and common element condos all decreased in sale price as the age of the unit increased, until around the 50-year mark, where some stabilization is seen. Units with ages greater than 100 years were mostly not significant. Compared to new units, condo apartments built between 6 and 15 years before sale sold for about 6% less. Condo apartments built 16-30 years prior to sale went for roughly 21% less than comparable new units, bottoming out at 33% less for units built 31-50 years before sale. Similar trends (with generally smaller magnitudes) were found for condo townhouses and common element condos.

Compared to newly-built condo townhouses, units 6-15 years old sold for 9.9% less; units 16-30 years old sold for 11.3% less; units 31-50 years old sold for 17.6% less; and units 51-99 years old sold for 21.6% less.

Compared to newly-built common element condos, units 6-15 years old sold for 5.2% less; units 16-30 years old sold for 20.6% less; units 31-50 years old sold for 31.4% less; and units 51-99 years old sold for 26.5% less.

6.1.8 Parking Included

Parking included is a categorical variable used only in models looking at condo and related housing types. Inclusion of parking was only found to correlate significantly with condo apartment housing types (at the 0.01 level), adding a premium of about 5.6% to the price of the unit. Condo townhouse and common element condo types were found not to be significant.

6.1.9 Hydro Included

The inclusion of hydro in the sale price of a condo-type unit was found to have a negative effect on sale price, and was significant for all housing types (at the 0.01 level for condo apartments, 0.05 level for condo townhouses, and 0.10 level for common element condos. For condo apartments, hydro inclusion incurred a 5.2% sale price penalty. For condo townhouses and common element condos, this penalty was 6.3% and 5.1%, respectively.

6.1.10 Heat Included

The inclusion of heat in the sale price of a condo-type unit also was found to incur a price penalty, but was only statistically significant for condo apartments and condo townhouses. For condo apartments, the inclusion of heat reduced the sale price by roughly 2.8%. For condo townhouses, this reduction was 5.7%

6.1.11 Locker Included

Compared to units that had a locker, condo apartments without a locker had lower sale prices of 3.5% (at the 0.01 confidence level). Condo townhouses without a locker had lower sale prices of about 2.3% (at the 0.05 confidence level). The inclusion of a locker in common element apartments did not have a statistically significant correlation to sale price.

6.1.12 Ensuite Laundry

The inclusion of ensuite laundry was found to correlate positively with sale price for all condo-related housing types, except for condo townhouses. For condo apartments, ensuite laundry drove a 9.2% premium for sale price. For common element condos, this premium was about 11.1%.

6.1.13 Exposure

The majority of exposure directions for condo units was determined to not be statistically significant, except for east/west-facing units (0.01 confidence level, condo apartments only), north-facing units (0.01 confidence level, condo apartments only), and north/south-facing units (0.05 confidence level, condo townhouses only), which commanded a -5.6%, -1.3%, and +4.3% price impact, respectively.

6.2 Locational Variables

For locational variables, a positive β indicates that an increased distance from X_i will effect a sale price increase on the property in question, and is expected with generally undesirable factors, such as proximity to an industrial or noisy environment. Conversely, a negative β indicates that an increased distance from X_i will reduce the sale price of the property, and is expected with generally desirable factors, such as distance to a subway. Visual data descriptions of key locational variables are presented in the ***Appendix***.

6.2.1 Distance from CBD

For low-rise type property units, an increase in distance from the central business district (CBD)—in this case, the area surrounding Yonge St and King St—decreases the sale price of the unit, and is significant at the 0.01 confidence level for all low-rise property types, except for multiplexes, which were found to be significant at the 0.05 level. For detached homes, a 1-km increase in distance from the CBD decreased sale price by roughly 0.5%; for semi-detached homes, 1.5%; for row/townhouses, 1.5%; and for multiplexes, 1.5%.

For condo and related property types, all impacts of distance from the CBD were found to be negative and statistically significant at the 0.01 level. For condo apartments, a 1-km increase in distance from the CBD decreased unit sale price by 2.2%; for condo townhouses, 1.8%; and for common element condos, 1.9%.

6.2.2 Distance from Mall

For low-rise property types, only semi-detached and row/townhouse homes were found to be impacted by increased distance to a mall in a statistically significant manner (both at 0.01 confidence level). For semi-detached homes, a 1-km increase in mall distance reduced sale price by roughly 1.8%. For row/townhouses, this reduction was 2.1%.

Distance to a mall was found to have a statistically significant impact on sale price for condo apartments (at the 0.01 level), condo townhouses (at the 0.01 level), and common element condos (at the 0.10 level). A 1-km increase in distance to a mall reduced condo apartment sale price by 1.1%; reduced condo townhouse price by 1.1%; and reduced common element condo price by 1.0%.

6.2.3 Distance from Highway

Distance from a highway was only found to be statistically significant at the 0.01 level for detached homes and condo apartments. For detached homes, a 1-km increase in distance from a highway decreased sale price by roughly 1.1%. For condo apartments, a 1-km increase in distance from a highway decreased sale price by about 3.5%.

6.2.4 Distance from Subway

Distance from a subway station was found to be statistically significant for detached (0.01 confidence level), condo apartment (0.01 confidence level), condo townhouse (0.01 confidence level), and common element condo property types (0.05 confidence level). In general, an increased distance from a subway reduced property value in all cases. For detached homes, a 1-km increase to a subway was found to have a 4.1% reduction in sale price. This sale price reduction was 3.2% for condo apartments, 1.6% for condo townhouses, and 1.5% for common element condos.

6.2.5 Within 250m of Lake Ontario

A categorical variable that accounts for units with a high likelihood of direct waterfront access or view is considered. For low-rise type properties, this proximity indicator impacted sale price in statistically significant manner (at the 0.01 level for detached homes). For detached homes, being within 250m of Lake Ontario incurred a sale price premium of roughly 21.9%.

For condo and related units, the binary lake distance indicator was only significant for condo apartments (at the 0.01 level), carrying a 3.1% price premium.

6.2.6 Adjacent Road Speed

Adjacent road speed is considered as a locational variable in this model because it acts as a proxy to the built-up environment surrounding a property (or neighbourhood). The variable is treated categorically, as posted speed limit, as standard speed limit designations throughout Toronto are discrete (even if actual traffic speed is not discrete).

For detached houses, increasing the posted speed limit to 50 km/hr or 60 km/hr (suggesting a busier, noisier road) decreased sale price by 4.8% and 9.8%, respectively, compared to the baseline of 30 km/hr. This finding was significant at the 0.05 level for 50 km/hr, and at the 0.01 level for 60 km/hr. Increases to 100 km/hr were not found to be significant (and are likely not relevant, being that this designation is typically reserved for major highways). Semi-detached homes were impacted by speed increases to 60 km/hr, with a reduced sale price of 12.7% (significant at the 0.01 confidence level). Row houses were slightly impacted at this posted speed, but were only confidence at the 0.10 level. Multiplex house prices decreased by 20.6% for a posted speed increase to 60 km/hr form 30 km/hr (at the 0.05 confidence level).

For condo and related housing types, the effect of adjacent road speed limit was positive, with only condo townhouses and common element condos found to be impacted at the 0.05 confidence level and 0.01 confidence level, respectively. Condo townhouses in a 50 km/hr zone incurred a 5.2% price premium compared to those in a 30 km/hr zone, but took a 2.7% price hit for 60 km/hr zones. Common element condos built in a 50 km/hr zone had a price premium of 14.4% compared to those in a 30 km/hr zone.

6.3 Demographic Variables

For demographical variables, census-tract level characteristics are applied to unit-level sales data, which, while important for the model, must be carefully considered before extrapolating, as variation naturally exists within the census tract level to varying degrees.

6.3.1 After-Tax Income (Census Tract)

After-tax income was found to be a high-impact contributor to modelling housing sale price, and for low-rise housing types was significant at the 0.01 confidence level for all types. The natural logarithm of after-tax income was used as the predictor, for ease of comparability and readability.[5] The distribution of after tax income and the logarithm of after tax income by property type are illustrated in ***Figure 17*** and ***Figure 18***.

For detached homes, a 1% increase in census tract after-tax income resulted in a 0.55% increase in property sale price. Similarly, a 10% increase in census tract after-tax income incurred a sale price premium of 5.4%. For semi-detached homes, a 10% increase in after-tax income commanded an additional 4.7% in sale price; for row/townhouse homes, an additional 5.4%; and for multiplexes, an additional 3.4%. For all condo and related property types, the relationship between the logarithm of after-tax census tract income and housing sale price was found to be statistically significant at the 0.01 confidence level, although the impact was relatively lower compared to low-rise property types. A 10% increase in census tract after-tax income resulted in a sale price premium of 2.9% for condo apartments, 2.4% for condo townhouses, and 2.3% for common element condos.

[5] In the case for after tax income (and indeed for many demographic variables), it is often easier to think of effect sizes relatively. For instance, it is easier to understand that a 10% increase in after-tax income for a census tract might have a (for example) 5% impact on housing prices for homes sold in the census tract, than to state that a $10 increase in census tract after-tax income has some small fraction of a percent impact on those same houses in terms of sale price.

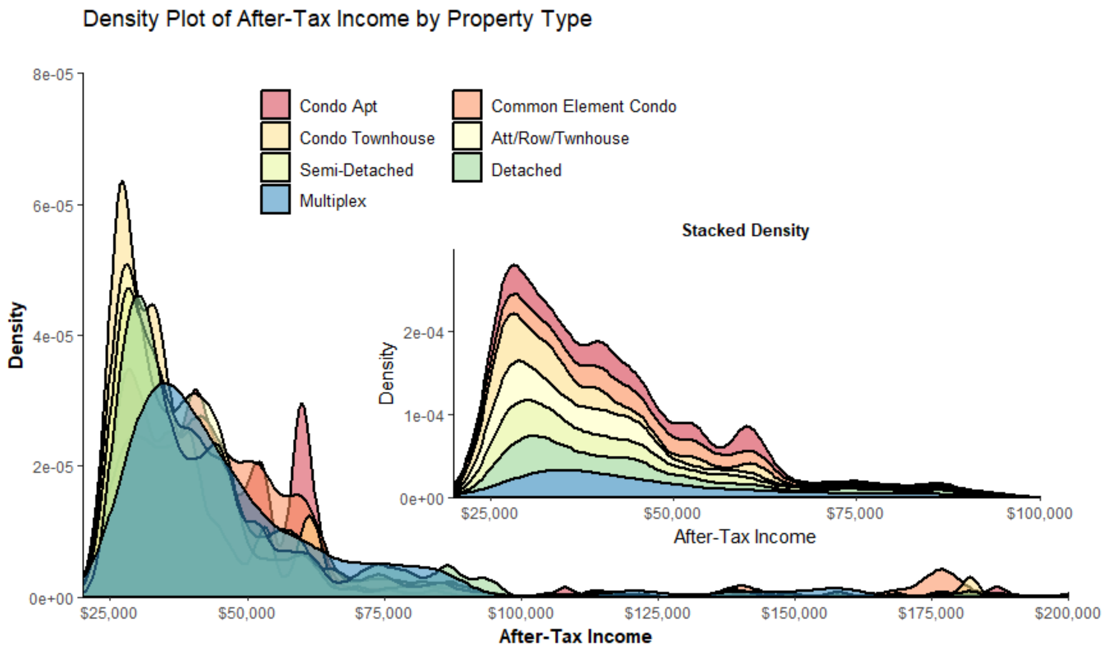


***Figure 17*:** Distribution visualization for after-tax income (census tract level) by property type (individual and cumulative densities)

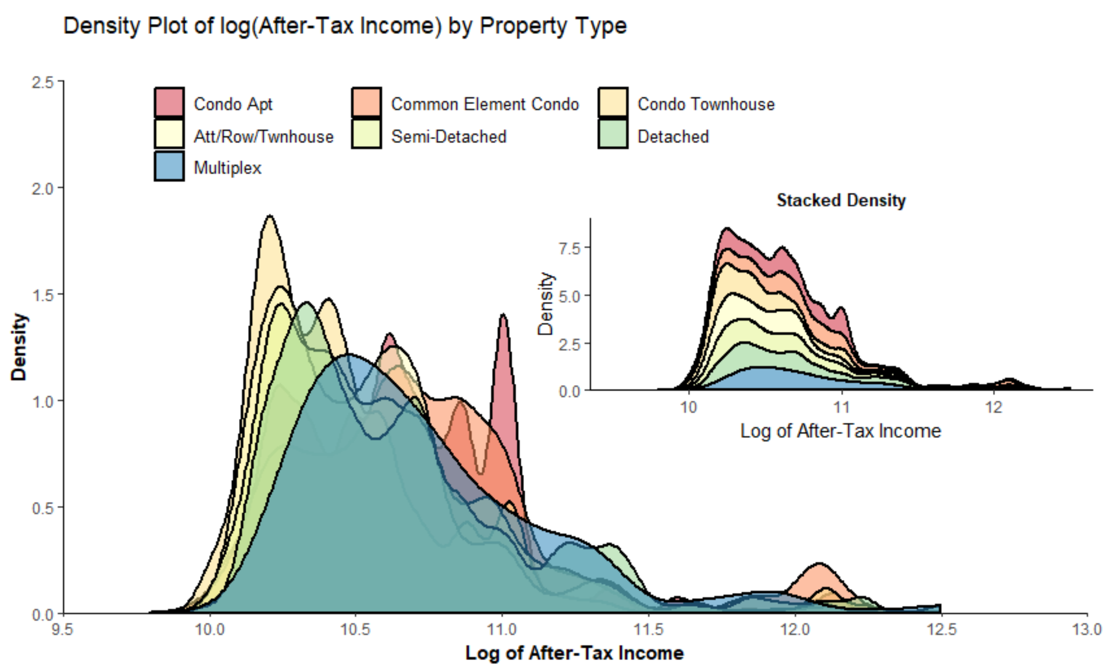


***Figure 18*:** Distribution visualization for logarithm of after-tax income (census tract level) by property type (individual and cumulative densities; outliers truncated past 12.5 for visualization purposes)

6.3.2 Population Density (Census Tract)

A 10% increase in population density incurs a housing price premium of 0.39% for detached homes. For semi-detached homes, a 10% population density increase at the census tract level incurs a

0.67% premium on sale price; for row/townhouse homes, a 0.64% premium. All low-rise property types were significant at the 0.01 level except for multiplexes which were not significant. For condo apartments, a 10% population density increase incurs roughly a 0.15% price premium. For condo townhouses, this premium is 0.33%, and for common element condos this premium is 0.32%. Condo and related property types were all significant at the 0.01 level.

6.3.3 Proportion of Immigrant Population (Census Tract)

The proportion of immigrants within a census tract population was found to have a low-magnitude effect on housing prices for all housing types, and was only statistically significant at the 0.01 level for detached homes, row houses, and condo apartments. A 1-percentage point increase in census tract immigrant population has roughly a 0.65% price impact on detached homes, a 0.55% impact on row houses, and a 0.42% increase effect on condo apartments.

7. Discussion

7.1 On Green View Index

As determined by the above regression models, a 5-percentage point increase in green view for detached homes has a 2.79% impact on housing price, or the equivalent of roughly $13,900 on a $500,000 property. Similarly, this relates to an additional $6,290 and $11,890 to sale price in the case of semi-detached and row houses, respectively. For condo townhouses (the only condo-related property type that was significantly affected in terms of magnitude), a sale price premium of roughly $12,400 is incurred (for condo apartments, this premium is about $3,260 on a $500,000 unit). On a broad level, buyers and sellers with direct views onto street-level greenery can directly experience their benefit. Despite not being able to quantify greenery for the most part compared to something like the number of washrooms in a house, sellers may include mention of a lush or aesthetically pleasing natural environment surrounding a unit, and are as such able to apply value (though not explicitly tangible value).

But what does a 5-percentage point increase in GVI look like to a buyer or seller? Conceptually, this change would describe the view onto a property (or nearby a property) and its surroundings and how it relates to *greenery* proportionally. ***Figure 19*** shows four 90^{o} view angles for a detached bungalow with detached parking and a GVI of roughly 15.

Figure 19: Four view angles (90^{o}) of an example detached property (bungalow, detached parking) with a GVI of approximately 15.

Comparatively, ***Figure 20*** depicts a different property of the same type, but with a GVI value of 20 as opposed to 15. Lastly, ***Figure* 21** depicts another different property of the same type, but with a GVI value of 30 (*i.e.* twice the proportion of the property in ***Figure 19***). All GSV image collections presented in ***Figures 19-21*** were taken in July 2016.

Figure 20: Four view angles (90^{o}) of an example detached property (bungalow, detached parking) with a GVI of approximately 20.

Figure 21: Four view angles (90^{o}) of an example detached property (bungalow, detached parking) with a GVI of approximately 30.

As demonstrated in ***Figures 19-21***, the increase in green space (quantified by GVI) is indeed noticeable. However, it must be noted that the GVI values corresponding to these properties are only proxies to the "actual GVI" directly in front of the unit. This is due to the sampling nature of Google Street View images. In the case of this research, most GVI values are at minimum 20 metres away from one another, and indeed in many cases even further, up to 50 m or 100 m (though the latter is reserved more for low-density areas, industrial zones, or high-speed road networks such as highways). Nevertheless, it is common for GVI values on the same street segment (*i.e.* a short street intersected by two parallel streets) to share a similar range with low to moderate variability. Conversely, adjacent parallel or nearby street segments themselves may have significantly different GVI values (see ***Figure 22*** as an example) but in general drastic same-street changes in GVI value is uncommon.

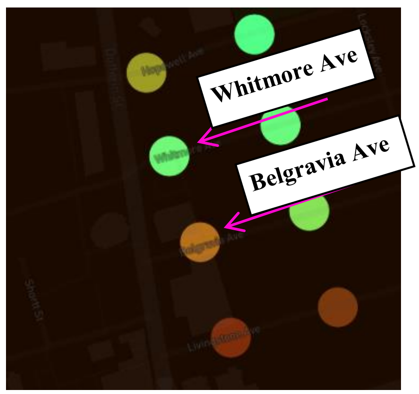


Figure 22: Whitmore Ave and Belgravia Ave run parallel to one another, separately by a distance of roughly 60 m. Despite being close together, these two GVI point values are vastly different, at 23.0 and 5.5. The adjacent GVI point on Belgravia Ave has a value of 18.2, although is roughly 100 m away (from *Treepedia*).

The average weighted per-street standard deviation of GVI values for this data set is approximately 8.75, so GVI variability should be considered when interpreting models.[6] Nevertheless, the correlation between GVI and house sale price was found to be significant at the 0.01 confidence level for all low-rise property types except for multiplexes. The impact of GVI on sale price according to each respective property type model is presented in ***Figure 23*** to ***Figure 27***. The plotting of confidence intervals for each beta value reveals a higher degree of overall variability for semi-detached and row/townhouse properties, and a more precise impact for detached houses. However, it is likely that there are diminishing returns to increasing adjacent greenery in the context of property sale price, due to an infringement on other characteristics such as view, and the costs associated with maintenance, *etc*.

[6] From Rudman (2010, p. 1): "The exact pooled variance is the mean of the variances plus the variance of the means of the component data sets." For this calculation, each unique street from the total data was treated as its own dataset. The number of counts per street, means of each GVI group, and variance of each GVI was calculated in R.

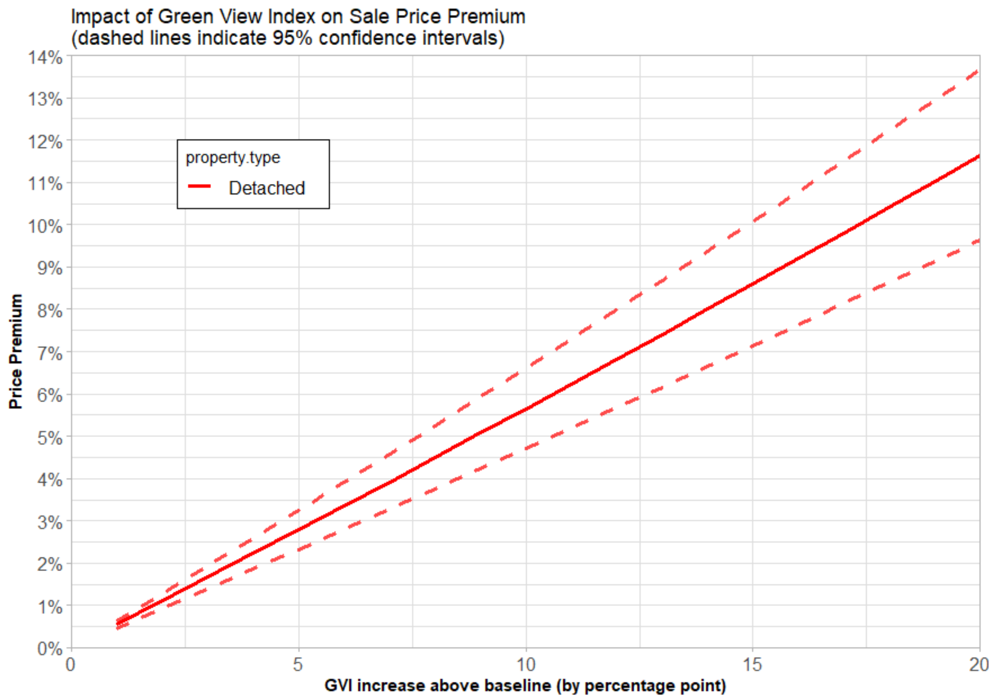


Figure 23: Impact of Green View Index increases above baseline value and associated sale price premium, for detached homes. The solid lines represent the $_{beta}$ value for GVI from each respective model, and the dashed lines represent the corresponding confidence intervals.

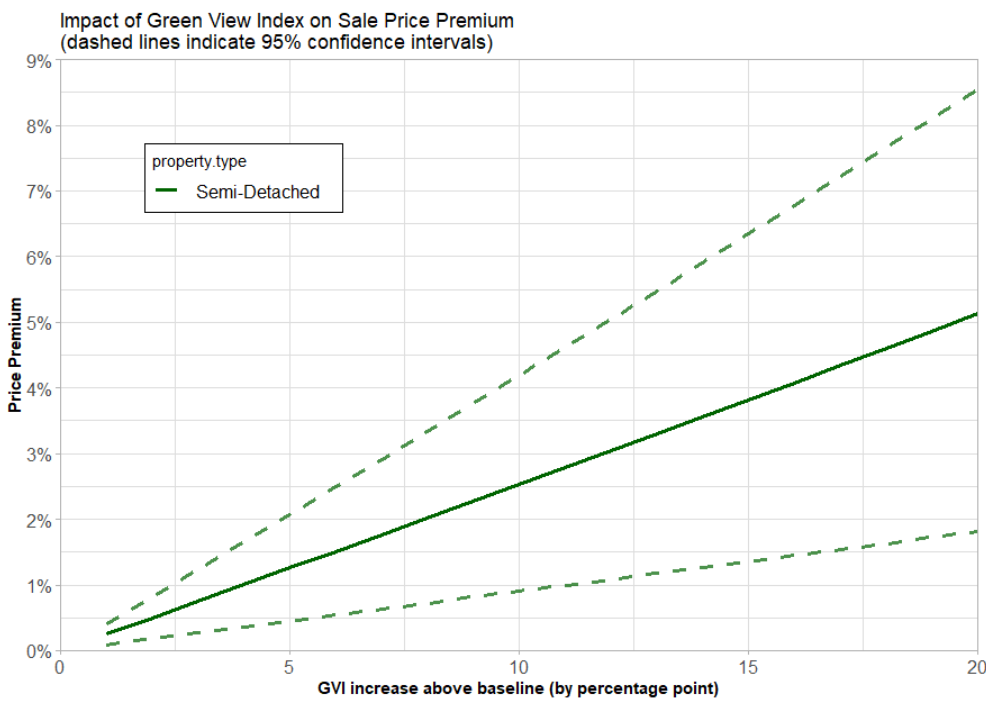


Figure 24: Impact of Green View Index increases above baseline value and associated sale price premium, for semi-detached homes. The solid lines represent the beta value for GVI from each respective model, and the dashed lines represent the corresponding confidence intervals.

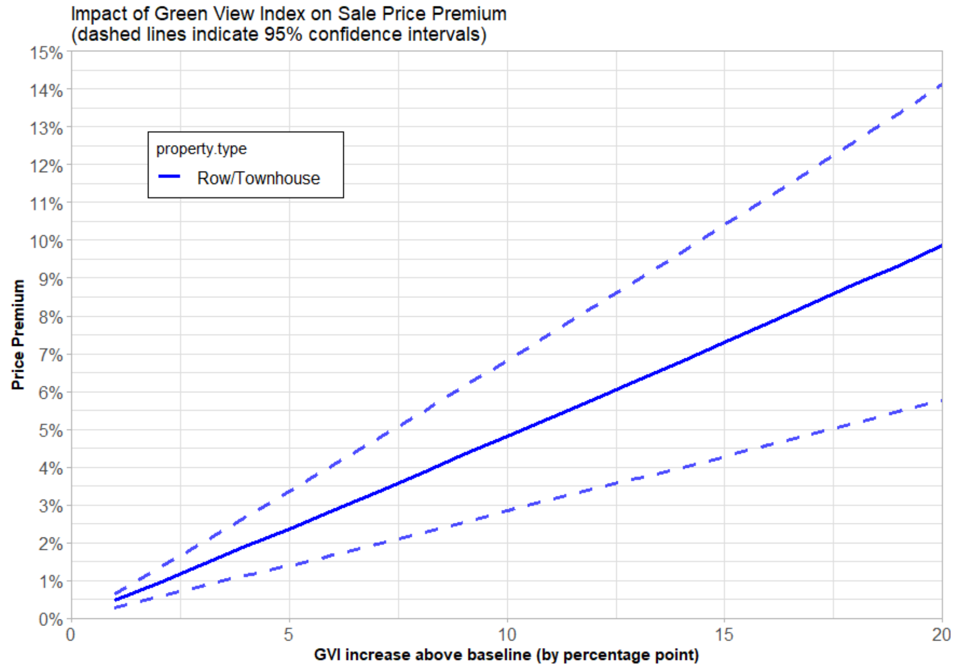


Figure 25: Impact of Green View Index increases above baseline value and associated sale price premium, for row houses/townhouses. The solid lines represent the beta value for GVI from each respective model, and the dashed lines represent the corresponding confidence intervals.

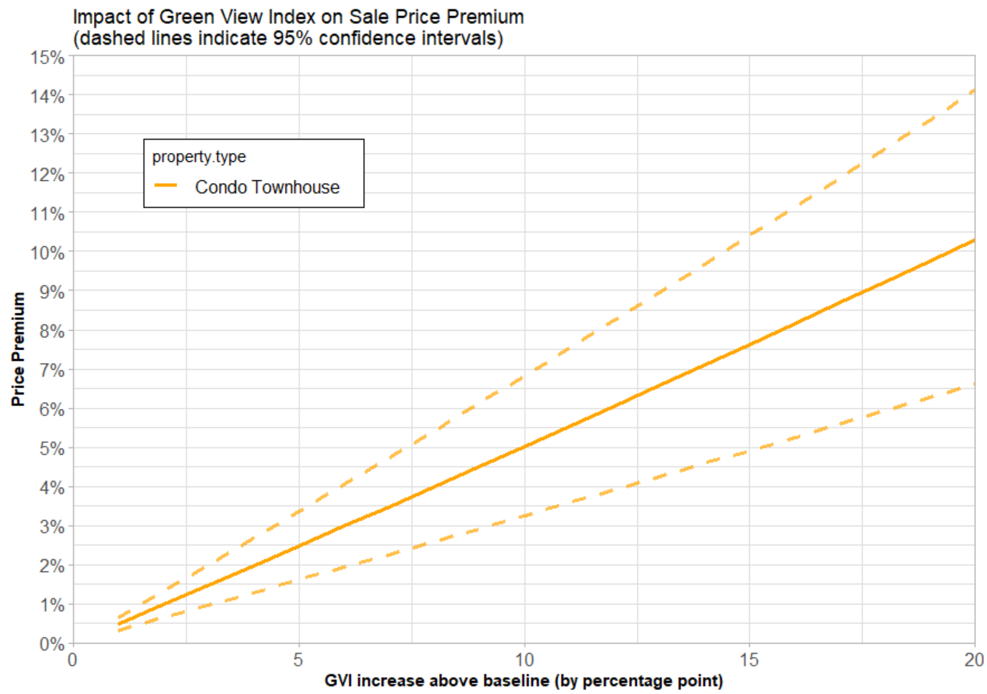


Figure 26: Impact of Green View Index increases above baseline value and associated sale price premium, for condo townhouses. The solid lines represent the beta value for GVI from each respective model, and the dashed lines represent the corresponding confidence intervals.

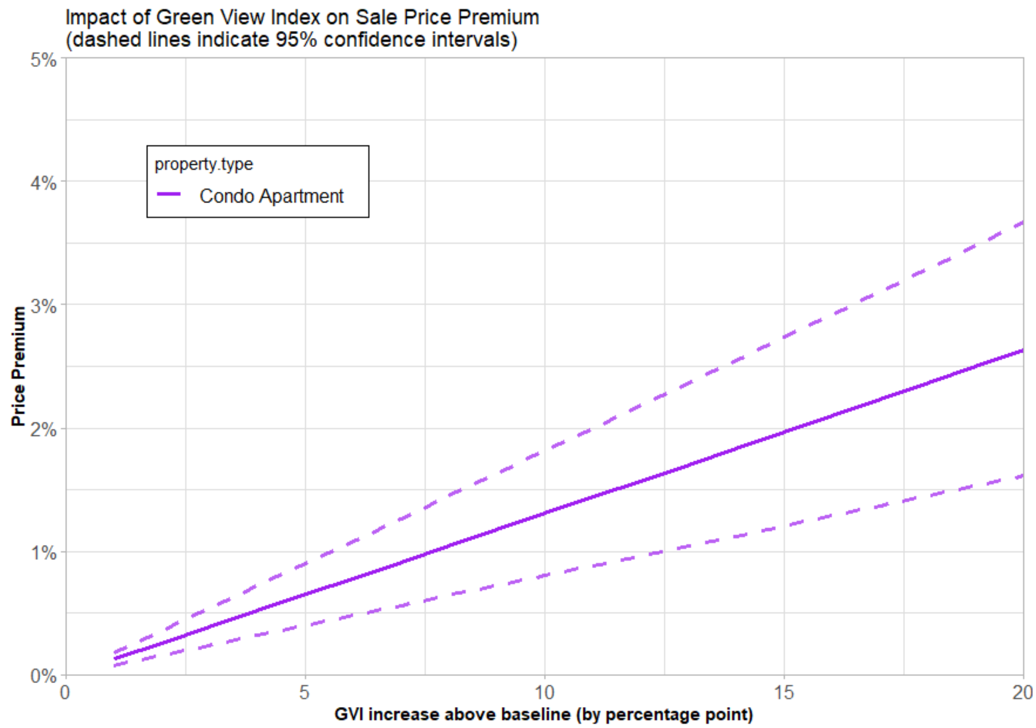


Figure 27: Impact of Green View Index increases above baseline value and associated sale price premium, for condo apartments. The solid lines represent the beta value for GVI from each respective model, and the dashed lines represent the corresponding confidence intervals.

Limits for GVI values exist within the hypothetical boundaries of unity, for a number of reasons. While a GVI of 0 is theoretically possible, it is not seen in this particular dataset. Extremely small GVI values (*i.e.* less than 1) are often recorded in instances where a road intersects the middle of an apartment block or industrial area. For instance, ***Figure 28*** depicts a street segment captured by GSV, and an earlier aerial image of the same location. For many condo apartments, the (new) units are often sold prior to construction being completed, which typically means that there is no appreciable green space around the unit at purchase time. This limits the accuracy of some of the models, and indeed is likely a factor in explaining why GVI is not a significant predictor (in terms of magnitude) for sale price in the case of condo apartments and common element condos. On the other hand, a GVI value of 100 is not observed either (the highest value in the data is roughly 45). Such a high degree of greenery coverage is unrealistic, as it would effectively block out street signs and lights, buildings, sidewalks, cars, and the majority of the sky and pavement. Though ultra-high GVI values may be theoretically possible (say, by driving a GSV-equipped vehicle through an arboretum), they are not applicable to urban areas. In most cases, a GVI above 30 is moderately lush, and most values higher than this are limited to wide yards in low-density neighbourhoods.[7]

Figure 28: Earlier aerial image (a) and current street-view (b) of a property unit with an abnormally low GVI. In actuality, the current GVI is far higher due to an adjacent park, but the GVI in the data was from a time during construction, when nearby greenery was limited/non-existent.

7.1.1 Limitations and Challenges with GVI Values

Though data was manually cleaned to remove non-applicable data such as street signs and cars, there is no way to determine the relative value of different types of street-level greenery in urban environments. For instance, perhaps a grouping of trees has a different effect or different effect magnitude on housing prices compared to a group of hedges or other foliage type such as grass. The authors of the Treepedia paper address the differences in greenery types briefly, noting that GVI and canopy coverage are more highly correlated at all measured distances compared to GVI and grass coverage, though the latter type of coverage accounts for only a small fraction of the data overall (Li et al., 2015).

Further, the Treepedia paper points out that accurately extracting green vegetation from GSV images is challenging in general. Even with areas that are clearly covered with greenery to the human eye, the existence of shadows can confound the GVI algorithm's processed results. Street view images are stored in three dimensions using RGB colour space. As Li et al. (2015) points out, the lack of infrared bands, which are primary indicators for green vegetation, are not available for image characterization (Li et al., 2015).

[7] A depiction of the highest-value GVI in the dataset can be found in the ***Appendix***.

The issues of classifying street-level greenery also encompass the non-inclusion of "non-green greenery". Though only making up a small minority of the overall street-level coverage, these different coloured plants and flora are for the most part unaccounted for in GVI values (see ***Figure 29***). Despite this, these plants still exhibit ecological and environmental benefits as outlined previously.

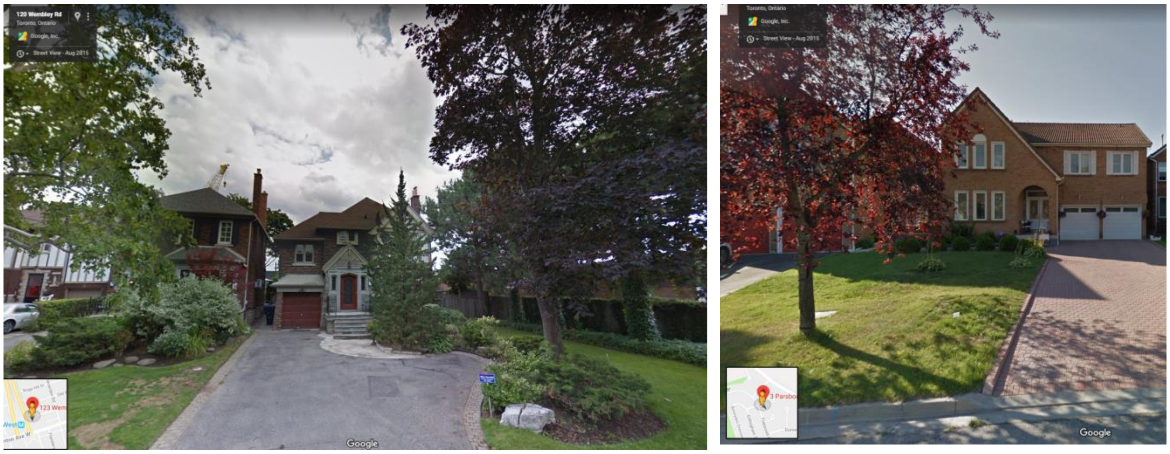


Figure 29: Tree species such as Schubert Cherry and Japanese Maple, while clearly adding to the natural aesthetic of a property, are not coded properly in green view index values, because they lack the necessary green band for proper RGB interpolation. The left image has a GVI of 8.8; the right image 12.9 (for the whole panorama, though these images capture instances where non-green greenery takes up a sizeable proportion of the frame).

Additionally, a yard (or series of adjacent yards) represented by a GVI value may undergo climatic variations. Heat waves, droughts, or long stretches of conditions unsuitable for optimal growth can decrease the proportion (saturation) of greenery for an area. An improved dataset might consider an average of several GSV images for each GVI point, such that values whose variance crosses some predefined threshold are filtered out, though it is difficult to say to what extent the corresponding models would improve.

Another limitation is the nature of the lots themselves and how they relate to the GSV collection process. In general, lots closer to the road allowance (and hence the image capture source) have greenery that takes up a greater degree of visual space than lots further away (down a driveway for instance). As such, large lots with a high degree of greenery that is further away from the road may actually report a lower GVI value than small lots with a single adjacent broad-leaf tree, due to the latter taking up more visual space. Incorporating lot size or dimensions as a controlling variable in the model may help mitigate this issue. While this effect goes both ways (in that small barren lots take up a large visual area as well compared to large lots with barren areas further from the image source), it is more pronounced for positive instances of recorded green areas, due to the verticality of trees (see ***Figure 30***).

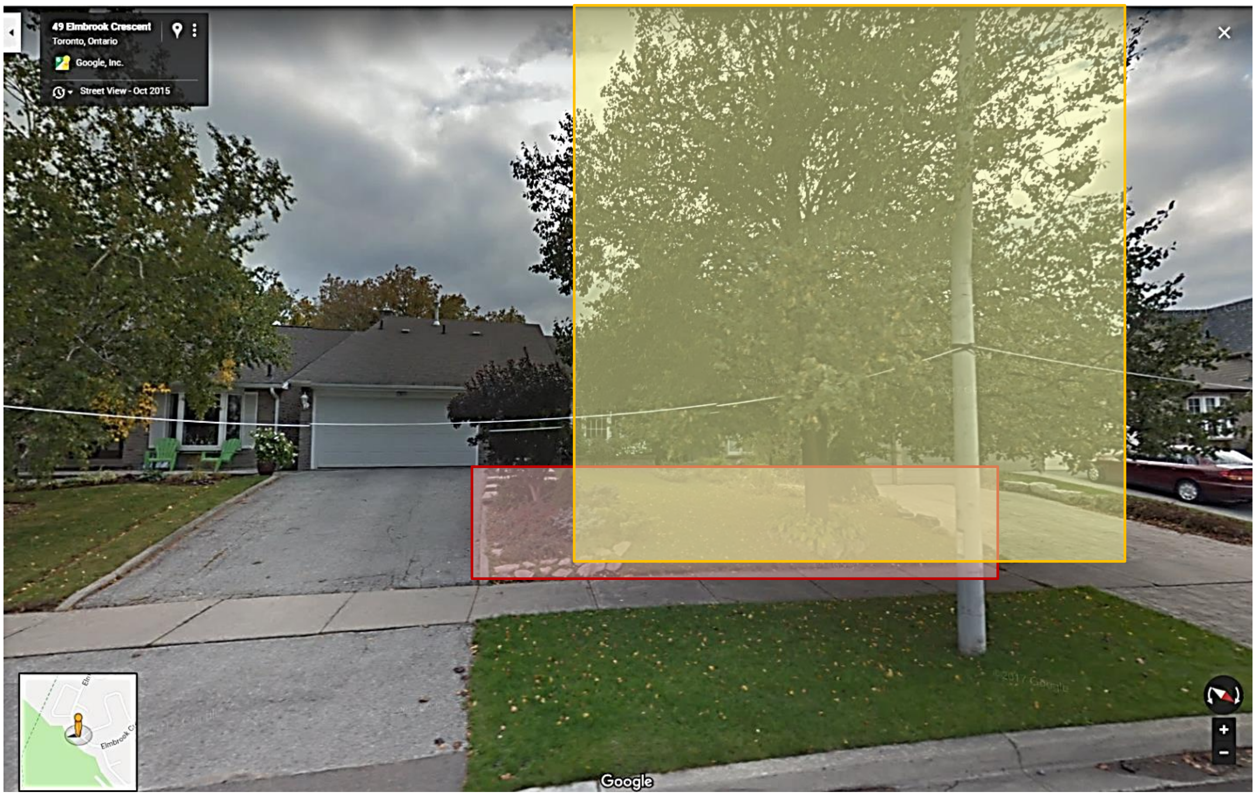


Figure 30: Because trees take up a large degree of vertical space in the GSV images, smaller lots that are closer to the road (and thus closer to the image capture source) impact GVI values proportionally more than larger lots that are further away, even if the larger lots have more greenery overall.

In this instance above, the area covered by the tree on the front of the lawn (orange) is roughly 6 times larger than the lawn itself (red). Thus, a barren lawn has less impact on GVI value than a lack of a tree for a single GSV image.

In terms of temporal effects, because green view indices are recorded (and can only be *observed*) during warmer months, there exists an interaction effect between time of year and green view values. “Treated” months, or those in which people can directly experience street greenery, include May through September. “Untreated” months, therefore, include October through April. Negative coefficients were observed for all property types except for multiplexes, but only detached homes experienced a statistically significant impact on the green-view/treated-month interaction term (at the 0.05 level). The model estimated that the sale price of detached homes sold during treated (summer) months is about 0.2% lower than those sold during untreated (winter months), for each 1-percentage point increase in GVI.

At face value, this suggests that for greener neighbourhoods, buyers are willing to pay more in the winter months than summer months (for detached homes), despite being unable to visually quantify or appreciate the greenery itself. In this case, the *perceived* density of greenery in the neighbourhood is for them higher than the actual density of greenery, implying that buyers are overpaying based on their notion of how lush a street may be. Between 2016 and 2017, sale prices of detached homes increased significantly in Toronto. Because the magnitude of sale price increases is comparatively large over the two year period, the overall results are skewed upwards by sales in 2017. Further, a decrease in the effect on unit sale price due to that unit being sold during treated months in 2017 versus being sold in untreated months in 2017 implies that the overall market fell during these months. In this case, homes sold in "treated" months in 2017 would appear to sell for lower amounts than comparable homes just a few months prior. In fact, there was a sharp decline in both housing sales and average selling price for the summer months in 2017 (Wong & Hertzberg, 2017). This is supported by the data used by the models within this paper as well (see Appendix). In particular, detached and semi-detached homes saw the sharpest decline. Several factors are important to consider for understanding this short-term price decline, primarily due to relevant legislature.

Indeed, the former Ontario Liberal government's introduction of the Rental Fairness Act in April 2017 expanded rent control to all private rental units, restricting rent increases to 1.5 per cent in 2017 (among other stipulations). Haider and Moranis (2018) point out that both the Canada Mortgage and Housing Corporation (CMHC) and the Toronto Real Estate Board (TREB) reported accelerating rental rates in the second quarter of 2017 onward. Rent controls in general reduce the growth in available rental stock, which exacerbates the increase in rents overall (Haider & Moranis, 2018). For Toronto, the propensity of individuals to rent is stymied by the rate of condominium development, which eclipses that of purpose-built rentals. In a CBC article in 2017 on rent control, economist Benjamin Tal (2017) opines that Torontonians are increasingly willing to buy in at greater and greater costs, which inflates the market. As such, this consistent increase in demand above that of supply precludes a consistent increase in price.

Other factors likely contribute to this discrepancy. Increases in immigration to Toronto specifically, paired with a massive spur towards condominium development in 2017 compared to 2016 increased demand for housing, especially in the downtown area. Altus Group (2018) reported a pre-construction sales decline of single-family homes in the GTA of 58% in 2017, whereas condo units saw a 25% increase in sales during the same period (McFarland, 2018). 60% of these units were built in Toronto specifically (McFarland, 2018).

However, in attempting to reconcile the lower sale prices due to the effect of visible greenery, the separate analysis of 2016 and 2017 proves unfruitful. Comparisons between separate 2016 and 2017 data models (see Appendix) show that summer months have a negative impact on the sale price of a house that is explained by greenery, for detached and semi-detached homes (other low-rise property types are non-significant). Conversely for 2017, it is observed that detached homes are no longer impacted in this sense to a statistically significant degree, but other low-rise property types are, and detached and multiplex homes are in fact positively affected. In the case of the relationship between housing sale price and greenery (GVI values), the true relationship, though resembling linearity close to median GVI values, is likely biased in extreme GVI cases. For example, it is hypothesized that very low GVI value homes have a significantly higher marginal value benefit with regards to increasing greenery, compared to already lush neighbourhoods. Conversely, diminishing returns are likely for areas with extraordinary levels of greenery, and in fact may adversely affect prices, for example when views become blocked, or maintenance times and costs become significant relative to the utility of the green space. Using a variant of local regression (locally estimated scatterplot smoothing, LOESS) in R, it can be shown that this postulate is supported in a general sense (see Appendix). A disadvantage of this type of analysis is that LOESS becomes decreasingly accurate towards extreme values because it relies on a local data structure, which is significantly less dense at either end of the data.

Because a large proportion of the housing stock reflected in the data tends to exhibit GVI values close to the mean (roughly around 20-25), the data is limited in its scale to measure the above scenario for property types other than detached homes. Indeed, for when the data is limited to units with a GVI of 25 or greater, all housing types except for detached homes lose statistical significance with respect to greenery having an impact on sale price. Nevertheless, in comparing detached home sale models across different GVI constraints (see Appendix), increasing returns on sale price with respect to GVI values are seen until above the GVI_{35} constraint, which implies that a threshold for utility exists. Interestingly, negative coefficients are still reported for the interaction between greenery and homes sold during treated months, suggesting that homebuyers are still overestimating the value of greenery during winter months compared to summer months, though this overestimation *decreases* as greenery increases. However, this interaction is not found to be statistically significant.

Seasonality was accounted for in the data by including months as factor variables within the models. Though a greater number of units are indeed sold in spring months (April in particular), only detached and semi-detached homes were estimated to have statistically significant increases in sale price (for low-rise property types). Compared to January, detached homes sold for 3.4% more in March, 3.9% more in April, 6.1% more in May, 5.5% more in August, and 7.2% more in September. For semi-detached homes, sale price increases were 6.9% in March, 9.4% in April, and 6.3% in October compared to January. These findings were significant at or better than the 0.05 confidence level.

For condo and related units, only condo apartments were found to be statistically significant, with units sold in February selling for 4.9% less, in July for 1.9% less, in September for 1.9% more, in November for 4.1% more, and in December for 4.1% more, compared to January.

7.2 Other Characteristic Variables

Living space area (in square feet) was significant at the 0.01 confidence level for all property types. When individuals consider the price per square foot of a potential home, it is in coordination with distance from amenities to which they most require or want access. For instance, a person working in the downtown core chooses between living space (in the case of living in low-density areas) and accessibility to work (in the case of living near downtown) for a given price point.

For low-rise type properties, detached and semi-detached homes were roughly comparable in terms of price premiums, commanding between 3-4% increases for every 10% increase in square footage. Multiplexes stood out as incurring the largest premium for space (for low-rise properties), at 5.09% for a 10% increase in square footage. In the case of multiplexes, buyers look to rent out the individual units. Compared to a single-unit purchase as an investment vehicle (*e.g.* a buyer purchasing a small bungalow for extra rental income), multiplexes offer multiple units that may be rented, and as such generally command a higher price overall. As such, because of the per-unit versus per-property relationship of size and rental price, multiplexes command a high premium for square footage increases because it precludes higher rents for each constituent unit (which in turn provides a higher income return).

Condo units saw an even greater impact on sale price due to living space area compared to low-rise units, with condo apartments commanding an 8.05% price premium for a 10% increase in living space (a premium of nearly 7% for condo townhouses and common element condos). This impact is primarily due to the high value of space in high-density environments in urban areas. This directly refers to the premium balance in accordance with location (people will pay more for less space if they are closer to more desirable areas).

In a related fashion, the number of above-ground bedrooms had insignificant and low-impact effects on sale price in the case of low-rise property types. For homes in comparatively low-density environments (property types such as detached or semi-detached), two issues are present. Firstly, the model effect sizes illustrate the effect of an additional bedroom, holding other factors (namely square footage) constant. This implies that as bedrooms are added to a detached home (for example), the effective living space-per-person declines. This is antithetical to the main desirability factor of detached homes—that is, more living space at the cost of distance to amenities. Secondly, an increase in the number of bedrooms compared to a constant floor space may still be attractive to some buyers, but also removes potential room for other amenities (living room/family room/washroom/kitchen space). Combining these two considerations yields a situation that depends on the needs of the specific individual, and is such not significantly impactful for the models presented.

On the other hand, condos do experience a small but statistically significant impact on sale price based on increasing the number of bedrooms in the unit. The impact is negative, which (as described above) illustrates the greater value weighting of floor space compared to other characteristics, at roughly a 2.5% price penalty for each bedroom added, keeping total floor space constant. Interestingly, the impact on common element condos was positive, with about a 4.2% price premium for a one-bedroom increase. Though the statistical significant of this result is limited to a 0.10 confidence interval, it is possible that the natural of shared elements across these condo units make the reduction in space less (comparatively) of a concern compared to the value added of another bedroom.

Conversely, the number of washrooms was found to have a significant effect on sale price for all property types. Washrooms in this context may be thought of as a proxy for living space, and by extension, the degree of *comfortability* or *adequacy* of the living space. Certainly, a housing unit inhabited by one person must have one washroom. Similarly, a comparable housing unit with two inhabitants may also be suited adequately by a single washroom. Even a three-inhabitant unit might be suited adequately by a single washroom. However, it is unlikely a three-inhabitant unit is suited by a single bedroom. In the case of the data used, controlling for square footage and increasing the number of above-ground bedrooms by one impacts the expected number of washrooms by roughly 0.25. Alternatively, for every four bedrooms in a unit, an additional washroom is expected, controlling for living space.

For parking type, benefits were limited primarily to detached homes. For detached units, individuals pay premiums for a greater amount of space (including space to park one or more vehicles) at the cost of distance. For detached homes, because the area in which they are built is generally low-density, there is more room afforded for amenities such as detached or built-in parking entities. Compared to no private parking type at all, detached homes incurred a sale price premium of 6.57% for attached parking, 9.85% for built-in parking, 4.89% for detached parking, and 5.02% for other parking types. In this case, the higher premium for something like built-in parking may stem from the implicit notion that the unit is in a higher-density area compared to a unit with detached or attached parking types. These areas likely constitute a higher-value in terms of accessibility (such as a closer distance to the central business district), which means that the individual must sacrifice one kind of space (*i.e.* for a detached parking garage) for another—living space that is comparatively closer to desirable areas.

7.3 On Locational Variables

The major trade-off for living space in purchasing a home is location. Access to areas of employment, leisure amenities, and major neighbourhood junctions are important considerations for buyers. For many individuals living throughout Toronto, work exists within a close proximity to the central business district (CBD). This is an area surrounding Yonge St and King St in downtown Toronto and extending radially.

For low-rise properties, a distance further away from the CBD correlates negatively with sale price. The per-kilometre penalty incurred is relatively small in magnitude for detached homes at roughly 0.5%. In 2007, Toronto's downtown had a population density of 7,950 persons per square kilometre, but had a job density of 39,450 per square kilometre (Filion, 2007). With a nearly 5-to-1 employment density to population density ratio, it is implied that a large number of Torontonians travel into the downtown core for work. As such, they are willing to pay a premium to be in an accessible location relative to their place of work. Conversely, the "work accessibility" price premium decreases as distance from the CBD increases—in the case of the models, the implicit assumption is that the average person works in or near the CBD. For condos, the finding was also statistically significant, with price penalties between 1.8% and 2.2% per kilometre, depending on specific property type. For similar reasons as with low-rise homes, the distance of these condo units to downtown is accordingly considered for unit price.

The finding of a negative correlation between distance to the CBD and housing price has been shown in numerous instances in the literature. Song and Knaap (2004) reported negative coefficients for distance variables in their hedonic model describing mixed land use values in Washington County, Orengon (Song & Knaap, 2004). Gilderbloom et al. (2015) determined that a one mile increase from the CBD in Louisville, Kentucky incurred roughly a US$2,800 penalty (2010 dollars) on property median assessed value (Gilderbloom, et al., 2015). Recent similar findings were reported by Soler and Gemar (2018), which modelled a combination of distance vectors to desirable city centre amenities and found that hotel room price decreased with increased distance (Soler & Gemar, 2018).

Property distance to a mall was found to have a mixed impact on sale prices for low-rise property types, and a generally negative impact on condo-type properties. For semi-detached homes, a 1-km increase in mall distance reduced sale price by roughly 1.8%. For row/townhouses, this reduction was

2.3%. A 1-km increase in distance to a mall reduced condo-type property sale prices around 1%. It is postulated that significant effect sizes are not seen when considering mall-distance due to the geographically spread-out nature of mall locations in Toronto (see ***Appendix***). Most radial distances of these mall locations begin to overlap around the 4-5 km mark, which means that distances after these points decrease (as one gets closer to a different mall). As noted by Liang et al. (2018), discrepancies in the literature exist with regards to price effects due to mall proximity, with both positive and negative relationships being found (Liang, et al., 2018). It is possible that the nature of residential development near malls is more inclined towards densities greater than those precluded by detached homes (*i.e.* semis, row homes, or condo apartments), however the case may in fact be the contrapositive.

Accessibility to different areas around the city may also play a role in pricing considerations for different property types, however the actual value depends on individual need. Distance from a highway was found to only be relevant as a predictor for sale price in the case of detached homes and condo apartments, and for detached homes the magnitude was modest, at 1.1% per kilometre. For condo apartments, the penalty incurred by distance was 3.5% per kilometre. While highways preclude a degree of noise and traffic, they provide a high degree of accessibility across cities (or city boundaries, in the case of Toronto). However, the large geographical span of Toronto's highways intersects or passes by a wide variety of different neighbourhoods in terms of median household income (***Figure 3*** qualitatively shows a subset of this concept). This large comparison range possibly makes any actual relationship unclear.

While accessibility in the context of proximity to a highway implies the use of a private vehicle for commute purposes, public transit also provides a means of access to employment areas (and other desirable locations), most prominently in Toronto with the use of subways. As such, it is reasonable to hypothesize that an increased distance from a subway station may incur a price penalty, particularly for higher-density property types (more specifically, ones that do not have high proportions of private parking—non-detached homes for instance). Condo-type properties and detached homes experienced a reduction in sale price as distance to subways increased. These reductions for detached homes were consistent with findings by Haider and Miller (2000), which reported an increase in value for properties in proximity to subway stations in Toronto (Haider & Miller, 2000). Zielstra and Hochmair (2011) postulated a viable walking distance for most transit rail station passengers of roughly 800 metres (~0.5 miles), which has since been used as a basis for transit proximity in the literature (Zielstra & Hochmair, 2011). Due to the relatively small and geographically-narrow area covered by Toronto's subway lines, it may be more productive to consider (categorically) properties sold within walking distance of transit stations, rather than applying a continuous distance scale in general.

Toronto City Planning reports a significant trend in the past 15 years towards higher major development projects, with 57% of development applications submitted between 2003 and 2007 being for buildings 12 storeys or less, and 35% of applications since 2013 being for buildings taller than 30 storeys, many of which are situated in proximity to the Lakeshore (Ostler, 2014).

A categorical predictor for *direct* proximity to the lake estimated that certain units built with direct lake access incur price premiums. Detached homes built within 250 metres of the lake incurred a near 22% price premium compared to otherwise comparable homes. The premium of direct lakeshore access here comes from a combination of limited supply and aesthetic value. Indeed, Luttik (2000) notes in their hedonic price modelling that homes built in proximity to bodies of water incurred an 8-10% price premium over comparable homes (Luttik, 2000). As Tyrväinen and Meittinen (2000) point out, direct proximity to a body of water is generally an appreciated feature in a housing are, though they do not include such a predictor in their model (Tyrväinen & Meittinen, 2000).

Findings with property values *decreasing* as beach proximity increased in Toronto have also been reported in the literature (Haider & Miller, 2000). However, Haider and Miller (2000) noted that Toronto's lakeshore contains pockets of aged and deteriorated small residential units (Haider & Miller, 2000), a notion that has changed significantly due to development in the past decade. The current Growth Plan for the Greater Golden Horseshoe describes an intensification target of a minimum of 40 per cent for all new residential development occurring within urban areas in and around Toronto (Ontario Ministry of Municipal Affairs, 2015). Indeed, between 2007 and 2010, the City of Toronto experienced and average annual residential intensification of between 80 and 100 percent, owing in part to a high degree of high-density housing forms being built (Ontario Ministry of Municipal Affairs, 2015).

For detached houses, increasing the posted speed limit to 50 km/hr or 60 km/hr (suggesting a busier, noisier road) decreased sale price by 4.8% and 9.8%, respectively, compared to the baseline of 30 km/hr. Semi-detached homes were impacted by speed increases to 60 km/hr, with a reduced sale price of 12.7%. Multiplex house prices decreased by 20.6% for a posted speed increase to 60 km/hr form 30 km/hr. Condo townhouses in a 50 km/hr zone incurred a 5.2% price premium compared to those in a 30 km/hr zone, but took a 2.7% price hit for 60 km/hr zones. Common element condos built in a 50 km/hr zone had a price premium of 14.4% compared to those in a 30 km/hr zone.

Posted road speed limits are used here as a proxy for density in the context of *accessibility* (*i.e.* traffic). In this sense, while accessibility is in general a desirable quality for a property, its value is in conflict with other neighbourhood characteristics, such as street noise and privacy. As such, for condo-type properties, the impact of posted speed limit is far lower because condo purchasers are not as perturbed (in the context of price) by noise and traffic compared to detached home-purchasers due to a higher tolerance for neighbourhood density.

7.4 On Demographic Variables

It was determined that for detached homes, a 10% increase in census tract after-tax income was associated with a sale price premium of 5.4%. For semi-detached homes, a 10% increase in after-tax income commanded an additional 4.7% in sale price; for row/townhouse homes, an additional 5.4%. The impact on multiplex houses was lower (around 3.4% for a 10% income increase). It is noted that the *n* for multiplexes was low (107; roughly 1% of low-rise property type cases). It is possible that multiplex homes attract a significant number of variable-income occupants, such that census tracts with high densities of multiplex units may produce a high-variability value for census tract household income. However, due to the relatively low number of multiplex units in the data, effect sizes for certain *neighbourhood* (census tract) characteristics are less meaningful in general.

For condo units, the impact of census tract after-tax income on sale price was found to be significant, but of lower magnitude compared to low-rise units. For high-density living environments, it is hypothesized that because of characteristic similarities between condo units within a building (especially ultra-high-rise condo buildings), the variability in intra-building unit price is low compared to low-rise homes on a given street (which may consist of detached homes, duplexes, bungalows with a detached garage, row houses, *etc.*). Indeed, ***Figure 11*** shows that the sale price distribution for condo-type units has a higher kurtosis than low-rise housing types. As such, despite potential high variability of after-tax income at the census tract level in areas with high densities of condo units, sale price of these units has a lower variability compared to low-rise homes (due to characteristic consistency across units), and as such is impacted to a lesser degree.

Population density was found to have a relatively low impact on sale prices for nearly all property types, though all are statistically significant at the 0.01 level (except for multiplexes). For example, detached homes experience less than 1/25th of a percent price increase for a 1% increase in census tract population density. Even a 10% increase only impacts sale prices by 0.39% for detached homes. In accordance with the current rate of intensification in Toronto (especially downtown), the impact of increasing a census tract's population density by 10%, 25%, 50%, and so on has far wider implications that housing sale prices alone (and indeed likely confound many of the other predictors in the models) which fall outside of the scope of this paper. It is possible that a "cancelling-out" effect exists, where increases in population density lower the living space per-person in an area, but simultaneously increase the demand for the space.

Other demographic variable effects were explored in earlier models, but were found to have a low impact (in the case of low-income population) with regards to the hedonic housing price models. For low-income population percentages, the effect of any significant-magnitude increases has a series of complex effects. These effects are not limited to housing sale prices, although the sale prices themselves may change for different reasons. For example, the low-income population of a census tract might increase because more low-income earners move into the area, or it may increase because high-income earners in the census tract move out at a higher rate than low-income earners. The impact on housing sale prices for each scenario is different, and the underlying causes for each scenario require specific research efforts themselves.

On the other hand, increasing in immigrant population makeup of a census tract was found to have a positive effect on housing sale price within the tract, for specific property types. For detached homes for instance, a 10 percentage point increase in census tract immigrant population is associated with a sale price premium of 6.7% (significant at the 0.01 confidence level). Similar impacts are observed for row houses and all condo units, though at lower magnitudes. It is hypothesized that part of this impact may be due to the increased demand for housing by immigrant populations coming into Canada (specifically Toronto) in tandem with the total number of incoming people. The 2018 Canadian immigration target is set at 310,000 individuals, up from 300,000 in 2017, and from 260,000-285,000 in 2015 (Ontario Ministry of Finance, 2018). Roughly 30% of these immigrant populations move to Toronto specifically (Ballingall, 2017). It is possible that is it not the *immigrant* population itself that is effecting the price impacts, but rather the notion that the population itself is both increasing and becoming more dense, spurring greater demand for housing (and as such raising property values).

8. Conclusions

The role of urban forestry has become increasingly important in the context of sustainability, both from an environmental context, and from a developmental context. Greenery in an urban environment has demonstrable implications for health, air quality, aesthetics, and land value, as described broadly across the literature.

From an environmental context, Lafortezza et al. (2009) illustrated how urban canopy coverage acts to block shortwave radiation in city centres, increasing water evaporation and lowering urban temperatures. Urban canopy growth strategies employed by cities have been shown to mitigate air pollution caused by everyday urban activities (Jim & Chen, 2008). Further, Zhang et al. (2015) has shown that increasing green canopy coverage reduces stormwater runoff (through the absorptive capacities of soil). This reduction has significant implications for problems such as flooding, soil acidity, and water-based structural damages.

Beyond the physical characteristic effects of urban greenery, economic externalities also exist. Several accounts in the literature describe the nature of income inequality as it relates to canopy coverage (with particular regards to urban environments). Research by Iverson and Cook (2000) found that both household income and household density and strongly related to land in the Chicago region. Work by Schwarz et al. (2015) also determined a positive correlation between urban tree canopy cover and median household income across several US cities. There are several externalities that arise from income challenges for households. In Canada, low household income has consistently been associated with poor health, especially in city centres (McLeod et al., 2003). Work by Astell-Burt et al. (2014) suggested that inequitable distribution of green spaces could exacerbate health inequalities of people with lower incomes. Further, these people are already at a greater risk of preventable diseases, due to poorer access, compounding the degree of inequality.

Larger housing lots have more room for trees and other greenery, which in turn are able to sequester more pollutants compared to a bustling downtown neighbourhood (Holcombe, 1999). However, while the draw of these areas lies in their affordability (with suburban land being generally less expensive than property within a city center), the cost is their accessibility.

Distance to public green space has been cited in the literature as a contributor to neighbourhood property valuation increases. Morancho (2003) found an inverse relationship between the selling price of a dwelling and its distance from a green urban area in a study in Spain. One study in the Netherlands demonstrated an increase in housing sale prices of up to 28% due to environmental factors (Luttik, 2000). A 2016 meta-analysis on hedonic property values demonstrated a positive and significant relationship between property values and proximal tree canopy coverage in the U.S. (Siriwardena, Boyle, Holmes, & Wiseman, 2016).

Past work in the literature on the relationship between property value and urban greenery has been restricted primarily to canopy-level descriptions of the foliage considered. The Treepedia project in 2015 allowed for a robust quantification of street-level greenery across many urban centres around the world. Using this data, a more accurate representation of the visual space occupied by greenery is established.

Using the green view index (GVI) data from the Treepedia project, street-level greenery densities were compared against housing prices across Toronto. The hedonic models used compared property types, accounting for characteristic, locational, and demographic variables. It was determined that a statistically significant relationship between street-level greenery and housing prices exists in Toronto for detached homes, semi-detached homes, row/townhouse units, condo apartments, and condo townhouses. The relationship was strongest for detached homes, with a 5-percentage point increase in proximal GVI values constituting a 2.79% price premium on the home. This equates to an additional $13,900 for a $500,000 unit. Similarly, this relates to an additional $6,290 and $11,890 to sale price in the case of semi-detached and row houses, respectively. For condo townhouses a sale price premium of roughly $12,400 is incurred. Condo apartments incurred the smallest premium, at about $3,260 on a $500,000 unit, for a 5-percentage point increase in GVI value. Further, the detached house regression model produced the lowest standard error values for green view indices (for low-rise housing types), suggesting a lower variability in price due to greenery compared to other comparable, non-detached units.

These findings are important because they aid in the classification of urban greenery as an *asset* in addition to an amenity. Prior research in the literature primarily considers canopy-level (*i.e.* aerial, top-down) coverage and its relationship to property values. However, this methodology does not produce a description of what people (homebuyers and sellers) actually see as they walk down a street (or as they gaze from their front window). Conversely, this paper outlines such a description, using Google Street View images to generate a portfolio of street-level data.

The next step in this research path is to take the models and apply them as predictors to new homes. This has applications in a variety of scenarios, such as for appraisal or planning purposes. As aforementioned, consideration of green space during the land use/city-building process is essential and is most effective when financial components are able to be accurately determined (Vandermeulen et al., 2011; Hotte, et al., 2015). Provided consistency can be achieved for new data using the presented models, the following step is to apply the methods to other Treepedia datasets in comparable urban centres in different geographical areas, for example in Boston, Vancouver, Dublin, and so forth. In general, comparable cities will be those with relatively similar demographics and climate.

There are several caveats with the findings in this paper. Firstly, the GVI value collection process is not continuous with regards to location. The values are at a minimum of 20 metres away from one another, making direct relationships to each and every housing sale not possible. As such, the reliability of each GVI data point used in the models relies on a low overall degree of variability of greenery on a per-street basis, which is common for many instances but not all.

Further, the actual quantification of "green" faces its own set of challenges. Because the extraction algorithm functions by using only the images' green band, it can be confounded by light levels, such as with the presence of shadows. Li et al. (2015) points out that the lack of infrared bands, which are primary indicators for green vegetation, are not available for image characterization. There are also accounts of "non-green" greenery—that is, plants whose primary colour may be red, purple, or another shade with a low green band value. This includes plants such as the Schubert Cherry or Japanese Maple, which have found popularity in recent years across Toronto lawns.

Climate plays a significant role in the level and quality of greenery across a city, and can change significantly year-over-year. Heat waves, droughts, or long stretches of conditions unsuitable for optimal growth can decrease the proportion (saturation) of greenery for an area. Further, distance from the street must also be considered, as larger lots may have an "equivalent" green space coverage as small lots with a tree close to the road allowance, which confounds the GVI values.

Despite these limitations, the description of street-level greenery and its relationship to property values in Toronto presents a new way of quantifying urban green space in the context of a hedonic pricing model. This paper provides support for the further consideration of enhancing Toronto's canopy, providing value from the perspective of green space as both an amenity and an asset.

Appendices

A: Data Tables

Air Conditioning Type by Property Type

	Condo Apt	Detached	Semi-Detached	Condo Townhouse	Att/Row/Twnhouse	Common Element Condo	Multiplex
n	40278	22773	6811	5193	2549	1315	356
f.ac.type (%)							
None	1307 (3.2)	2240 (9.8)	972 (14.3)	495 (9.5)	264 (10.4)	107 (8.1)	165 (46.3)
Central Air	37729 (93.7)	19075 (83.8)	5422 (79.6)	4485 (86.4)	2210 (86.7)	1017 (77.3)	106 (29.8)
Wall Unit	420 (1.0)	849 (3.7)	247 (3.6)	87 (1.7)	40 (1.6)	91 (6.9)	34 (9.6)
Window Unit	616 (1.5)	351 (1.5)	111 (1.6)	87 (1.7)	24 (0.9)	92 (7.0)	39 (11.0)
Other	206 (0.5)	257 (1.1)	59 (0.9)	39 (0.8)	11 (0.4)	8 (0.6)	12 (3.4)

Basement Type by Property Type

	Condo Apt	Detached	Semi-Detached	Condo Townhouse	Att/Row/Twnhouse	Common Element Condo	Multiplex
n	40278	22773	6811	5193	2549	1315	356
f.basement (%)							
None	39104 (97.1)	100 (0.4)	43 (0.6)	2686 (51.8)	234 (9.2)	1223 (93.1)	3 (0.8)
Finished	76 (0.2)	14349 (63.1)	3810 (56.0)	1681 (32.4)	1400 (55.1)	10 (0.8)	91 (25.6)
Apartment	402 (1.0)	3150 (13.8)	1224 (18.0)	103 (2.0)	213 (8.4)	23 (1.8)	195 (54.8)
Walk-Out	12 (0.0)	2423 (10.6)	760 (11.2)	454 (8.8)	311 (12.2)	0 (0.0)	21 (5.9)
Other	683 (1.7)	2732 (12.0)	968 (14.2)	262 (5.1)	382 (15.0)	58 (4.4)	46 (12.9)

Building Age Range by Property Type

	Condo Apt	Detached	Semi-Detached	Condo Townhouse	Att/Row/Twnhouse	Common Element Condo	Multiplex
n	40278	22773	6811	5193	2549	1315	356
f.age.range (%)							
0-5	11819 (61.7)	994 (16.7)	103 (5.5)	657 (37.1)	219 (20.1)	375 (54.8)	3 (2.5)
6-15	4720 (24.6)	572 (9.6)	164 (8.8)	641 (36.2)	392 (36.0)	147 (21.5)	0 (0.0)
16-30	1560 (8.1)	348 (5.9)	83 (4.4)	177 (10.0)	118 (10.8)	44 (6.4)	1 (0.8)
31-50	981 (5.1)	707 (11.9)	253 (13.5)	277 (15.6)	84 (7.7)	70 (10.2)	14 (11.7)
51-99	49 (0.3)	2913 (49.0)	730 (39.0)	14 (0.8)	36 (3.3)	45 (6.6)	65 (54.2)
100+	23 (0.1)	407 (6.9)	539 (28.8)	7 (0.4)	241 (22.1)	3 (0.4)	37 (30.8)

Balcony Type by Property Type (condo & related only)

	Condo Apt	Condo Townhouse	Common Element Condo
n	40278	5193	1315
f.balcony (%)			
None	6229 (15.5)	1869 (36.0)	217 (16.5)
Open	28524 (70.8)	1364 (26.3)	914 (69.5)
Encl	1100 (2.7)	62 (1.2)	50 (3.8)
Jlte	1153 (2.9)	88 (1.7)	20 (1.5)
Terr	3266 (8.1)	1810 (34.9)	114 (8.7)

Number of Bedrooms above ground by Property Type (summary)

```
$`Condo Apt`
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
    1.0     1.0     2.0     1.6     2.0     5.0     839 

$ Detached
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   1.00    3.00    3.00    3.33    4.00    9.00      43 

$`Semi-Detached`
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   1.00    3.00    3.00    3.22    3.75    9.00       5 

$`Condo Townhouse`
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   1.00    2.00    3.00    2.67    3.00    6.00       8 

$`Att/Row/Twnhouse`
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
    1.0     3.0     3.0     3.1     3.0     9.0       1 

$`Common Element Condo`
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   1.00    1.00    1.00    1.56    2.00    5.00      37 

$ Multiplex
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   1.00    4.00    5.00    5.28    6.00    9.00       7 
```

Condo & Related: Binary variable amenities included, by type

	level	Condo Apt	Condo Townhouse	Common Element Condo
n		40278	5193	1315
f.ensuite.laundry (%)	Not Included	1683 (4.2)	246 (4.7)	257 (19.5)
	Included	38589 (95.8)	4947 (95.3)	1058 (80.5)
f.heat.included (%)	Not Included	6879 (17.1)	4517 (87.0)	197 (15.0)
	Included	33393 (82.9)	676 (13.0)	1118 (85.0)
water.included (%)	Not Included	1885 (4.7)	1010 (19.4)	84 (6.4)
	Included	38392 (95.3)	4183 (80.6)	1231 (93.6)
f.hydro.included (%)	Not Included	29064 (72.2)	4860 (93.6)	963 (73.2)
	Included	11210 (27.8)	333 (6.4)	352 (26.8)
f.locker (%)	Locker	28750 (71.4)	1878 (36.2)	966 (73.5)
	No Locker	11522 (28.6)	3315 (63.8)	349 (26.5)
f.parking.included (%)	Not Included	7903 (19.6)	206 (4.0)	360 (27.4)
	Included	32375 (80.4)	4987 (96.0)	955 (72.6)

Exposure by Property Type (condo & related only)

	Condo Apt	Condo Townhouse	Common Element Condo
n	40278	5193	1315
f.exposure (%)			
e	6246 (15.5)	1032 (19.9)	166 (12.6)
ew	112 (0.3)	268 (5.2)	9 (0.7)
n	5623 (14.0)	939 (18.1)	197 (15.0)
ne	3374 (8.4)	145 (2.8)	107 (8.1)
ns	113 (0.3)	286 (5.5)	4 (0.3)
nw	3319 (8.2)	145 (2.8)	126 (9.6)
s	6376 (15.8)	1123 (21.6)	219 (16.7)
se	4421 (11.0)	169 (3.3)	138 (10.5)
sw	4820 (12.0)	177 (3.4)	152 (11.6)
w	5868 (14.6)	909 (17.5)	197 (15.0)

Family Room Included by Property Type (0 = not included, 1 = included)

	Condo Apt	Detached	Semi-Detached	Condo Townhouse	Att/Row/Twnhouse	Common Element Condo	Multiplex
	40278	22773	6811	5193	2549	1315	356
f.family.room (%) 0	37395 (92.9)	12246 (53.8)	4990 (73.3)	4094 (78.8)	1567 (61.5)	1134 (86.2)	283 (79.5)
1	2879 (7.1)	10526 (46.2)	1821 (26.7)	1099 (21.2)	982 (38.5)	181 (13.8)	73 (20.5)

Heat Source by Property Type

Property type	Condo Apt	Detached	Semi-Detached	Condo Townhouse	Att/Row/Twnhouse	Common Element Condo	Multiplex
n	40278	22773	6811	5193	2549	1315	356
f.heat.source (%)							
Other	696 (1.7)	130 (0.6)	22 (0.3)	25 (0.5)	19 (0.7)	35 (2.7)	6 (1.7)
Electric	2792 (6.9)	286 (1.3)	97 (1.4)	659 (12.7)	72 (2.8)	120 (9.1)	22 (6.2)
Gas	36782 (91.3)	21815 (95.8)	6602 (96.9)	4507 (86.8)	2454 (96.3)	1159 (88.1)	321 (90.2)
Oil	8 (0.0)	541 (2.4)	90 (1.3)	2 (0.0)	4 (0.2)	1 (0.1)	7 (2.0)

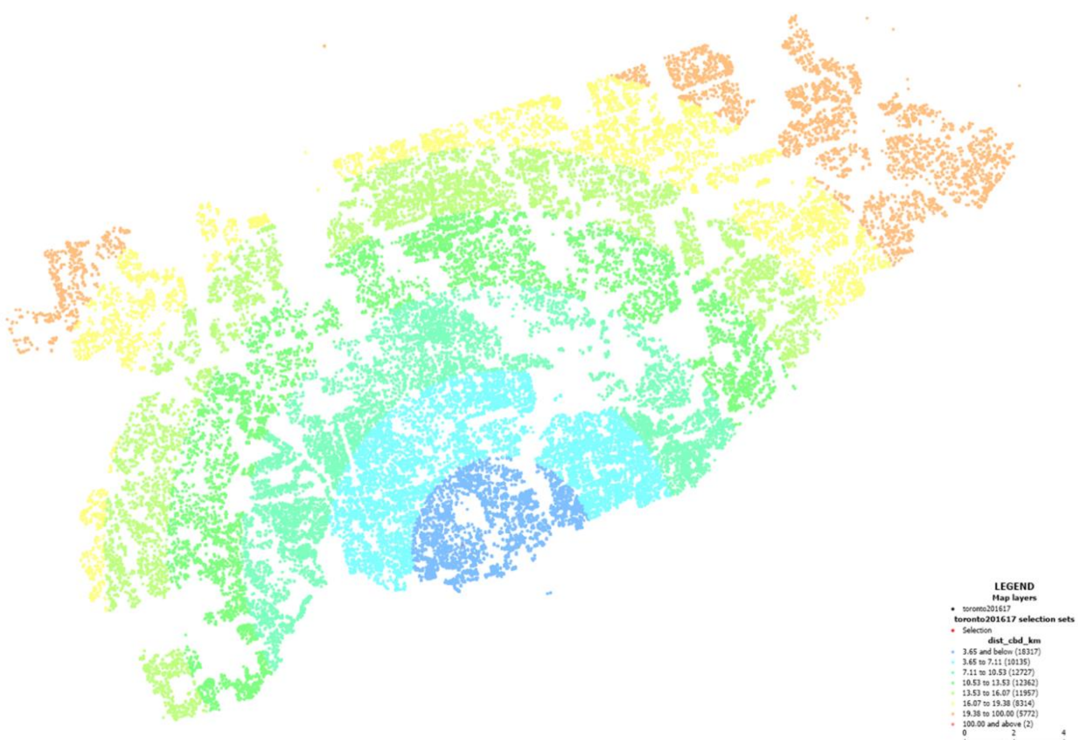
Parking Type by Property Type

	Condo Apt	Detached	Semi-Detached	Condo Townhouse	Att/Row/Twnhouse	Common Element Condo	Multiplex
n	40278	22773	6811	5193	2549	1315	356
f.parking.type (%)							
None	2829 (7.0)	5270 (23.1)	3283 (48.2)	350 (6.7)	583 (22.9)	140 (10.6)	158 (44.4)
Attached	78 (0.2)	8225 (36.1)	676 (9.9)	629 (12.1)	719 (28.2)	6 (0.5)	28 (7.9)
Built-In	103 (0.3)	3498 (15.4)	921 (13.5)	1033 (19.9)	858 (33.7)	10 (0.8)	22 (6.2)
Detached	41 (0.1)	4733 (20.8)	1667 (24.5)	41 (0.8)	323 (12.7)	5 (0.4)	131 (36.8)
Undergrnd	36586 (90.8)	0 (0.0)	0 (0.0)	2877 (55.4)	0 (0.0)	1087 (82.7)	0 (0.0)
Surface	358 (0.9)	0 (0.0)	0 (0.0)	212 (4.1)	0 (0.0)	49 (3.7)	0 (0.0)
Other	281 (0.7)	1046 (4.6)	264 (3.9)	51 (1.0)	66 (2.6)	18 (1.4)	17 (4.8)
	2 (0.0)	1 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)

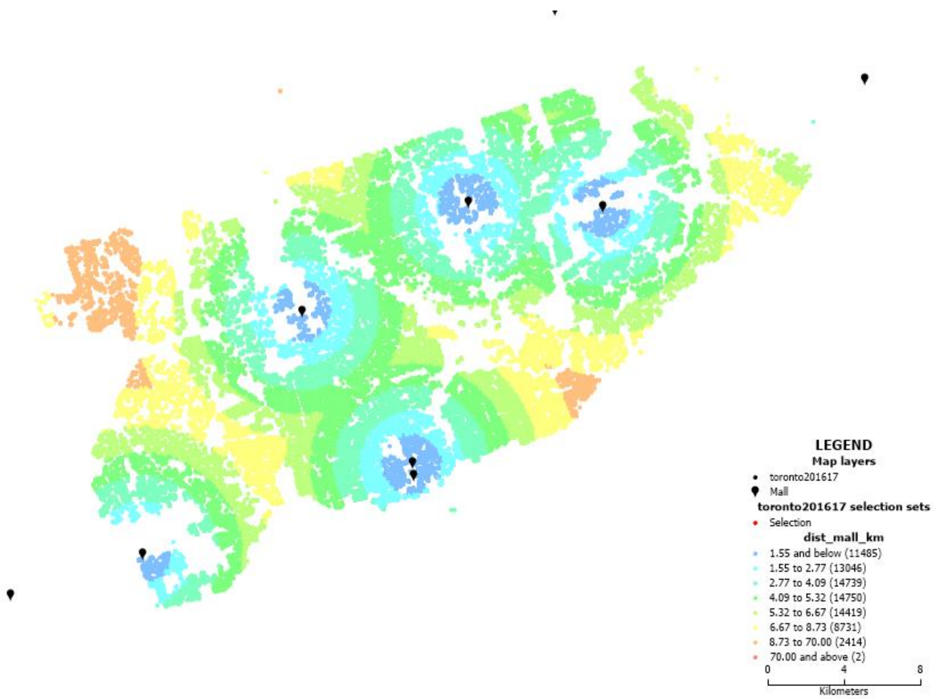
B: Locational Variable Illustrations

Distance to subway locations

Distance to CBD, central business district

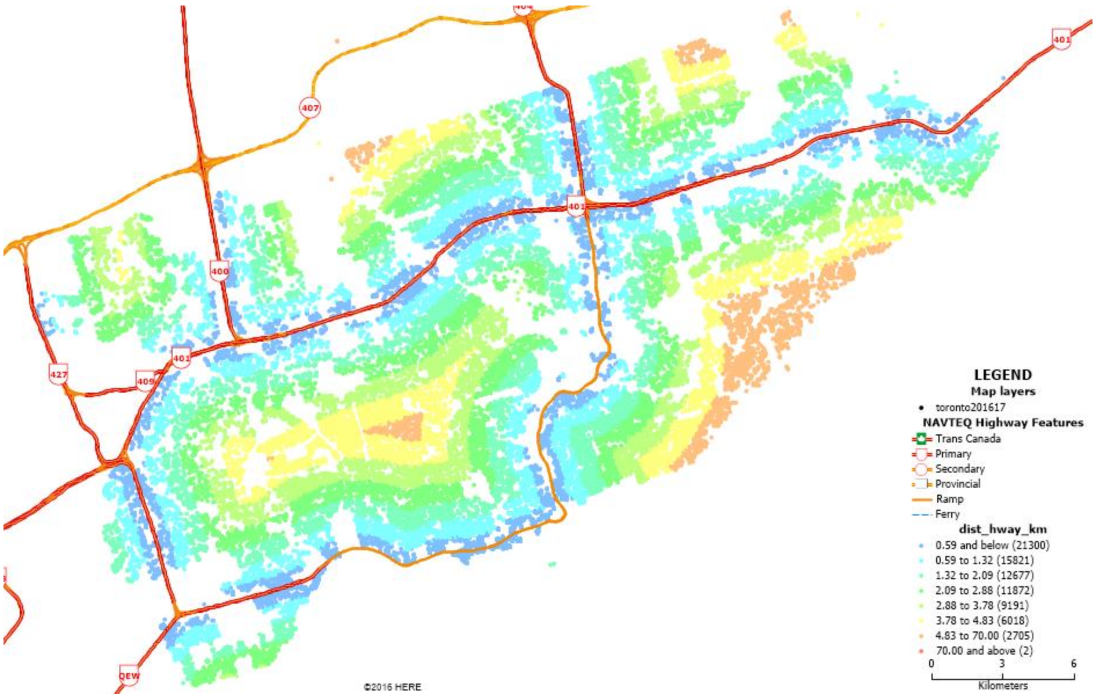


Distance to a mall



Distance to Lake Ontario

Distance to a highway



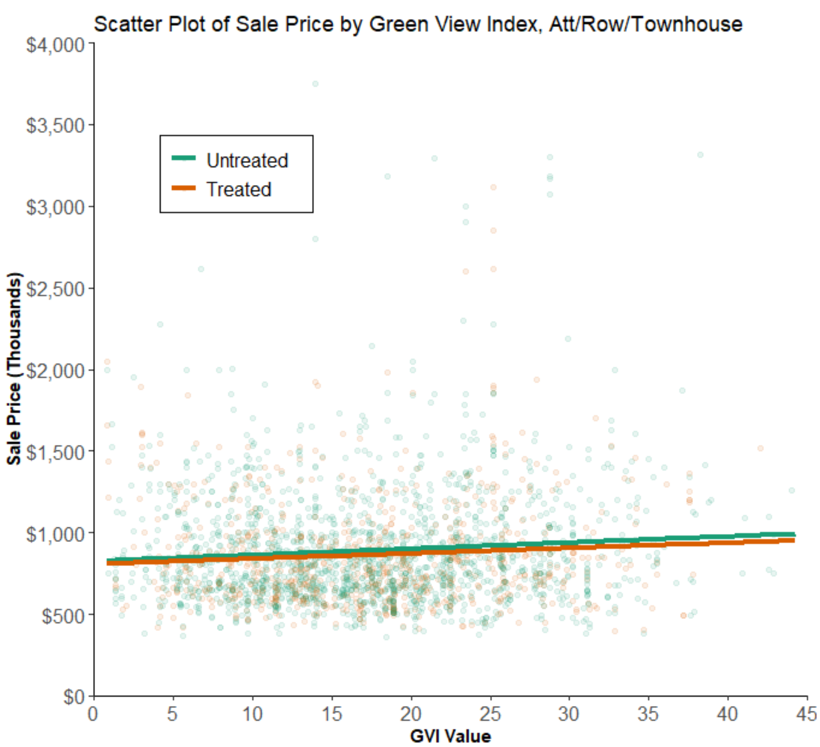
C: Miscellaneous Google Street View images

Google Street View images for the highest GVI value in the available dataset for Toronto (in Etobicoke), at 45.02. At (a) 0^{o}, (b) 90^{o}, (c) 180^{o}, and (d) 270^{o} rotations.

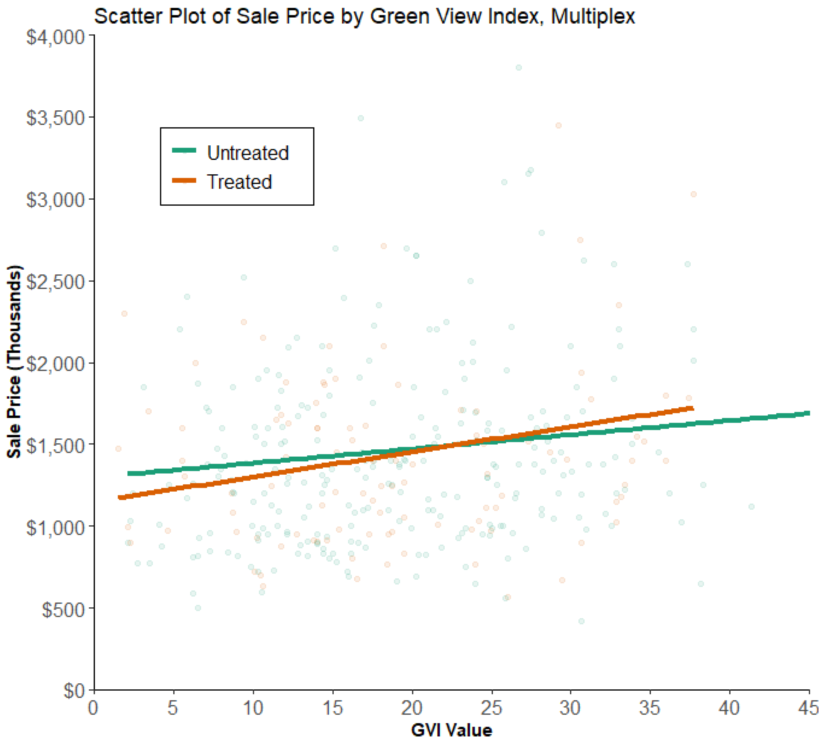
D: Treated and Untreated sale month effects on sale price due to GVI value

Semi-Detached

Attached/Row/Townhouse

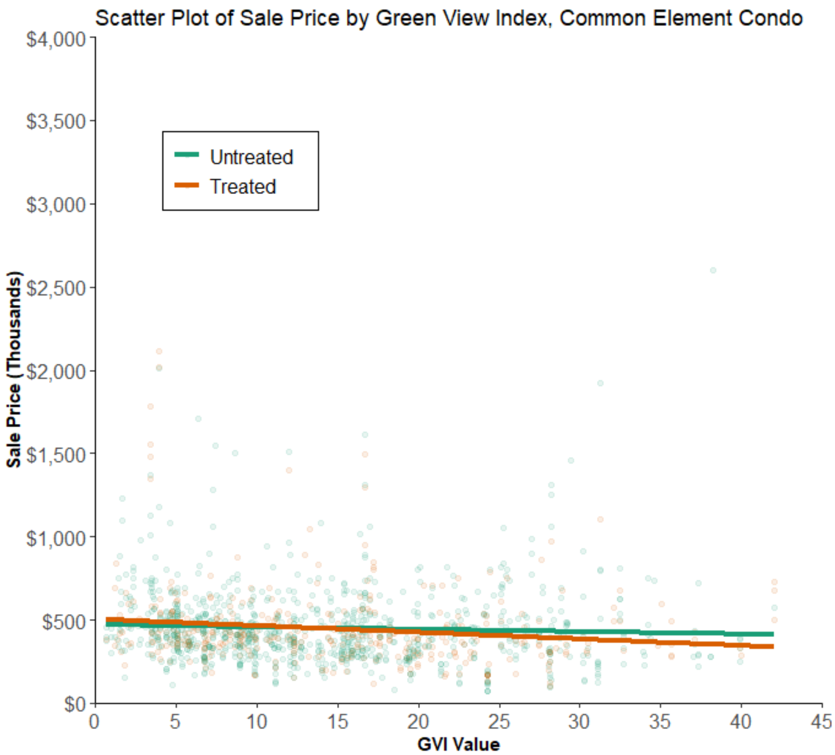


Multiplexes

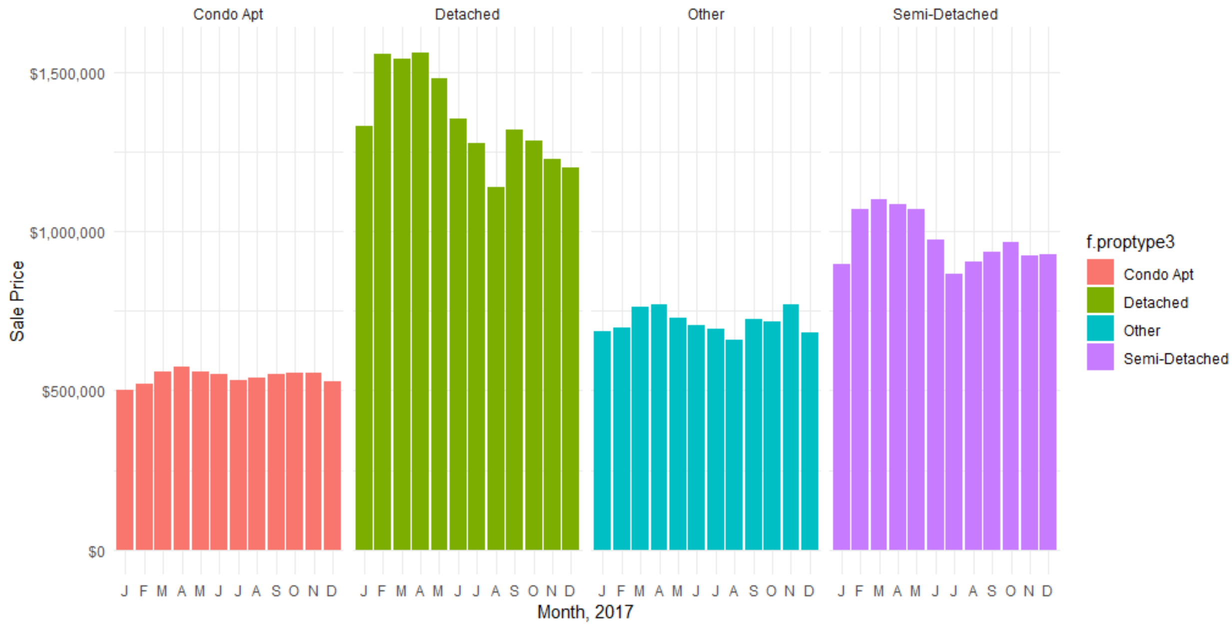


Condo Townhouse

Common Element Condo



Housing sale trends by property type, 2017



E: Additional Regression Models

Low Rise Housing Types: Regression Models, 2016 Data

	Dependent variable:			
	Log(sale price)			
	Detached	Semi-Detached	Att/Row/Townhouse	Multiplex
	(1)	(2)	(3)	(4)
green_new	0.0055***	0.0046***	0.0034***	-0.0050
	(0.0006)	(0.0010)	(0.0012)	(0.0037)
month.soldFebruary	0.0831***	0.0114	0.0088	-0.1821
	(0.0280)	(0.0452)	(0.0501)	(0.1663)
month.soldMarch	0.0707***	0.0331	0.1076**	-0.2159
	(0.0274)	(0.0441)	(0.0490)	(0.1736)
month.soldApril	0.1111***	0.0983**	0.0245	-0.2014
	(0.0270)	(0.0433)	(0.0483)	(0.1739)
month.soldMay	0.1836***	0.1562***	0.1058*	-0.1751
	(0.0330)	(0.0503)	(0.0562)	(0.2170)
month.soldJune	0.1750***	0.2005***	0.1373**	-0.1229
	(0.0330)	(0.0518)	(0.0572)	(0.1961)
month.soldJuly	0.1821***	0.1662***	0.1462**	-0.3196
	(0.0337)	(0.0512)	(0.0585)	(0.2649)
month.soldAugust	0.2399***	0.1783***	0.0794	0.0116
	(0.0341)	(0.0544)	(0.0572)	(0.2173)
month.soldSeptember	0.2319***	0.2379***	0.1191**	-0.0038
	(0.0333)	(0.0519)	(0.0577)	(0.2061)
month.soldOctober	0.1772***	0.1388***	0.1473***	-0.1249
	(0.0278)	(0.0438)	(0.0492)	(0.1619)
month.soldNovember	0.1909***	0.1363***	0.1552***	-0.1788
	(0.0277)	(0.0448)	(0.0492)	(0.1525)
month.soldDecember	0.2016***	0.1004**	0.2118***	0.4125
	(0.0305)	(0.0500)	(0.0592)	(0.2604)
bedrooms.ag	0.0028	0.0078	-0.0180	0.0260
	(0.0055)	(0.0085)	(0.0113)	(0.0280)
washrooms	0.0746***	0.0671***	0.0621***	0.0550**
	(0.0040)	(0.0073)	(0.0108)	(0.0254)
f.family.room1	0.0082	0.0323**	-0.0377***	-0.0496
	(0.0097)	(0.0140)	(0.0146)	(0.0723)
log(square.feet.int)	0.3991***	0.3410***	0.4476***	0.4979***
	(0.0162)	(0.0291)	(0.0372)	(0.1186)
f.parking.typeAttached	0.0511***	-0.0252	-0.0455	-0.0734
	(0.0123)	(0.0235)	(0.0294)	(0.1728)
f.parking.typeBuilt-In	0.0897***	-0.0070	-0.0414	-0.2361
	(0.0136)	(0.0202)	(0.0263)	(0.2228)
f.parking.typeDetached	0.0437***	0.0476***	0.0082	0.0840
	(0.0124)	(0.0158)	(0.0297)	(0.0720)
f.parking.typeOther	0.0558**	0.0553	0.0202	-0.2901
	(0.0234)	(0.0338)	(0.0479)	(0.1738)
dist_cbd_km	-0.0037**	-0.0137***	-0.0171***	-0.0142
	(0.0017)	(0.0029)	(0.0030)	(0.0220)
dist_hway_km	-0.0138***	-0.0001	0.0072	-0.0026
	(0.0028)	(0.0053)	(0.0060)	(0.0228)
dist_mall_km	0.0095***	-0.0209***	-0.0249***	-0.0376
	(0.0023)	(0.0046)	(0.0046)	(0.0289)
dist_stn_km	-0.0464***	0.0009	-0.0017	-0.0706**
	(0.0023)	(0.0047)	(0.0045)	(0.0327)
within_250m_lake1	0.2168***	0.2340***	-0.0073	0.8321***
	(0.0333)	(0.0797)	(0.0655)	(0.2666)
f.speed_kmh50	-0.0939***	-0.0101	0.0211	-0.3475
	(0.0326)	(0.0265)	(0.0327)	(0.2386)
f.speed_kmh60	-0.0960***	-0.1331***	-0.0520**	-0.2187**
	(0.0189)	(0.0284)	(0.0229)	(0.0945)
f.speed_kmh100	-0.1250			
	(0.2112)			
immigrants_per	0.0073***	0.0018*	0.0070***	0.0021
	(0.0004)	(0.0009)	(0.0009)	(0.0057)
log(aftertax_inc)	0.5674***	0.5286***	0.5734***	0.2512**
	(0.0136)	(0.0266)	(0.0306)	(0.1189)

log(pop_dens)	0.0332***	0.0762***	0.0548***	0.1331
	(0.0079)	(0.0112)	(0.0112)	(0.0850)
green_new:month.in.green.rangeTreated	-0.0020**	-0.0056***	-0.0011	0.0009
	(0.0009)	(0.0015)	(0.0018)	(0.0063)
Constant	3.8896***	4.6503***	3.4542***	6.4806***
	(0.2057)	(0.3701)	(0.4129)	(1.9818)
Observations	3,438	817	597	56
R2	0.8552	0.8331	0.7982	0.9116
Residual Std. Error	0.2103 (df = 3405)	0.1706 (df = 785)	0.1649 (df = 565)	0.1519 (df = 24)
Note:				*p<0.1; **p<0.05; ***p<0.01

Low Rise Housing Types: Regression Models: 2017 Data

	Dependent variable:			
	Log(sale price)			
	Detached	Semi-Detached	Att/Row/Townhouse	Multiplex
	(1)	(2)	(3)	(4)
green_new	0.0052***	0.0006	0.0072***	-0.0096
	(0.0006)	(0.0012)	(0.0013)	(0.0091)
month.soldFebruary	0.0642***	0.0991**	0.0378	0.3400
	(0.0192)	(0.0426)	(0.0425)	(0.2780)
month.soldMarch	0.0931***	0.1419***	0.0475	0.2236
	(0.0176)	(0.0377)	(0.0360)	(0.1990)
month.soldApril	0.0879***	0.1375***	0.0814**	-0.0583
	(0.0178)	(0.0380)	(0.0371)	(0.2147)
month.soldMay	0.0777***	0.0054	0.0833	-0.4720
	(0.0281)	(0.0500)	(0.0531)	(0.3122)
month.soldJune	0.0518*	-0.0509	0.0908*	-0.0810
	(0.0283)	(0.0493)	(0.0520)	(0.3280)
month.soldJuly	0.0058	-0.0981*	0.0049	-0.3223
	(0.0307)	(0.0537)	(0.0538)	(0.4137)
month.soldAugust	-0.0208	-0.0794	0.0253	-0.3782
	(0.0310)	(0.0526)	(0.0548)	(0.3291)
month.soldSeptember	0.0360	-0.0772	0.1077*	-0.7849**
	(0.0298)	(0.0490)	(0.0552)	(0.3565)
month.soldOctober	-0.0091	0.0488	-0.0249	0.6909**
	(0.0196)	(0.0403)	(0.0399)	(0.2882)
month.soldNovember	-0.0434**	0.0143	0.0199	0.0533
	(0.0197)	(0.0403)	(0.0381)	(0.1938)
month.soldDecember	-0.0337	-0.0186	-0.0531	0.2872
	(0.0230)	(0.0424)	(0.0508)	(0.1775)
bedrooms.ag	-0.0064	0.0064	0.0018	0.0313
	(0.0059)	(0.0098)	(0.0147)	(0.0394)
washrooms	0.0763***	0.0749***	0.0421***	0.0309***
	(0.0042)	(0.0084)	(0.0095)	(0.0101)
f.family.room1	0.0023	0.0299*	-0.0126	0.1374
	(0.0103)	(0.0155)	(0.0179)	(0.1130)
log(square.feet.int)	0.4317***	0.3677***	0.4657***	0.1150
	(0.0174)	(0.0342)	(0.0424)	(0.2351)
f.parking.typeAttached	0.0701***	0.0392	-0.0196	0.0220
	(0.0132)	(0.0294)	(0.0324)	(0.2237)
f.parking.typeBuilt-In	0.0879***	0.0097	0.0037	-0.5240*
	(0.0144)	(0.0239)	(0.0292)	(0.2540)
f.parking.typeDetached	0.0370***	0.0258	0.0369	-0.1564
	(0.0131)	(0.0181)	(0.0339)	(0.1332)
f.parking.typeOther	0.0366	0.0241	-0.0655	0.5865**
	(0.0235)	(0.0392)	(0.0629)	(0.2316)
dist_cbd_km	-0.0066***	-0.0185***	-0.0151***	-0.0379
	(0.0018)	(0.0033)	(0.0038)	(0.0284)

dist_hway_km	-0.0102***	-0.0117*	0.0002	-0.0598
	(0.0031)	(0.0061)	(0.0073)	(0.0525)
dist_mall_km	-0.0015	-0.0102**	-0.0180***	-0.0306
	(0.0024)	(0.0052)	(0.0058)	(0.0317)
dist_stn_km	-0.0362***	0.0055	-0.0020	0.0455
	(0.0026)	(0.0055)	(0.0058)	(0.0558)
within_250m_lake1	0.1650***	-0.1391	0.0039	-0.3251
	(0.0363)	(0.1094)	(0.0698)	(0.3589)
f.speed_kmh50	-0.0142	0.0096	0.0053	0.2314
	(0.0328)	(0.0322)	(0.0367)	(0.1623)
f.speed_kmh60	-0.1161***	-0.1287***	-0.0346	-0.5512***
	(0.0208)	(0.0359)	(0.0288)	(0.1797)
immigrants_per	0.0058***	0.000003	0.0045***	-0.0066
	(0.0005)	(0.0010)	(0.0011)	(0.0081)
log(aftertax_inc)	0.5288***	0.4206***	0.5139***	0.1461
	(0.0144)	(0.0290)	(0.0380)	(0.2173)
log(pop_dens)	0.0397***	0.0632***	0.0544***	-0.3008
	(0.0084)	(0.0138)	(0.0132)	(0.1811)
green_new:month.in.green.rangeTreated	-0.0015	0.0036**	-0.0043**	0.0273**
	(0.0010)	(0.0017)	(0.0020)	(0.0126)
Constant	4.3849***	6.0008***	4.1612***	14.9504***
	(0.2185)	(0.4141)	(0.4921)	(4.4420)
Observations	2,782	712	465	51
R2	0.8624	0.7954	0.7826	0.9042
Residual Std. Error	0.2039 (df = 2750)	0.1845 (df = 680)	0.1750 (df = 433)	0.2396 (df = 19)
Note:				*p<0.1; **p<0.05; ***p<0.01

Low Rise Housing Types: Regression Models where GVI > 25, 2016 data

	Dependent variable:			
	Log(sale price)			
	Detached	Semi-Detached	Att/Row/Townhouse	Multiplex
	(1)	(2)	(3)	(4)
green_new	0.0065***	0.0067	-0.0039	0.3984
	(0.0021)	(0.0053)	(0.0082)	
month.soldFebruary	0.0802	0.1327	-0.1231	1.2574
	(0.0504)	(0.1532)	(0.1789)	
month.soldMarch	0.0576	0.1121	0.0768	
	(0.0495)	(0.1504)	(0.1811)	
month.soldApril	0.0753	0.1613	-0.1051	6.5222
	(0.0490)	(0.1473)	(0.1779)	
month.soldMay	0.1192	0.0693	-0.2424	-3.0464
	(0.1037)	(0.3017)	(0.3418)	
month.soldJune	0.0916	0.0566	-0.2187	-9.5502
	(0.1034)	(0.3080)	(0.3376)	
month.soldJuly	0.1036	0.1059	-0.2650	
	(0.1056)	(0.3015)	(0.3377)	
month.soldAugust	0.1576	0.0852	-0.2792	
	(0.1048)	(0.3198)	(0.3361)	
month.soldSeptember	0.2178**	0.0779	-0.2542	-6.2111
	(0.1043)	(0.3075)	(0.3354)	
month.soldOctober	0.1410***	0.2049	0.0395	-17.9606
	(0.0506)	(0.1541)	(0.1807)	
month.soldNovember	0.1710***	0.1739	0.0255	-5.1788
	(0.0509)	(0.1549)	(0.1782)	
month.soldDecember	0.2270***	0.1537	-0.0349	
	(0.0557)	(0.1642)	(0.2121)	
washrooms	0.0868***	0.0820***	0.0994***	4.6193
	(0.0070)	(0.0175)	(0.0286)	
log(square.feet.int)	0.3982***	0.4219***	0.4013***	2.8431
	(0.0263)	(0.0618)	(0.0840)	
dist_cbd_km	-0.0031	-0.0101	-0.0158*	0.6230
	(0.0030)	(0.0081)	(0.0081)	
dist_hway_km	-0.0063	-0.0068	-0.0113	

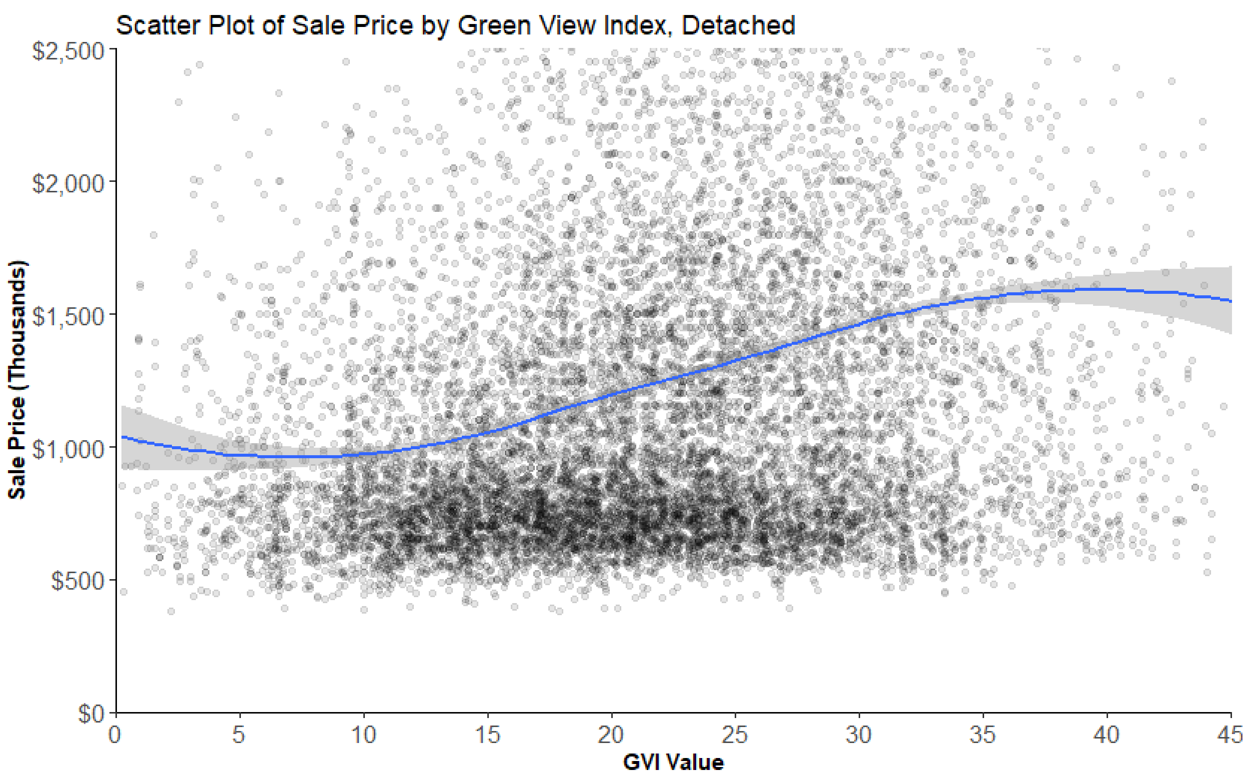
	(0.0053)	(0.0136)	(0.0150)	
dist_mall_km	0.0092**	-0.0092	-0.0397***	
	(0.0042)	(0.0133)	(0.0117)	
dist_stn_km	-0.0516***	-0.0180	-0.0003	
	(0.0043)	(0.0144)	(0.0124)	
immigrants_per	0.0081***	0.0014	0.0028	
	(0.0007)	(0.0025)	(0.0024)	
log(aftertax_inc)	0.5066***	0.4336***	0.4693***	
	(0.0226)	(0.0557)	(0.0734)	
log(pop_dens)	0.0224	0.1002***	0.0683***	
	(0.0154)	(0.0341)	(0.0247)	
green_new:month.in.green.rangeTreated	-0.0006	0.0001	0.0077	
	(0.0029)	(0.0085)	(0.0105)	
Constant	4.6192***	4.7104***	5.1685***	-36.7582
	(0.3689)	(0.9242)	(1.0377)	
Observations	1,172	184	116	12
R2	0.8558	0.8240	0.8457	1.0000
Residual Std. Error	0.2239 (df = 1149)	0.1982 (df = 161)	0.1647 (df = 93)	
Note:				*p<0.1; **p<0.05; ***p<0.01

Detached Houses: Regression Models, 2016 data, GVI comparison

	Dependent variable:			
	Log(sale price)			
	GVI < 15	15 < GVI < 25	25 < GVI < 35	GVI > 35
	(1)	(2)	(3)	(4)
green_new	0.0055*	0.0080***	0.0084**	-0.0044
	(0.0031)	(0.0026)	(0.0037)	(0.0076)
month.soldFebruary	0.1367**	0.0907**	0.1000*	-0.0364
	(0.0555)	(0.0428)	(0.0543)	(0.1408)
month.soldMarch	0.1502***	0.0627	0.0693	0.0039
	(0.0551)	(0.0415)	(0.0536)	(0.1369)
month.soldApril	0.1915***	0.1205***	0.1074**	-0.0582
	(0.0535)	(0.0410)	(0.0532)	(0.1367)
month.soldMay	0.2490***	0.2500***	0.1196	-0.3180
	(0.0691)	(0.0878)	(0.1683)	(0.4380)
month.soldJune	0.2399***	0.2578***	0.1179	-0.4818
	(0.0697)	(0.0872)	(0.1676)	(0.4319)
month.soldJuly	0.2335***	0.2512***	0.1222	-0.4175
	(0.0710)	(0.0875)	(0.1691)	(0.4462)
month.soldAugust	0.3024***	0.2965***	0.1780	-0.3931
	(0.0735)	(0.0886)	(0.1688)	(0.4393)
month.soldSeptember	0.2677***	0.2677***	0.2228	-0.2434
	(0.0698)	(0.0875)	(0.1672)	(0.4459)
month.soldOctober	0.2326***	0.1889***	0.1601***	0.0363
	(0.0547)	(0.0420)	(0.0544)	(0.1438)
month.soldNovember	0.2596***	0.1838***	0.1808***	0.1197
	(0.0548)	(0.0417)	(0.0558)	(0.1381)
month.soldDecember	0.2271***	0.1825***	0.2513***	0.1206
	(0.0603)	(0.0460)	(0.0611)	(0.1467)
washrooms	0.0643***	0.0768***	0.0897***	0.0816***
	(0.0084)	(0.0057)	(0.0078)	(0.0174)
log(square.feet.int)	0.4796***	0.3981***	0.3832***	0.4269***
	(0.0280)	(0.0202)	(0.0291)	(0.0647)
dist_cbd_km	-0.0021	-0.0031	-0.0011	-0.0077
	(0.0032)	(0.0024)	(0.0033)	(0.0075)
dist_hway_km	-0.0176***	-0.0084**	-0.0085	0.0031
	(0.0057)	(0.0041)	(0.0060)	(0.0128)
dist_mall_km	0.0041	0.0078**	0.0093**	0.0102
	(0.0044)	(0.0034)	(0.0046)	(0.0117)
dist_stn_km	-0.0357***	-0.0437***	-0.0587***	-0.0276**
	(0.0046)	(0.0036)	(0.0048)	(0.0108)
immigrants_per	0.0045***	0.0087***	0.0077***	0.0108***

	(0.0010)	(0.0006)	(0.0008)	(0.0016)
log(aftertax_inc)	0.5634***	0.6647***	0.4955***	0.5709***
	(0.0348)	(0.0214)	(0.0250)	(0.0545)
log(pop_dens)	0.0391***	0.0261**	0.0274	0.0238
	(0.0150)	(0.0115)	(0.0172)	(0.0372)
green_new:month.in.green.rangeTreated	-0.0029	-0.0044	-0.0003	0.0098
	(0.0043)	(0.0038)	(0.0053)	(0.0111)
Constant	3.4151***	2.8314***	4.7473***	4.0595***
	(0.4434)	(0.3002)	(0.4173)	(0.9594)
Observations	743	1,526	970	202
R2	0.7998	0.8476	0.8543	0.8798
Residual Std. Error	0.2001 (df = 720)	0.2071 (df = 1503)	0.2241 (df = 947)	0.2184 (df = 179)
Note:				*p<0.1; **p<0.05; ***p<0.01

LOESS Regression, detached housing: the relationship of GVI to housing prices deviates from linearity at extreme values



References

Alexander, C. & McDonald, C. (2014). Urban forests: The value of trees in the City of Toronto. [Research Report]. TD Economics. June 9, 2014. Retrieved from https://www.td.com/document/PDF/economics/special/UrbanForests.pdf

Astell-Burt, T., Feng, X., Mavoa, S., Badland, H. M., & Giles-Corti, B. (2014). Do low-income neighbourhoods have the least green space? A cross-sectional study of Australia's most populous cities. *BMC Public Health 14*(292), 1-11.

Ballingall, A. (2017). Toronto still top-choice for recent immigrants, as more people flock to the Prairies. Toronto Star. Retrieved from https://www.thestar.com/news/gta/2017/10/25/toronto-still-top-choice-for-recent-immigrants-as-more-people-flock-to-the-prairies.html

Beacon Environmental Limited. (2016). Actions to grow Toronto's tree canopy [Research Report]. Urban Forest Innovations Inc. Retrieved from https://www.toronto.ca/legdocs/mmis/2016/pe/bgrd/backgroundfile-97020.pdf

Benoit, K. (2011). Linear regression models with logarithmic transformations. Methodology Institute. London School of Economics: London, UK. Retrieved from http://kenbenoit.net/assets/courses/ME104/logmodels2.pdf

Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. L. (2004). Cost-Benefit Analysis: Concepts and Practice. 4th Ed. Prentice Hall: New Jersey, NY.

Byrne, J. & Sipe, N., (2010). Green and open space planning for urban consolidation – A review of the literature and best practice, Urban Research Program, ISBN 978-1-921291-96-8.

Cain, P. (2017). Census 2016: Canadians embrace downtown living. Global News. Retrieved from https://globalnews.ca/news/3234918/census-2016-canadians-embrace-downtown-living/

CBC. (2017). Rent control makes Toronto affordability worse, not better, CIBC says. *CBC*. Retrieved from https://www.cbc.ca/news/business/cibc-rent-control-1.4053228

Cho, S.-H., Poudal, N. C., & Roberts, R. K. (2008). Spatial analysis of the amenity value of green open space. *Ecological Economics* 66(2

City of Toronto. (2015). Housing occupancy trends 1996-2011 [Research Report]. In *Profile Toronto*. Retrieved from https://www.toronto.ca/legdocs/mmis/2015/pg/bgrd/backgroundfile-84816.pdf

City of Toronto. (2016a). 2016 Neighbourhood Profiles. In *Data, Research & Maps*. Retrieved from https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/neighbourhood-profiles/

City of Toronto. (2016b). 2016 Census: Income. In *2016 Census Backgrounder Income 2017 09 14*. Retrieved from https://www.toronto.ca/wp-content/uploads/2017/10/8f41-2016-Census-Backgrounder-Income.pdf

City of Toronto. (2016c). Social atlas 2016 maps. From *2016 Census*. Retrieved from https://www.toronto.ca/city-government/data-research-maps/neighbourhoods-communities/toronto-social-atlas/2016-maps/

City of Toronto. (2017a). Tree Planting. In *Trees in Toronto*. Retrieved from https://www.toronto.ca/services-payments/water-environment/trees/tree-planting/

City of Toronto. (2017b). 2016 Census: Income. In *Backgrounder*. Retrieved from https://www.toronto.ca/wp-content/uploads/2017/10/8f41-2016-Census-Backgrounder-Income.pdf

City of Toronto. (2017c). Parks & Recreation Facilities Master Plan. In *Long-Term Vision, Plans & Strategies*. Retrieved from https://www.toronto.ca/city-government/accountability-operations-customer-service/long-term-vision-plans-and-strategies/parks-forestry-recreation/parks-and-recreation-facilities-master-plan/

City of Toronto. (2018). Tree planting on City property – species selection. In *Urban Forestry*. Retrieved from https://www.toronto.ca/311/knowledgebase/kb/docs/articles/parks,-forestry-and-recreation/urban-forestry/tree-planting-on-city-property-species-selection.html

DiPasquale, D., & Wheaton, W. (1996). Urban economics and real estate markets. New Jersey: Prentice Hall.

Donovan, G. H., & Butry, D. T. (2010). Trees in the city: Valuing street trees in Portland, Oregon. *Landscape and Urban Planning 94*, 77-83.

Farr, K. (2004). Evolving urban forest concepts and policies in Canada [Research Brief]. In *Horizons: Policy Research Initiatives. 6*(4), 38-39.

Filion, P. (2007). The urban growth centres strategy in the Greater Golden Horseshoe: Lessons from downtowns, nodes, and corridors. [Research Report]. Neptis Studies on the Toronto Metropolitan

Region. Retrieved from http://www.neptis.org/sites/default/files/nodes_and_corridors/filion_electronic_report_20070528.pdf

Filipowicz, J. (2018). Room to grow: comparing urban density in Canada and abroad [Research Report]. In *Fraser Research Bulletin*. The Fraser Institute. Retrieved from https://www.fraserinstitute.org/sites/default/files/room-to-grow-comparing-urban-density-in-canada-and-abroad.pdf

Gilderbloom, J. I.; Riggs, W. W.; and Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. *Cities, 42*, 13-24.

Giles-Corti, B. & Donovan, R. J. (2003). Relative influences of individual, social environmental, and physical environmental correlates of walking. *American Journal of Public Health, 93*(9), 1583-1589.

Greene, C. S., Robinson, P. J., and Millward, A. A. (2018). Canopy of advantage: who benefits most from city trees? *Journal of Environmental Management, 208*, 24-35.

Haider, M. and Miller, E. (2000). Effects of transportation infrastructure and location on residential real estate values: Application of spatial autoregressive techniques. *Journal of the Transportation Research Board, 1722*, 1-8.

Haider, M. and Moranis, S. (2018). Rent control is doing little to curb Toronto's soaring rents. *Financial Post*. Retrieved from https://business.financialpost.com/real-estate/rent-control-is-doing-little-to-curb-torontos-soaring-rents

Haq, S. M. A., (2011). Urban green spaces and an integrative approach to sustainable environment. *Journal of Environmental Protection, 2*(5), 601-608.

Hedman, L. van Ham, M., and Manley, D. (2011). Neighbourhood choice and neighbourhood reproduction. *Environment and Planning A 43*, 1381–1399.

Heynen, N. C., & Lindsey, G. (2003). Correlates of urban forest canopy cover: Implications for public works. *Public Works Management & Policy*. *8*(1), 33-47.

Holcombe, R. G. (1999). Urban sprawl: Pro and con. Property and Environment Research Center (PERC). Retrieved from https://www.perc.org/1999/02/10/urban-sprawl-pro-and-con/

Hotte, N. Nesbitt, L., Barron, S., Cowan, J., & Cheng, Z. C. (2015). The social and economic values of Canada's urban forests: A national synthesis. Canadian Forest Service. UBC Faculty of Forestry: Vancouver, BC.

Iverson, L. R., & Cook, E. A. (2000). Urban forest cover of the Chicago region and its relation to household density and income. *Urban Ecosystems. 4*, 105-124.

Jim, C.Y., and Chen, W. (2008). Assessing the ecosystem service of air pollutant removal by urban trees in Guangzhou (China). *Journal of Environmental Management. 88*, 665–676.

Jorgensen, E. (1974). Towards an urban forestry concept. *The Commonwealth Forestry Review: Proceedings from the Tenth Commonwealth Forestry Conference 53*(4) (pp. 251-279).

Kalinowski, T. (2016). Growth plan fuelling GTA housing prices, developers told [Article]. The Toronto Star. Retrieved from https://www.thestar.com/business/real_estate/2016/10/13/growth-plan-fuelling-gta-housing-prices-developers-told.html

Lafortezza, R., Carrus, G., Sanesi, G., and Davies, C. (2009). Benefits and well-being perceived by people visiting green spaces in periods of heat stress. *Urban Forestry & Urban Greenery*. *8*(2), 97–108.

Lawrence, H.W. (1995). Changing forms and persistent values: historical perspectives on the urban forest. In: Bradley, G.A. (Ed.), Urban Forest Landscapes: Integrating Multidisciplinary Perspectives. University of Washington Press, Seattle, pp. 17–40.

Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., and Zhang, W. (2015). Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban Forestry & Urban Greening 14*(3), 675-685.

Liang, X., Liu, Y., Qiu, T., Jing, Y., and Fang, F. (2018). The effects of locational factors on the housing prices of residential communities: The case of Ningbo, China. *Habitat International, 81*, 1-11.

Luttik, J. (2000). The value of trees, water, and open space as reflected by house prices in the Netherlands. *Landscape and Urban Planning 48*, 161-167.

Mass, J., Verheij, R. A., Groenewegen, P. P., de Vries, S., & Spreeuwenberg, P. (2006). Green space, urbanity, and health: how strong is the relation? *Journal of Epidemiology & Community Health. 60*, 587-592.

McFarland, J. (2018). Tale of two markets: 2017 Toronto condo demand soared while sales of new single-family homes slumped. *The Globe and Mail*. Retrieved from https://www.theglobeandmail.com/real-estate/tale-of-two-markets-2017-toronto-condo-demand-soared-while-sales-of-new-single-family-homes-slumped/article37738503/

McLeod, C. B., Lavis, J. N., Mustard, C. A., and Stoddart, G. L. (2003). Income inequality, household income, and health status in Canada: A prospective cohort study. *American Journal of Public Health. 93*(8), 1287-1293.

McPherson, E. G., van Doorn, N., & de Goede, J. (2016). Structure, function and value of street trees in California, USA. *Urban Forestry & Urban Greening 17*, 104-115.

Meese, R. and Wallace, N. (1991). Nonparametric estimation of dynamic hedonic price models and the construction of residential housing price indices. *American Real Estate and Urban Economics Association Journal*, *19*(3), 308-332.

Ministry of Finance. (2017). Ontario population projections update, 2016-2014 [Research Report]. Retrieved from https://www.fin.gov.on.ca/en/economy/demographics/projections/

MIT Senseable City Lab (2015). Treepedia: Exploring the green canopy in cities around the world. Retrieved from http://senseable.mit.edu/treepedia

Mok, H. M., Chain, P. P. K., and Cho, Y.-S. (1995). A hedonic price model for private properties in Hong Kong. *Journal of Real Estate Finance and Economics*, *10*, 37-48.

Monsebraaten, L. (2017). Toronto region becoming more divided along income lines [Article]. The Toronto Star. Retrieved from https://www.thestar.com/news/gta/2017/11/01/toronto-region-becoming-more-divided-along-income-lines.html

Morancho, A. B. (2003). A hedonic valuation of urban green areas. *Landscape and Urban Planning*. *66*, 35-41.

Nichols, A. and Zimmerman, S. (2008). Measuring trends in income variability [Research Report]. Urban Institute. Retrieved from https://www.urban.org/research/publication/measuring-trends-income-variability

Nowak, D. J., Crane, D. E., & Dwyer, J. F. (2002). Compensatory value of urban trees in the United States. *Journal of Aboriculture. 28*(4), 194-199.

Ontario Ministry of Finance. (2018). Ontario Population Projections Update, 2017-2041. In *Population Projections*. Retrieved from https://www.fin.gov.on.ca/en/economy/demographics/projections/#s4e

Ontario Ministry of Municipal Affairs. (2015). Growth Plan for the Greater Golden Horseshoe. In *At A Glance: Performance Indicators*. Retrieved from http://www.mah.gov.on.ca/AssetFactory.aspx?did=10848

Ontario Ministry of Natural Resources. (2007). Municipal Road Allowances. In *Land Management*. Report No. PL 4.11.03. Retrieved from http://files.ontario.ca/environment-and-energy/crown-land/mnr_e000098.pdf

Ostler, P. (2014). Downtown Toronto: Trends, Issues, Intensification. [Report]. *City of Toronto, City Planning*: Toronto, ON. Retrieved from https://www.toronto.ca/legdocs/mmis/2014/te/bgrd/backgroundfile-69192.pdf

Pandit, R., Polyakov, M., Tapsuwan, S., & Moran T. (2013). The effect on street trees on property value in Perth, Western Australia. *Landscape and Urban Planning. 110*, 134-142.

Perkins, K. and Zizys, T. (2005). St. James Town neighbourhood Toronto: Overview and prospects for community-based poverty alleviation initiatives [Research Report]. Presented to World Vision Canada. Retrieved from http://www.stjamestown.org/wp-2014/wp-content/uploads/2015/05/Final-report-to-WVC.pdf

PRB. (2009). Human population. In *Population Change*. Population Reference Bureau. Retrieved from https://www.prb.org/humanpopulation/

RBC Economics Research. (2018). Housing trends and affordability. In *RBC Housing Affordability Measures.* Retrieved from http://www.rbc.com/economics/economic-reports/pdf/canadian-housing/house-apr2018.pdf

Richardson, E., Pearce, J., Mitchell, R., Day, P., & Kingham, S. (2010). The association between green space and cause-specific mortality in urban New Zealand: An ecological analysis of green space utility. *BMC Public Health, 10*, 240-254.

Rogers, G. F., & Rowntree, R. A. (1988). Intensive surveys of structure and change in urban natural areas. *Landscape and Urban Planning 15*, 59-78.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy 82*(1), 34-55.

Roy, S., Byrne, J., & Pickering, C. (2012). A systematic quantitative review of urban tree benefits, costs, and assessment methods across cities in different climatic zones. *Urban Forestry & Urban Greening 11*, 351-363.

Rush, B. (1789). Medical Inquiries and Observations 1. Philadelphia, Carey, 1st ed., 1789, 4th ed.,

Ryerson City Building Institute. (2017). Getting to 8,000: Building a healthier rental market for the Toronto Area. Retrieved from https://www.citybuildinginstitute.ca/wp-content/uploads/2017/10/Gettingto8000_Report-web.pdf

Rudman, J. W. (2010). Calculating the exact pooled variance. James Madison University: Harrisonburg, VA. Retrieved from https://arxiv.org/ftp/arxiv/papers/1007/1007.1012.pdf

Schwarz, K., Fragkias, M., Boone, C. G., Zhou, W., Mchale, M., Grove, J. M., . . . Cadenasso, M. L. (2015). Trees Grow on Money: Urban Tree Canopy Cover and Environmental Justice. *Plos One, 10*(4). doi:10.1371/journal.pone.0122051

Seiferling, I., Naikc, N., Ratti, C., and Proulx, R. (2017). Green streets − Quantifying and mapping urban trees with street-level imagery and computer vision. *Landscape and Urban Planning 165,* 93–101.

Siriwardena, S. D., Boyle, K. J., Holmes, T. P., & Wiseman, P. E. (2016). The implicit value of tree cover in the U.S.: A meta-analysis of hedonic property value studies. *Ecological Economics, 128,* 68-76.

Soler, I. P., and Gemar, G. (2018). Hedonic price models with geographically weighted regression: An application to hospitality. *Journal of Destination Marketing & Management, 9*, 126-137.

Song, Y., and Knaap, G.-J. (2004). Measuring the effects of mixed land uses on housing values. *Regional Science and Urban Economics, 34,* 663-680.

Statistics Canada. (2011). Supporting documentation for 2011 Census of Population Program data. Retrieved from https://www12.statcan.gc.ca/census-recensement/2011/ref/index-eng.cfm

Statistics Canada. (2014). *Canadian Demographics at a Glance*. Catalogue no. 91-003-X.

Statistics Canada. (2017a). *Focus on Geography Series, 2016 Census*. Statistics Canada Catalogue no. 98-404-X2016001. Ottawa, Ontario. Analytical products, 2016 Census. Retrieved from http://www12.statcan.gc.ca/census-recensement/2016/as-sa/fogs-spg/Facts-cma-eng.cfm?LANG=Eng&GK=CMA&GC=535

Statistics Canada. (2017b). Household income in Canada: Key results from the 2016 Census. From *The Daily*. Retrieved from https://www150.statcan.gc.ca/n1/daily-quotidien/170913/dq170913a-eng.htm

Tajima, K. (2016). New estimates of the demand for urban green space: Implications for valuing the environmental benefits of Boston's big dig project. *Journal of Urban Affairs 25*(5). 641-655.

Thompson, K. (1978). Trees as a theme in medical geography and public health. *Bull N Y Acad. Med 54*(5), 517-531.

Toronto and Region Conservation Authority [TRCA]. (2018). The Meadoway: Creating an active greenspace connection between downtown Toronto and rouge national urban park. Retrieved from https://trca.ca/news/meadoway-greenspace-connection-downtown-toronto-rouge-park/

Tyrväinen, L. & Meittinen, A. (2000). Property prices and urban forest amenities. *Journal of Environmental Economics and Management 39*, 205-223.

Vandermeulen, V., Verspecht, A., Vermeire, B., Van Huylenbroeck, G., & Gellynck, X. (2011). The use of economic valuation to create public support for green infrastructure investments in urban areas. *Landscape and Urban Planning, 103*(2), 198-206.

Van den Berg, M., Wendel-Vos, W., van Poppel, M., Kemper, H., van Mechelen, W., & Mass, J. (2015). Health benefits of green spaces in the living environment: A systematic review of epidemiological studies. *Urban Forestry & Urban Greening. 14,* 806-816.

Whalen, J. (2017). Census 2016: More than half of Torontonians identify as visible minorities. CBC. Retrieved from http://www.cbc.ca/news/canada/toronto/census-visible-minorities-1.4371018

World Health Organization [WHO]. (1989). Health principles of housing. Geneva: World Health Organization. Retrieved from http://www.who.int/iris/handle/10665/39847

Zabel, F. (2015). The hedonic model and the housing cycle. *Regional Science and Urban Economics, 54*, 74-86.

Zielstra, D., and Hochmair, H. H. (2011). A comparative study of pedestrian accessibility to transit stations using free and proprietary network data. *Transportation Research Board of the National Academies. Research Board – 89th Annual Meeting*. Washington, D.C.

Zhang, Q., Miao, L., Wang, X., Liu, D., Zhu, L., Zhou, B., . . . Liu, J. (2015). The capacity of greening roof to reduce stormwater runoff and pollution. *Landscape and Urban Planning, 144*, 142-150. doi:10.1016/j.landurbplan.2015.08.017