City Change: The Impact of New Housing Construction on Commercial Diversity

Tom Benson[a,*], Timur Abbiasov[a], You Xuan Thung[a], Fábio Duarte[a,b], Lukas Ljungqvist[c], Carlo Ratti[a]

[a] *Senseable City Lab, Massachusetts Institute of Technology, Cambridge, MA, United States of America,*
[b] *Center for Real Estate, Massachusetts Institute of Technology, Cambridge, MA, United States of America,*
[c] *Department of Urban Planning, Stockholms Stad, Stockholm, Sweden,*

Abstract

New housing projects often face opposition and controversy due to concerns about altering the character of a neighbourhood and leading to negative cycles of neighbourhood change such as gentrification and displacement. Even though the impact of new housing on the real estate market has been well studied, the effect on commercial diversity is not as well understood. Our research in Stockholm aims to estimate the impact of newly constructed housing on commercial diversity using a difference-in-difference approach that compares 78 housing projects that were planned but ultimately cancelled to those of 1283 that were completed. We analyse individual business data reported to the city from 2007 to 2020 and Google Street View images to assess changes in the languages represented on physical objects such as storefronts and commercial advertisements. Our findings reveal that business diversity increases following the construction of new housing, but language diversity in low-income neighbourhoods decreases.

Keywords: Housing, Business diversity, Language diversity, Gentrification, Stockholm, Spatial Spillovers

*Corresponding author
Email address: bensont@mit.edu (Tom Benson)

February 17, 2023

1. Introduction

1.1. New Housing and Urban Diversity

The construction of new houses can greatly affect the distinctive characteristics of a neighbourhood. Social groups have different preferences for amenities and services, often influenced by market demand. When new residents move into an area, the mix of amenities may change to cater to their tastes, which can sometimes lead to gentrification and other negative cycles of neighbourhood change (Almagro and Domınguez-Iino, 2019). On the one hand, the mix of commercial establishments may change to align with the preferences of new residents, which can result in the displacement of the 'mom-and-pop shops' ethnic convenience stores and restaurants with higher-end establishments and more expensive grocery options. Similarly, middle, and high-income neighbourhoods can lose their preferred amenities to new social housing. On the other hand, new businesses can also bring increased diversity and enhance the economic well-being of the neighbourhood (Brunes et al., 2020; Esaiasson, 2014; Green et al., 2003; Evans, 2008; Malpezzi, 1996; Wolsink, 1994).

One of the biggest challenges with constructing new housing is opposition from current residents, often called Nimbyism (not in my backyard). Generally, high-income residents often oppose new construction, concerned that it will lower their assets' value, increasing traffic and pollution. On the contrary, low-income residents would oppose new housing with concerns over increasing current rent and economic costs for living, leading to displacement. Moreover, it has been shown that the changes in amenities in response to shifts in the demographic composition of the neighbourhood might hurt some of the incumbent residents (Zukin et al., 2009). Further, low-income residents have seen the displacement of local stores and services through new housing construction, which also dilutes the ethnic character of the neighbourhood"

The diversity of services and goods offered in a neighbourhood is essential to understanding its commercial character. Studies have shown that the diversity of amenities in an urban area is closely linked to its economic productivity (Chong et al., 2020). Jane Jacobs also argued that a diverse neighbourhood leads to a more socially and culturally vibrant environment and improves the quality of life for residents (Fuller and Moore, 2017). However, understanding the diversity of a neighbourhood's commercial character goes beyond simply the selection of amenities. The visual information from the streetscape, such as ethnic commercial character and the types of people who frequent the area, can offer additional insight.

In this paper, we aim to understand how new housing construction impacts the diversity of businesses and languages expressed on street signs and other physical objects using detailed spatiotemporal data in Stockholm, Sweden.

We examine this question in the context of Stockholm, which is particularly interesting because of its housing shortage and plans for significant population growth for the next 20 years, with 140,000 planned to be built from 2010 to 2030 (City of Stockholm, 2018). Housing construction is a main priority of the city, especially in the suburbs, as the city aims to foster economic growth in areas outside the city centre. Crucially, several academics have characterized housing projects in Sweden today as luxury goods that express one's lifestyle (Christophers, 2013; Grundström and Molina, 2016; Hedin et al., 2012). Therefore, it is likely that these new housing projects attract middle-income and high-income types with a stronger appetite for the diversity of businesses in the neighbourhood.

First, we ask how the composition of businesses changes in a neighbourhood. The availability of diverse retail and service establishments in a neighbourhood is essential in building environmentally, socially, and economically sustainable neighbourhoods. A diverse selection of firms reduces residents' reliance on cars, decreases urban energy consumption, promotes walking, enhances patrons' health, builds community, and fosters social cohesion. Also, the diversity of goods and services within a city neighbourhood is the most significant single factor in driving human mobility and economic growth (Chong et al., 2020). The desirability of diverse amenities is a critical reason to attract people and encourage engagement and interaction, leading to idea creation, innovation, and further citizen opportunities (Fuller and Moore, 2017; Glaeser et al., 2001).

Second, we ask how language diversity appearing on physical objects such as billboards, signposts, or store signs in an area has changed through housing construction. We measure diversity across four languages in Stockholm: Swedish, English, Chinese and Arabic. Apart from Swedish, we chose three global languages that are also easily distinguished from one another. In a country that has recently experienced large-scale immigration, the consequences of new housing projects on social integration, whether intended or unintended, are also of concern. Most studies investigate the effects of new policies or projects on social segregation (Schone, 2022; Marcus, 2007;

Schone, 2022), which provides an objective measure of where people live, allowing us to infer the level of integration then. While some ethnic enclaves are easily identifiable on a map (Little Italy, Chinatown, and Koreatown, which populates many major cities), not all enclaves have self-explanatory names. For instance, nothing about the name Skärholmen in Stockholm suggests that the neighbourhood has a significant Arabic-speaking population. Still, visual clues from the languages on these streets reveal more, giving us clues not only about the people who live there but also about those who work in and frequent the area. After all, the choice of language in a sign is strongly influenced by the type of establishment associated with the sign; for instance, the use of English is strongly positively correlated with an establishment being an international chain (Onofri et al., 2013).

Moreover, many studies have made the distinction between low-income and high-income areas. Asquith et al. noted that high-income areas might have a better reputation, broader appeal, and better amenities than low-income areas, with the interaction of underlying differences contributing to different empirical impacts. They focused on low-income areas in their study of the effects of large new apartments. Diamond and McQuade also distinguished between high-income and low-income areas. They found that properties financed by the Low Income Housing Tax Credit (LIHTC) have different qualitative impacts in high-income and low-income areas. Therefore, in our study, we also distinguish between high-income and low-income areas

1.2. Casual Identification

To conduct our analysis, we combine various microdata sources from 2007 to 2020 to determine how new construction affects a neighbourhood's commercial landscape. We use a dataset from the City of Stockholm on new housing construction that provides location, year of build, number of units and if the housing project was approved and built or approved and cancelled. Furthermore, we access over 100,000 individual business records for Stockholm. This yearly dataset provides information on the number of employees, turnover, opening date and its associated sector. In addition, we use street-view images from Google and apply visual intelligence to extract text and classify the language from the built environment objects. Finally, our analysis uses census data for each neighbourhood's median income.

We then estimate the causal effect of housing for business and language diversity of a neighbourhood for high and low-income areas. In this context, casual identification is challenging as developers choose new construction locations based on unobserved local characteristics and trends. To overcome this, we utilise data on approved but cancelled housing projects. Using unbuilt projects that were legally approved but cancelled for various reasons provides a natural experiment that helps isolate the causal influence of housing projects on the local commercial landscape (Salazar Miranda, 2021). Because the treatment and control areas are not necessarily in the same neighbourhood, this specification can detect changes driven by the broader effects of housing construction.

1.3. Urban Planning Process in Sweden

Planning in Sweden is carried out at the municipal level according to two national laws, PBL (Planning and Building Act) and Miljöbalken (Environmental Act). Urban planners in the planning administration and regional civil servants ensure compliance with the law throughout the process, including public consultations at various stages. In Stockholm, most land allocation is done through the Stockholm model, where a private developer applies for the allocation of publicly owned land. The City of Stockholm owns around 70% of the undeveloped land in the city, though this percentage has decreased over time.

The formal planning phase begins with a feasibility check by the development department and city planning administration. The developer and city representatives jointly develop and evaluate the proposal, resulting in a legally binding zoning plan and development agreement.

The design and implementation phase involves detailed project development, and the city planning administration board grants the building permit. The final phase is construction.

Many projects change the planning phase. Some may be cancelled due to budget constraints or unforeseen planning requirements, such as preservation of rare species, noise levels, air pollution, daylight, rising sea levels, cloudbursts, or complaints from neighbours. Market changes can also impact the budget and halt projects.

1.4. Main Findings

By comparing planned and cancelled housing projects with planned and built housing projects, we find evidence that commercial diversity impact differently across business and language diversity and critical differences across high and low-income neighbourhoods. For business entropy, we see a max increase of a 0.56 standard deviation which slowly builds before construction and stays consistent after construction. Further, we mainly see a broad spatially spread in high-income neighbourhoods, with an increase occurring up to 400m, while in low-income neighbourhoods, this increase is solely within 100m of the construction. This overall increase in the diversity of goods and services is positive for neighbourhoods and is labelled as one of the four critical urban amenities (Glaeser et al., 2001). But we see this effect making more of an impact in high-income neighbourhoods but not in low-income neighbourhoods.

Interestingly, we find critical differences between the impact across business diversity and expressed language diversity. For language diversity, we see some increase of around 0.57 standard deviations in high-income neighbourhoods within 100m of construction. But importantly, we see a significant decrease of 0.52 standard deviations in low-income neighbourhoods. This could be an early sign of gentrification with the lower-quality ethnic stores and services closing.

1.5. Literature

This research contributes to the literature in four areas. First, we contribute to the studies of spillover impact from urban interventions affect various types of city dynamics such as racial diversity (Abbiasov, 2021), pedestrian usage (Salazar-Miranda et al., 2022) and business performance (Abbiasov and Sedov, 2022). Further, existing work analysing the impact of new housing on the local vicinity has focused on socio-economic indicators such as land values (Rossi-Hansberg et al., 2010), housing prices (Guerrieri et al., 2013; Brunes et al., 2020; Diamond and McQuade, 2017; Blanco and Neri, 2021), crime rate, income and racial diversity (Diamond and McQuade, 2017) displacement (Pennington, 2021). However, this research focuses on the impact of housing construction on commercial diversity.

Second, we contribute to the body of literature around gentrification and neighbourhood change and its relationship to businesses and commercial character. Neighbourhood change has been measured against socio-economic indicators such as crime (O'Sullivan, 2005) and housing prices (Guerrieri et al., 2013); however, only a couple of studies link gentrification with the business activity which highlights how a neighbourhood sectoral landscape transforms (Lester and Hartley, 2014; Schuetz, 2014; Meltzer, 2016; Behrens et al.). Furthermore, the growth of a neighbourhood's housing prices and educational level has been related to the changes in specific amenities such as groceries, cafes and restaurants measured through restaurant-ranking apps (such as Yelp) (Glaeser et al., 2020). We contribute to the gentrification and neighbourhood change by teasing out how increasing the housing supply could put economic pressures through endogenous amenities across different social groups.

Third, we add to sociolinguistic literature. Current studies in this area use small-scale ethnographic methods to study these specifics in neighbourhoods (Tang and Long, 2019). This area of literature is currently motivated by the abundance of linguistic features littered across streetscapes—public road signs, advertising billboards, street names, place names, commercial shop signs, street art, and public signs on government buildings (Landry and Bourhis, 1997). Although current studies only focus on language measures in a spatiotemporal context, we apply them in a DID setting to uncover causal relationships between housing construction and how the dynamics of the linguistic mix change.

Fourth, evaluating the effects of urban interventions on metrics constructed from street view imagery (SVI) follows from a body of literature that views cities as centres of aesthetic and recreational value and uses images to characterise cities (Carlino and Saiz, 2008; Glaeser et al., 2018; Naik et al., 2017). While these studies demonstrate the usefulness of SVI in predicting socioeconomic variables and vice versa, we go one step further by testing how metrics constructed with SVI change in response to urban interventions. We see this as an opportunity to evaluate how valuable metrics constructed from SVI can be beyond the spatiotemporal characterisation of urban areas.

The rest of the paper is organised as follows. Section 2 describes our data. Section 3 presents how we measure streetscape diversity. Section 4 describes our main empirical strategies. Section 5 presents the results. Section 6 concludes, and Section 7 for a finishing discussion.

2. Data

2.1. Housing Projects

We use a dataset from the City Planning Authority in Stockholm for housing projects that have been constructed and housing projects that have been legally approved but cancelled. Our sample contains 1283 for built projects and 78 for unbuilt projects over 11 years from 2009-2020. Each observation in the dataset is attributed to its location, year of construction and number of units.

2.2. Business composition

To observe business diversity changes in the built environment, we use data containing 110,000 limited liability companies with yearly financial records from 2007-2020 in Stockholm. This data was purchased from Enento Group and included the type of business, year of opening, number of employees and turnover.

2.3. Displayed Language

To study linguistic diversity in the streetscape in Stockholm, we use a novel multilingual dataset from 2009-2020 containing over a million Google Street View (GSV) images from Stockholm, covering four languages—English, Swedish, Arabic and Chinese (Thung et al., 2022).

2.4. Socio-demographics

Finally, to facilitate comparison with public socioeconomic data, we collect yearly aggregated employment income median levels from 2007-2020 at the Basområde level (a spatial granularity between city districts and blocks), dividing Stockholm into 408 base units.

3. Streetscape Diversity in Stockholm

3.1. Definition

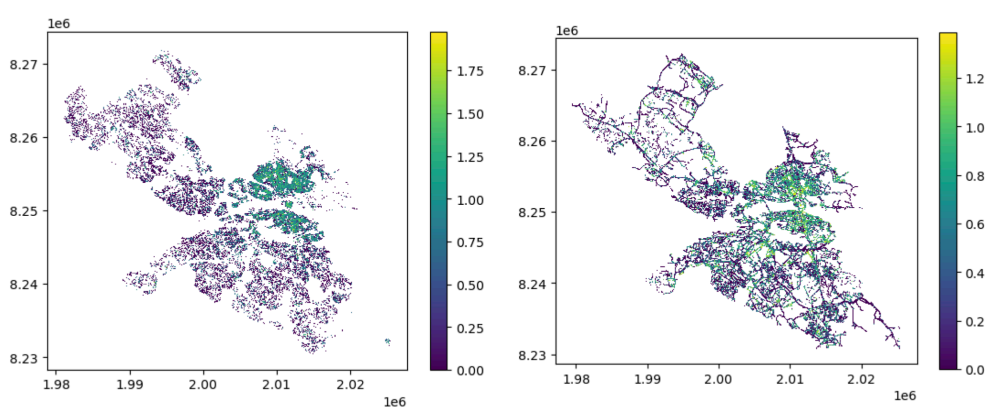


Figure 1: Shannon Entropy scores at the 100 grid scale for Businesses (left) and Languages (right) in Stockholm

To quantify the linguistic and business diversity in an urban area, we use the concept of Shannon Entropy from statistical physics, which is commonly applied to capture the notion of diversity in urban studies (Amcoff, 2022; Mora and Ruiz-Castillo, 2011; Song et al., 2013; Yoshimura et al., 2022).

$$E_x = \sum_i -P_{x,i} \log(P_{x,i}) \tag{1}$$

Where $P_{x,i}$ corresponds to either the share of businesses in each category[1] or the share of expressed languages detected on street signs for a given cell in a 100m square grid, which is our baseline spatial resolution. In Figure 1, we provide a visual representation of the entropy scores. Similarly, Table 1 presents the summary statistics of the entropy measures.

3.2. Spatial Scale

Defining which spatial scale to use for our studies is fundamental. The relative strength of a spatial cluster could be radically different depending on the geographical scale used. To capture neighbourhood dynamics, we first capture the Shannon Entropy for language and business mix at Stockholm's 100m grid scale. For businesses, we capture how diverse an area is by measuring the entropy across several types of businesses: retail, food, health stores, education, tradable, construction, and sports. For the language entropy, we measure this across four critical languages in Stockholm: Swedish, English, Arabic and Chinese. We test different ways to capture the business entropy and compare it against the language entropy in Appendix A.4.

The relative strength of a spatial cluster could be radically different depending on the geographical scale used (Fujita and Thisse, 1996). For this reason, we also repeat the regressions by capturing the treatment at 100m and 250m levels of spatial granularity.

Table 1: Summary Statistics for Business and Lannguage Entropy

	Business Entropy			***Lanugage Entropy***		
Year	mean_B	median_B	sd_B	mean_L	median_L	sd_L
2007	0.253	0	0.391	NA	NA	NA
2008	0.281	0	0.406	NA	NA	NA
2009	0.286	0	0.410	0.331	0.000	0.397
2010	0.295	0	0.417	0.405	0.377	0.430
2011	0.305	0	0.424	0.427	0.410	0.440
2012	0.307	0	0.430	0.270	0.000	0.441
2013	0.325	0	0.438	NA	NA	NA
2014	0.332	0	0.440	0.470	0.500	0.439
2015	0.338	0	0.443	NA	NA	NA
2016	0.356	0	0.450	0.513	0.566	0.466
2017	0.364	0	0.453	0.520	0.562	0.452
2018	0.370	0	0.456	0.383	0.234	0.425
2019	0.376	0	0.459	0.374	0.271	0.408
2020	0.364	0	0.453	0.417	0.429	0.386
Average	0.323	0	0.439	0.402	0.343	0.420

3.3. Language Diversity and comparison with other socioeconomic characteristics

For this section, based on (Thung et al., 2022), we aggregate our data at the DeSO (Demographic Statistical Areas) level to facilitate comparison with public socioeconomic data from Statistics Sweden. In this case, we differ from the Basområde level as the DeSo level offers more data about the population of the census area, while the Basområde provides better temporal resolution. In Figure 2, we present choropleth maps of the linguistic concentration in Stockholm for 2020-2021. Swedish (unsurprisingly) has the most

[1] We split the businesses into ten key categories based on conversations with the urban planning department in the City of Stockholm. These include construction, sports, education, hotels, health, manufacturing, retail, food services, hair salons and tradable businesses. In appendix Appendix A.4, we show a strong correlation using different business groupings.

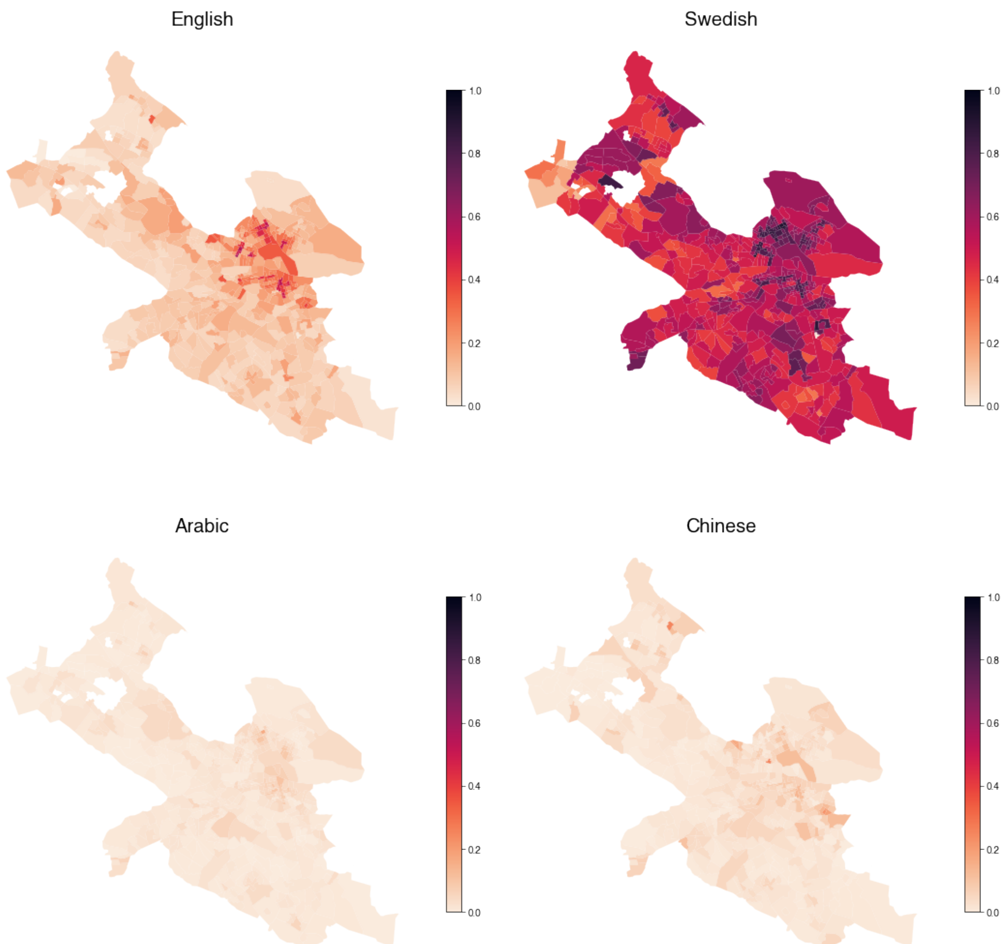


Figure 2: Language distribution across Stockholm

substantial presence among the four languages across the city. English has a moderate presence, while Arabic and Chinese have a minimal presence, and these three languages are more concentrated around the downtown area. As Hult observed in Sweden, English is not imposed from above but arises from socioeconomic interests

Statistics Sweden provides aggregated data on residents' citizenship — residents are classified as "Swedish", "Europeans except for Swedish", or "Others". To facilitate comparison with our measures of linguistic diversity, we construct a measure of population entropy in the same way we constructed

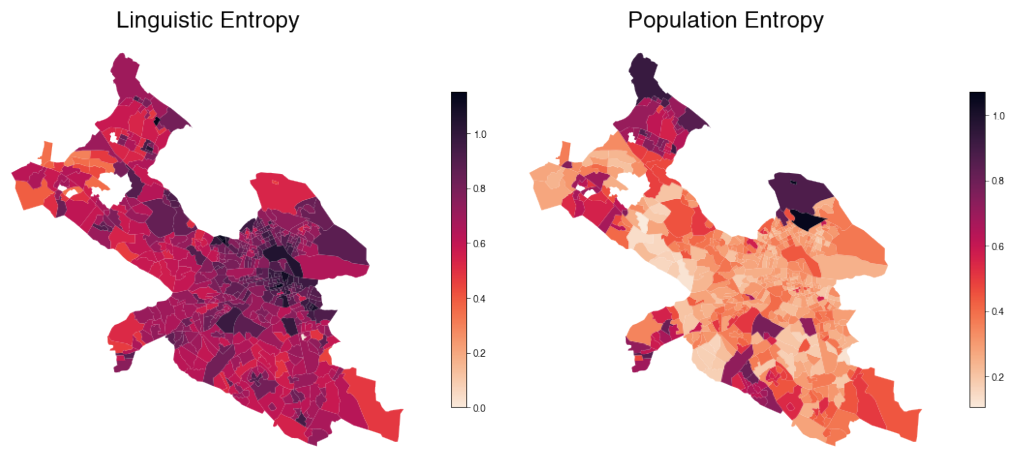


Figure 3: Language and population entropy measures

our measure of linguistic entropy. Figure 3 presents choropleth maps of linguistic and population entropy in Stockholm in 2020-2021. We also include a choropleth map of median employment income to facilitate comparison.

Interestingly, and perhaps counterintuitively, the spatial distributions of the two measures are reversed, with areas with higher linguistic entropy having lower population entropy. In fact, the correlation of the two measures across all years is -0.205, implying a weak negative correlation. Although this might not make sense at face value, this observation aligns well with our understanding of Swedish society. Crucially, we need to recognise that a high linguistic mix need not arise from a high population mix, particularly in a country whose heritage and culture are hallmarked by homogeneity. Instead, the linguistic diversity we see in Stockholm is not so much resultant of a diverse resident population along ethnolinguistic lines but is likely a feature of globalization. In fact, in a study of linguistic landscapes in Seoul, Hong finds an increased prevalence of Chinese signs despite a relatively whole Chinese population and attributes this to “the recent popularity of Chinese food in the Korean society”

On the other hand, despite the strong population entropy in the city’s outskirts, the lower linguistic entropy suggests that minorities are not necessarily comfortable expressing themselves in their mother tongues in a country that prides itself on its cultural homogeneity. In fact, Daun notes that differences in cultural backgrounds are downplayed in accordance with the Swedish “emphasis on conflict avoidance”

4. Empirical Strategy

4.1. Overview

If we consider the hypothetical ideal experiment - building new housing projects in Stockholm with locations assigned randomly, we could compare commercial diversity changes at different spatial distances to the newly constructed housing project - creating comparable treatment and control groups. However, as the developers' decisions on housing development are determined by other external factors, such as choosing a site in an already economically thriving area, the identification of spillover effects from construction from observational data is challenging.

To overcome this, we utilise unbuilt projects, which act as a natural experiment comparing the area around planned and built housing projects (treatment group) and housing projects that were planned and legally approved but cancelled (control group). Because the control buildings can be in different neighbourhoods, as shown in Figure 4, from the treated ones, we can detect broader effects of a new building. Furthermore, because the control housing projects were cancelled before construction, the identification assumption is that commercial diversity would have changed in parallel with the unbuilt and built areas in the absence of construction. This allows us to uncover the causal effect of housing projects on commercial diversity.

To understand the differences between unbuilt and built projects, we first visualize the trends of demographic variables in the Basområde areas where those projects are located. Furthermore, to quantify differences in both average demographic levels, and demographic trends observed prior to the construction data, we run a logit regression model to predict if a Basområde area has built or unbuilt housing projects using observations on demographic variables in the three years prior to construction year (including the year of construction).

The results in Figure 5 reveal that we do witness similar trends across income but see neighbourhoods with cancelled projects have a flatter trajectory across the total student count for secondary school and post-secondary schools and, to a lesser extent, in the total population.

Further, in Table 2, we find a difference in neighbourhoods between built and unbuilt projects with regards to average demographic levels; however, in terms of demographic changes before construction, they are statistically the same as completed ones in terms of income, population, and elementary school. Still, declines in the number of students for secondary or post-

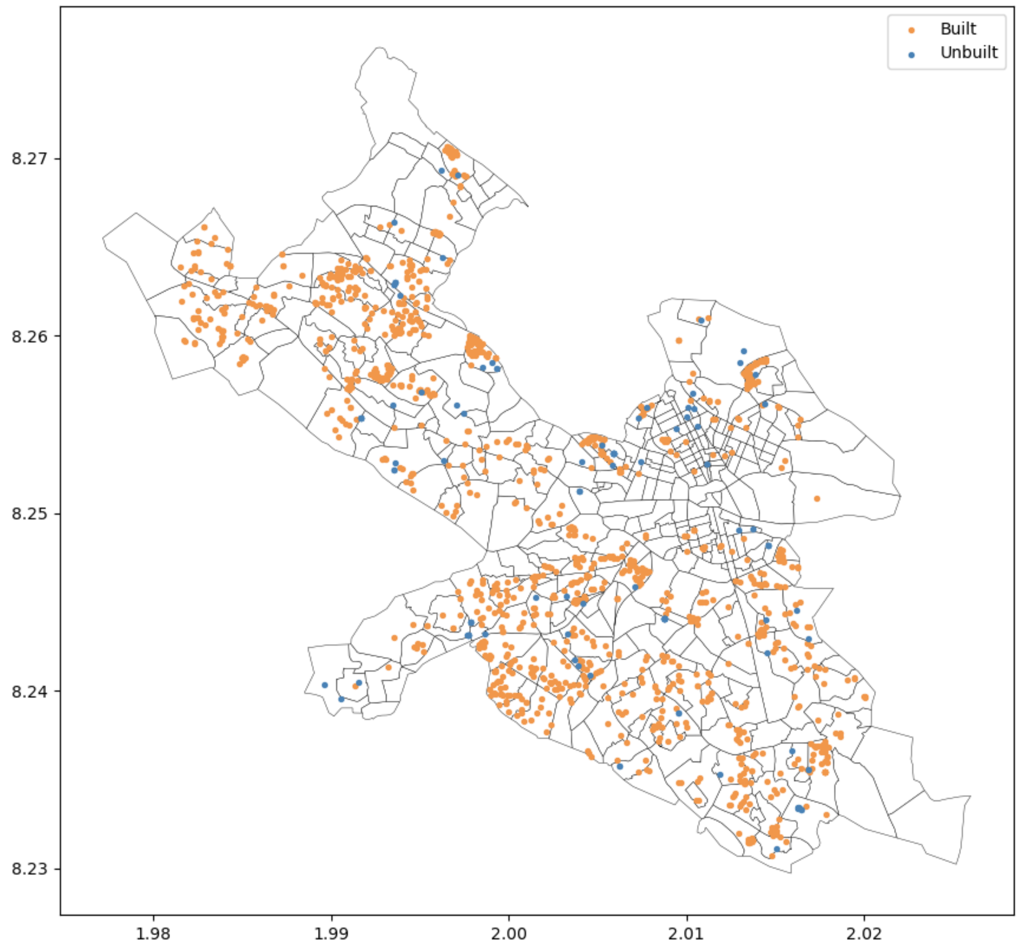


Figure 4: Housing locations for built and unbuilt housing projects

secondary schools are associated with higher chances of cancellation. Overall, we see similar trends in built and unbuilt locations across employment income and population, which are some of the main potential confounders in our analysis. Although we do see some differences between neighbourhoods built and unbuilt in educational trends, the magnitudes of these differences are small.

Importantly, it's probably expected to see demographic changes across built and unbuilt neighborhoods in the periods following the planned construction date as the changes in the supply of housing would likely affect the total population, for instance. Hence, in this case, controlling for those

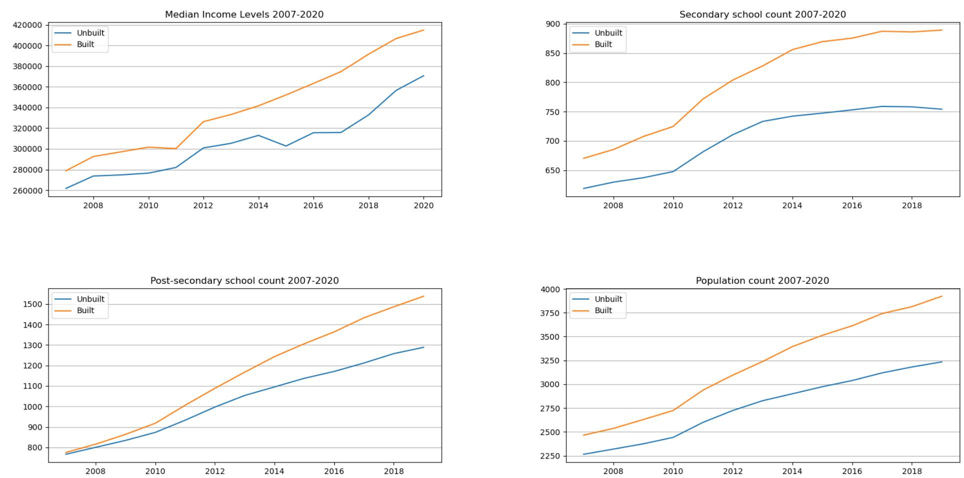


Figure 5: Differences in demographic trends in Basområde areas with built and unbuilt housing projects. (top left: Median Income), (top right: average number of secondary school students), (bottom left: average number of post-secondary school students), (bottom right: average population count)

variables in our main specifications could potentially bias our results(Cinelli et al., 2020). Nevertheless, we show the results of adding controls at the treatment level for education and population in Appendix A.2, and our results remain qualitatively similar.

4.2. Difference-in-differences Estimation

First, this study utilises a dynamic two-way fixed effects regressions model (TWFE) (also known as an event-study regression) that allows for spatial and temporal fixed effects.

The study area consists of built and unbuilt housing projects with offset concentric radius rings every 100m up to 500m and then every 200m until 900m. The language and business entropy scores at the 100m grid cell are captured for each radius ring. To deal with 100m grid treatment cells captured by more than one housing project's radius ring, we test two methods commonly used in literature (Blanco and Neri, 2021). In our main specifications, we run the regression with all treatments captured by the radius rings included. In the appendix Appendix A.1, we only include the grid cell associated with its closest housing projects and drop all other grid cells.

The event year variable is constructed from the year of construction of the housing project, which captures the temporal lags and leads from the

Table 2: Logit regressions for differences in pre-trends across demographic variables for finished versus cancelled projects. In Column 1, the explanatory variables are averages of each demographic variable in the two-year period before construction. In Column 2, the explanatory variables are the average annual changes of each demographic variable over the two-year period before construction. All explanatory variables are standardized to have zero mean and standard deviation of 1. The regression coefficients correspond to the estimated increase in the log odds of the project being cancelled.

	Dependent variable:	
	Construction cancelled	
	$\sim$ *levels*	$\sim$ *change*
	(1)	(2)
Median income	-0.368^{***}	0.134
	(0.137)	(0.112)
Population	-5.964^{***}	2.218
	(1.599)	(1.360)
Secondary School	3.353^{***}	-2.026^{**}
	(0.826)	(0.973)
Post-secondary	1.563^{***}	-1.821^{***}
	(0.601)	(0.602)
Elementary School	1.782^{***}	-0.352
	(0.581)	(0.255)
Construction Year FE	Y	Y
Observations	1,167	1,152
Log Likelihood	-230.847	-225.897
Akaike Inf. Crit.	493.693	483.794
Note:	*p<0.1; **p<0.05; ***p<0.01	

planned construction date. The sample is restricted to observations within four years before construction to four years after construction. Further, as mentioned, we distinguish between high-income and low-income areas in our study. We broadly define high-income areas as Basområde areas whose median income exceeds the Stockholm median income in the period of concern and low-income areas as Basområde areas whose median income falls below the Stockholm mean income in the period of concern.

For each treatment unit i (100m grid cell) in year t with nearest construction project b within radius ring r, we estimate the following regression separately for each ring:

$$Entropy_{itr} = \gamma_{tr} + \kappa_{br} + \sum_{\tau=-4}^{4} \beta_{\tau r} \mathbb{1}(t - t^* = \tau) \times Built_i + \epsilon_{it} \tag{2}$$

Where $Entropy_{itr}$ is either the language or business diversity outcome variable, κ_{br} is the location fixed effect at the construction building level, γ_{tr} is the year fixed effect, and $Built_i$ indicates if the housing project was built (1) or cancelled (0). The variable τ represents the year relative to construction, and $\epsilon_{i,r,t}$ is the error term. The standard errors are clustered at the housing project level.

We also report a pooled version with equation 2 where we estimate the periods before and after construction are grouped:

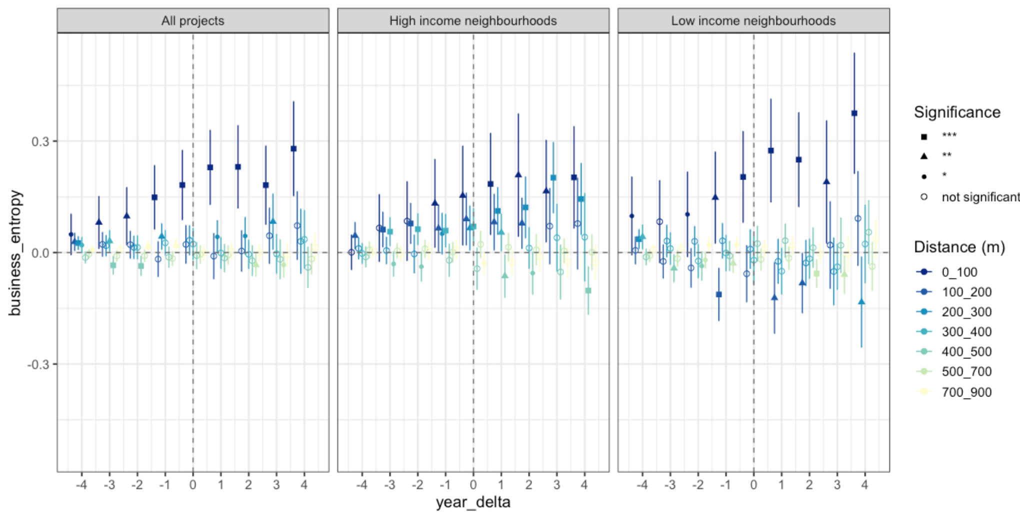
$$Entropy_{itr} = \gamma_{tr} + \beta_r \times Post_{it} \times Built_i + \epsilon_{it} \tag{3}$$

where $Post_{it}$ is a binary indicator to denote event years zero to four since the year of planned construction.

5. Casual Impact of Housing Construction on Commercial Diversity

5.1. Effects on Business Diversity

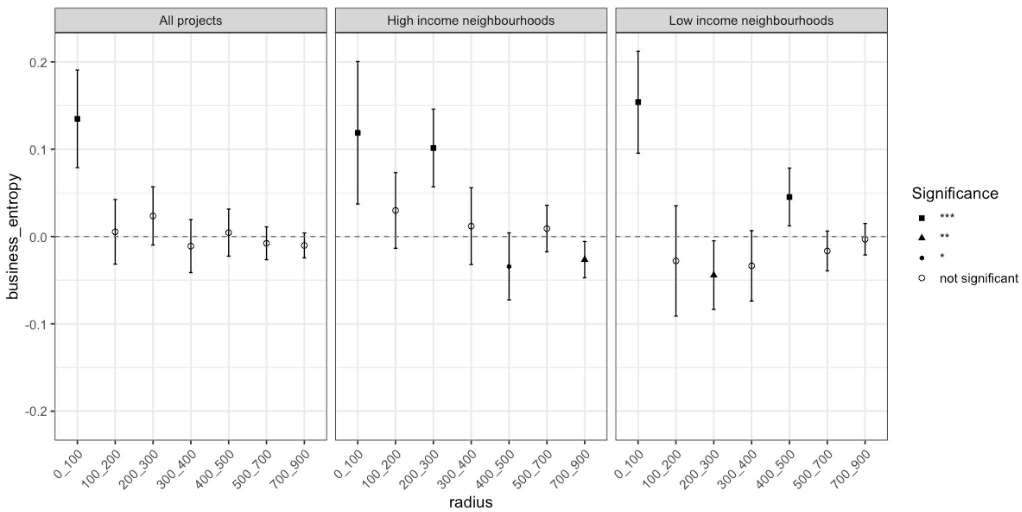
In equation 2, we run the event study regression and see an apparent increase in business diversity caused by housing projects. Based on figure 6, being within 100m of a new housing project increases the diversity of businesses in a neighbourhood by an average of a 0.25 entropy score which equates to 0.56 standard deviations in our sample as seen from table 1. This change in business entropy increases yearly from four years before construction to around two years post-construction before tapering off at 0.56 standard deviations. Interestingly, when we split by high and low-income neighbourhoods, to see that while the increase within 100 meters of the housing construction stays consistent between both, we reveal some critical differences between them. For high-income neighbourhoods, the increase in business diversity reaches up to around 400m. On the contrary, the increase for low-income neighbourhoods stays very close to the construction at 100m.



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure 6: Business Diversity: Event Study

Figure 7 presents the results of estimating the pooled DID in equation 3 where we group the years before construction and the year of construction and following. We find similar spatial trends as we do in the event studies, with high-income neighbourhoods seeing a larger spillover effect of up to 300m. In contrast, in low-income neighbourhoods, we see the spillover effect occurring up to 100m. We see the results for both peak at an increase of 0.31 standard deviations for business diversity.

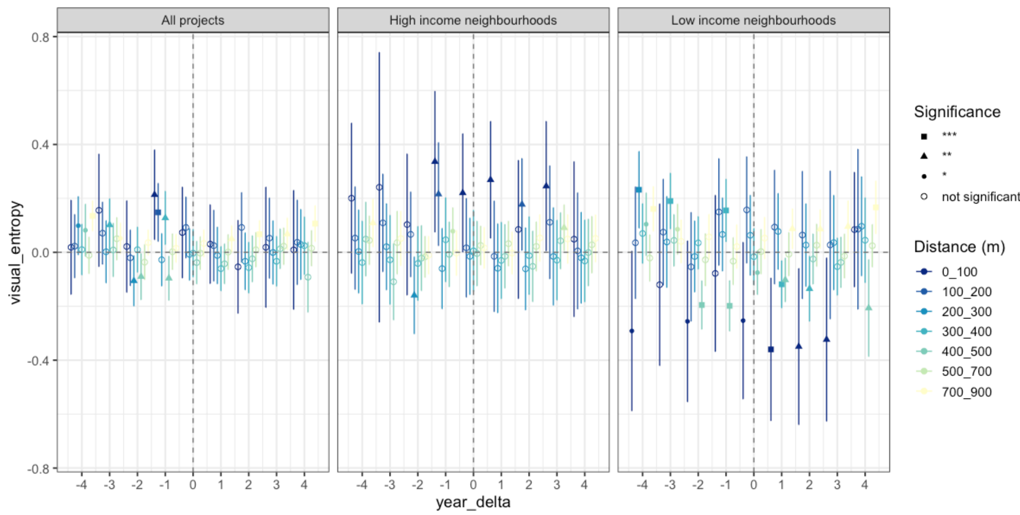


Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure 7: Business Diversity: Pre-Post

5.2. Effects on Language Diversity

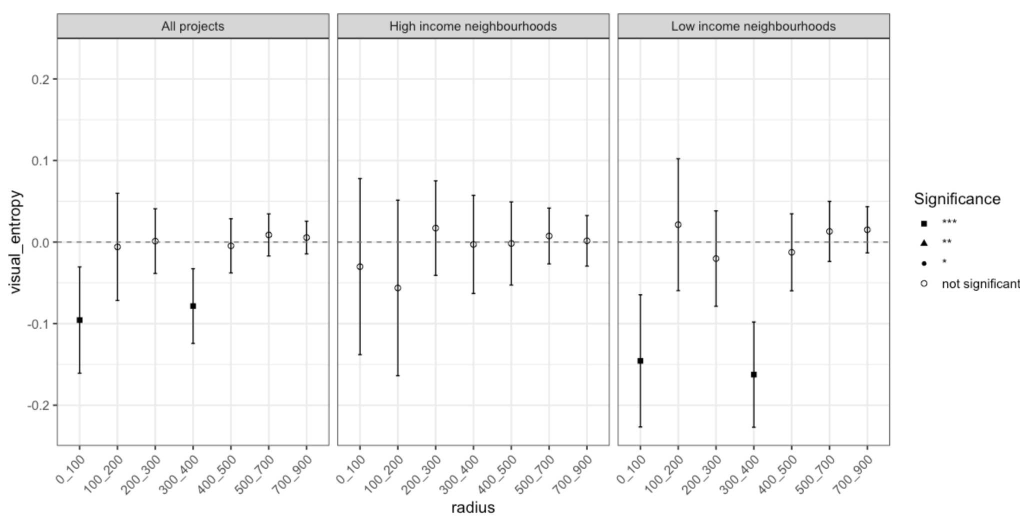
In equation 2, we run the event study regression for language entropy score across the Chinese, Arabic, Swedish and English languages and in Figure 8, we see an increase of an entropy score of 0.25 which equates to 0.57 standard deviations in our sample as seen from table 1, mainly close to the year of construction and in high-income areas. Furthermore, at 200-400m, in low-income areas, we see a decrease of 0.52 standard deviations in language diversity.



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure 8: Language Diversity: Event Study

For the pooled results for language diversity using equation 3, we see an interesting pattern in low-income neighbourhoods in Figure 9 with entropy decreasing in both 0-100m and 300-400m radius rings around housing construction.



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure 9: Language Diversity: Pre-Post

5.3. Results conclusion

Earlier, we mention that business diversity is a critical measure for neighbourhoods, which is an essential element in economic growth. Furthermore, it attracts visits and encourages engagement and interaction between social groups. The finding is that we see housing construction causing this larger mix of businesses, and the spillover effect is geographically more widespread in high-income neighbourhoods.

For language diversity, we see differing results from business diversity impacts. Although we see similar results with some increase close to construction in high-income for language diversity, our most significant findings are in 9 with a decrease in low-income neighbourhoods. This could signify that a neighbourhood is losing its cultural character and early signs of gentrification with lower-quality ethnic stores closing.

We provide additional robustness checks in Appendix A.1.

6. Concluding Remarks

This paper studies whether housing construction has a causal effect on the commercial diversity measured by business and language diversity displayed on commercial signs. It examines this question in the context of Stockholm, analysing 1283 housing projects. To isolate the causal influence of housing construction on the commercial landscape, we compare these built projects (treated housing projects) with 83 projects that were legally approved but cancelled (control housing projects). We find strong evidence that commercial diversity increases following new housing construction. Still, the diversity of the mix of businesses and expressed languages only increase in high-income areas.

In summary, our research provides important insights into the relationship between new housing and commercial diversity in Stockholm. Our findings suggest that new housing construction can positively impact commercial diversity in high-income areas. Still, a nuanced approach is necessary to ensure that this impact is inclusive and benefits all community members.

7. Discussion

We have shown that housing construction can significantly impact the mix of businesses and languages expressed in neighbourhoods. This can result in both positive and negative consequences for a community. We can witness various effects, such as displacement of lower-income residents, gentrification and changes in the commercial landscape.

As mentioned, one of the significant challenges in constructing new housing is the opposition from existing residents, which can be significant and often cause long delays in the planning process. However, housing construction can bring various goods and services which can be crucial for building sustainable, economically productive, and culturally vibrant communities. A neighbourhood's wide range of services and businesses reduces residents' dependence on cars, promotes walking and healthy lifestyles, builds community, and fosters social cohesion.

Moreover, as cities experience large-scale urban growth and immigration, the appearance of language diversity in the urban environment will provide a critical metric for monitoring social integration. Whether intended or unintended, this information will provide beneficial insights into the impact of housing construction on social integration. Furthermore, it's critical to understand the linguistic diversity in urban neighbourhoods over time to ensure that the introduction of new housing construction does not undermine a neighbourhood community's social and cultural fabric.

Finally, approving new housing in low-income areas is often contentious because of worries that new housing will accelerate rent increases and gentrification. High-income areas often oppose new construction because they believe it will reduce the value of their property prices (Hankinson, 2018; Been et al., 2019). Furthermore, changes in the commercial character of gentrifying neighbourhoods have led to a new policy debate on gentrification and housing affordability. These changes have led to anti-gentrification protests and a renewed interest in policy circles for maintaining social diversity in urban neighbourhoods.

Appendix A. Supplementary Appendix

Appendix A.1. Robustness checks

In the figures below, we present event study plots corresponding to positive results in Section 5 using different measures of the spatial treatment scale, radius rings and how to deal with treatments captured multiple times.

Results using more board spatially aggregated radius rings:

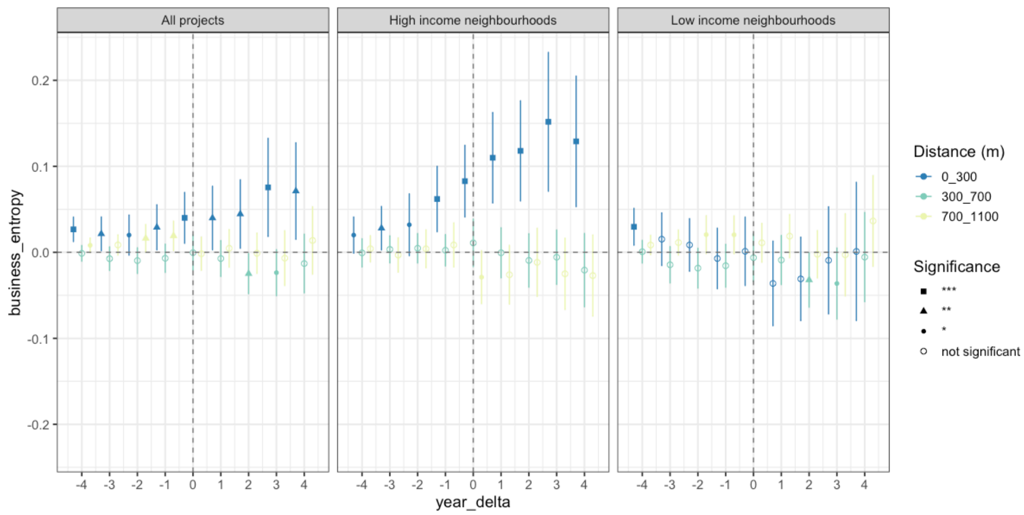


Figure A.10: Business Diversity
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

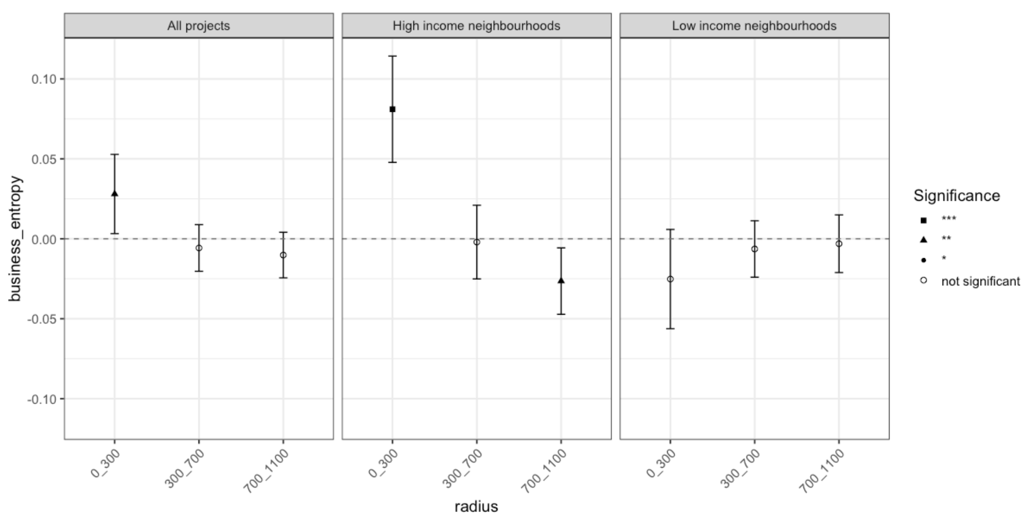


Figure A.11: Business Diversity Pre-post
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

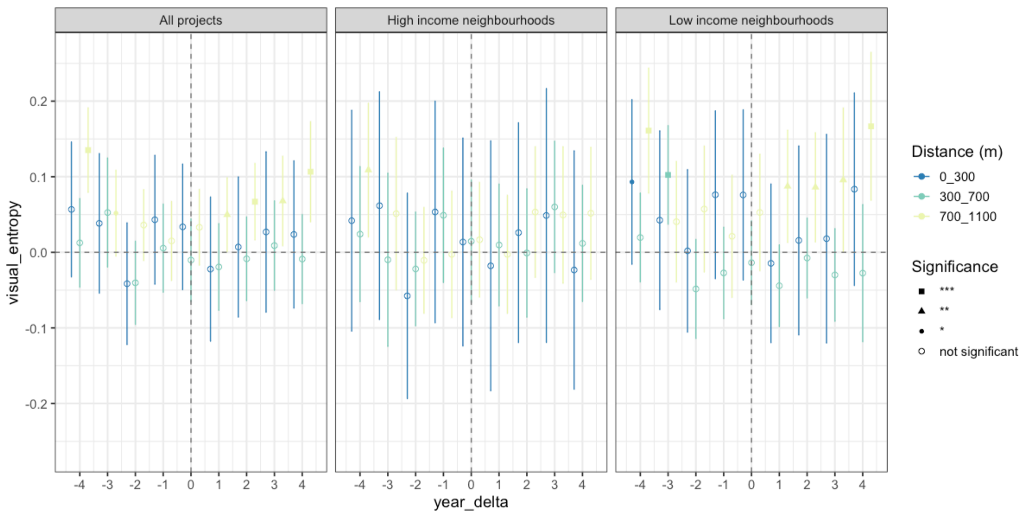


Figure A.12: Language Diversity
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

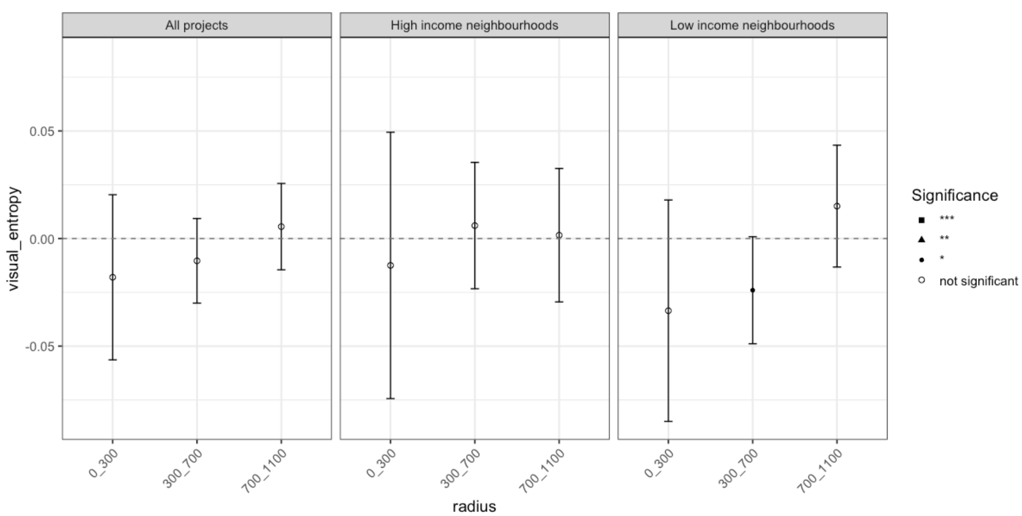
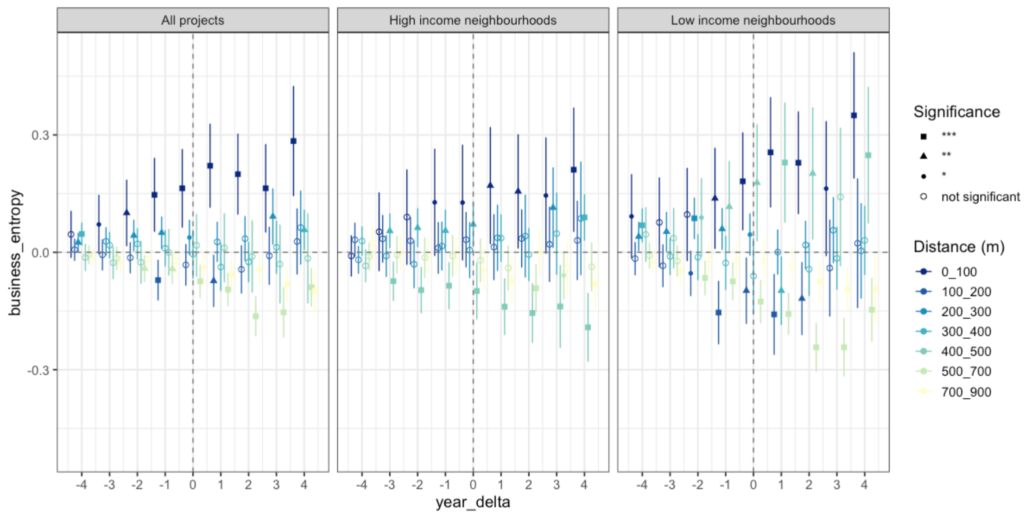


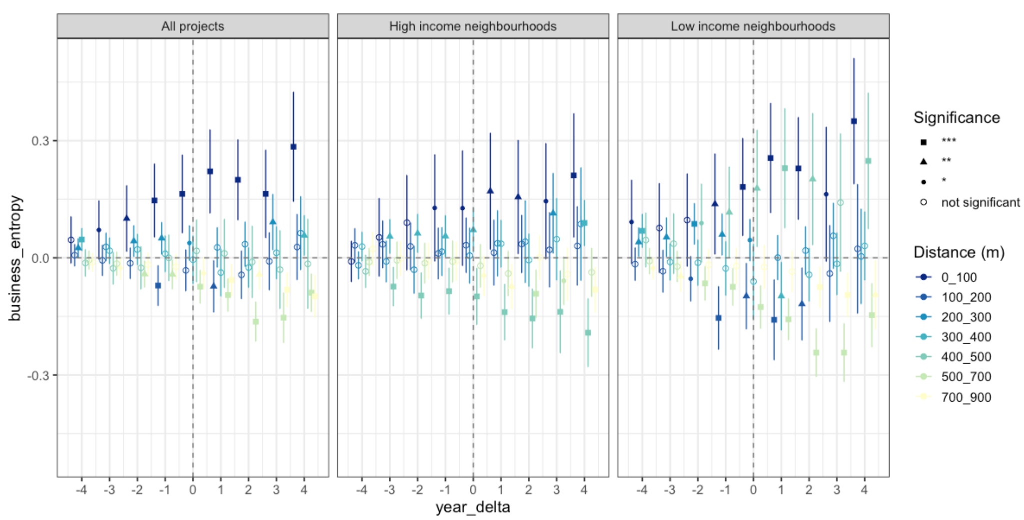
Figure A.13: Language Diversity Pre-post
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Results using data that only includes treatments that are captured a single time by a housing project:



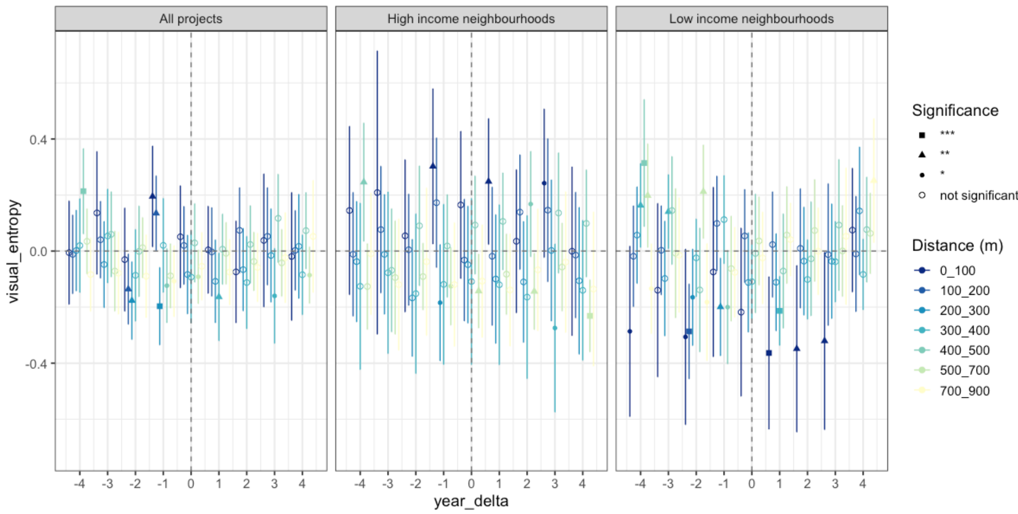
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure A.14: Business Diversity



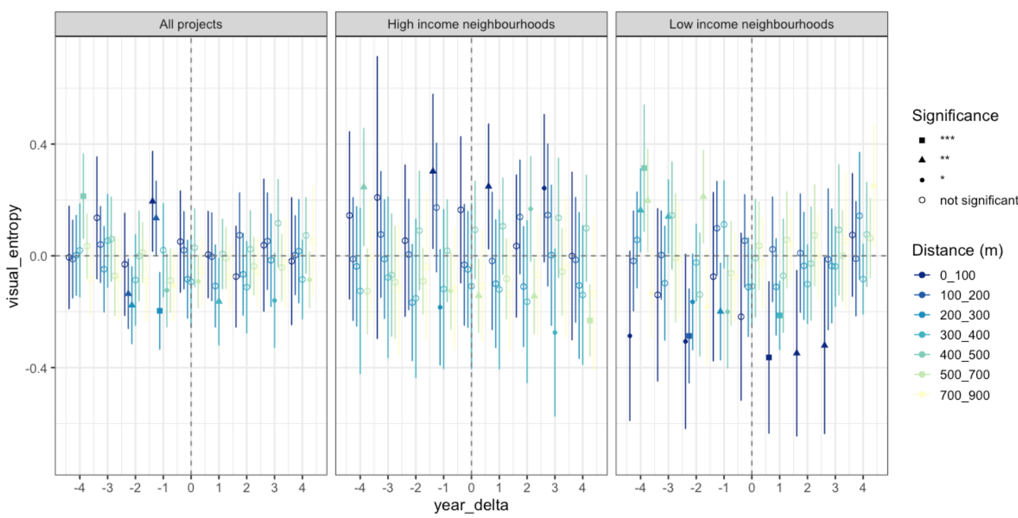
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure A.15: Business Diversity Pre-post



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

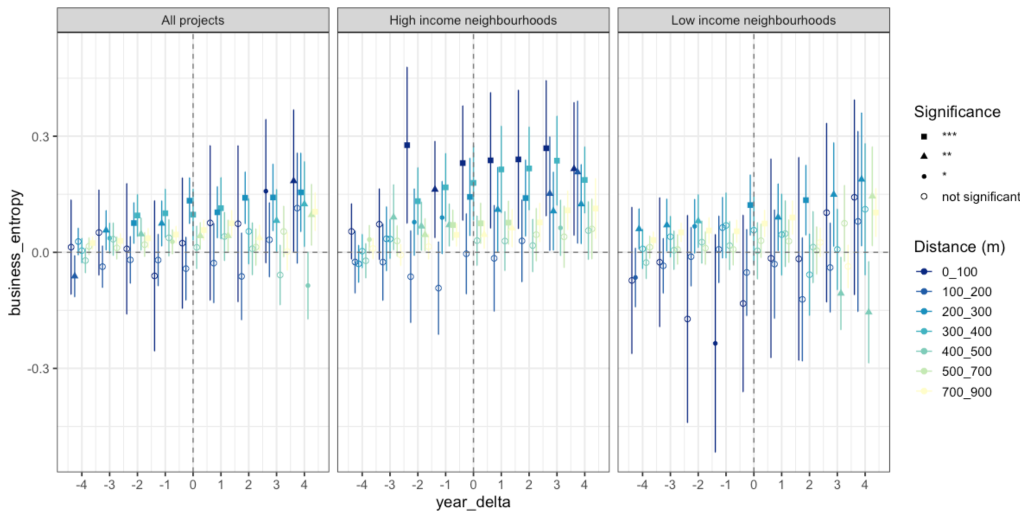
Figure A.16: Language Diversity



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

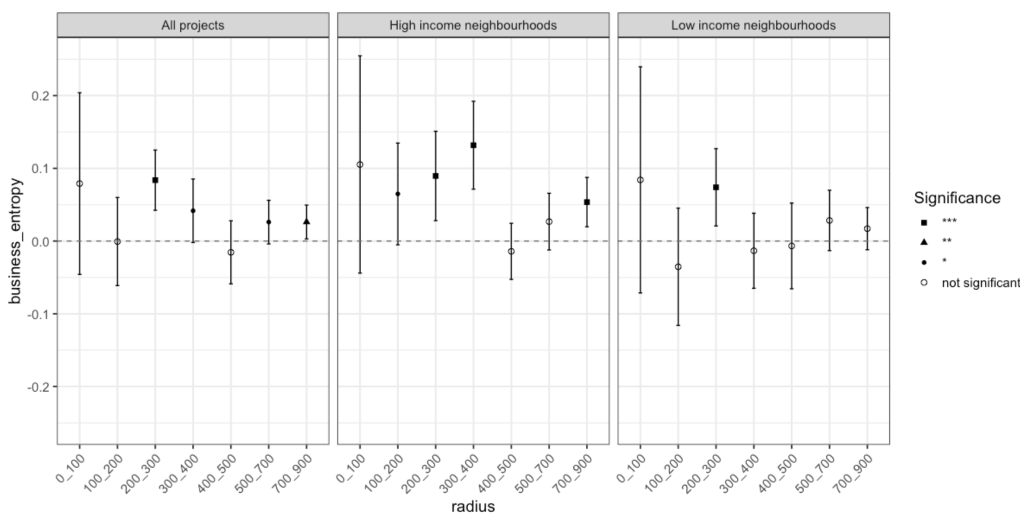
Figure A.17: Language Diversity Pre-post

Results using 250 grid cells for the treatment spatial scale:



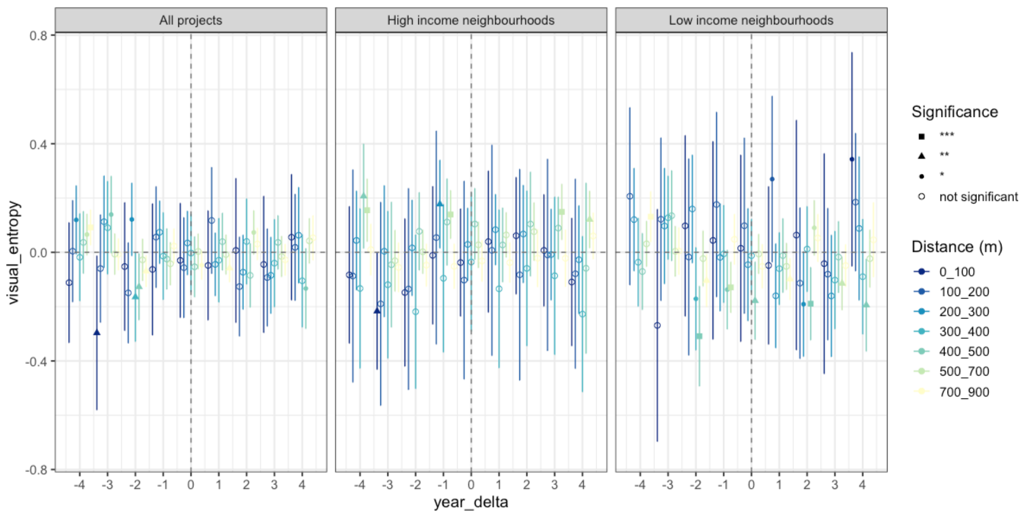
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure A.18: Business Diversity



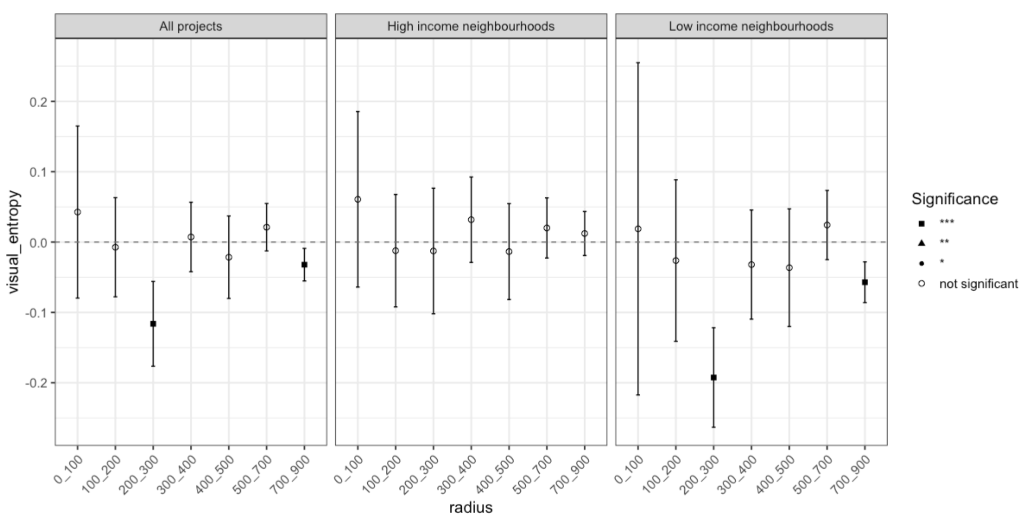
Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure A.19: Business Diversity Pre-post



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure A.20: Language Diversity



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

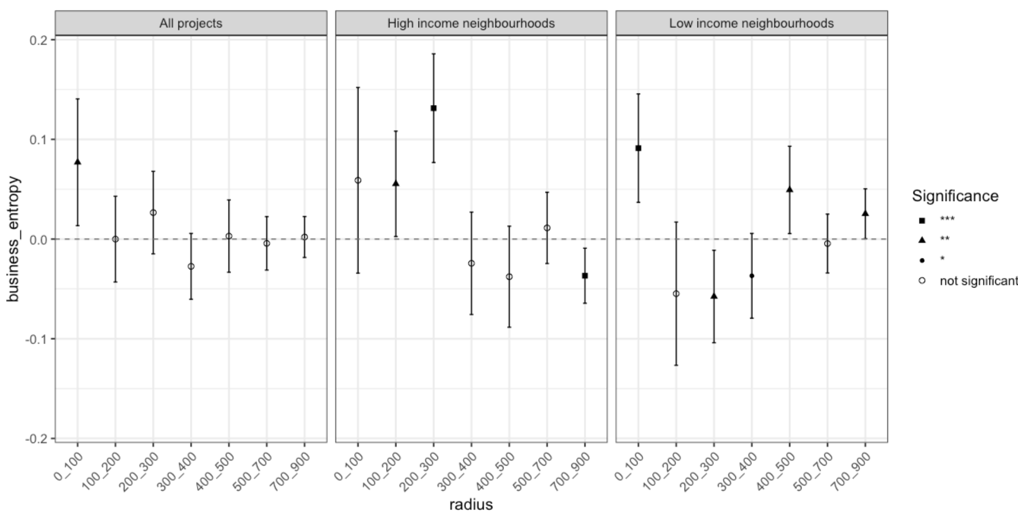
Figure A.21: Language Diversity Pre-post

Appendix A.2. Controlling for socio-demographic changes

As noted in 4, we find differing demographic trends across particular variables. While this is expected as not construction housing will directly affect population and other variables, we control for these variables where we estimate the following regression:

$$Entropy_{itr} = \gamma_{tr} + \kappa_{br} + \mu_{br} + \zeta_{br} \times Post_{it} \times Built_i + \epsilon_{it} \tag{A.1}$$

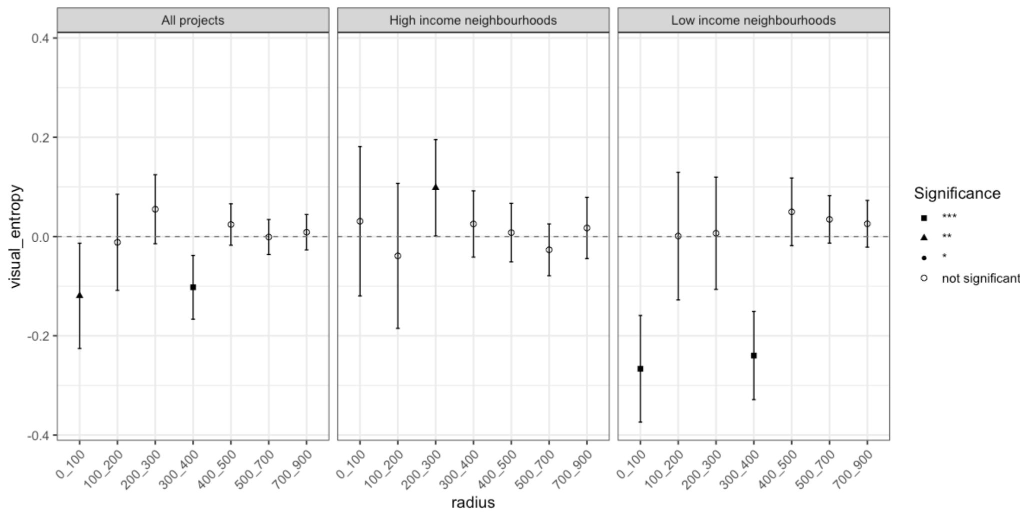
Where we control at the treatment level for average population count μ_{br} and average number of secondary school students ζ_{br}. This model allows us to control for other factors that could affect commercial diversity and compare the results.



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure A.22: Business Diversity: Pre-Post & Controls

For Figure A.22 and Figure A.22, we run equation A.23, adding the population and secondary school controls to the regression. Interestingly, we witness a very similar trend according to our main specification, with increased business diversity occurring in both high and low-income neighbourhoods, but a more significant spillover effect in high-income areas. While language diversity decreases near new housing construction in low-income neighbourhoods.



Note: The standard errors are clustered at the housing project level. The error bars correspond to 95% confidence intervals.

Figure A.23: Language Diversity: Pre-Post & Controls

Appendix A.3. Language Classifier

The model was trained on real streetscapes from GSV, which were manually labelled with `pigeon`,[2], an open-source labelling tool. To apply this tool to Stockholm, we scraped images from densely populated areas that allowed the text to be captured in the scene. The dataset comprises images from cities where the target languages are dominant—Stockholm for Swedish, Ramallah, Bethlehem and Beirut for Arabic and Hong Kong for Chinese. To avoid overfitting in these cities where the target languages are highly prevalent, we also include images from London and New York City, both global metropolis where minority languages feature less prominently. Therefore, the dataset has good coverage of the four target languages, with variations in how prominently they are featured and the architectural styles of the scenes captured. This ensures that the resultant model is generalisable to our case study of Stockholm. The summary statistics of data obtained from each city are presented in Table A.3.

[2]Source code available at: https://github.com/agermanidis/pigeon

Table A.3: Size of dataset by city

City	En	Sv	Ar	Cn	None	Total
London	2836	0	103	0	2543	5383
New York City	355	0	29	0	302	660
Stockholm	590	1175	2	15	1195	2633
Ramallah	873	0	1048	0	988	2214
Bethlehem	188	0	217	0	240	522
Beirut	48	0	35	0	59	127
Hong Kong	1215	0	0	1150	722	2034
Total	6105	1175	1434	1165	6049	13573

To obtain GSV images, sampling points were generated along the road network in areas of interest at 50-meter intervals using OpenStreetMap. We then make API requests from GSV using these sampled coordinates and the following parameters—90 field-of-vision, 0 pitch, 50m radius. For each set of coordinates, we obtain images at compass headings of 0°, 90°, 180° and 270°, thereby capturing the whole panorama at each point. We apply the computer vision model for each image to extract if each of the four languages appears in the built environment.

The model is first trained the model purely on a synthetic dataset before training the best-performing model on the real dataset for another 150 epochs. Given the labour cost of manual labelling, the process was automated using the data generation process using SynthText,[3] a tool for generating text onto given background images. Generating synthetic data is a common technique used in scene text recognition

The model predicts if a language is present in an image (outputs 1) or not (outputs 0), lending itself to a measure of language concentration in an urban area as defined as:

$$P_{x,\ell} = \frac{1}{|x|} \sum_{i \in \mathcal{S}(x)} \mathbb{1}(\text{language } \ell \text{ is in image } i) \tag{A.2}$$

where $\mathcal{S}(x)$ is the set of images in an urban area x.

The test accuracy of the different models is presented in Table A.4. To evaluate the performance of the model, a comparison between the author's

[3]Source code available at: https://github.com/ankush-me/SynthText

Table A.4: Test accuracy of EasyOCR, Google OCR and our models

Model	En	Sv	Ar	Cn	Total
EasyOCR	75.2	67.0	68.6	64.0	71.9
Google OCR	71.6	67.6	74.7	62.6	70.5
Synthetic	55.3	53.4	48.1	53.1	53.9
Synth + Real	71.6	82.4	**88.6**	88.9	77.2
Real	**76.4**	**85.5**	88.1	**91.1**	**80.8**

Notes: For each training paradigm, we only include the test accuracy of the model with the highest total validation accuracy. Highest test accuracy bolded.

initially built dataset of 2964 images scraped from GSV was used and compared to those of ready-to-use OCR tools. Both OCR tools have around 60-70% accuracy across the four languages. On the other hand, we find that our language detection model works well for all four languages. The overall accuracy of both models trained with real data is higher than that of both OCR tools.

Appendix A.4. Entropy Measures

In Figure A.24, we show a strong correlation across different entropy scores for businesses at the 100 grid scale by testing the business grouping we used in our analysis (Business Entropy) with different grouping variations using the Swedish Standard Industrial Classification (SNI) number which is used to classify enterprises and workplaces according to their activity. We test capturing the first two, three and four digits from the SNI number. Further, we see no correlation between Business Entropy and Language Entropy scores to ensure we are not capturing the same pattern.

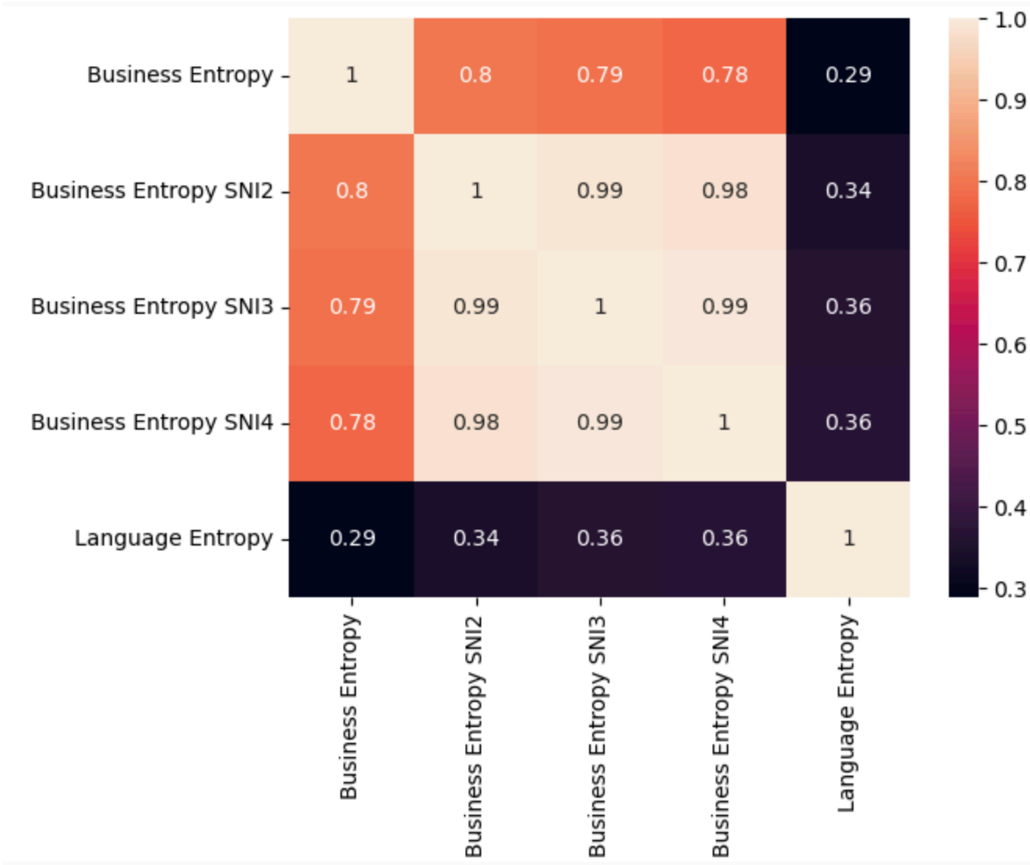


Figure A.24: Correlation analysis between entropy scores

Acknowledgements

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The authors would like to acknowledge the financial support from the Senseable Stockholm Lab funded by the City of Stockholm, KTH Royal Institute of Technology, the Stockholm Chamber of Commerce and Newsec, and in collaboration with MIT Senseable City Lab.

References

Timur Abbiasov. Do urban parks promote racial diversity? evidence from new york city. 2021.

Timur Abbiasov and Dmitry Sedov. Do local businesses benefit from sports facilities? the case of major league sports stadiums and arenas. *Regional Science and Urban Economics*, page 103853, 2022.

Milena Almagro and Tomás Domınguez-Iino. Location sorting and endogenous amenities: Evidence from amsterdam. *NYU, mimeograph*, 2019.

Jan Amcoff. Searching for new ways to achieve mixed neighbourhoods. *Cities*, 121(103496), 2022.

Vicki Been, Ingrid Gould Ellen, and Katherine O'Regan. Supply skepticism: Housing supply and affordability. *Housing Policy Debate*, 29(1):25–40, 2019.

Kristian Behrens, Brahim Boualam, Julien Martin, and Florian Mayneris. Gentrification and pioneer businesses. *The Review of Economics and Statistics*, pages 1–45.

Hector Blanco and Lorenzo Neri. Knocking it down and mixing it up: The impact of public housing regenerations. 2021.

Fredrik Brunes, Cecilia Hermansson, Han-Suck Song, and Mats Wilhelmsson. Nimbys for the rich and yimbys for the poor: analyzing the property price effects of infill development. *Journal of European Real Estate Research*, 2020.

Gerald A Carlino and Albert Saiz. Beautiful city: Leisure amenities and urban growth. 2008.

Shi Kai Chong, Mohsen Bahrami, Hao Chen, Selim Balcisoy, Burcin Bozkaya, et al. Economic outcomes predicted by diversity in cities. *EPJ Data Science*, 9(1):17, 2020.

Brett Christophers. A monstrous hybrid: The political economy of housing in early twenty-first century sweden. *New Political Economy*, 18(6):885–911, 2013.

Carlos Cinelli, Andrew Forney, and Judea Pearl. A crash course in good and bad controls. *Sociological Methods & Research*, page 00491241221099552, 2020.

Plan City of Stockholm. Stockholm city plan. 2018.

Rebecca Diamond and Tim McQuade. Who wants affordable housing in their backyard. *An Equilibrium Analysis of Low Income Property Development*, 2017.

Peter Esaiasson. Nimbyism–a re-examination of the phenomenon. *Social science research*, 48:185–195, 2014.

Alan W Evans. *Economics and land use planning*. John Wiley & Sons, 2008.

Masahisa Fujita and Jacques-François Thisse. Economics of agglomeration. *Journal of the Japanese and international economies*, 10(4):339–378, 1996.

Martin Fuller and Ryan Moore. *An Analysis of Jane Jacobs's: The Death and Life of Great American Cities*. Macat Library, 2017.

Edward L Glaeser, Jed Kolko, and Albert Saiz. Consumer city. *Journal of economic geography*, 1(1):27–50, 2001.

Edward L Glaeser, Scott Duke Kominers, Michael Luca, and Nikhil Naik. Big data and big cities: The promises and limitations of improved measures of urban life. *Economic Inquiry*, 56(1):114–137, 2018.

Edward L Glaeser, Michael Luca, and Erica Moszkowski. Gentrification and neighborhood change: Evidence from yelp. Technical report, National Bureau of Economic Research, 2020.

Richard K Green, Richard K Green, and Stephen Malpezzi. *A primer on US housing markets and housing policy*. The Urban Insitute, 2003.

Karin Grundström and Irene Molina. From folkhem to lifestyle housing in sweden: segregation and urban form, 1930s–2010s. *International Journal of Housing Policy*, 16(3):316–336, 2016.

Veronica Guerrieri, Daniel Hartley, and Erik Hurst. Endogenous gentrification and housing price dynamics. *Journal of Public Economics*, 100:45–60, 2013.

Michael Hankinson. When do renters behave like homeowners? high rent, price anxiety, and nimbyism. *American Political Science Review*, 112(3): 473–493, 2018.

Karin Hedin, Eric Clark, Emma Lundholm, and Gunnar Malmberg. Neoliberalization of housing in sweden: Gentrification, filtering, and social polarization. *Annals of the association of American geographers*, 102(2): 443–463, 2012.

Rodrigue Landry and Richard Y Bourhis. Linguistic landscape and ethnolinguistic vitality: An empirical study. *Journal of language and social psychology*, 16(1):23–49, 1997.

T William Lester and Daniel A Hartley. The long term employment impacts of gentrification in the 1990s. *Regional Science and Urban Economics*, 45: 80–89, 2014.

Stephen Malpezzi. Housing prices, externalities, and regulation in us metropolitan areas. *Journal of Housing Research*, pages 209–241, 1996.

Lars Marcus. Social housing and segregation in sweden: from residential segregation to social integration in public space. *Progress in planning*, 67 (3):251–263, 2007.

Rachel Meltzer. Gentrification and small business: Threat or opportunity? *Cityscape*, 18(3):57–86, 2016.

Ricardo Mora and Javier Ruiz-Castillo. Entropy-based segregation indices. *Sociological Methodology*, 41(1):159–194, 2011.

Nikhil Naik, Scott Duke Kominers, Ramesh Raskar, Edward L Glaeser, and César A Hidalgo. Computer vision uncovers predictors of physical urban change. *Proceedings of the National Academy of Sciences*, 114(29):7571–7576, 2017.

Laura Onofri, PALD Nunes, Jasone Cenoz, Durk Gorter, et al. Linguistic diversity and preferences: Econometric evidence from european cities. *Journal of Economics and Econometrics*, 56(1):39–60, 2013.

Arthur O'Sullivan. Gentrification and crime. *Journal of urban economics*, 57 (1):73–85, 2005.

Kate Pennington. Does building new housing cause displacement?: the supply and demand effects of construction in san francisco. *The Supply and Demand Effects of Construction in San Francisco (June 15, 2021)*, 2021.

Esteban Rossi-Hansberg, Pierre-Daniel Sarte, and Raymond Owens III. Housing externalities. *Journal of political Economy*, 118(3):485–535, 2010.

Arianna Salazar Miranda. The micro persistence of layouts and design: Quasi-experimental evidence from the united states housing corporation. *MIT Center for Real Estate Research Paper*, (21/16), 2021.

Arianna Salazar-Miranda, Cate Heine, Fabio Duarte, Katja Schechtner, and Carlo Ratti. Measuring the impact of slow zones on street life using social media. *Cities*, page 104010, 2022.

Katharina Schone. The impact of inter-municipal land use plans on social segregation: first lessons from the french experience. *Local Government Studies*, pages 1–24, 2022.

Jenny Schuetz. Do art galleries stimulate redevelopment? *Journal of Urban Economics*, 83:59–72, 2014.

Yan Song, Louis Merlin, and Daniel Rodriguez. Comparing measures of urban land use mix. *Computers, Environment and Urban Systems*, 42: 1–13, 2013.

Jingxian Tang and Ying Long. Measuring visual quality of street space and its temporal variation: Methodology and its application in the hutong area in beijing. *Landscape and Urban Planning*, 191:103436, 2019.

You Xuan Thung, Tom Benson, and Nikita Klimenko. Detecting languages in streetscapes using deep convolutional neural networks. In *2022 IEEE International Conference on Big Data (Big Data)*, pages 1711–1718. IEEE, 2022.

Maarten Wolsink. Entanglement of interests and motives: assumptions behind the nimby-theory on facility siting. *Urban studies*, 31(6):851–866, 1994.

Yuji Yoshimura, Yusuke Kumakoshi, Sebastiano Milardo, Paolo Santi, Juan Murillo Arias, Hideki Koizumi, and Carlo Ratti. Revisiting jane jacobs: Quantifying urban diversity. *Environment and Planning B: Urban Analytics and City Science*, 49(4):1228–1244, 2022.

Sharon Zukin, Valerie Trujillo, Peter Frase, Danielle Jackson, Tim Recuber, and Abraham Walker. New retail capital and neighborhood change: Boutiques and gentrification in new york city. *City & Community*, 8(1):47–64, 2009.