Descriptive analysis of sorting and income dynamics in Canadian Census Metropolitan Areas (2001-2016)

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Executive summary.

The key findings of this report can be summarized as follows.

I- How heterogeneous are Canadian CMAs from a spatial point of view?

A- Spatially heterogeneous characteristics

- the characteristics of the residents and of the housing market exhibit a fair amount of heterogeneity, both between and within census tracts of Canadian CMAs, the former type of variation being more important than the latter.
- spatial variations in terms of average household income have increased but those in terms of share of highly educated residents have decreased.
- the residents of major Canadian CMAs are on average wealthier and more educated, but the biggest CMAs also exhibit far more spatial variations along these two characteristics; this is coherent with big cities attracting both more talented/wealthier and less educated/poorer residents than smaller-sized cities.
- the huge spatial heterogeneity in terms of average household income observed in Toronto and Montreal cannot be explained by a commensurate heterogeneity in terms of share of high skilled workers.
- not all of the biggest Canadian CMAs are more expensive in terms of housing than the other Canadian cities, but they all exhibit more spatial variation in terms of housing prices, especially between census tracts. This is in line with the fact that they host a more diverse population in terms of income.

B- Spatially heterogeneous dynamics

- the evolutions of the characteristics of the local residents and of housing prices exhibit more spatial heterogeneity than the level of these characteristics.
- contrary to the levels, the evolution of local characteristics exhibits more spatial variation within census tracts than between census tracts.
- compared to the average CMA, the six biggest Canadian CMAs exhibit greater spatial heterogeneity in terms of growth rates of the average household income and of the share of highly-educated residents. This might be consistent with gentrification patterns at play in these cities.
- while in the first half of the 2000s all of the six biggest Canadian CMAs experienced higher-than-the-average growth rates of housing prices, skyrocketing housing prices have been driven by Toronto and Vancouver in the more recent years.
- housing prices grow more homogeneously across census tracts and census blocks in Toronto and Vancouver than in the other four Canadian CMAs above one million inhabitants, suggesting that prices exploded everywhere in those two CMAs.
- no massive spatial convergence within CMAs in terms of income and housing prices is detected, but there is some spatial convergence in terms of the share of the highly educated population.

C- Residents' characteristics and distance to urban centers

- like in US cities, wealthy residents used to sort in less central neighbourhoods in Canadian CMAs, especially families with kids.
- such a pattern is less and less true, and has even reversed in the three biggest Canadian cities when we consider the average individual income of the residents.
- as a mirror of the gentrification and urban revival phenomena experienced by Canadian cities, we observe an increased concentration over time of highly educated residents close to urban centres, and a gradient of average housing prices with respect to the distance to the city-centre that has become steeper.

II- Descriptive facts on CMA-level concentration of high-income and highly-educated residents and trends in that concentration

A – Three descriptive facts

Fact 1

- high-income residents exhibit significant spatial concentration at very short distances (less than one kilometer) in several, but not all, Canadian CMAs.
- in most of the biggest Canadian CMAs, the spatial concentration of high-income residents is stronger than the spatial concentration of the population: there is excess concentration of high-income residents at short distances.
- Toronto and Vancouver are on a distinct path compared to the other big CMAs: the spatial concentration of wealthy residents is stronger there, and it increases over time, contrary to the other four CMAs above one million inhabitants.

Fact 2

- the highly educated are spatially concentrated within Canadian CMAs for all years between 2001 and 2016, but less than the high-income residents.
- the spatial concentration of the highly educated in Canadian CMAs has stagnated or decreased over time for all CMAs. This may be due to a larger share of the population holding a university degree in 2016.
- the comparison of the patterns observed for the high-income residents and for the highly-educated ones shows again that the formers cannot be approximated by the latters; hence income and education shape the urban structure differently.

Fact 3

- while new housing tends to be spatially dispersed in most Canadian CMAs, it tends to be more concentrated in Toronto and Vancouver
- Toronto and Vancouver being also the CMAs where the spatial concentration of high-income residents has mostly increased, this suggests that a filtering phenomenon might be at play in both cities

B – Some controlled correlations

- High-income residents concentrate more (or disperse less) when population size increases within a city.

- Highly educated residents concentrate more (or disperse less) when population size increases within a city.
- There is no significant relationship between the excess concentration of high incomes and the excess concentration of the highly educated.
- Growing CMAs in terms of population experience more excessive concentration of the high incomes. For the very high incomes (90^{th} percentile) this effect is only marginally affected when also accounting for the excessive concentration of the highly educated. For the high incomes (75^{th} percentile), this effect is more strongly driven by the excessive concentration of the highly skilled compared to CMA population growth in general.
- There is no significant relationship between the excess concentration of new housing construction and the excess concentration of the highly educated.

III- Dissimilarity, exposure, mean reversion, and spatial correlation.

A – Dissimilarity in the distribution of characteristics

- highly educated individuals and lowly educated individuals are more unevenly distributed than the total population, with more unevenness in the distribution of the highly educated individuals.
- rich and poor residents are more unevenly distributed than the total population, with more unevenness for the rich than for the poor.
- new and old housing units tend to be clustered, but new developments are more clustered than old housing units.

B – Exposure between different characteristics

- the degree of exposure of highly educated residents to lowly educated ones within Canadian CMAs is small, revealing a small probability of sharing the same area.
- among the largest cities, Montreal has more mixing of low- and high-income types than Toronto and Vancouver, where high and low incomes are less exposed to one another.
- old and new units are more exposed to one another than poor and rich residents, thus suggesting the presence of substantial redevelopment.
- exposure between the (very) rich and the (very) poor has fallen, suggesting more mixing with intermediate income levels.

C – Changes over time

- high- and low-educated individuals tend to become less clustered between 2001 and 2016 as compared to the total population.
- the poor are more unevenly distributed than the rich and this changes little over time.
- high- and low-educated individuals are getting less likely to share common areas, as revealed by less exposure between the groups.
- there is relatively little change in exposure between old and new houses over time.
- rich and poor are increasingly less exposed to one another, thus suggesting that there is increased mixing of the poor and the rich with middle-income individuals.

D – Mean reversion and spatial correlation within CMAs

- there is mean reversion for average income, the number of highly educated residents, and the number of new housing units across all of the five largest Canadian CMAs between 2001 and 2016. This convergence process is stronger for the number of highly educated residents and the number of recent housing units than it is for average income.
- stronger mean reversion for education than for income is consistent with the initial steps of the gentrification process being generally characterized by the inflow of residents that are certainly more educated than the initial residents but who are not necessarily at the very top of the income distribution.
- we find positive spatial correlation between the growth rate of a block between 2001 and 2016 and the initial characteristics of its neighbors in 2001. In other words, blocks that were surrounded by blocks with wealthier and more educated residents tend to experience faster growth conditional on mean reversion.

Introduction and context

Metropolitan areas have experienced tremendous change over the past decades, both in developed and in developing countries: growing population, rising housing prices, de-industrialization, gentrification, air pollution, congestion—the challenges faced by urban development are multiple.

This report deals with one of these challenges, namely spatial inequality, and focuses on the Canadian Census Metropolitan Areas (CMAs) over the past twenty years. To analyze especially spatial inequality within cities, we assemble the data from the 2001, 2006, 2011, and 2016 population censuses at the finest geographic scale for which they are made publicly available: the dissemination areas (DAs). As the number and the shape of the dissemination areas vary over time, we first construct a stable geography from 2001 to 2016. We then analyze these data and present a thorough description of spatial inequality—reflecting the spatial sorting of heterogeneous households with the cities—and of its evolution over time in the Canadian CMAs, with a special focus on the largest cities. Three main dimensions of inequality are studied: spatial inequality in terms of income (measured by average household income); spatial inequality in terms of education (measured by the share of residents with a university degree); and spatial inequality in terms of housing prices (measured by average housing prices). We also provide descriptive evidence on the spatial distribution of new housing projects and changes in the geographic distribution of housing by vintage.

This report is purely descriptive and there is nothing causal implied by the analyses we provide here. Analyzing the causes and consequences of the patterns described in this report would require a detailed investigation using more disaggregated data and a clear econometric strategy for causal inference. However, given the skyrocketing housing prices in several Canadian cities over the past two decades, especially in Vancouver and Toronto, and the mandate of the CMHC to ensure affordability and balanced supply of housing for all the Canadians residents over the country, having a clear picture of the dynamics of the residential segregation within Canadian cities is of prime importance. Hopefully, this report will contribute to offering a precise panorama of the spatial sorting of households within Canadian CMAs and of its evolution over time, so as to help design adequate housing policies able to favour a sustainable and inclusive development of Canadian cities.

This report has three parts. **Part I** assesses the extent of spatial heterogeneity within Canadian cities, both between neighbourhoods (i.e., across census tracts) and within neighbourhoods (i.e. across dissemination areas within census tracts). We also investigate how household characteristics and housing prices change depending on the distance to the city-centre. **Part II** of the report goes one step further by assessing the distance at which residents with similar characteristics in terms of income or education tend to cluster. To do so, we leverage the spatial granularity of our data and rely on the most recent spatial concentration indices developed in the literature. Last, in **Part III** we focus more specifically on the issue of spatial segregation, by building indices that capture the tendency of different types of residents in terms of income or education to collocate within the city. Finally, we also investigate whether the dissemination areas tend to converge over time in terms of the characteristics of their residents and if yes, at which speed.

The main insights that emerge from our analysis can be summarized as follows. First, Canadian CMAs are highly heterogeneous in terms of their residents' average income and level of education and in terms of housing prices. They are even more heterogeneous in terms of the dynamics of these characteristics. This heterogeneity is observed both between and within census tracts. However, the between heterogeneity is more important for the levels of the residents and housing characteristics, while the within heterogeneity dominates for the dynamics of these characteristics. In other words, spatial evolutions are highly heterogeneous, especially within census tracts. The fact that the largest CMAs are particularly heterogeneous from a spatial point of view reflects the fact that big cities attract disproportionately both wealthy and poor residents. While wealthy residents have long sorted within Canadian CMAs at longer distances from the city centre, this pattern has tended to reverse over the past ten years, in line with gentrification and urban revival phenomena observed in many North-American and European cities starting in the late 1990s and early 2000s.

Second, stratification within Canadian cities occurs predominantly along income, whereas higher education—as measured by university education—does not seem to be driving the changes in observed patterns. While there is some sorting along education in the Canadian CMAs, the patterns remain relatively stable and are not much more pronounced in large or growing cities. This result is likely driven by the fact that more and more residents in the large cities are university educated, which implies that they are mechanically more evenly distributed within the CMAs. However, the top incomes tend to cluster more and are not necessarily very highly correlated with formal university education. While most Canadian CMAs experience a relative dispersion of the highest incomes between 2001 and 2016, Toronto and Vancouver clearly stand out as the two CMAs where the spatial concentration of the very wealthy has increased over the last twenty years, as well as the concentration of new housing projects, which suggests the existence of a filtering phenomenon in those two cities.

Finally, while rich and poor as well as highly and lowly educated residents tend do be more unevenly distributed than the overall population, this unevenness tends to be stronger for the highly educated and for the poor residents. Moreover, both rich and poor and highly and lowly educated residents tend to collocate less and less in the same blocks over time. This suggests more mixing of both groups with middle-type residents over time. Finally, a convergence analysis shows that neighbourhoods within Canadian cities exhibit convergence, especially in terms of number of highly educated residents and in terms of recent housing units. We also spatial correlation: conditional on their own initial characteristics, blocks that were surrounded by blocks with wealthier and more educated residents tend to experience faster growth; the same applies for the number of recent housing units.

I- How heterogeneous are Canadian CMAs from a spatial point of view?

The first part of the report describes how heterogeneous the major Canadian CMAs are from a spatial point of view. Three dimensions are explored in detail: (i) household average income; (ii) the share of highly educated residents; and (iii) average housing prices.

More precisely, Canadian CMAs are divided into census tracts, and each census tract is sub-divided into dissemination areas (akin to 'census blocks' in the US). While the shape and the number of dissemination areas can vary over time, we work with spatial units that are stable over time. This stable geography is obtained by using an algorithm based on graph theory that allows to define, based on the geography of dissemination areas, the smallest combinations of these units that are stable over the four census waves (2001-2016).[2] We call these stable units "concorded blocks". In the remainder of this report, the terms "dissemination areas", "blocks" and "concorded blocks" will be used interchangeably. For short, we mostly refer to "blocks" when there is no possible confusion.

For each concorded block, we know the average income of the households living there, the share of highly educated residents—where high education is measured by a university degree—in the working-age population, and the average price of houses. We can compute the average of these three characteristics at the level of the census tracts and at the level of the CMAs where the tracts fit in. Note that we compute here simple averages, meaning that we give an equal weight to each block. These averages might differ from weighted averages where bigger blocks are given a higher weight. By doing so, we can assess how much of the socio-economic differences observed across census blocks within a CMA are related to differences between census tracts and how much are related to differences across blocks within census tracts. The first type of variation is informative on how heterogeneous neighbourhoods are within a CMA; we call it the "between variation", equal to the standard deviation of the average value of a variable at the level of the census tracts with respect to its mean at the level of the CMA. The second type of variation is informative on how heterogeneous neighbourhoods (census tracts) themselves are; we call it the "within variation", equal to the standard deviation of the value of a variable at the level of the blocks with respect to its mean at the level of the tract containing these blocks. Both types of variation are expressed as a percentage of the average value of the variable at the level of the CMA.

A- Spatially heterogeneous characteristics

Table 1 shows these simple statistics for 2001 and 2016 and for the six Canadian CMAs with more than one million inhabitants: Toronto, Montreal, Vancouver, Ottawa-Gatineau, Calgary, and Edmonton. The figures for the four census waves and the ten largest Canadian CMAs are relegated to Table B1 in the Appendix II. In both tables, we also present the weighted average of each variable across all Canadian CMAs, using as weights the share of each CMA in the total population living in CMAs. Several messages emerge from this table.

First, there is substantial spatial heterogeneity in terms of the characteristics of the residents, both between and within the census tracts of Canadian CMAs. As expected, the former type of heterogeneity is more important than the latter. For example, as can be seen from the last row of Table 1, in 2016, the block-level average household income in Canadian CMAs is equal to 80 428$. However, this average masks considerable variations across census tracts within the CMAs, since the tract-level average household income differs from this mean by 39% on average. Moreover, the blocks within the tracts also exhibit significant heterogeneity: the average difference between the block-level average income and the average household income in the tract it belongs to is equal to 29% of the block-level average household income in the CMA. The share of highly educated residents also displays spatial variations both between and within the census tracts of the Canadian CMAs, even though this spatial heterogeneity has decreased over time. This decline in the spatial variations of the share of highly educated residents certainly mirrors the generalization of post-secondary education in the Canadian population, with a block-level share of highly educated residents rising from 14% to 20% on average between 2001 and 2016. Note that the declining spatial

[2] To this end, we use an algorithm based on graph theory (maximal connected components). See Behrens, Boualam, Martin, and Mayneris (2018) for technical details and a description of that procedure.

variation in terms of the share of highly educated residents does not imply lower spatial inequality in terms of household average income. On the opposite, the variations between and within tracts in terms of average income have increased over the past twenty years. This suggests that rising income inequality across blocks within cities is not driven by rising inequality in terms of skills, at least in terms of measurable skills such as a university degree.

Not only do the characteristics of the residents change from one block to the other in Canadian CMAs, but also the quality and the desirability of the housing stock. We can consider that the appeal of the housing stock in a given neighbourhood is reflected by the average housing price in this neighbourhood. Here again, we observe substantial spatial disparities. While the block-level average housing price is equal to 420 636$ across the different Canadian CMAs in 2016, the tract-level housing price differs from this mean by 31% of it on average. Even though non negligible, the differences between blocks within neighbourhoods are less impressive, equal to 19% of the mean of the block-level average housing value observed across Canadian CMAs. The lower within-tract variation may be explained by spatial correlations in the vintage of the housing stock (with new housing being developed in some areas and being more expensive than older housing) and with spatially correlated amenities that operate locally across certain areas.

If we now consider individually the largest Canadian CMAs, several observations can be made. First, the residents of Canadian CMAs with more than one million inhabitants are wealthier and more educated on average (with Montreal being closer to the average than the other five CMAs). However, they also exhibit far more spatial variation both between and, to a lesser extent, within census tracts. These results are not surprising. A huge literature has substantiated that big cities tend to attract both the wealthiest or most talented individuals but also the poorest or least educated ones (see, e.g., Combes et al., 2012; Behrens et al., 2014; and Eeckhout et al., 2014). Note, however, that not all CMAs exhibit the same amount of spatial heterogeneity in terms of block-level household average income. More precisely, Toronto and Montreal are spatially more heterogeneous in terms of average household income than the other CMAs, both between and within tracts. Regarding the share of highly educated residents, the two CMAs also tend to exhibit more spatial variation than the others, but the difference here is less striking. This suggests again that the level of education explains only imperfectly the spatial inequality in terms of income within cities, and that other determinants such as the sector of activity, the occupation, or other unobserved characteristics of the workers also play a role.[3] We will return to these points later. Regarding the housing market, Toronto, Vancouver and, to a lesser extent, Calgary are unsurprisingly far more expensive than the other CMAs, while Montreal, Edmonton, and Ottawa-Gatineau are significantly cheaper. However, all of these big CMAs exhibit far more spatial variation in terms of housing prices than the average Canadian CMA, especially between tracts, which is consistent with the fact that they host a more diverse population in terms of income.

Summary:

- the characteristics of the residents and of the housing market exhibit a fair amount of heterogeneity, both between and within census tracts of Canadian CMAs, the former type of variation being more important than the latter.

[3] See Combes et al. (2008) for evidence on the role of workers' unobserved characteristics as an explanation for spatial wage inequality in France.

- spatial variations in terms of average household income have increased but those in terms of the share of highly educated residents have decreased.
- the residents of major Canadian CMAs are on average wealthier and more educated, but the biggest CMAs also exhibit far more spatial variations in these two characteristics; this is coherent with big cities attracting both more talented or wealthier and less educated or poorer residents than smaller-sized cities.
- the large spatial heterogeneity in terms of average household income observed in Toronto and Montreal cannot be explained by a commensurate heterogeneity in terms of the geographic distribution of highly educated workers.
- not all of the largest Canadian CMAs are more expensive in terms of housing than the other Canadian cities, but they all exhibit more spatial variation in terms of housing prices, especially between census tracts. This is in line with the fact that they host a more diverse population in terms of income.

Table 1 – Heterogeneity between and within tracts in the largest Canadian CMAs

CMA	Year	Average household income			Share of highly-educated among the population age 15+			Average house value		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Toronto	2001	83315	.55	.38	.23	.62	.35	276164	.49	.25
	2016	121152	.79	.51	.32	.50	.25	787211	.49	.27
Montreal	2001	56074	.52	.30	.18	.80	.40	145823	.52	.24
	2016	83306	.73	.41	.25	.63	.27	392428	.50	.21
Vancouver	2001	67278	.41	.31	.20	.60	.35	302251	.49	.26
	2016	104751	.44	.33	.30	.41	.24	1161996	.60	.30
Calgary	2001	73452	.40	.38	.20	.54	.39	187894	.31	.27
	2016	136099	.56	.55	.31	.49	.26	504607	.41	.33
Edmonton	2001	59817	.31	.31	.16	.73	.43	135091	.26	.22
	2016	109173	.37	.44	.24	.54	.29	395844	.30	.23
Ottawa-Gatineau	2001	74822	.36	.28	.24	.61	.37	162705	.56	.26
	2016	101128	.43	.30	.31	.51	.29	378393	.49	.25
All CMAs (average)	2001	50868	.29	.23	.14	.45	.32	143255	.29	.19
	2016	80428	.39	.29	.20	.37	.24	420636	.31	.19

Notes: Authors' calculations based on information from the 2001 and 2016 population censuses. "Mean" is the simple average of the variables across blocks with the CMAs. "Variation between" is the standard deviation of the variable across census tracts as a fraction of the CMA-level average across census blocks. "Variation within" is the standard deviation of the variable across census blocks within tracts as a fraction of the CMA-level average across blocks. "Average household income" and "Average house value" are expressed in current Canadian dollars.

B- Spatially heterogeneous dynamics

The previous section showed that Canadian CMAs exhibit a fair amount of spatial variation in their residents' income and education levels and in the level of their housing prices. This section focuses instead on the dynamics of these characteristics in the six largest CMAs and shows they are also highly heterogeneous both between and within neighbourhoods (see Table B2 in Appendix II for the figures for the ten largest CMAs).

Two general observations are immediately recognizable when comparing the figures in the last rows of Tables 1 and 2. First, for all of the characteristics considered here, the spatial heterogeneity within CMAs in terms of growth rates is far more important than the spatial heterogeneity in terms of levels. Second, the heterogeneity of growth rates within census tracts tends to be more important than the heterogeneity between census tracts, while the opposite is true for levels. This suggests that not only neighbourhoods, but even more so blocks within neighbourhoods, face trajectories that are sometimes very different. While most of the variation in levels is "between", most of the variation over time is "within". Changes in the composition of cities operate at a geographically fine scale, thus highlighting the need for a geographically disaggregate analysis.

In more details, income growth has been stronger in Canadian CMAs between 2011 and 2016 than between 2001 and 2006, certainly due to a catching up phenomenon after the economic crisis. This growth in block-level average household income has been stronger in the biggest Canadian CMAs than in the other CMAs (except for Ottawa-Gatineau), and it has also been far more heterogeneous both between and within tracts. The largest Canadian CMAs also display more spatial heterogeneity in terms of growth rates of the share of highly educated residents, especially within census tracts. These patterns observed for the growth of average household income and for the share of highly educated residents are consistent with big Canadian CMAs experiencing rapid gentrification of formerly poorer neighbourhoods. However, a full characterization of the gentrification patterns within Canadian CMAs would require a closer look at the data and the maps (see, for example, the work of Behrens et al., 2018 on New York).

As for the evolution of housing prices, the six largest Canadian CMAs experienced housing price increases that were generally fairly above those observed in the other CMAs. However, between 2011 and 2016, the skyrocketing housing prices are definitely driven by the dynamics of housing prices in Vancouver and Toronto. Quite interestingly, the degree of spatial heterogeneity in the growth of housing prices varies substantially across CMAs. Between 2011 and 2016, Vancouver and Toronto exhibit less spatial heterogeneity between and within tracts than the average heterogeneity observed in Canadian CMAs: this suggests that housing prices increased everywhere in these two cities. On the opposite, the growth of housing prices has been much more heterogeneous from a spatial point of view in Montreal over the same period of time, suggesting that tracts and blocks faced very different fates there, some of them thriving and some others stagnating or even losing attractiveness. This would be consistent with a "putty-clay pattern" of gentrification, where parts of cheaper neighborhoods all over the CMA move up in the income and house value distribution.

When analyzing local dynamics within cities, an interesting question revolves around the possible convergence or divergence processes at play: is it the case that poor and cheap neighbourhoods catch up with wealthy and expensive ones, or do trendy places become even more trendy so that the gap between tracts or blocks widens over time? One way to address this issue is to re-compute the figures in Table 2 for the 50% of blocks at the top of the distribution for each variable. This is what we do in Table 3. Regarding block-level average household income and housing prices, no clear patterns appear and the dynamics seem to be pretty much similar for the top 50% of blocks within Canadian CMAs as compared to the entire sample. This suggests that thriving and stagnating/declining neighbourhoods are found among both the most and the less affluent ones, which is consistent with the analyses on housing cycles surveyed in Rosenthal and Ross (2015). Things are different for the share of highly educated residents, since the most skilled blocks exhibit substantially lower growth rates at all periods (but with a similar degree of spatial heterogeneity in this growth rate). There is thus convergence between and within census tracts in terms of the skills of the residents, but it does not trigger massive convergence in terms of income or housing prices. There is thus a kind of disconnect between the dynamics of skills and the dynamics of income within Canadian cities, which is in line with one of the key findings from the level analysis in the previous subsection. It is also a finding that we will reconfirm later in this report when analyzing more finely the spatial concentration of the highly educated and wealthy residents within CMAs, as well as convergence patterns within CMAs with an econometric approach.

Summary:

- the evolutions of the characteristics of the local residents and of housing prices exhibit more spatial heterogeneity than the level of these characteristics.
- contrary to the levels, the evolution of local characteristics exhibits more spatial variation within census tracts than between census tracts.
- compared to the average CMA, the six largest Canadian CMAs exhibit greater spatial heterogeneity in terms of growth rates of the average household income and of the share of highly-educated residents. This might be consistent with gentrification patterns at play in these cities, but more analysis is required to understand those patterns.
- while in the first half of the 2000s all of the six largest Canadian CMAs experienced higher-than-average growth rates of housing prices, the skyrocketing housing prices have been driven by Toronto and Vancouver in the more recent years.
- housing prices grow more homogeneously across census tracts and census blocks in Toronto and Vancouver than in the other four Canadian CMAs above one million inhabitants, suggesting that prices exploded everywhere in those two CMAs
- no massive spatial convergence within CMAs in terms of income and housing prices is detected, but there is some spatial convergence in terms of share of the highly educated population.

Table 2 – Heterogeneous dynamics between and within tracts in the largest Canadian CMAs

CMA	Year	Average household income			Share of highly-educated among the population age 15+			Average house value		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Toronto	2001-2006	.14	1.02	1.75	.63	.86	1.39	.54	.62	.71
	2011-2016	.49	1.06	1.01	.23	1.07	2.34	.52	.27	.39
Montreal	2001-2006	.16	.73	1.2	.85	.69	1.23	.79	.43	.47
	2011-2016	.46	.85	.82	.21	1.06	2.4	.17	.63	1.04
Vancouver	2001-2006	.17	.54	1.47	.77	.54	1.27	.83	.23	.44
	2011-2016	.49	.58	.90	.22	.77	2.2	.51	.38	.47
Calgary	2001-2006	.25	.93	1.19	.65	.66	1.56	.92	.33	.41
	2011-2016	.62	.76	.91	.24	.94	2.4	.15	.58	1.18
Edmonton	2001-2006	.25	.33	.79	.62	.80	1.43	.79	.20	.39
	2011-2016	.46	.48	.80	.30	1.45	2.24	.11	.78	1.28
Ottawa-Gatineau	2001-2006	.13	1.01	1.42	.45	.98	1.51	.58	.40	.47
	2011-2016	.28	.74	.97	.14	2.27	3.19	.16	.79	.85
All CMAs (average)	2001-2006	.14	.56	.94	.54	.68	1.05	.50	.32	.43
	2011-2016	.35	.54	.68	.19	.94	1.74	.23	.42	.66

Notes: Authors' calculations based on information from the 2001, 2006, 2011 and 2016 population censuses. "Mean" is the simple average of the variables across blocks with the CMAs. "Variation between" is the standard deviation of the variable across census tracts as a fraction of the CMA-level average across blocks. "Variation within" is the standard deviation of the variable across blocks within tracts as a fraction of the CMA-level average across blocks. "Average household income" and "Average house value" are expressed in current Canadian dollars.

Table 3 – Heterogeneous dynamics between and within tracts in the largest Canadian CMAs - top 50% of blocks

CMA	Year	Average household income growth			Share of highly-educated among the population age 15+ growth			Average house value growth		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Toronto	2001-2006	.16	.96	1.35	.34	.50	.72	.53	.25	.34
	2011-2016	.49	1.17	.81	.09	1.16	2.02	.56	.25	.29
Montreal	2001-2006	.16	.74	1.09	.46	.54	.68	.78	.40	.39
	2011-2016	.38	1.05	.90	.10	1.31	1.97	.19	.62	.76
Vancouver	2001-2006	.19	.71	1.13	.43	.42	.64	.80	.18	.27
	2011-2016	.44	.62	.82	.10	1.12	1.91	.66	.22	.27
Calgary	2001-2006	.31	.96	.97	.32	.48	.90	.95	.21	.24
	2011-2016	.63	.95	.61	.11	1.1	1.69	.17	.58	.72
Edmonton	2001-2006	.26	.41	.69	.36	.49	.87	.81	.16	.28
	2011-2016	.41	.51	.75	.10	1.55	2.07	.13	.68	.81
Ottawa-Gatineau	2001-2006	.13	.87	1.16	.22	.80	.93	.52	.33	.28
	2011-2016	.24	.75	.93	.06	1.79	2.5	.17	.59	.57
All CMAs (average)	2001-2006	.14	.56	.96	.31	.43	.57	.48	.23	.25
	2011-2016	.31	.61	.58	.08	1.18	1.79	.25	.35	.51

Notes: Authors' calculations based on information from the 2001, 2006, 2011 and 2016 population censuses. Sample restricted to the top 50% of blocks for each variable within each CMA. "Mean" is the simple average of the variables across blocks with the CMAs. "Variation between" is the standard deviation of the variable across census tracts as a fraction of the CMA-level average across blocks. "Variation within" is the standard deviation of the variable across blocks within tracts as a fraction of the CMA-level average across blocks. "Average household income" and "Average house value" are expressed in current Canadian dollars.

C- Residents' characteristics and distance to urban centers

While in most European cities the wealthiest residents tend to locate close to the urban centers and the poorer households sort to the periphery (Brueckner et al., 1999), American cities have long displayed the opposite pattern: amenity-poor city centers (downtowns) used to host poor residents while the rich households chose to locate in comfortable middle- and upper-class suburbs. These patterns have reversed over the past twenty years, as documented in several recent contributions on 'urban revival' in the US (Baum-Snow and Hartley, 2019; Couture and Handbury, 2019). We propose here to have a look at these patterns for Canadian CMAs.

We first identify urban centers based on an algorithm that detects contiguous clusters of densely populated dissemination areas within a CMA. We detect in total 225 urban centers in Canadian CMAs, the biggest CMAs having several centers (6 in Toronto and 3 in Montreal, for example). Technical details on the procedure are provided in Appendix I-C.

We then use a simple regression analysis to compute the correlation between several block-level characteristics and the distance of that block to the closest urban center. These coefficients are usually referred to as 'gradients' in the urban economics literature. For the US, income gradients have been usually increasing with distance to the city center, although that relationship has tended to flatten out in more recent years due to the aforementioned 'urban revival'. Our results are summarized in Tables 4 to 7 below.

Our estimates of the distance gradients of income, education, and house prices convey several interesting messages. First, the first two columns of Tables 4 and 5 show that Canadian CMAs display a spatial sorting of households based on income that is qualitatively similar to the one observed in the US: the average household and the average individual incomes grow as we move further away from the urban centers, meaning that wealthy residents tend to live in more affluent suburbs on average. However, whatever the year we consider, the correlation is stronger for average household income than for average individual income. This latter finding is consistent with patterns where wealthy families prefer to live in detached houses or bigger apartments in the less expensive suburbs, while a significant share of high-income single residents prefer to live in smaller condos in more central locations (to benefit from the "buzz" and amenities of the central cities). Moreover, as clearly shown in the tables, the magnitude of the correlation has decreased over time, which is consistent with an increased attractiveness of central neighbourhoods for wealthy households, a phenomenon commonly referred to as "the urban revival" as mentioned before. As shown in the last two columns of both tables, this decrease in the positive correlation between average income and distance to the center is particularly pronounced in the three biggest Canadian CMAs. For average individual income, the sorting pattern has actually reversed between 2001 and 2016 in Toronto, Montreal, and Vancouver: in 2016, the average individual income of residents decreases on average with distance to urban centers. This is an extreme reversal which shows that central cities become again more attractive to rich individuals.

Table 4 – Average household income and distance to the center

	Average household income			
	All CMAs		Toronto, Montreal and Vancouver	
	Year 2001	Year 2016	Year 2001	Year 2016
Distance to the closest center	0.120[a]	0.087[a]	0.110[a]	0.053[a]
	(0.003)	(0.003)	(0.004)	(0.004)

Notes: Robust standard errors clustered at the block level. [a] p<0.01, [b] p<0.05, [c] p<0.1

Table 5 – Average individual income and distance to the center

	Average individual income			
	All CMAs		Toronto, Montreal and Vancouver	
	Year 2001	Year 2016	Year 2001	Year 2016
Distance to the closest center	0.042[a]	0.012[a]	0.024[a]	-0.036[a]
	(0.002)	(0.002)	(0.003)	(0.004)

Notes: Robust standard errors clustered at the block level. [a] p<0.01, [b] p<0.05, [c] p<0.1

In Table 6, we repeat the analysis for the share of highly educated residents. Here, we find a negative correlation between this share and the distance of the block to urban centers. Highly educated people prefer living close to the city centers, and this pattern is stronger in the biggest CMAs and has actually increased in magnitude over time. The fact that the spatial patterns observed for average income differ from those observed for the share of high-skill residents again exemplifies the disconnect between income and education at the top of the income distribution. Looking at university education does not carry, on average, substantial information when it comes to understanding the locations of the top incomes in the Canadian CMAs.

Finally, in Table 7, we examine how average house values change with distance to urban centers. The correlation is negative, on average, corroborating the intuition that central locations tend to be more expensive in terms of housing even if the wealthiest households do not always populate them.[4] More interestingly, this negative correlation has increased over time and is

[4] This is a standard prediction of the monocentric urban model and holds for most cities in North America. See, e.g., Fujita (1989) and Duranton and Puga (2015).

stronger in the largest CMAs, namely Toronto, Montreal, and Vancouver. These patterns are coherent with the gentrification and urban revival phenomena experienced in the biggest cities over the past two decades that have increased the residential attractiveness of city centers.

Table 6 – Share of highly educated and distance to the center

	Share of highly-educated in the population 15+			
	All CMAs		Toronto, Montreal and Vancouver	
	Year 2001	Year 2016	Year 2001	Year 2016
Distance to the closest center	-0.033[a]	-0.051[a]	-0.052[a]	-0.077[a]
	(0.001)	(0.001)	(0.001)	(0.001)

Notes: Robust standard errors clustered at the block level. [a] p<0.01, [b] p<0.05, [c] p<0.1

Table 7 – Average house value and distance to the center

	Average house value			
	All CMAs		Toronto, Montreal and Vancouver	
	Year 2001	Year 2016	Year 2001	Year 2016
Distance to the closest center	-0.020[a]	-0.059[a]	-0.087[a]	-0.150[a]
	(0.003)	(0.003)	(0.004)	(0.005)

Notes: Robust standard errors clustered at the block level. [a] p<0.01, [b] p<0.05, [c] p<0.1

Summary:

- as in US cities, wealthy residents used to sort into less central neighbourhoods in Canadian CMAs, especially families with children.
- such a pattern is less and less true, and has even reversed in the three biggest Canadian cities when we consider the average individual income of the residents. Hence, rich single individuals or power couples ("double income, no kids"; DINKS) tend to recently favor central locations in the largest Canadian CMAs.
- as a mirror of the gentrification and urban revival phenomena experienced by Canadian cities, we observe an increased concentration over time of highly educated residents close to urban centers, and a gradient of average house prices with respect to the distance to the city-center that has become steeper over time.

II- Descriptive facts on CMA-level concentration of high-income and highly-educated residents and trends in that concentration

As compared to the previous section where we documented considerable spatial heterogeneity within Canadian CMAs, we now want to document whether rich and highly educated residents tend to locate in tracts and blocks that are close to each other or widespread across the city. The geographic concentration of high-income earners in the large cities has been documented for a number of countries (see, e.g., Baum-Snow and Hartley, 2019, and Couture and Handbury, 2019, for the US; and Combes et al., 2012 for France). In particular, it seems that there is an increasing "urban revival" in the sense that young, educated, and affluent people move back to the central cities in the US. We have seen in Part I above that a similar trend holds for Canada. We now propose to document CMA-level aggregate trends for the large Canadian cities concerning: (i) the geographic concentration of high incomes; (ii) the geographic concentration of highly educated residents; and (iii) the geographic concentration of new housing supplied in these CMAs.

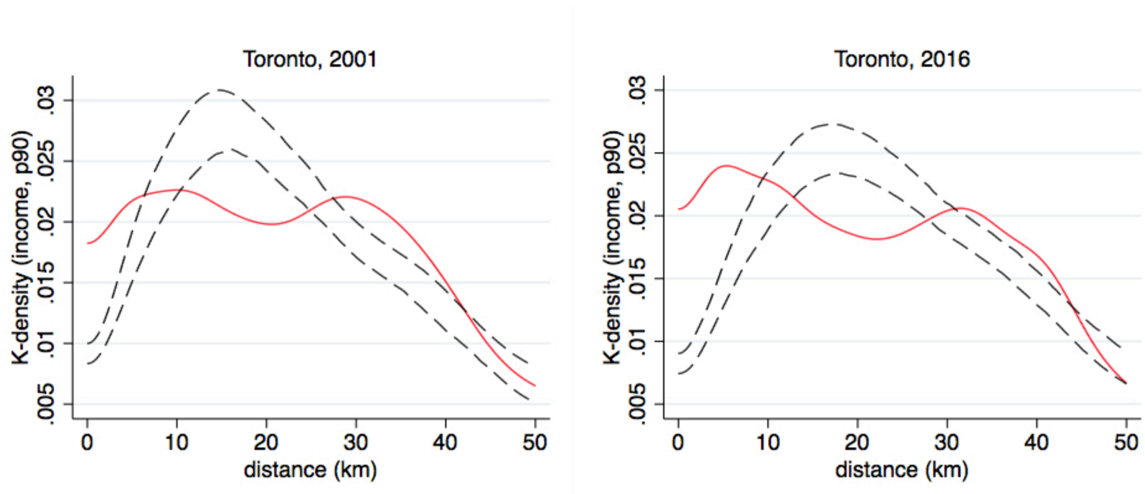
A- Three descriptive facts

Fact 1. High incomes are significantly concentrated at short distances.

We first report a number of facts concerning the geographic concentration of high incomes in the large Canadian CMAs. As in Part I of this report, we measure income using household income as this is the relevant income for important decisions such as acquiring real estate. Moreover, since we do not observe the incomes of each household from the publicly available census data, we henceforth assume that all the residents of a block live in households whose income equals the average household income in that block. In the following, for each CMA, we will call "high-income residents" people living in blocks with an average household income above the 90^{th} percentile observed in a given census year among the blocks of that CMA. Thus, we focus on the top decile of the income distribution in each CMA.

There are various ways to measure the geographic concentration of incomes. In what follows, we make use of the fact that we have access to relatively fine-grained geographic data at the dissemination area level to compute measures of geographic concentration that *explicitly account for the spatial structure of the distribution*. More precisely, we use the Duranton and Overman (2005) measure, which we prefer to alternative measures such as the Ellison and Glaeser (1997) index. The intuition underlying this measure is simple. If one knows the exact location of each "wealthy" resident, it is possible to compute the bilateral distances of all the pairs of wealthy residents within a CMA and to estimate their kernel density distribution. Then, by generating random counterfactual spatial distributions within the CMA for the same number of wealthy residents, we can compute the kernel density of bilateral distances associated with those counterfactual distributions. If the spatial distribution of the high incomes we observe were indeed random, we should see no differences between the counterfactual distributions generated a sufficiently large number of times and the observed distribution. Hence, by comparing the observed distribution and the confidence interval generated from the counterfactual distributions, we can assess whether there is *significant spatial concentration* or dispersion of wealthy residents and at which distance it occurs.

Figure 1 – Geographic concentration of high incomes (90th pctl) in the Toronto CMA.



Figures 1 to 3 depict the kernel-smoothed distribution of observed bilateral distances between high-income residents (the red lines) and the 90% confidence bands that approximate a distribution that would be "as good as random" (the dashed black lines). The figures show that high income residents—measured here at the 90th percentile of the block-level average household income distribution within the CMA—are significantly clustered at short distances in 2001 in the Toronto, Vancouver, and Montreal CMAs. The strength of that clustering is the strongest in Toronto, followed by Vancouver and, to a lesser extent, Montreal. Note two important observations. First, there has been an increase in the concentration between 2001 and 2016, both in terms of magnitude (gap between confidence band and the K-density in red) and in terms of spatial extent in both Toronto and Vancouver (see Figures 1 and 2). In other words, there is increasing clustering of high-income residents at short distances in those cities.

Second, this pattern seems however to be rather specific to Toronto and Vancouver. While the high incomes are also significantly more concentrated in Montreal than a random distribution would predict (see Figure 3), the strength and the spatial extent of that concentration are slightly decreasing in Montreal between 2001 and 2016. Clearly, it is *not increasing*, contrary to Toronto and Vancouver which display a very marked trend for more geographic clustering of the very high incomes in the CMA.

Figure 2 – Geographic concentration of high incomes (90th pctl) in the Vancouver CMA.

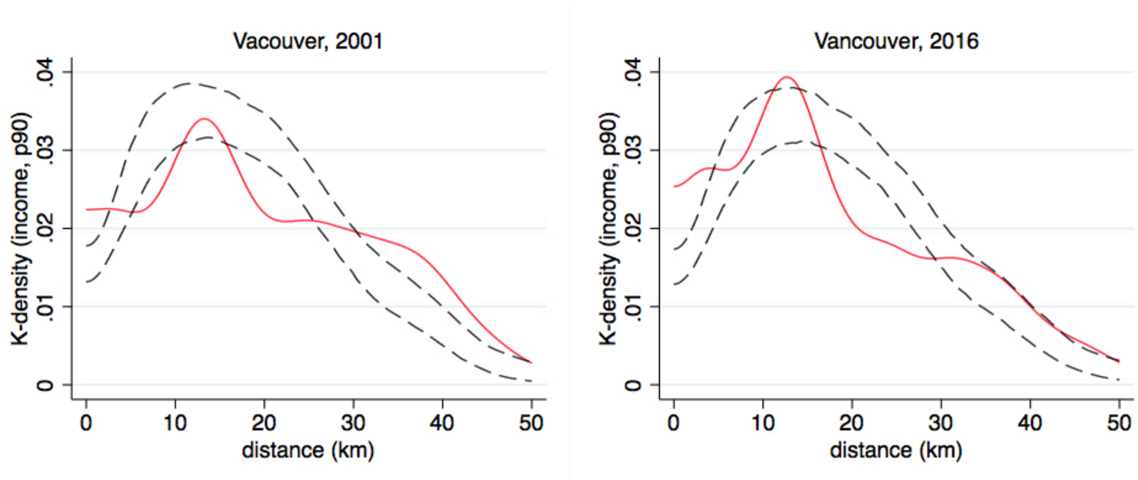
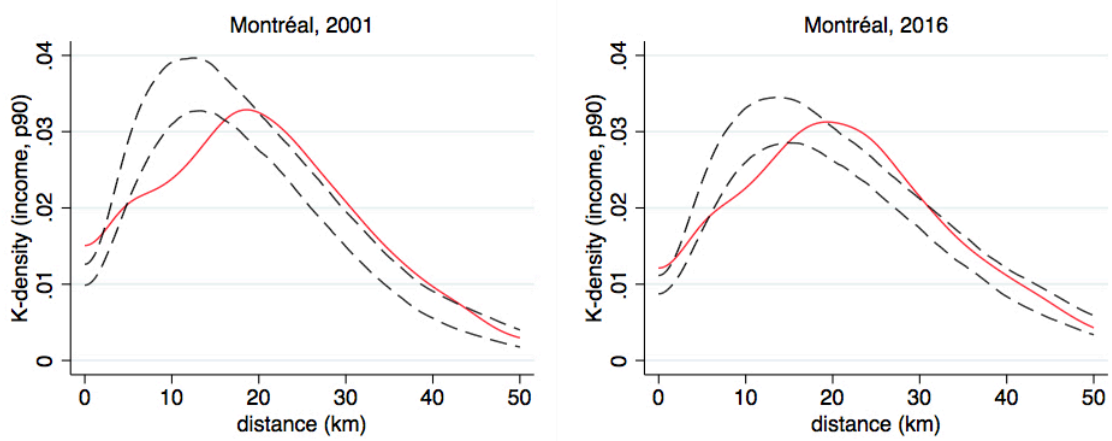
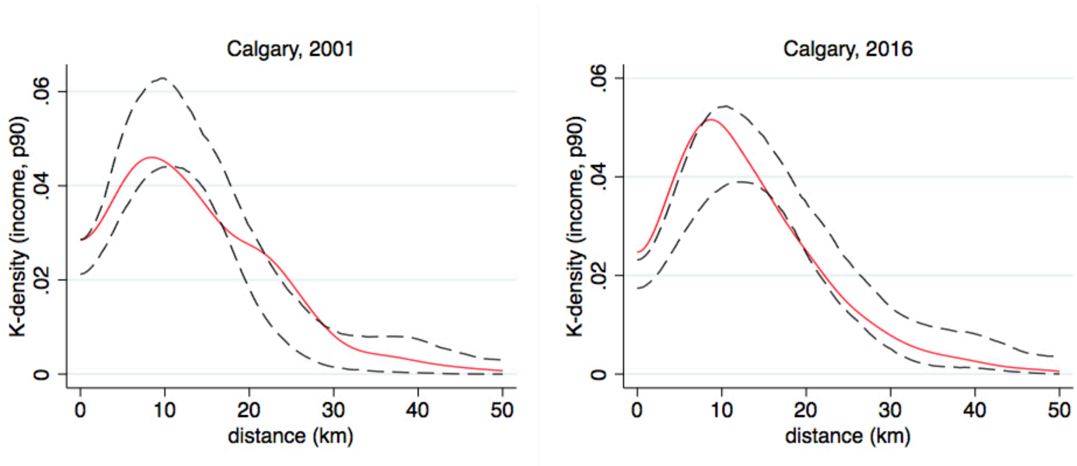


Figure 3 – Geographic concentration of high incomes (90th pctl) in the Montreal CMA.



The other large Canadian CMAs—Calgary, Ottawa-Gatineau, and Edmonton—display a pattern that is closer to that of Montreal than to that of either Toronto or Vancouver. As Figure 4 shows, Calgary is somewhere in between, with high incomes getting more concentrated over the 2001-2016 period, but only marginally so (compared to Toronto and Vancouver). In unreported graphs, we also find that while high-income residents are significantly concentrated in Edmonton compared to a random allocation, the strength and the extent of this spatial concentration have decreased between 2001 and 2016, as for Montreal. For Ottawa-Gatineau, we find no significant concentration and little upwards change therein over the 2001-2016 period.

Figure 4 – Geographic concentration of high incomes (90th pctl) in the Calgary CMA.



Our first observation is hence that Toronto and Vancouver clearly display a dynamic of geographic concentration of high-income residents that is different—both qualitatively and quantitatively—from that of the other large Canadian CMAs. This differential trend is most visible in Figure 5 below, which depicts for the six largest Canadian CMAs the density distributions of bilateral distances between wealthy residents in 2001 (black line) and 2016 (red line) on the same graphs.[5] While concentration of high-income residents at short distances has decreased or remained stable in Montreal, Calgary, Edmonton, and Ottawa, it has substantially increased in both Toronto and Vancouver. Hence, Toronto and Vancouver display a pattern of the geographic concentration of the top-10% income households between 2001 and 2016.

We next look at what we call the "excess geographic concentration" of high-income households. More precisely, we first compute the share of pairs of high-income households that are located at less than x km from each other. This is what we call the cumulative distribution of bilateral distances between high-income households. For example, the cumulative distribution at 1000 meters distance is 0.0183 in Toronto in 2001; this means that a randomly drawn pair of residents residing in dissemination areas belonging to the 90th percentile of the household income distribution in Toronto in 2001 have a 1.83% chance to be located less than 1000 meters from one another. The corresponding figure for any pair of households (irrespectively of their income) being only 0.49%, there is an 'excess' of 1.34% in the clustering of high-income residents compared to the general clustering of the population.

[5] All descriptive results for the K-densities are computed using the dissemination areas of the respective census years. These geographic units are *not* stable across time. This does not matter substantially for our analysis at the aggregate CMA level. We provide the analogue of Figure 5, computed now on our stable "concorded blocks" in the Appendix (see Figure B1). Our qualitative message remains unchanged. Of course, some of our analysis in Parts I and III of this report are at the dissemination area level, and in that case having stable spatial units is crucial, as explained before. For those analyses, we use the stable spatial units that we constructed for the 2001-2016 census waves.

Our summary results for excess geographic concentration of high-income households are summarized in Table 8 below. That table basically makes the same point as the foregoing figures: Toronto and Vancouver have seen a substantial uptick in the geographic concentration of high-income households, whereas Ottawa-Gatineau has seen a positive but more moderate increase. The other large metropolitan areas—Montreal, Calgary, and Edmonton—experienced a decrease or stagnation in the geographic concentration of high-income households.

Note that excess concentration is naturally stronger at the top of the income distribution than at lower income percentiles (see Table 8, where we report results for the 50th, the 75th and the 90th percentiles, respectively). This is partly mechanical, yet the strength of the effect suggests that there is more than a strictly mechanical effect at work.[6] In particular, the spatial structure of the above median incomes (50th percentile) tends to be almost indistinguishable from that of the overall distribution of incomes, which suggests that the excessive spatial concentration of incomes is really something driven by the very top of the income distribution. In a nutshell, the very high incomes have a very distinct spatial pattern and dynamics.

Finally, Figure 6 depicts the concentration of high incomes in excess of the concentration of population in general for the three largest Canadian CMAs. Clearly, there has been a substantial increase in Toronto and Vancouver, while the excess concentration remained largely unchanged in Montreal.

Summary:

- high-income residents exhibit significant spatial concentration at very short distances (less than one kilometer) in several, but not all, Canadian CMAs.
- in most of the largest Canadian CMAs, the spatial concentration of high-income residents is stronger than the spatial concentration of the population: there is excess concentration of high-income residents at short distances.
- Toronto and Vancouver are on a distinct path compared to the other large CMAs: the spatial concentration of the very wealthy residents is stronger there, and it increases over time, contrary to the other four CMAs above one million inhabitants.

[6] Since the cumulative of the incomes and the cumulative of the population both tend to one at the limit, their difference must go to zero.

Figure 5 – Changes in the geographic concentration of high incomes (90th pctl), 2001-2016.

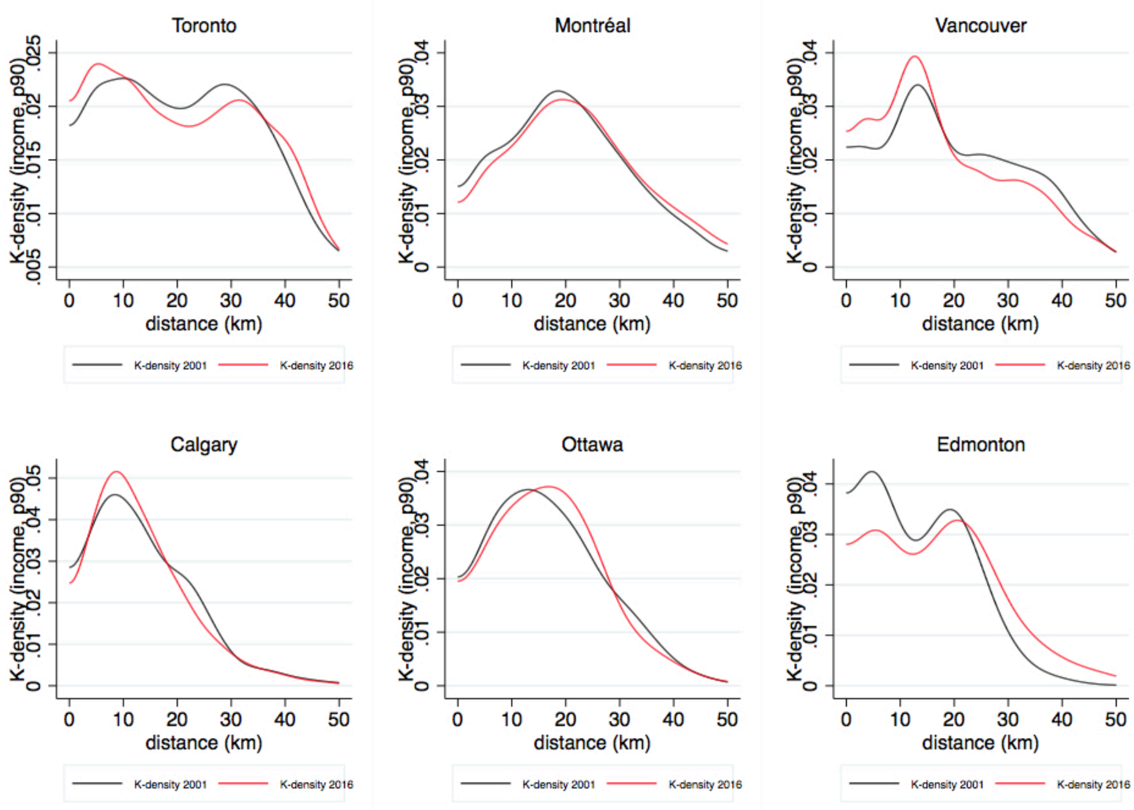
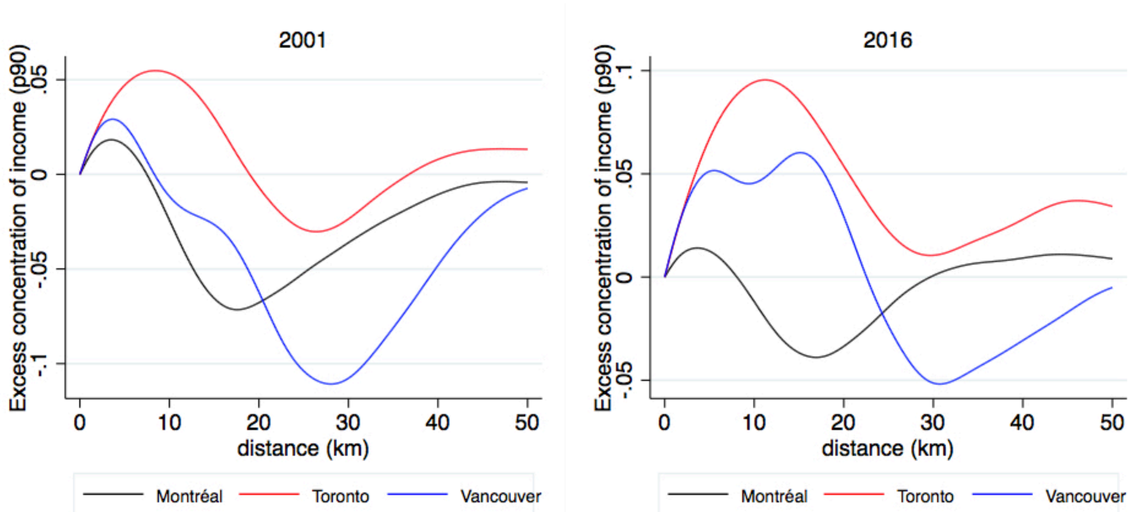


Table 8 – Excess concentration (below 1000 meters distance) of selected income percentiles.

	Excess concentration of households by income							
CMA	90th percentile		75th percentile		50th percentile		Population	
	2001	2016	2001	2016	2001	2016	2001	2016
Edmonton	2.63%	1.81%	0.52%	0.52%	0.12%	0.05%	937,575	1,321,426
Calgary	1.51%	1.44%	1.01%	0.79%	0.37%	0.28%	950,994	1,392,609
Vancouver	1.35%	1.69%	0.28%	0.34%	-0.01%	0.01%	1,985,568	2,463,431
Toronto	1.34%	1.63%	0.38%	0.42%	0.06%	0.08%	4,678,979	5,928,040
Montréal	0.90%	0.68%	0.16%	0.09%	-0.09%	-0.08%	3,424,724	4,098,927
Ottawa	0.86%	0.98%	0.49%	0.41%	0.14%	0.14%	1,062,177	1,323,783

Figure 6 - Excess geographic concentration of income (90th pctl), 2001-2016.



Fact 2. The highly educated are less concentrated than high incomes.

What is the role of the highly educated in driving the patterns observed within cities in Canada regarding the spatial concentration of high-income residents? In particular, how strong is their geographic concentration compared to that of the high incomes? This question is important to analyze since it is well known that education translates, on average, into higher incomes. Hence, the geographic concentration of high incomes might just pick up the geographic concentration of highly educated residents. As shown in Figures 7 to 9 below, there is a weak but statistically significant geographic concentration of highly educated individuals within the large CMAs in Canada. In both Toronto, Vancouver, and Montreal—as well as in the other large CMAs that we do not depict explicitly here—the highly educated are statistically significantly concentrated at short distances within the CMAs. This result should not come as a surprise since the spatial sorting of high-skilled individuals across and within cities has been previously documented in the literature (see, e.g., Behrens et al., 2014; Eeckhout et al., 2014; Davis and Dingel, 2019).[7]

[7] We depict in Figures B2 to B5 in Appendix II the spatial distribution of the clusters of highly educated and high income (90th percentile) households in the centers of Montreal and Toronto. While there is overlap, these figures show that the zones where we have contiguous blocks of highly educated and high incomes is not necessarily perfect. For example, the Plateau in Montreal (a hip uptrend neighborhood) displays a very high degree of the clustering of highly educated people, but does not belong to the zones with very high incomes. Conversely, Hampstead (a very rich neighborhood) is not among the most highly educated in Montreal. Last, a very interesting example of local urban dynamics is given by Ile des Soeurs in Montreal. That area experienced a large supply of new housing, and a strong growth in incomes and the share of highly educated residents. New high-end condominiums and amenities (view on downtown and the St-Lawrence waterfront) certainly explain part of these dynamics.

Figure 7 - Geographic concentration of the highly educated (university degree) in the Toronto CMA.

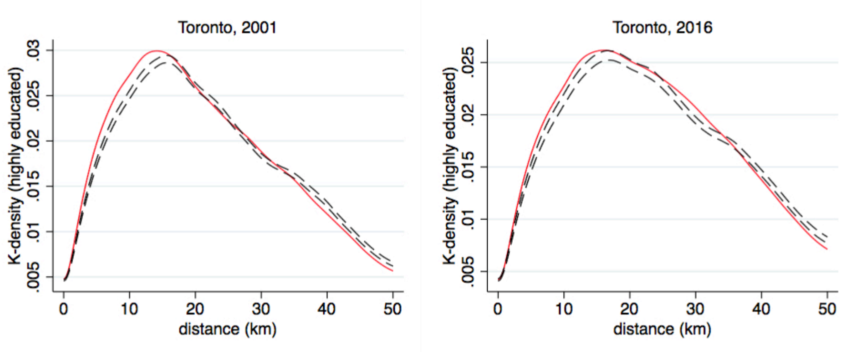


Figure 8 - Geographic concentration of the highly educated (university degree) in the Vancouver CMA.

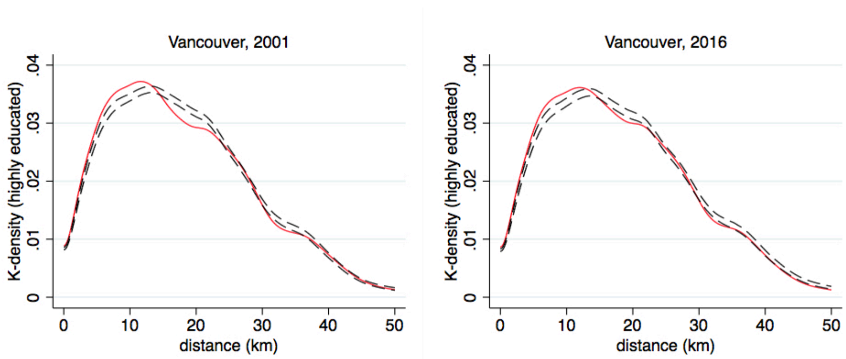
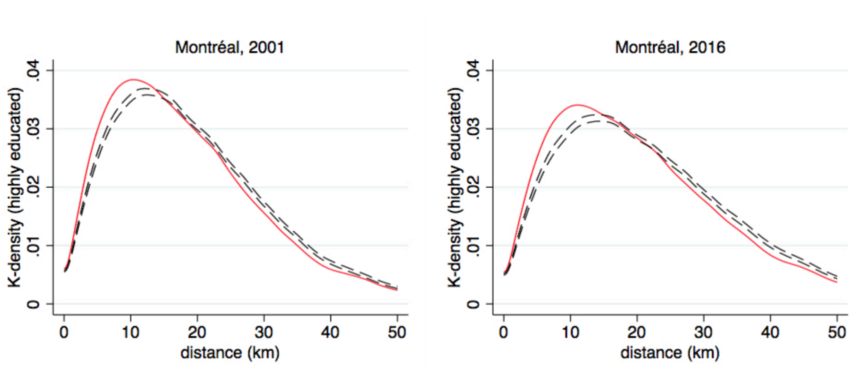
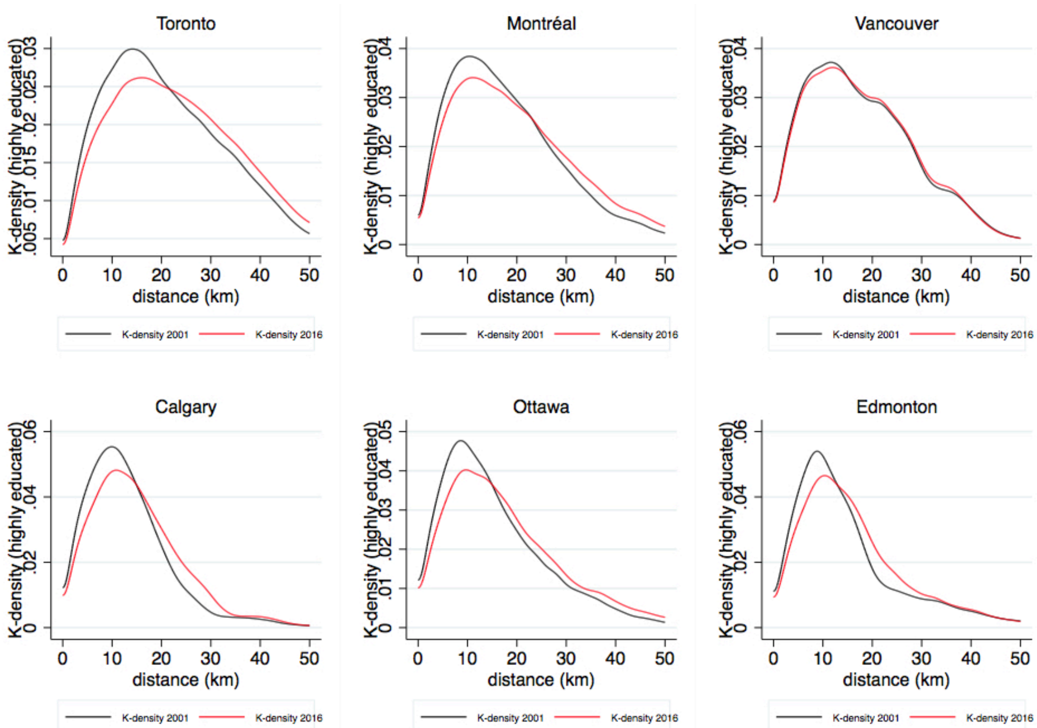


Figure 9 - Geographic concentration of the highly educated (university degree) in the Montreal CMA.



Beyond this general observation, two important and interesting findings emerge from these figures. First, the magnitude of that phenomenon is not extremely large compared to the spatial concentration of wealthy residents. Indeed, the observed distributions are much closer to the confidence bands that correspond to a random allocation than in the case of the spatial distribution of high-income residents (see above). Second, the spatial concentration of the highly educated within Canadian CMAs is not a new phenomenon: it holds for 2001 as well as for 2016.

Figure 10 - Changes in the geographic concentration of the highly educated (university degree), 2001-2016.



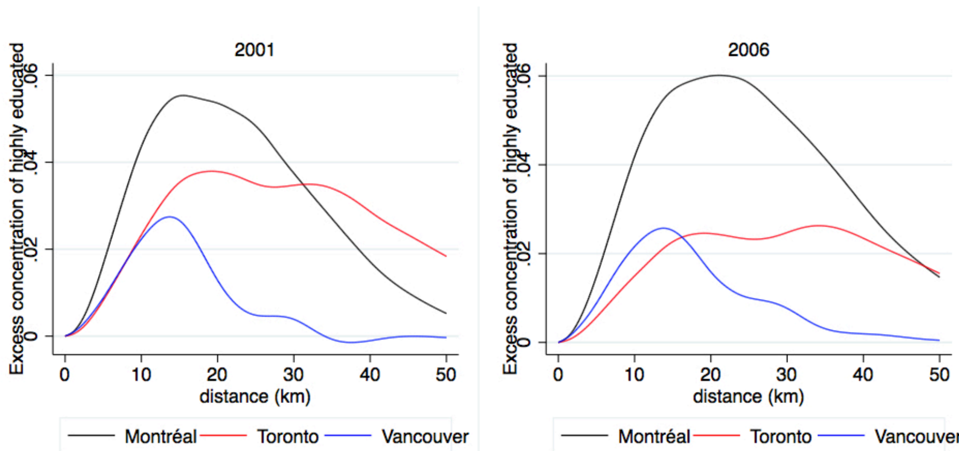
Furthermore, Figures 10 and 11 show a very consistent pattern: between 2001 and 2016, the geographic concentration of the highly educated, as well as their excess concentration, has not increased in Canadian CMAs. If anything, it has decreased. This holds across the board for all large CMAs, including Toronto and Vancouver. The figures in Table 9 also show that the excess concentration of the highly educated is, in general, relatively weak compared to that of income documented in Table 8 above. This pattern might be driven by the fact that the number of people with a university degree has increased over time, thus making that part of the population larger and hence its geographic distribution more similar to that of the overall population.

All of these results indicate that the geographic concentration of the (very) high-income residents within Canadian CMAs and its evolution over time are not primarily driven by the location of the highly educated. Put differently, holding a university degree is a far from perfect predictor of the probability of belonging to the top 10% of the household income distribution.

Summary:

- the highly educated are spatially concentrated within Canadian CMAs for all years between 2001 and 2016, but less than the high-income residents.
- the spatial concentration of the highly educated in Canadian CMAs has stagnated or decreased over time for all CMAs. This may be due to a larger share of the population holding a university degree in 2016.
- the comparison of the patterns observed for the high-income residents and for the highly-educated ones shows again that the formers cannot be approximated by the latter; hence income and education shape the urban structure differently.

Figure 11 - Excess geographic concentration of the highly educated (university degree), 2001-2016.



Fact 3. New housing construction has a spatial profile that varies substantially across CMAs. There are no strong patterns for retirees.

Table 9 below also provides two additional measures of interest to understand the geographic structure of cities: the excess concentration of retirees (measured here as the population above 65 years old) compared to the overall population; and the excess concentration of new housing units (measured here as units built less than 10 years ago) compared to the overall stock of all housing units. We also did a similar analysis for old housing units (more than 40 years of age), but we do not report the results here.[8]

[8] It is difficult to measure "old units" consistently across Census years, 40 years is the maximum, and this is still relatively young. See the appendix for some more discussion on our choices of housing vintage categories.

Table 9 - Excess concentration (below 1000 meters distance) of highly educated, retirees, and new housing stock.

	Excess concentration of…							
CMA	**highly educated**		**retirees**		**new housing**		**Population**	
	2001	**2016**	**2001**	**2016**	**2001**	**2016**	**2001**	**2016**
Ottawa	0.14%	0.10%	0.09%	0.04%	-0.22%	-0.12%	1,062,177	1,323,783
Montréal	0.09%	0.09%	0.05%	-0.01%	-0.19%	-0.06%	3,424,724	4,098,927
Vancouver	0.08%	0.09%	0.02%	-0.01%	0.00%	-0.01%	1,985,568	2,463,431
Toronto	0.05%	0.04%	0.01%	0.00%	0.00%	0.13%	4,678,979	5.928.040
Edmonton	0.02%	0.02%	0.10%	0.07%	-0.25%	-0.22%	937,575	1,321,426
Calgary	0.00%	0.01%	0.03%	0.05%	-0.17%	0.18%	950,994	1,392,609

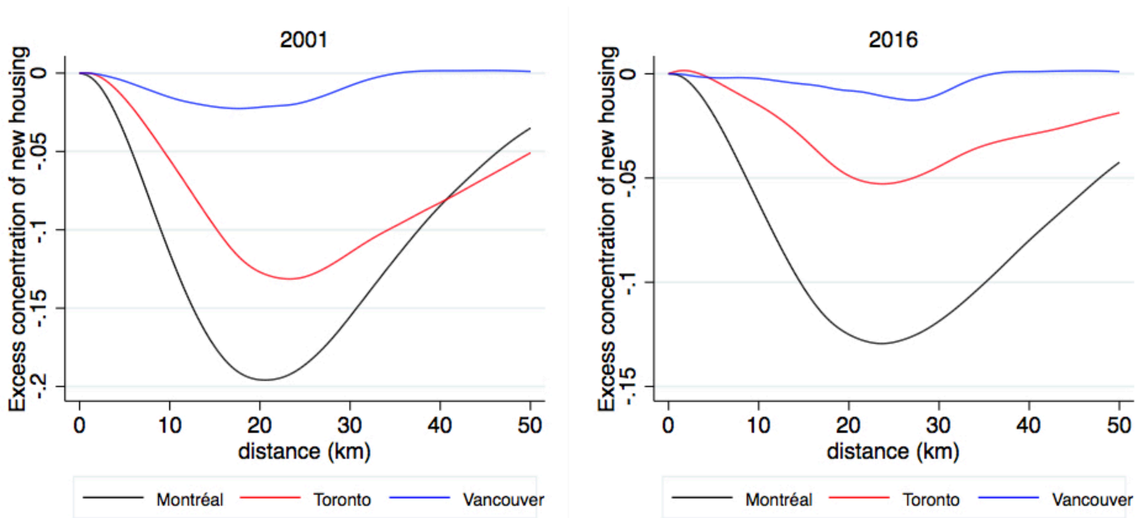
The main observations from Table 9 are as follows. First, we do not find any strong geographic patterns in the concentration of retirees. The overall effects are quite weak and there is no systematic variation across cities. If anything, we can note that Edmonton and Ottawa have higher levels of geographic clustering of retirees, but overall the levels are weak and they tend to decrease from 2001 to 2016. Second, there are substantial differences in the geographic distribution of new constructions. Whereas all CMAs have in general their new constructions more dispersed than the total existing stock of housing—negative excess concentration at 1000 meters—Toronto and Vancouver are again qualitatively different from the other CMAs. In both of these CMAs, the new housing stock in 2001 was *geographically less dispersed* than in the other large CMAs, and this trend has continued into the 2016 census. Figure 12 depicts this graphically by showing that new housing stock is: (i) more geographically concentrated in Toronto and Vancouver than in Montreal, both in 2001 and in 2016; and (ii) that concentration has substantially increased in Toronto (and to a lesser degree in Vancouver) between 2001 and 2016.

Interestingly, Toronto and Vancouver have also seen the largest increase in the geographic concentration of high-income residents between 2001 and 2016 (see Table 4 and the associated discussions before). This correlation between the spatial concentration of wealthy residents and the spatial concentration of new housing units could be explained by filtering mechanisms, where high-income households tend to sort into newly-built houses or apartments, leaving the older housing stock to "filter down" to the lower-income residents. Indeed, the literature has widely shown that high-income households are sensitive to the quality and age of the housing stock (see, e.g., Rosenthal, 2014; Brueckner and Rosenthal, 2009; and Rosenthal and Ross, 2015, for evidence). While we cannot investigate in more depth these issues with our data, it would certainly be worthwhile to understand this better in the Canadian context.

Summary:

- while new housing tends to be spatially dispersed in most Canadian CMAs (as cities are generally built up from the center to the outskirts), it tends to be more concentrated in Toronto and Vancouver.
- Toronto and Vancouver being also the CMAs where the spatial concentration of high-income residents has mostly increased, this suggests that a filtering phenomenon might be at play in both cities.

Figure 12 - Excess concentration of new housing, 2001-2016.



B – Some controlled correlations

As noted from the outset of this report, we do not make any causal claims given the data at hand and the level of aggregation of our analysis. We now nevertheless provide some econometric evidence on the correlations between the evolution of the excess concentration of wealthy residents within cities, the evolution of city size, and the evolution of the excess concentration of the highly educated residents. While in the previous analyses we were comparing the Canadian CMAs with one another, we here focus on the evolutions within CMAs over time. In order to work with CMAs where the density distributions have been estimated using a meaningfully large number of blocks, we restrict the analysis mostly to 'large CMAs', namely, CMAs with more than 100,000 inhabitants. We then estimate a panel model with CMA fixed effects to control for time-invariant CMA-specific unobservables. The regressions we estimate are the following:

$$y_{ct} = X_{ct}\beta + \gamma_t + \mu_c + \epsilon_{ct}$$

where y_{ct} is either measure of the excess concentration of the rich (90$^{\text{th}}$ percentile of the income distribution) or a measure of the excess concentration of the highly educated. To control for the geographic structure of the CMA, we measure the concentration of income or education 'in excess of the general concentration of the population'. More technically, y_{ct} is (for income) the cumulative distance distribution of the rich households minus the cumulative distance distribution of the population in general. If, e.g., $y_{ct} = 0.1$ at a distance of 1 kilometer, this means that there are 10% more bilateral distances between rich residents that lie below 1 kilometer than there are bilateral distances between residents of the CMA in general that lie below this same threshold. This is why we refer to these measures as 'excess geographic concentration' measures. The higher these measures, the more excessively concentrated are the rich or the highly educated.

Table 10 – Excess geographic concentration of high incomes and CMA size

	Excess concentration of high incomes			
	90th percentile		75th percentile	
	500m	1000m	500m	1000m
CMA population	0.071[a]	0.083[a]	0.085[a]	0.085[a]
(large cities, N=146)	(0.023)	(0.028)	(0.030)	(0.031)
CMA population	0.036		-0.042	
(all cities, N=516)	(0.113)		(0.086)	

Notes: Controls included: year fixed effects, CMA fixed effects, CMA maximum distance for which we observe population. We use 2001, 2006, 2011, and 2016 census waves. Robust standard errors. [a] p<0.01, [b] p<0.05, [c] p<0.1

In Table 10, we first explore the correlation between the excess concentration of wealthy residents and city size. Whatever the threshold used for the definition of high-income residents (top 25% or top 10%) and for the computation of excess concentration (excess concentration at 500 meters or 1000 meters), the picture remains the same: the wealthy residents tend to become more concentrated (or equivalently to disperse less) as a city grows. Since in Canada, big cities grow faster than the others (one can statistically test that there is no mean reversion in the population growth of Canadian CMAs), this means that the biggest Canadian CMAs, which we know already from Part I to be more spatially unequal in terms of average household income, have become relatively even more unequal over time as compared to the other CMAs. The same observation applies for the correlation between excess concentration of the highly educated and population growth as shown in Table 11: fast-growing cities in terms of population are also cities where the highly educated concentrate more. This effect is, however, less significant than for high incomes.

Table 11 – Excess geographic concentration of highly educated and CMA size

	Excess concentration of highly educated, 90th percentile			
	Large cities (N=146)		All cities (N=516)	
	500m	1000m	500m	1000m
CMA population	0.087[b]	0.088[b]	0.192[b]	0.210[b]
	(0.041)	(0.039)	(0.098)	(0.099)

Notes: Controls included: year fixed effects, CMA fixed effects, CMA maximum distance for which we observe population. We use 2001, 2006, 2011, and 2016 census waves. Robust standard errors. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

In Table 12, we investigate how the excessive concentration of the high incomes is related to the growth of both CMA population and the excess geographic concentration of the highly educated. The results show that growing CMAs in terms of population experience more excessive concentration of the high incomes. For the very high incomes (90th percentile) this correlation is much more significant than the one with the excessive concentration of the highly educated. On the opposite, the spatial concentration of the high incomes (75th percentile) is more driven by the concentration of the highly educated than by the CMA population growth in general. Hence, the spatial concentration of high educational attainment helps in predicting if high incomes concentrate, but not for the very high incomes. For the very high incomes, CMA growth in terms of population is the best predictor of the increased geographic concentration of the top incomes. While we cannot provide any test of mechanisms, it is possible that superstar and 'superstar city' explanations are at work (Rosen, 1981; Glaeser, Gyourko, and Saiz, 2010).

Table 12 – Excess geographic concentration of high incomes, excess concentration of highly educated, and CMA population size

	Excess concentration of high incomes			
	90th percentile		75th percentile	
	500m	1000m	500m	1000m
CMA population	0.057[a]	0.065[b]	0.058[c]	0.056[c]
	(0.022)	(0.026)	(0.029)	(0.028)
Excess concentration of highly educated	0.162[c]	0.208[c]	0.320[a]	0.335[a]
	(0.092)	(0.112)	(0.113)	(0.118)

Notes: Large cities only (N=146). Controls included: year fixed effects, CMA fixed effects, CMA maximum distance for which we observe population. We use 2001, 2006, 2011, and 2016 census waves. Robust standard errors. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Last, in unreported results we also investigated the correlation between the excess concentration of high incomes (90^{th}, 75^{th} and 50^{th} percentile) with both CMA population and the excess concentration of new housing stock (of age less than 10 years). While the CMA population coefficient remains of similar magnitude and is precisely estimated, the excess concentration of new housing stock is never statistically significant at any conventional level.

Summary:

- high-income residents concentrate more (or disperse less) when population size increases within a city.
- highly educated residents concentrate more (or disperse less) when population size increases within a city.
- there is no significant relationship between the excess concentration of high incomes and the excess concentration of the highly educated.
- growing CMAs in terms of population experience more excessive concentration of the high incomes. For the very high incomes (90^{th} percentile) this effect is only marginally affected when also accounting for the excessive concentration of the highly educated. For the high incomes (75^{th} percentile), this effect is more strongly driven by the excessive concentration of the highly skilled compared to CMA population growth in general.
- there is no significant relationship between the excess concentration of new housing construction and the excess concentration of the highly educated.

III- Dissimilarity, exposure, mean reversion, and spatial correlation.

We next investigate the spatial agglomeration patterns of different population subgroups in the ten largest Canadian CMAs using tools from the literature on segregation and spatial statistics. We first look at how different groups—in terms of income, education, and age of the housing stock—are distributed across different geographic units in the ten largest CMAs. More precisely, borrowing the tools from the literature on segregation, we first analyse how dissimilar the spatial distributions of some groups are in the CMAs and how different groups are exposed to each other. We provide both cross-sectional results and results for changes between 2001 and 2016. We finally also look at possible spillover effects, i.e. at how the characteristics of spatial units change as a function of the characteristics of the spatial units surrounding them. More precisely, we first run convergence regressions to understand whether there is mean reversion, i.e. whether there is a negative correlation between the growth rate of a variable and its initial level. Second, we add to these convergence regressions the initial characteristics of the neighbours to capture potential spatial spillovers in the dynamics at play.

A- Dissimilarity in the distribution of characteristics

We begin by analyzing how a group with certain characteristics (highly educated individuals, high-income individuals or newly built housing units) is distributed compared to a benchmark provided by some reference population (all individuals or all housing units). If the group is evenly distributed among units in the metropolitan area (compared to the reference population), then the dissimilarity measure is small.[9] Conceptually, the dissimilarity index measures the percentage of a group's population that would have to move to obtain a geographic distribution of that group that is even across the city. It ranges from 0 to 1, with higher values meaning a more uneven geographic distribution of that group across spatial units. We compute this index at the smallest geographic unit, i.e., dissemination areas. We report results for both 'contemporaneous dissemination areas' (which change through time) and stable blocks as explained before. Our results are not sensitive to that choice.

We define our different groups as follows. First, concerning income, we use different bins to define poor and rich individuals. Second, regarding education, we define high- and low- skill groups using the highest level of education as a proxy. Finally, we define 'new' and 'old' housing units as units that are less than 10 years and more than 40 years of age. This will allow us to assess how even or uneven the distributions of new and old housing units are compared to the total housing in each of the metropolitan areas.[10]

Educational attainment. We first look at the evenness of the distribution of the highly educated in the large Canadian CMAs. Table 13 shows that the high- and low-skill groups are spatially unevenly distributed compared to the total population. The larger the figures in Table 13, the more uneven the groups are distributed compared to the rest of the population. Table 13 shows that the highly educated are systematically less evenly distributed than the low educated in all CMAs and for the four census waves. As Table 13 further shows, there is a clear tendency for lower segregation of both the highly educated and the low educated between 2001 and 2016. Both effects seem general, with a larger magnitude for the highly educated than for the low educated. This suggests—consistently with our findings in the previous sections—that there is less stratification along educational lines in the large Canadian cities in 2016 compared to 2001.[11]

Income. We next turn to the uneven geographic distribution of rich and poor households. Table 15 summarizes the dissimilarity index of how poor and rich households are geographically concentrated compared to total population in 2006, 2011, and 2016.[12] Several results are worth mentioning. First, the poor tend to be generally more concentrated then the rich compared to the total population. Second, there was a significant increase in the dissimilarity gap between poor and rich in 2011 and then a slight decrease in 2016, but the concentration of poor remains more important than that of the rich. Third, there is heterogeneity in the unevenness of the spatial distribution of the rich and the poor across Canadian CMAs.

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[9] See, e.g., Massey and Denton (1988) for a review of the literature on segregation that discusses these measures.
[10] All details on how the groups are created and which formulas are computed for the measures can be found in the appendix material to this report. See Tables A2 and A3 in Appendix I for details.
[11] However, one needs to keep in mind that the dissimilarity measures do not control for the spatial relationships between geographic units. Hence, while the mix of each unit can become less uneven, these units could progressively cluster and therefore create zones in the CMA that are much more educated than others. That this problem does not arise in the CMAs we consider is shown in the second part, where we report analogous results using *K*-densities that control for the relative positions of the spatial units.
[12] We cannot report results for 2001 since there are no data on the distribution of income within dissemination areas for that year. However, we can use a measure of poverty incidence, provided by Statistics Canada and available in 2001, that proxies for the number of poor by dissemination area. See Table B3 in Appendix II-C for results that include 2001 as well as 2006, 2011 and 2016.

Table 13 – Uneven distribution of high- and low-skilled individuals

	2001		2006		2011		2016	
CMA	High Skill	Low Skill	High Skill	Low Skill	High Skill	Low Skill	High Skill	Low Skill
Québec	0.29	0.17	0.23	0.14	0.25	0.15	0.22	0.14
Montréal	0.31	0.16	0.24	0.13	0.27	0.14	0.25	0.13
Ottawa	0.25	0.21	0.20	0.13	0.20	0.15	0.19	0.13
Toronto	0.25	0.17	0.19	0.11	0.21	0.13	0.19	0.12
Hamilton	0.29	0.16	0.24	0.11	0.25	0.14	0.22	0.12
London	0.31	0.15	0.27	0.10	0.29	0.13	0.26	0.12
Winnipeg	0.30	0.16	0.23	0.10	0.24	0.11	0.20	0.10
Calgary	0.26	0.18	0.21	0.12	0.21	0.14	0.19	0.13
Edmonton	0.29	0.15	0.24	0.10	0.26	0.12	0.23	0.11
Vancouver	0.25	0.16	0.19	0.11	0.21	0.12	0.19	0.12

Table 14 – Uneven distribution of rich and poor households

	2006		2011		2016	
CMA	Rich	Poor	Rich	Poor	Rich	Poor
Québec	0.31	0.28	0.34	0.44	0.22	0.32
Montréal	0.3	0.25	0.35	0.39	0.22	0.27
Ottawa	0.25	0.35	0.24	0.59	0.19	0.36
Toronto	0.22	0.29	0.25	0.47	0.17	0.28
Hamilton	0.26	0.31	0.3	0.54	0.2	0.34
London	0.27	0.28	0.33	0.47	0.24	0.32
Winnipeg	0.32	0.3	0.34	0.51	0.21	0.32
Calgary	0.21	0.31	0.19	0.56	0.12	0.29
Edmonton	0.24	0.31	0.19	0.54	0.13	0.31
Vancouver	0.23	0.23	0.24	0.4	0.15	0.22

Without going into details, one possible explanation for the lower unevenness in the spatial concentration of the rich, as compared to the poor, may lie in the choice between owning or renting. Poorer households are more likely to rent their apartment or their house, so that differences in the geographic supply of rental properties will translate into differences in the geographic concentration of different income groups. Furthermore, cross-city heterogeneity in patterns could result from the availability and, more importantly, the location of low-income rental supply and affordable housing since the poor are more strongly constrained in their choice set than the rich. Last, the age of the housing stock is strongly linked to the socio-economic characteristics of the occupants. For the US, Rosenthal and Ross (2015) document that housing 'filters down' the income distribution as it ages. Hence, the geographic pattern of the distribution of housing in general—and of rental housing in particular, might have a strong bearing on the spatial distribution of income.

Turning to the changes in patterns, Table 14 shows that between 2006 and 2016 the geographic concentration of the poor has remained very stable (and has even increased in some cases), whereas that of the rich has tended to decrease. Hence, income mixing seems to have increased, at least for middle- and high-income households. We will not speculate on the reasons, but central city revival and the gentrification of middle-class neighborhoods loom large among the possible causes.

Finally, comparing Tables 13 and 14, it is interesting to note that while highly educated residents tend to be more unevenly distributed within cities, the opposite is true for poor residents. This highlights again the disconnect between income and education when studying the spatial sorting of households.

Housing. We now switch from the analysis of the geographic concentration of characteristics of individuals to the geographic concentration of the characteristics of housing units. Given the data at hand, we only look at a single dimension: the uneven distribution of the new and the old housing stocks. To do so, we adapt the dissimilarity index by changing our unit of analysis to housing units. More precisely, we compare how new (less than 10 years of age) and old (more than 40 years of age) housing units are distributed against the benchmark of the total housing stock in a CMA. In this case, the dissimilarity index shows how 'segregated' housing units of a specific type— where type is their 'vintage'—are compared to the population of all units. As with education and income before, higher values of the measure reflect a higher concentration of that type of housing, i.e., more unevenness in its geographic distribution compared to that of housing in general.

Table 15 provides, unsurprisingly, evidence for a high concentration of new housing units. It shows that old housing is also concentrated, but to a somewhat lesser extent (the concentration of new housing at one point will, of course, directly translate into the concentration of old housing in the future). We further see heterogeneity across cities for all census waves. For instance, in 2001, Winnipeg, Toronto, and Hamilton had the highest concentration of new housing units, with a value of 0.70, 0.65 and 0.64 of their dissimilarity indices, respectively; whereas, Vancouver, Québec, and London had the lowest values at 0.45, 0.51, and 0.56, respectively. These patterns remain fairly stable over time.

Table 15 – Uneven distribution of new and old housing units

	2001		2006		2011		2016	
CMA	New	Old	New	Old	New	Old	New	Old
Québec	0.51	0.44	0.54	0.37	0.64	0.25	0.51	0.27
Montréal	0.62	0.41	0.62	0.33	0.72	0.24	0.58	0.26
Ottawa	0.58	0.49	0.58	0.42	0.66	0.31	0.58	0.34
Toronto	0.65	0.49	0.63	0.43	0.71	0.32	0.61	0.38
Hamilton	0.64	0.41	0.65	0.34	0.77	0.24	0.65	0.27
London	0.56	0.44	0.61	0.36	0.75	0.25	0.65	0.26
Winnipeg	0.70	0.44	0.71	0.34	0.81	0.23	0.64	0.23
Calgary	0.61	0.61	0.56	0.55	0.61	0.38	0.56	0.46
Edmonton	0.60	0.54	0.59	0.49	0.63	0.33	0.55	0.39
Vancouver	0.45	0.42	0.47	0.38	0.62	0.28	0.46	0.32

As Table 15 shows, new housing is often more clustered than old housing. These patterns are consistent with cities expanding spatially and with new developments occurring mostly in the periphery of the CMA.

Summary:

- highly educated individuals and lowly educated individuals are more unevenly distributed than the total population, with more unevenness in the distribution of the highly educated individuals.
- rich and poor residents are more unevenly distributed than the total population, with more unevenness for the rich than for the poor.
- new and old housing units tend to be clustered, but new developments are more clustered than old housing units.

B- Exposure between different characteristics

We next document another dimension of the unequal distribution of education and income across Canadian CMAs: the 'between-group dimension of segregation'. To this end, we provide measures of exposure which capture the potential for contact and interactions between two groups.[13] The exposure index measures the likelihood that two groups interact with one another because they share common geographic areas.[14] This measure is interesting because it allows us to explore how groups interact instead of only looking at the spatial distribution of one group as compared to the benchmark of the overall population. It allows us to assess more finely the dimensions of mixing within CMAs along education, income, and age of the housing stock by looking at the same characteristics than before: high and low educated individuals; rich and poor households; and old and new housing units.

We compute the exposure index, which can be interpreted as the probability that an individual from group A (e.g., rich) shares a geographic area with an individual from group B (e.g., poor).[15] The normalized index ranges from zero to one. For two given groups, a higher value means that these two groups are more exposed to each other, and a lower value means that they are more isolated from one another. As in the previous section, we compute this index at the smallest geographic unit, i.e., dissemination areas, for the ten largest Canadian CMAs.

Table 16 – Exposure between different characteristics

	2001			2006			2011			2016		
CMA	Low-High[a]	New-Old[b]	Rich-Poor[c]	Low-High	New-Old	Rich-Poor	Low-High	New-Old	Rich-Poor	Low-High	New-Old	Rich-Poor
Québec	0.23	0.65	-	0.16	0.62	0.40	0.18	0.65	0.62	0.15	0.50	0.32
Montréal	0.24	0.71	-	0.16	0.68	0.36	0.19	0.72	0.58	0.17	0.58	0.28
Ottawa	0.23	0.72	-	0.13	0.72	0.40	0.15	0.79	0.61	0.13	0.68	0.31
Toronto	0.20	0.79	-	0.12	0.80	0.31	0.15	0.86	0.48	0.13	0.77	0.23
Hamilton	0.20	0.75	-	0.13	0.74	0.38	0.16	0.80	0.66	0.12	0.70	0.32
London	0.23	0.66	-	0.15	0.66	0.35	0.18	0.77	0.61	0.15	0.67	0.34
Winnipeg	0.23	0.74	-	0.12	0.72	0.44	0.13	0.79	0.67	0.10	0.66	0.32
Calgary	0.22	0.82	-	0.13	0.81	0.29	0.15	0.86	0.39	0.12	0.78	0.14
Edmonton	0.22	0.78	-	0.13	0.79	0.35	0.15	0.84	0.44	0.13	0.77	0.18
Vancouver	0.19	0.55	-	0.11	0.56	0.27	0.14	0.72	0.42	0.11	0.54	0.17

Notes: [a] Low-High stands for low and high education groups; [b] New-Old for new and old housing stock; [c] Rich-Poor for high and low income groups. We do not report the exposure index for poor and rich in 2001 since data are not available for each group for that year.

[13] See, e.g., Massey and Denton (1988) for a review of the literature on segregation that discusses these measures.
[14] While the exposure dimension is correlated with the evenness dimension we analyzed before, it captures a different aspect of segregation. A group can indeed be unevenly distributed (compared to the total population) but still be more exposed to another group. Conversely, a group can be exposed to another group but evenly distributed across space.
[15] We use the same groups and characteristics (housing, education, and income) as the foregoing analysis. Details and formulas are again relegated to the appendix.

Table 16 shows the exposure index for different groups across our four census waves. Starting with education, our results show that the level of exposure of high and low educated individuals is rather small and tends to decrease across all CMAs between 2001 and 2016. These patterns are consistent with substantial segregation between the low and high educated (as expected) and increasing trend of this segregation between the two groups, which might suggest an increased mixing of those types with residents of intermediate education types (less expected). These changes may be driven by the rapid gentrification of previously lower-educated neighborhoods, where mixing increases due to an inflow of a more educated population in poorer and less educated neighborhoods. As explained before, the effect also stems in part from the increased presence of university educated people in the population of the large CMAs (and in Canada in general).

As for the mixing of housing units of different ages, exposure seems to be relatively high between old and new buildings across all CMAs. While these results may seem surprising at a first glance, one should keep in mind the fact that most neighborhoods go through long-run cycles of building, aging, and redevelopment. Once the housing stock gets old enough, new development will occur. Hence, there are many places where old and new building coexist, a sign of local redevelopment and gentrification.

Last, turning to income, the figures in Table 16 show that rich and poor households tend to be more exposed to one another than high- and low-educated individuals, with some heterogeneity across cities. Calgary, Edmonton, and Vancouver display a lower exposure of rich to poor, whereas London, Hamilton, and Québec show a higher exposure index. Finally, as for education, the (very) rich and the (very poor) tend to become less exposed to each other suggesting more mixing with intermediate income levels (even though mixing seems to have reached a peak in 2011, probably due to the effects of the economic crisis or to different sampling frames for the 2011 Census).

Summary:

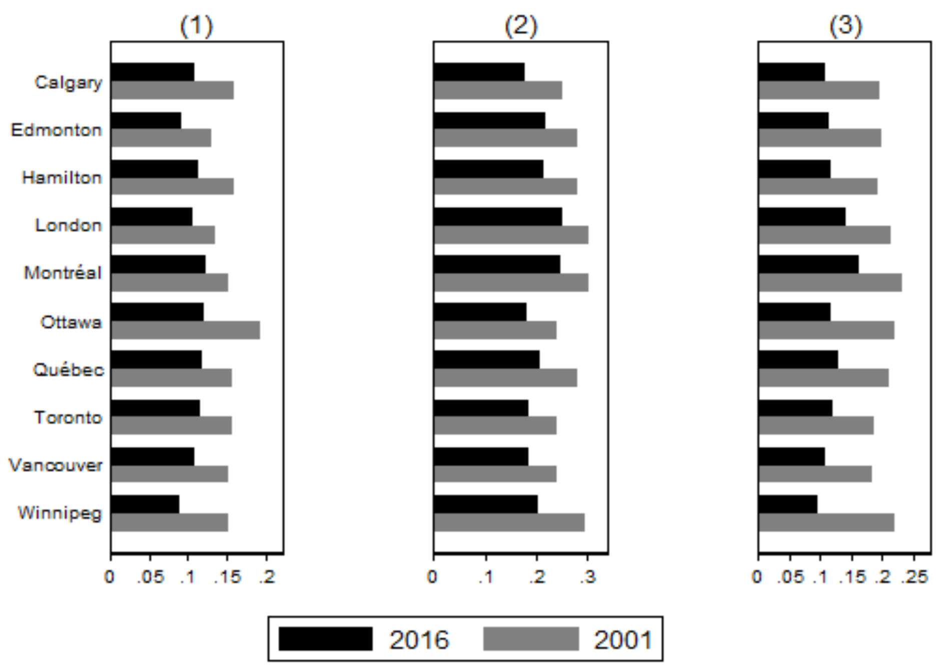
- the degree of exposure of highly educated residents to lowly educated ones within Canadian CMAs is small, revealing a small probability of sharing the same area.
- among the largest cities, Montreal has more mixing of low- and high-income types than Toronto and Vancouver, where high and low incomes are less exposed to one another.
- old and new units are more exposed to one another than poor and rich residents, thus suggesting the presence of substantial redevelopment.
- exposure between the (very) rich and the (very) poor has fallen, suggesting more mixing with intermediate income levels.

C- Changes over time

We next analyze how the measures we computed in the previous section change between 2001 and 2016. To do so in the most meaningful way, we use stable geographic units to compute the dissimilarity and exposure index for each CMA and for the four census waves. Using stable units is important since evenness and exposure indices may be quite sensitive to the geographic units of the analysis. Without a stable unit, the values of our indices might change partly because of a change in the boundaries of the administrative units used in the analysis.[16]

Starting with education, Figure 13 plots the dissimilarity and exposure indices for different groups and their change between 2001 and 2016. Panel (1) depicts the dissimilarity index for low education, with total population as the benchmark. It shows that there is a slight decrease over time, thus suggesting that the spatial distribution of the low educated individuals becomes more even. Similarly, panel (2) of Figure 13 compares highly educated individuals to the total population and shows that this group is also getting closer to the distribution of the total population between 2001 and 2016. However, panel (3) shows that even if the distributions of the two groups tend to get closer to that of the total population, they tend to get farther away from one another as well (recall that the as the exposure index decreases, groups are more separated). This means that while the two groups tend to get slightly closer to the rest of the population, they are also getting further away from one another and less likely to be found in the same area.

Figure 13 – Changes (2001-2006) in evenness and exposure for education groups

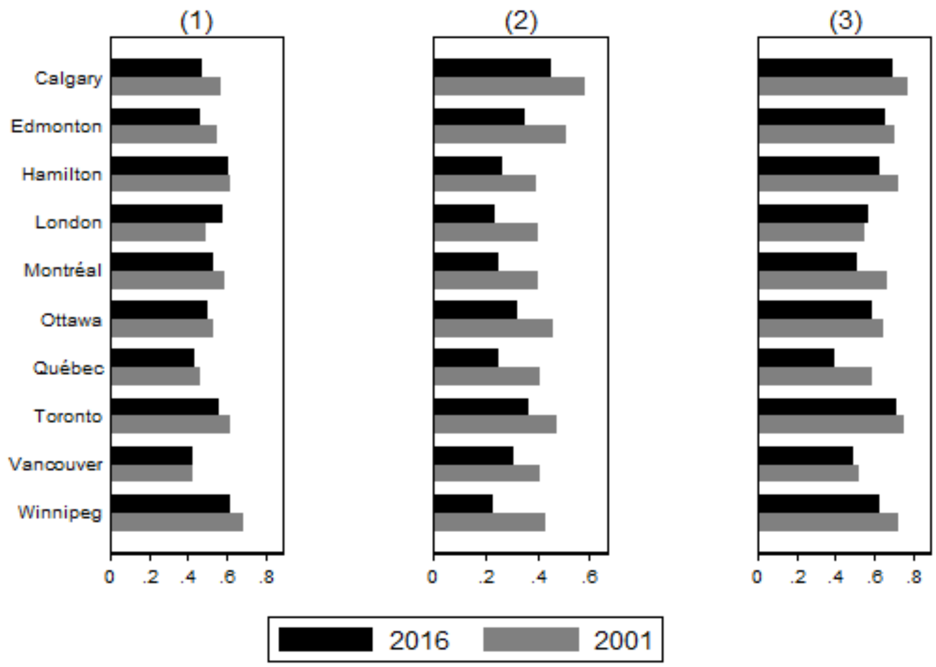


Turning to housing units, panel (2) of Figure 14 shows that the geographic distribution of new housing units is getting closer to that of all housing over time. This effect can also be observed for old housing units. Looking at the exposure between groups in panel (3), we note that the exposure of old to new housing is rather stable over time. There is a slight decrease

[16] Note that the results using stable units are very similar to those using directly the dissemination areas. In other words, changes across time are not strongly driven by changes in the boundaries of the administrative units. Indeed, the latter are relatively stable in the densely populated parts of the large CMAs.

between 2001 and 2016, but the overall picture remains one of many blocks where both old and new housing coexist.

Figure 14 – Changes (2001-2006) in evenness and exposure for housing units



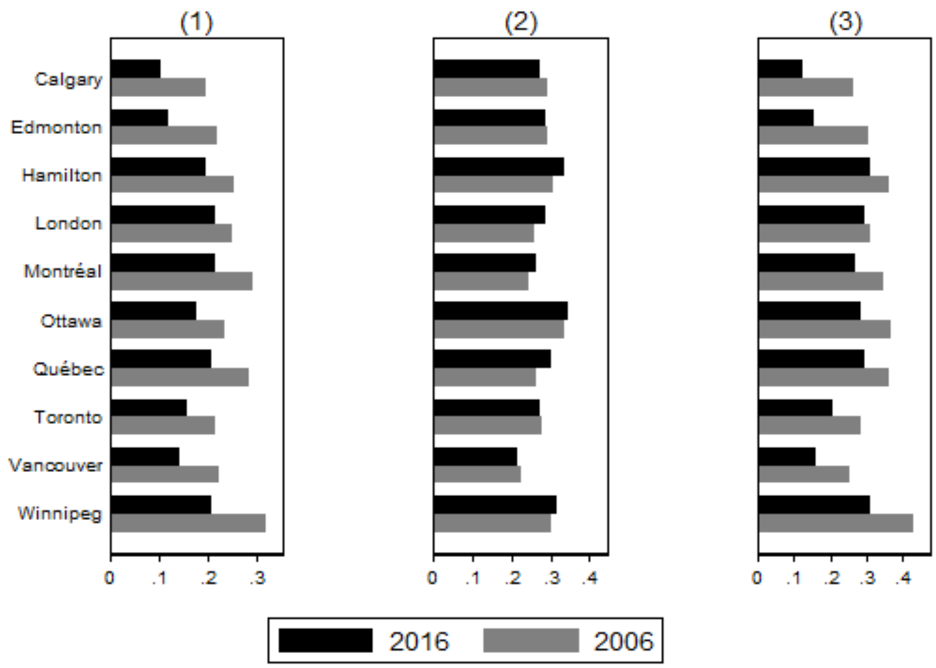
Last, turning to income, panel (1) of Figure 15 shows that the dissimilarity index for rich households decreased over time, thus suggesting that the rich have become less unevenly distributed within the large CMAs. Panel (2) shows that the same measure has remained basically stable for the poor between 2006 and 2016, thus suggesting that there has not been much change in the geographic concentration of the lower end of the income distribution. The exposure index, in panel (3), tends to decrease over time. This reveals that rich and poor are becoming less likely to share common geographic units over time. Looking at both dissimilarity and exposure, Figure 15 illustrates that while the rich are slightly less concentrated over time, they are also getting further away from the poor. Hence, the mixing of the rich and poor might occur more and more with the intermediate income levels, which would suggest a process in which middle-income neighborhoods (but not very poor ones) experience an inflow of more affluent households.

Summary:

- high- and low-educated individuals tend to become less clustered between 2001 and 2016 as compared to the total population.
- the poor are more unevenly distributed than the rich and this changes little over time.
- high- and low-educated individuals are getting less likely to share common areas, as revealed by less exposure between the groups.

- there is relatively little change in exposure between old and new houses over time.
- rich and poor are increasingly less exposed to one another, thus suggesting that there is increased mixing of poor and the rich with middle-income individuals.

Figure 15 – Changes (2001-2006) in evenness and exposure for rich and poor



D- Mean reversion and spatial correlation within CMAs

In this section, we focus on the five largest Canadian cities and explore two points. First, we look at how the initial levels of different characteristics in 2001 are related to the evolution of these characteristics between 2001 and 2016 (mean reversion). Second, we explore how the initial characteristics of surrounding areas of a given location in 2001 correlate with the evolution of these characteristics between 2001 and 2016 (spatial correlations). Once again, we also use stable geographic units to make sure that our results are not drive by changes in the boundaries of dissemination areas.

Mean reversion. There is mean reversion when the growth rate of a given variable is negatively correlated with its initial level. To analyze the existence of mean reversion in terms of the characteristics of residents and housing units within Canadian CMAs, we proceed with two different specifications. In the first one, we estimate a first-differenced specification where we regress the 2001-2016 log difference in household average income, number of highly educated residents, and number of new houses on the initial values of each variable. This specification is a convergence regression and allows us to know whether the average income of residents, the number of highly skilled residents, and the number of new housing units tend to increase more in dissemination areas where that number was initially already high.

Table 17 shows that, for all the variables we consider, there is evidence for mean reversion in the five largest Canadian CMAs. Convergence is the most pronounced for the number of new housing units and the number of highly educated residents. Those patterns are coherent with gentrification dynamics triggered by the arrival of highly educated residents in neighborhoods where the housing stock is rebuilt (see, e.g., Rosenthal and Ross, 2015). Regarding household average income, there is also statistically significant convergence, but the speed of that convergence is lower than the one observed for the other two variables. This is consistent with the fact that the initial steps of the gentrification process are generally associated with the inflow of residents that are certainly more educated than the initial residents, but who are not necessarily at the very top of the income distribution, so that convergence in terms of income is slower than convergence in terms of the share of highly educated.

Table 17: Mean Reversion: Difference

	Montréal	Ottawa	Toronto	Calgary	Vancouver
Variables	Dependent Variable: Δ log Household Average Income (2016-2001).				
Log Income (2001)	-0.11[a]	-0.09[a]	-0.06[a]	-0.09[a]	-0.18[a]
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	5,179	1,287	5,517	1,150	2,827
R-squared	0.05	0.04	0.01	0.02	0.09
	Dependent Variable: Δ log Number Highly Educated (2016-2001).				
Log High Skill (2001)	-0.37[a]	-0.31[a]	-0.30[a]	-0.35[a]	-0.40[a]
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Observations	5,245	1,323	5,697	1,184	2,865
R-squared	0.28	0.25	0.19	0.29	0.31
	Dependent Variable: Δ log Number New Houses (2016-2001).				
Log New House (2001)	-0.57[a]	-0.53[a]	-0.63[a]	-0.61[a]	-0.63[a]
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Observations	5,245	1,323	5,697	1,184	2,865
R-squared	0.28	0.28	0.34	0.35	0.31

Notes: Standard errors in parentheses. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Spatial correlations. Finally, in this section, we explore the existence of spatial spillovers, i.e. the correlation between the evolution of the characteristics of the residents and housing units in a given block and the initial levels of these characteristics in the surrounding blocks. To this end, we use a contiguity matrix that contains, for each block, all the adjacent blocks (their ‘neighbors’). For each block, we compute the characteristics of its neighbors, i.e. the average household income and the total number of highly educated residents and new housing units in those blocks.

Table 18 shows that in all cities, controlling for mean reversion as in Table 17, blocks that were surrounded by neighbors where the residents are wealthier and more educated, and where housing units were more recent, experienced a faster growth of, respectively, their average income, their number of highly educated residents, and their number of newly built housing units. Observe that this correlation is stronger for evolution of the number of highly-skilled residents than for the other two variables.

Table 18: Neighborhood Effect

	Montréal	Ottawa	Toronto	Calgary	Vancouver
Variables	Dependent Variable: Δ log Household Average Income (2016-2001).				
Log Income (2001)	-0.16[a]	-0.11[a]	-0.11[a]	-0.14[a]	-0.24[a]
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Neighbor's Log Income (2001)	0.07[a]	0.02[c]	0.09[a]	0.08[a]	0.09[a]
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	5,179	1,287	5,517	1,150	2,827
R-squared	0.07	0.04	0.03	0.03	0.11
	Dependent Variable: Δ log Number Highly Educated (2016-2001).				
Log High Skill (2001)	-0.60[a]	-0.51[a]	-0.45[a]	-0.59[a]	-0.60[a]
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Neighbor's Log High Skill (2001)	0.43[a]	0.36[a]	0.28[a]	0.39[a]	0.37[a]
	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)
Observations	5,245	1,323	5,697	1,184	2,865
R-squared	0.39	0.37	0.26	0.40	0.39
	Dependent Variable: Δ log Number New Houses (2016-2001).				
Log New House (2001)	-0.67[a]	-0.62[a]	-0.69[a]	-0.65[a]	-0.70[a]
	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)
Neighbor's Log New House (2001)	0.19[a]	0.17[a]	0.10[a]	0.06[b]	0.19[a]
	(0.02)	(0.03)	(0.01)	(0.03)	(0.03)
Observations	5,245	1,323	5,697	1,184	2,865
R-squared	0.30	0.29	0.35	0.35	0.32

Notes: Standard errors in parentheses. [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

The results in Table 18 suggest that there is spatial propagation: conditional on their initial characteristics, areas surrounded by neighbors with high initial levels of those characteristics tend to experience faster growth (or less mean reversion) in those characteristics over the next 15 years.

Summary:

- there is mean reversion for average income, the number of highly educated residents, and the number of new housing units across all of the five largest Canadian CMAs between 2001 and 2016. This convergence process is stronger for the number of highly educated residents and the number of recent housing units than it is for average income.

- stronger mean reversion for education than for income is consistent with the initial steps of the gentrification process being generally characterized by the inflow of residents that are certainly more educated than the initial residents but who are not necessarily at the very top of the income distribution.
- we find positive spatial correlation between the growth rate of a block between 2001 and 2016 and the initial characteristics of its neighbors in 2001. In other words, blocks that were surrounded by blocks with wealthier and more educated residents tend to experience faster growth condition on mean reversion.

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Appendix

I – Technical details

A – Data.

We use Statistics Canada Census data from four census waves: 2001, 2006, 2011, and 2016.[17] The census provides, among others, information on education, income, and housing for different geographic units. To compute our indices and measures of concentration, we use mainly the smallest geographic units, i.e., the dissemination areas (DAs). Since we do a comparative analysis across time and space, it is important to recognize that there are some differences between the four census waves that are affected by different factors. Results for the 2001, 2006, and 2016 Census waves are derived from a long-form questionnaire, which were mandatory and had a high response rate. However, some of our 2011 variables were collected from the 2011 National Household Survey (NHS) which was a voluntary survey with a lower response rate: the NHS sample frame was approximately only one-third of all Canadian households.

In 2016, 2011, 2006, and 2001, there were respectively 56 590, 56 204, 52 973 and 49 153 dissemination areas in Canada. These can be concorded to a total of 31 978 stable geographic units across those four wages (see Behrens et al., 2018, for the methodology). For simplicity—and to have enough geographic units to ensure the statistical significance of our analysis—we focus mostly on the ten major Canadian CMAs that have a population of at least half a million and more than 700 dissemination areas. Table A1 summarises the number of dissemination areas (# DA) and total population for each CMA.

Table A1 – Top-10 CMAs by population and dissemination areas

	2001		2006		2011		2016	
	# DA	Population	# DA	Population	# DA	Population	# DA	Population
London	697	0.43	711	0.46	758	0.47	760	0.49
Hamilton	1107	0.66	1141	0.69	1180	0.72	1199	0.75
Winnipeg	1190	0.67	1203	0.69	1228	0.73	1229	0.78
Québec	1124	0.68	1262	0.71	1289	0.77	1291	0.80
Edmonton	1350	0.94	1527	1.03	1656	1.16	1688	1.32
Calgary	1441	0.95	1575	1.08	1755	1.21	1759	1.39
Ottawa	1701	1.06	1778	1.13	1889	1.24	1947	1.32
Vancouver	3286	1.99	3321	2.10	3438	2.31	3450	2.46
Montréal	5820	3.42	6047	3.63	6261	3.82	6469	4.10
Toronto	6961	4.68	6986	5.11	7442	5.58	7525	5.93

Notes: All population figures are given in millions.

[17] The data are extracted from CHASS ("Computing in the Humanities and Social Science", University of Toronto).

We define different groups for education, housing, and income. Concerning education, the census provides total population above 15 years old by highest level of schooling. The issue is that the definition of each education level can change over time. We thus need to make some choices. We define three main groups that are stable across the four census waves: high, medium, and low educational attainment. Table A2 shows how we precisely define these three groups using the information from the Census on schooling for each year.

Table A2 – Defining educational attainment across census waves

	2001	2006	2011	2016
High skill	University with a degree	University with a degree	University with a degree	University with a degree
Med Skill	Certificate or Diploma College without a degree College with a degree University without a degree	Certificate or Diploma College with a degree	Certificate or Diploma College with a degree	Certificate or Diploma College with a degree
Low skill	Grade 9 and less Grade 9 to 13	High school certificate or diploma No certificate or diploma	High school certificate or diploma No certificate or diploma	High school certificate or diploma No certificate or diploma

Turning to the housing-related variables, we define two groups that proxy for the supply of housing by vintage: new housing and old housing. To do so, we use the period of construction provided by the census and define each group as shown in Table A3. Note that while we can construct a stable variable for new housing (less than 10 years old), the variable for old housing changes slightly across time. We will not make extensive use of the latter one.

Table A3 – Defining groups of housing vintage

	2001	2006	2011	2016
Old	1960 and before	1960 and before (1961-1970)/2	1961 and before (1961-1980)/2	1962 and before 3*(1961-1980)/4
New	1991-2001	1996-2006	2001-2011	2006-2016

Last, turning to income, we mostly take household and individual income. Incomes are usually provided as median or average at the block level because of data disclosure concerns. For 2006, 2011, and 2016, we also have block-level information by income bins. For 2001, we only have information on average and median incomes and, therefore, are not able to construct poor and rich groups within each DA (an information needed to compute the Dissimilarity and Exposure indices). We hence do not report the indices for 2001. There is no clear consensus in the literature on what is a poor group and what is a rich group. We approximate poor groups as the households that earn 30 000 $ or less in the year previous to each census year. We define rich groups as the households that earn 80 000 $ or more in the year previous to each census year.

B – Estimating *K*-densities.

We follow Duranton and Overman (2005) and estimate the K-densities of the bilateral distances between our statistical units of observation in city c at a distance d as follows:

$$\widehat{K}_c(d) = \frac{1}{\sum_{i=1}^{N}\sum_{j>i}^{N} n_i n_j} \sum_{i=1}^{N}\sum_{j>i}^{N} n_i n_j f\left(\frac{d_{ij} - d}{h}\right)$$

where f is a Gaussian kernel density function, h the optimal bandwidth (set using Silverman's rule), and d_{ij} is the distance between observations i and j. Details on the exact procedure are given in Duranton and Overman (2005). For some of the statistical analyses, we use the cumulative distribution function, CDF, associated with the above density function. This is defined as follows:

$$\widehat{CDF}_c(\bar{d}) = \sum_{d \leq \bar{d}}^{N} \widehat{K}_c(d)$$

C – Detecting CMA centers.

To identify the city-centers of Canadian CMAs we use a two-step procedure. First, we identify clusters of population density following Behrens et al. (2019). In a second step, we define city-centers as the geographic centers of each of the identified clusters of population. Hence, with this procedure a CMA can have several centers.

More specifically, for each CMA, we work at the level of dissemination areas (DAs), which are the finest administrative spatial units in Canada. Each DA is represented by its geographic coordinates and its population density (population over surface area).

To identify the CMA centers, we proceed as follows:

- We flag all the DAs with a population density in the top quartile of the population densities observed across all the DAs in the CMA.

- For each flagged DA, we assess its proximity to other DAs flagged as densely populated DAs. To that end, we consider a circle of 500m radius around each DA, we count the number n of flagged DAs in that circle, and we compute the probability of having more than n DAs found in that circle, given the overall number of flagged DAs in the CMA. We also compute the total population of the flagged DAs within the circle as a share of the total population of the flagged DAs in the whole CMA.
  - A DA is finally considered as a "focal point of population concentration" if the computed probability is lower than a chosen threshold (1% in our case), and if the ratio of the total population of the flagged DAs in the circle over the total population of the flagged DAs in the CMA is greater than the median observed across all flagged DAs in the CMA. Intuitively, a "focal point of population concentration" hence corresponds to a DA that has less than 1% chance of being surrounded by the observed number of other high-density DAs in the metro area (i.e., the clustering is not due to pure chance), and which is sufficiently large in terms of population.
  - We construct the population clusters by merging all the "focal point of population concentration" within the same neighborhood. To do so, we build a buffer of 1 kilometer around each DA identified as "focal point of population concentration" and we merge all the overlapping buffers.

In the second step of the procedure, we pinpoint the geographic center of each disjoint population clusters and call the resulting coordinates a 'city center'.

D – Measuring dissimilarity and exposure.

Dissimilarity and Exposure indices are computed using the following formulas as given, e.g., by Massey and Denton (1988):

$$Dissimilarity = \sum_{i=1}^{n} \left[\frac{t_i |p_i - P|}{2TP\,(1-P)} \right]$$

$$Exposure = \sum_{i=1}^{n} \frac{x_i}{X} \frac{y_i}{t_i}$$

In the above formulae, p_i is a given group proportion (say the rich group) in an area i, T and P are the population size and a group proportion in the whole study area i.e., the CMA, and, x_i, y_i and t_i are the numbers of members of a given group X and Y, and the total population of a unit i, respectively (X denotes the number of individuals in group X at the CMA level). We use normalized versions of the indices that vary between 0 to 1. For dissimilarity, the closer the index to its maximum value of 1, the higher the geographic concentration of the group. For the exposure index, a higher value indicates a higher exposure of the two groups to each other.

II – Additional results (robustness checks)

A – Heterogeneity within Canadian CMAs.

We here present measures of heterogeneity between and within census tracts for the ten largest Canadian CMAs.

Table B1 – Heterogeneity between and within tracts in the largest Canadian CMAs

CMA	Year	Average household income			Share of highly-educated among the population age 15+			Average house value		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Calgary	2001	73452	.4	.38	.2	.54	.39	187894	.31	.27
Calgary	2006	89276	.46	.42	.28	.47	.32	357539	.38	.32
Calgary	2011	84819	.31	.34	.27	.52	.33	441572	.38	.32
Calgary	2016	136099	.56	.55	.31	.49	.26	504607	.41	.33
Edmonton	2001	59817	.31	.31	.16	.73	.43	135091	.26	.22
Edmonton	2006	73959	.33	.34	.22	.59	.36	239823	.28	.25
Edmonton	2011	76757	.29	.3	.22	.6	.37	356352	.26	.22
Edmonton	2016	109173	.37	.44	.24	.54	.29	395844	.3	.23
Hamilton	2001	65305	.36	.25	.14	.66	.44	167905	.36	.22
Hamilton	2006	75993	.37	.28	.19	.59	.37	250395	.42	.23
Hamilton	2011	71207	.35	.29	.17	.63	.4	308925	.4	.25
Hamilton	2016	93866	.38	.26	.2	.54	.34	435829	.41	.23
Kitchener - Cambridge - Waterloo	2001	66206	.25	.3	.15	.47	.47	161662	.23	.25
Kitchener - Cambridge - Waterloo	2006	74875	.33	.33	.2	.46	.41	238367	.27	.23
Kitchener - Cambridge - Waterloo	2011	70441	.29	.33	.19	.57	.47	288576	.23	.22
Kitchener - Cambridge - Waterloo	2016	88478	.39	.28	.21	.51	.37	352847	.27	.22
Montreal	2001	56074	.52	.3	.18	.8	.4	145823	.52	.24
Montreal	2006	63944	.5	.31	.26	.61	.34	254994	.49	.26
Montreal	2011	58847	.41	.32	.23	.69	.35	338361	.44	.23
Montreal	2016	83306	.73	.41	.25	.63	.27	392428	.5	.21

Table B1 (Cont) – Heterogeneity between and within tracts in the largest Canadian CMAs

CMA	Year	Average household income			Share of highly-educated among the population age 15+			Average house value		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Ottawa-Gatineau	2001	74822	.36	.28	.24	.61	.37	165668	.53	.23
Ottawa-Gatineau	2006	83224	.39	.29	.31	.49	.33	254259	.41	.22
Ottawa-Gatineau	2011	81438	.35	.28	.3	.58	.34	333240	.43	.2
Ottawa-Gatineau	2016	101128	.43	.3	.31	.51	.29	384366	.47	.22
Québec	2001	51679	.35	.28	.18	.67	.39	99083	.3	.2
Québec	2006	61772	.35	.29	.25	.52	.32	153567	.27	.2
Québec	2011	60544	.35	.3	.22	.59	.36	245724	.29	.24
Québec	2016	78841	.34	.28	.24	.49	.29	291119	.28	.18
Toronto	2001	83315	.55	.38	.23	.62	.35	276164	.49	.25
Toronto	2006	92136	.53	.37	.31	.48	.29	417327	.5	.27
Toronto	2011	82589	.39	.35	.29	.55	.31	520067	.5	.26
Toronto	2016	121152	.79	.51	.32	.5	.25	787211	.49	.27
Vancouver	2001	67278	.41	.31	.2	.6	.35	302251	.49	.26
Vancouver	2006	76756	.42	.29	.29	.44	.27	542971	.46	.27
Vancouver	2011	72667	.3	.29	.27	.49	.3	750935	.57	.27
Vancouver	2016	104751	.44	.33	.3	.41	.24	1161996	.6	.3

Table B1 (Cont) – Heterogeneity between and within tracts in the largest Canadian CMAs

CMA	Year	Average household income			Share of highly-educated among the population age 15+			Average house value		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Winnipeg	2001	57060	.35	.31	.16	.68	.43	97068	.36	.26
Winnipeg	2006	66220	.35	.32	.23	.53	.36	154812	.34	.26
Winnipeg	2011	65725	.32	.3	.21	.51	.37	244743	.29	.22
Winnipeg	2016	89727	.37	.39	.24	.45	.29	297008	.29	.21
All CMAs	2001	50868	.29	.23	.14	.45	.32	143255	.29	.19
All CMAs	2006	59415	.3	.24	.19	.37	.27	234928	.29	.2
All CMAs	2011	56804	.25	.24	.18	.42	.29	312838	.29	.19
All CMAs	2016	80428	.39	.29	.2	.37	.24	420636	.31	.19

Notes: Authors' calculations based on information from the 2001 and 2016 population censuses. "Mean" is the simple average of the variables across blocks with the CMAs. "Variation between" is the standard deviation of the variable across census tracts as a fraction of the CMA-level average across census blocks. "Variation within" is the standard deviation of the variable across census blocks within tracts as a fraction of the CMA-level average across blocks. "Average household income" and "Average house value" are expressed in current Canadian dollars.

Table B2 – Heterogeneous dynamics between and within tracts in the largest Canadian CMAs

CMA	Year	Average household income growth			Share of highly-educated among the population age 15+ growth			Average house value growth		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Calgary	2001-2006	.25	.93	1.19	.65	.66	1.56	.92	.33	.41
Calgary	2006-2011	0	42.98	71.06	.03	8.36	20.44	.26	.39	.99
Calgary	2011-2016	.62	.76	.91	.24	.94	2.4	.15	.58	1.18
Edmonton	2001-2006	.25	.33	.79	.62	.8	1.43	.79	.2	.39
Edmonton	2006-2011	.07	1.72	3.68	.05	5.75	12.17	.53	.23	.45
Edmonton	2011-2016	.46	.48	.8	.3	1.45	2.24	.11	.78	1.28
Hamilton	2001-2006	.18	.77	1.17	.6	1.07	1.56	.5	.4	.57
Hamilton	2006-2011	-.05	2.13	4.02	0	141.26	244.97	.26	1.06	1.06
Hamilton	2011-2016	.38	.53	.93	.29	1.25	2.02	.43	.3	.49
Kitchener - Cambridge - Waterloo	2001-2006	.15	1.16	1.25	.56	.74	1.84	.51	.38	.59
Kitchener - Cambridge - Waterloo	2006-2011	-.05	2.07	4.22	.06	4.33	10.81	.23	.45	.91
Kitchener - Cambridge - Waterloo	2011-2016	.32	.58	.97	.24	.81	2.45	.23	.44	.69
Montreal	2001-2006	.16	.73	1.2	.85	.69	1.23	.79	.43	.47
Montreal	2006-2011	-.07	1.72	2.73	-.08	2.86	5.88	.37	.53	.71
Montreal	2011-2016	.46	.85	.82	.21	1.06	2.4	.17	.63	1.04

Table B2 (Cont) – Heterogeneous dynamics between and within tracts in the largest Canadian CMAs

CMA	Year	Average household income growth			Share of highly-educated among the population age 15+ growth			Average house value growth		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Ottawa-Gatineau	2001-2006	.13	1.01	1.42	.45	.98	1.51	.58	.4	.47
Ottawa-Gatineau	2006-2011	-.01	20.94	36.51	.01	42.04	51.17	.32	.46	.55
Ottawa-Gatineau	2011-2016	.28	.74	.97	.14	2.27	3.19	.16	.79	.85
Québec	2001-2006	.21	.61	.91	.72	.87	1.3	.59	.43	.44
Québec	2006-2011	-.01	12.41	18.07	-.08	2.39	5.45	.62	.35	.39
Québec	2011-2016	.37	.57	.95	.25	1.08	2.16	.2	.55	.73
Toronto	2001-2006	.14	1.02	1.75	.63	.86	1.39	.54	.62	.71
Toronto	2006-2011	-.07	2.05	3.54	-.02	11.33	24.82	.26	.56	.81
Toronto	2011-2016	.49	1.06	1.01	.23	1.07	2.34	.52	.27	.39
Vancouver	2001-2006	.17	.54	1.47	.77	.54	1.27	.83	.23	.44
Vancouver	2006-2011	-.02	5.33	11.51	-.04	3.51	10.73	.38	.44	.58
Vancouver	2011-2016	.49	.58	.9	.22	.77	2.2	.51	.38	.47

Table B2 (Cont) – Heterogeneous dynamics between and within tracts in the largest Canadian CMAs

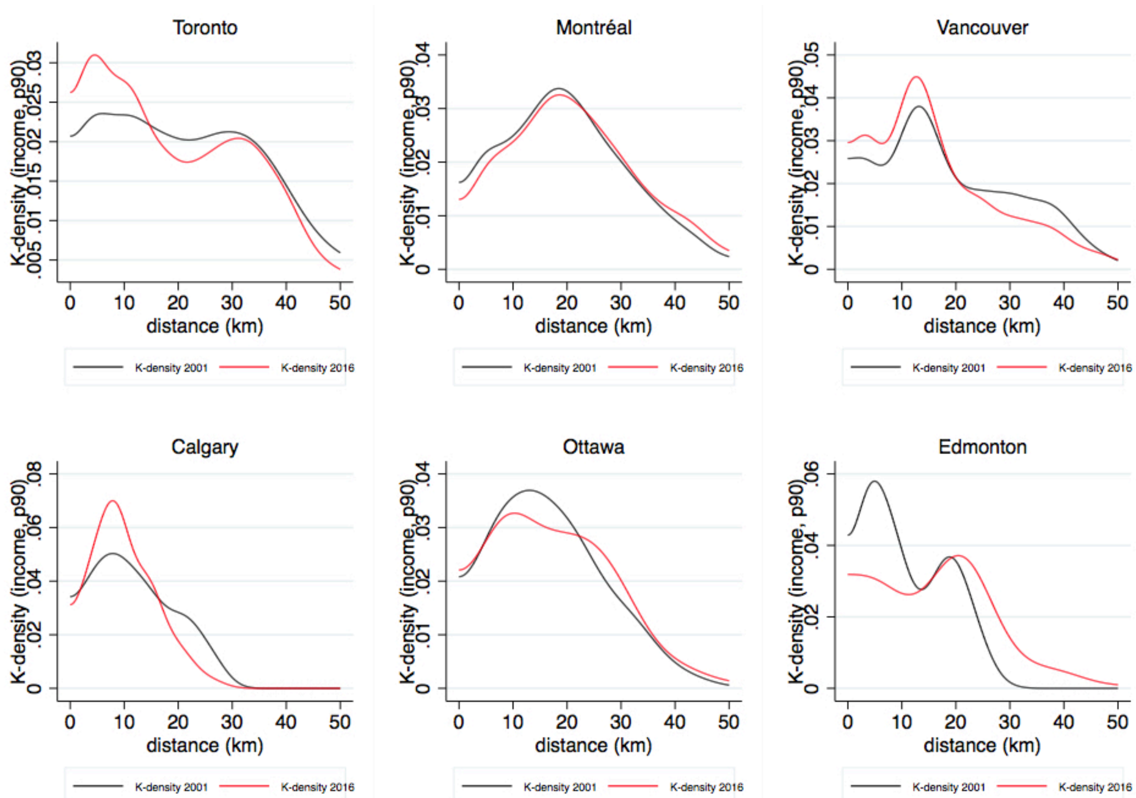
CMA	Year	Average household income growth			Share of highly-educated among the population age 15+ growth			Average house value growth		
		Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts	Mean	Variation between tracts	Variation within tracts
Winnipeg	2001-2006	.18	.47	1.08	.75	.87	1.3	.63	.29	.5
Winnipeg	2006-2011	.01	7.4	14.64	.06	5.16	9.91	.65	.62	.46
Winnipeg	2011-2016	.41	.48	.86	.3	1.44	2.08	.23	.45	.65
All CMAs	2001-2006	.14	.56	1.06	.54	.68	1.05	.5	.32	.43
All CMAs	2006-2011	-.03	5	8.88	-.03	10.01	18.47	.29	.4	.68
All CMAs	2011-2016	.35	.54	.68	.19	.94	1.98	.23	.42	.66

Notes: Authors' calculations based on information from the 2001, 2006, 2011 and 2016 population censuses. "Mean" is the simple average of the variables across blocks with the CMAs. "Variation between" is the standard deviation of the variable across census tracts as a fraction of the CMA-level average across blocks. "Variation within" is the standard deviation of the variable across blocks within tracts as a fraction of the CMA-level average across blocks. "Average household income" and "Average house value" are expressed in current Canadian dollars.

B – *K*-densities with stable units.

The kernel densities we report in the main text of Part II are constructed using the dissemination areas of each census wave. Once may thus be concerned that these change over time and blur the dynamic comparisons. However, one needs to keep in mind that the *K*-densities are kernel-smoothed over the whole CMA, and that they are computed at a small geographic scale. Changes in the spatial units only marginally affect the results. Indeed, as shown below in Figure B1, using stable spatial units yields the following analogue to Figure 5:

Figure B1 - Changes in *K*-densities of incomes (90th pctl), 2001-2016, based on stable geographic units.



C – Dissimilarity indices, mean reversion and spatial correlations (shares).

Table B3: Dissimilarity for poor using a measure of the incidence of poverty from Statistics Canada

CMA	2001	2006	2011	2016
Québec	0.32	0.38	0.34	0.35
Montréal	0.29	0.34	0.31	0.29
Ottawa	0.39	0.43	0.38	0.35
Toronto	0.34	0.32	0.30	0.27
Hamilton	0.37	0.39	0.39	0.35
London	0.35	0.39	0.35	0.31
Winnipeg	0.34	0.39	0.35	0.32
Calgary	0.31	0.34	0.30	0.25
Edmonton	0.32	0.38	0.33	0.29
Vancouver	0.26	0.27	0.25	0.21

D – Detecting clusters using block-level data.

The figures below depict the geographic clustering of high incomes (90th percentile; in green on the maps) and highly educated (in blue on the maps) in Montreal and in Toronto, respectively. Using our geographically fine-grained data, we use a cluster algorithm (see Behrens et al., 2018b) to detect 'abnormal' concentrations of rich or highly educated blocks. The latter are defined as the blocks that are above the 90th percentile in the CMA distribution of the block-level shares of residents with a university degree.

Figure B2- Montreal, clusters of high incomes (90th percentile) in 2016

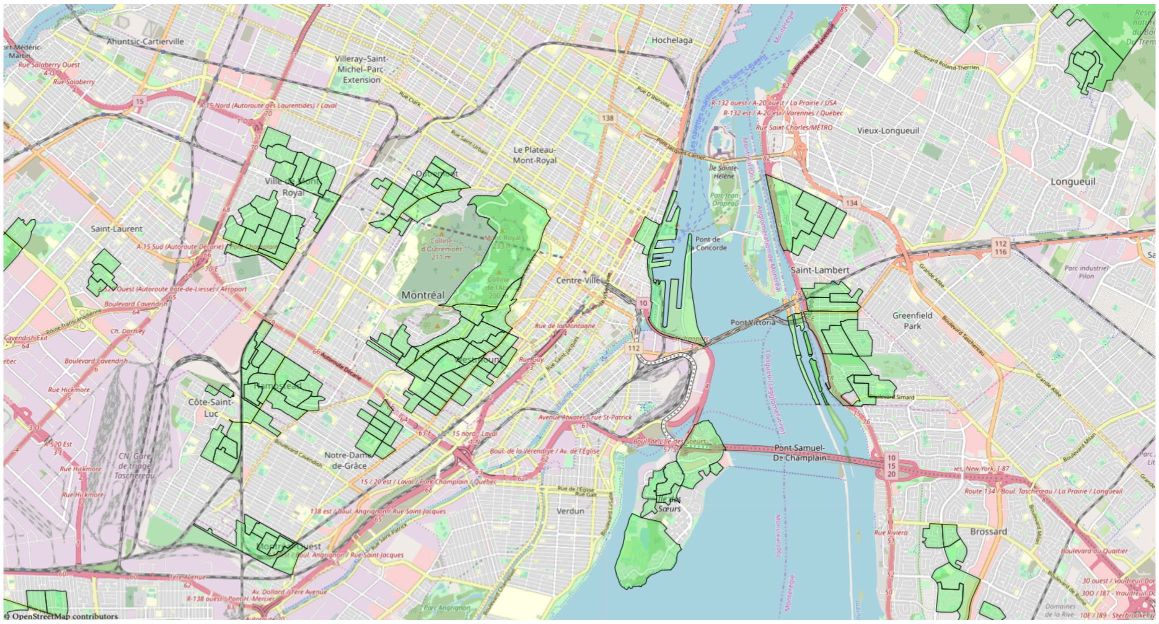


Figure B3- Montreal, clusters of high education (90th percentile) in 2016

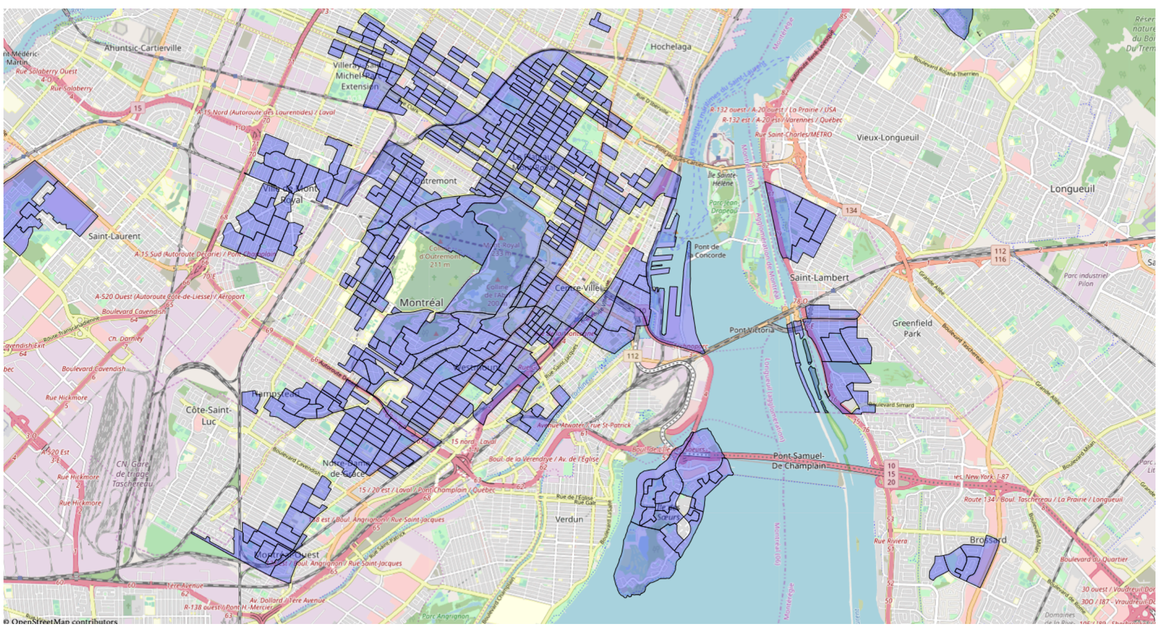


Figure B4- Toronto, clusters of high incomes (90th percentile) in 2016

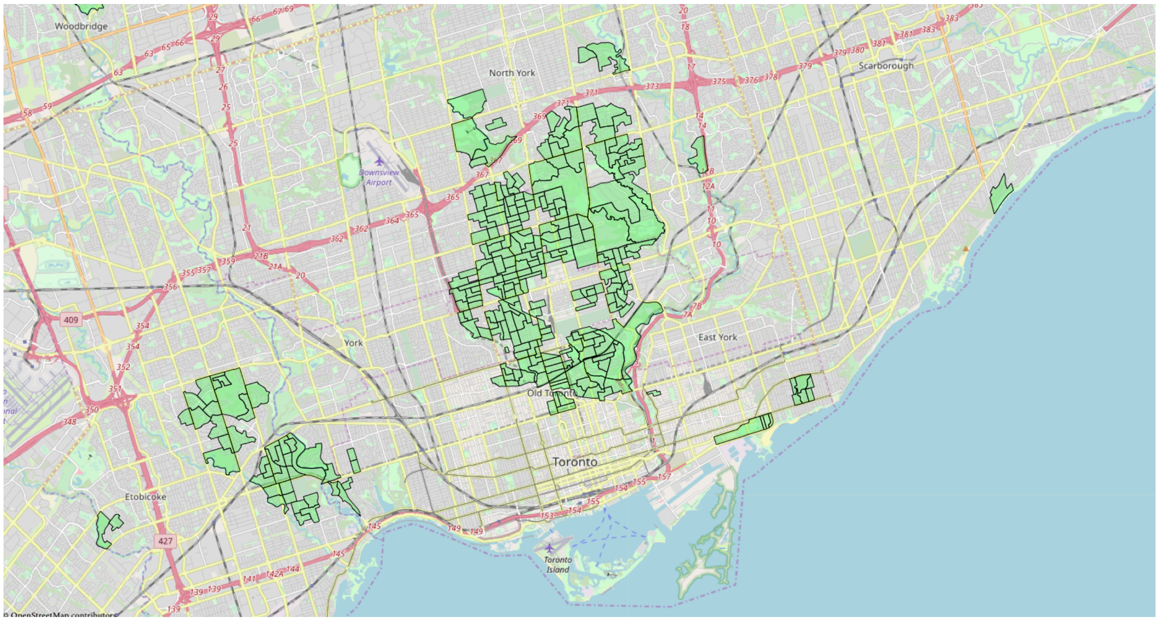


Figure B5- Toronto, clusters of high education (90th percentile) in 2016