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Land Scarcity and Urban Density within Cities

Abstract

This paper studies how limitations on land suitable for development affect within-city variation in urban density and its three components: crowding, residential coverage, and building height. We use the high variation in geographical obstacles − such as steep land slopes and the presence of water bodies within Norwegian cities − as exogenous sources of development limitations. We show that such constraints can create scarcity of certain types of land. Scarcer land types have higher urban density which arises mostly from higher buildings. The effect operates through the heterogeneous citywide supply of land types, rather than through local geography.

JEL-Codes: R520, R310, R210, R230, C800.

Keywords: urban density, building heights, geography, neighborhoods, inner-city differences.

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1 Introduction

Urban population density varies across different parts of cities. Apartments are smaller, and buildings are higher, or packed more tightly together in some neighborhoods than in others. Urban density has been linked to a wide range of welfare outcomes, including productivity, crime, pollution, and, most recently, the spread of COVID-19 (see, for example, Ahlfeldt and Pietrostefani, 2019, Brownstone and Thomas, 2013, Ciccone and Hall, 1996, Larsson, 2014, Rocklöv and Sjödin, 2020). Nevertheless, the question remains: What determines inner-city differences in density and its components? Distance to the central business district is the most-studied factor, both theoretically in the classical Alonso-Muth-Mills model (Brueckner, 1987) and empirically (Bertaud and Malpezzi, 2014, Zielinski, 1980). While distance to a city center often explains a significant share of the within-city variation in urban density, a large part remains unaccounted for. In this paper, we argue that building land limitations – by which we mean constraints that reduce land area available for development – play a crucial role.

We analyze the impact of building land limitations on the within-city variation in urban density and its three components: crowding, building height, and residential coverage. Restrictions that limit the availability of land that can be developed affect land prices. Thus, the availability of land might be determined by policies. This makes it hard to disentangle and study causal effects (Duranton and Puga, 2015, Fischel, 2004, Glaeser and Kahn, 2004). We overcome this challenge by utilizing the exogenous distribution of geography-induced building land limitations – such as steep grades on lands, and the presence of water bodies – and fine-grained data at the neighborhood-level to account for the effects of existing regulations within cities.

Our main argument is that land limitations create scarcity of certain types of land that can be developed, thereby pushing up land and rental prices in specific neighborhoods – not just in the immediate area, but also elsewhere, such as in those neighborhoods that may be on another side of town but are roughly the same distance from the city center. Hence, building land limitations can have heterogeneous effects on within-city population density if they change the availability of different land types. Geographical obstacles within cities can create such a scarcity exogenously. For example, geographical conditions may render sunny locations scarce in certain parts of a city. Housing options close to a city core may be rare. Crucially, this scarcity-inducing effect of citywide geography differs from local geography in and around a given location. It is well known that local geographical conditions affect house prices. For example, steep terrain increases building costs, and might provide amenities, such as an ocean view, which households are willing to pay for (see for instance Bourassa et al., 2004, Lee and Lin, 2018, Nelson, 1972). We argue that the scarcity channel works differently from the local geography effect. Steep inclines at the other side of the city can affect density in other neighborhoods, even those on another side of town, because these features change the overall availability of certain land types. To answer this question empirically, we assemble a novel, high-resolution geo-spatial data set at the neighborhood level for Norway. With an average residential area of 0.3 square kilometers, and an average population of 666 inhabitants, our unique data have the necessary granularity to study inner-city differences in density. In addition to providing data on the geographical variables, we construct measures on building footprints and height. We make use of high-resolution (10m $\times$ 10m) radar images on total elevation and ground elevation from the National Detailed Altitude Model project provided by the Norwegian mapping authority. Combining these data with residential development data from the European Settlement Map, we can compute a 10m $\times$ 10m raster reflecting heights of buildings in all of Norway. We then derive our final data set on neighborhood-level values of geographical variables (such as natural elevation and slope) and on density and its components.

To our knowledge, this is the first paper to empirically study neighborhood-level differences in terms of overall urban density and its components: crowding, building height, and residential coverage. Our data reveal substantial heterogeneity in overall urban density and in components parts – even between city neighborhoods with the same overall urban density levels. For example, looking at urban density gradients reveals that, as distance to the city core increases, building height decreases more uniformly than crowding does.

We obtain three main results, all related to the effects of building land limitations induced by geography. First, limiting available building land in one part of the city increases urban density in other parts of the city with similar characteristics. This is an overall supply effect independent of the neighborhood's *local* geography. Second, all three density components are affected, with particularly strong impacts on building height. Finally, a heterogeneous distribution of geographical obstacles that limit development leads to inner-city heterogeneity in urban density. Neighborhoods that are the same distance from the city core can have very different urban densities when geography is highly heterogeneous. Our results are robust to numerous specifications, including the addition of sociodemographic and income variables, and changes in the definition of the central business district and the unit of observation.

Our identification strategy rests on the exogeneity of geography-induced natural development limitations, and the ability to control for regulatory-induced development limitations. Both geographical and regulatory factors typically determine housing supply in terms of zoning laws (Duranton and Puga, 2015, Glaeser and Gyourko, 2018).[1] In our empirical study, we can account for regulatory effects because we utilize variation at the neighborhood level, and building regulations in Norway are set at a higher level of aggregation – at the *kommune* (Kommunal- og Moderniseringsdepartementet, 2008) level. We further control for a large spectrum of potential confounding factors, such as the geography in and around neighborhoods, and many sociodemographic characteristics, such as average income and sickness-related absence from work.

[1] For example, using British data, Hilber and Vermeulen (2016) find that regularity constraints affect the house price-earnings elasticity more strongly than uneven topography. Shertzer et al. (2018) show that zoning laws established in Chicago in 1923 still determine the inner-city variation of population density in that city. Green et al. (2005) find that the price elasticity of housing supply varies significantly across US metropolitan areas according to their regulatory regime.

The unique set-up in Norway is particularly appropriate for studying our research questions for three key reasons: (i) We have high-resolution data, which allow us to calculate density, its components, geography, and socioeconomic indicators at the neighborhood level. Such fine-grained data are not available for many other countries. (ii) We also have a high inner-city variation in geographical features. This variation provides an ideal testing ground for our hypothesis. (iii) The particular regulatory set-up in Norway make the direct building regulation effect at the neighborhood level much less of an issue than in other countries. Despite this relatively distinct feature, Norwegian cities share many features with other agglomerations worldwide, from their development around historic market places, to the life-cycle-based sorting behavior of their inhabitants (Andersen, 2011, Baum-Snow and Hartley, 2017, Helle et al., 2006, Jedwab et al., 2020). Therefore, our results can readily be generalized to other countries.

Taken together, our findings yield important implications for policymakers and urban planners. While geography per se is a given factor, understanding the mechanisms through which it works is vital for using the appropriate policy instruments to shape the city. Development can be regulated, and our findings reveal the far-reaching consequences of such policies. Limiting building land can increase overall urban density and its variation across cities – and perhaps in ways that regulators may not previously have anticipated. We show that regulating development in one part of town might substantially change urban density in other parts of town that share the same characteristics, but might have less of an effect on areas with different traits.

Our results add to the empirical literature on how building land limitations impact cities. Our work is most directly related to the literature that studies how geography impacts overall city density (Saiz, 2010) and shape (Harari, 2020). In contrast to these studies, we consider how within-city variation in geography leads to neighborhood-level variations in density, rather than overall city size and density. In this respect, we also add to the literature investigating urban sprawl (Burchfield et al., 2006, Glaeser and Kahn, 2004).

Another strand of literature to which we contribute is the small number of studies on urban density components. For example, Angel et al. (2019) look at average crowding, building height, and residential coverage through case studies of selected world cities. Ahlfeldt and Barr (2020) conduct a literature overview of the economics of building heights, a subject that is quickly garnering interest, as evidenced by recent applications. These include firm productivity in tall commercial buildings (Liu et al., 2018), the land price elasticity of skyscrapers in Chicago (Ahlfeldt and McMillen, 2018), and research into slums and building heights in Jakarta (Harari and Wong, 2018) and Nairobi (Henderson et al., 2019). To the best of our knowledge, our paper is the first to study the variation of density and its component parts at the within-city level across several cities.

The density effect of geography, we identify works through scarcity of building land across a city. However, we also account for other potential local effects of geography on density, thereby enriching the literature on geographical amenities and urban densities. Cities with more desirable geographical amenities, such as warm climate and ocean access, are known to have higher population densities (Albouy and Lue, 2015, Albouy and Stuart, 2014, Carlito and Saiz, 2019). Within cities, geographical amenities can contribute to the spatial income distribution; for example, Brueckner et al. (1999) examine related theoretical considerations, and Lee and Lin (2018) offer empirical results on how geographical amenities persistently anchor the rich to certain parts of the city. Our findings in this respect suggest that the clear patterns that have emerged *across* cities tend to be less sharp *within* cities; for example, more sunshine hours are associated with less crowding but also with higher residential coverage, which makes the local effect on urban density ambiguous.

We anchor our contribution to the classical literature of urban economic models. To frame our research question, we provide a simple way of incorporating geographical constraints on land suitability into the standard model by Alonso (1964), Muth (1969) and Mills (1967). In our framework, we consider geographical constraints that limit land availability for development, and we argue that this scarcity gives rise to market power on the side of land developers. Our stylized model yields testable predictions about the effects of building land restrictions on crowding and building height, .

Finally, we contribute to the methodological frontier. Our procedure for deriving high-resolution building height data at the 10-by-10-meter level adds to the remote-sensing literature. The method we propose uses the digital surface and terrain models provided by the Norwegian mapping authority. Similar data can also be obtained from Airbus, which commercially distributes the high-resolution TanDEM-X data generated by the European Space Agency (ESA). Hence, with sufficient funding, our method could be used to obtain building-height data for every city in the world.

2 Conceptual Framework

The focus of our empirical analysis is the effect of geography-induced building land limitations on urban density and its components. Following Angel et al. (2019), we define urban density as the ratio of population to the urban area, and split it up as follows:

$$\text{Urban Density} = \text{Crowding} \cdot \text{Building Height} \cdot \text{Residential Coverage} \quad (1)$$

$$\frac{\text{Pop}}{\text{Urban Extent}} = \frac{\text{Pop}}{\text{Floor Area}} \cdot \frac{\text{Floor Area}}{\text{Footprint}} \cdot \frac{\text{Footprint}}{\text{Urban Extent}} \quad (2)$$

To derive testable hypotheses for our empirical analysis, and to elucidate the underlying mechanisms, we derive a stylized theoretical model.

2.1 A Stylized Theoretical Model for Building Land Limitations and Density

We introduce two new components to the classical Alonso-Muth-Mills-style urban economic model: (i) geographical constraints limit the availability of land suitable for development, and (ii) scarcity of built-up land gives rise to market power on the side of land developers.

We assume that geography determines the urban equilibrium via two channels. First, local geography determines the properties of a land plot, affecting building costs, but also specific amenities consumers might value like ocean view and sunshine hours. We capture all these building land properties in a vector B except for distance x to the central business district. We have, in additional to local geography, city-wide geography, which determines the scarcity of land with similar properties:

Assumption 1. *At any given distance x to the city center, an exogenous number of land plots g are unsuitable for development because of geographical obstacles (such as water bodies or steep inclines), where*

$$\frac{\partial g}{\partial x} = 0 \tag{3}$$

Note that g is not only exogenous, but also assumed to be independent from x, so that geographical obstacles can occur at any distance to the city center.

We assume further that consumers behave as price takers. Land cannot be produced; it is scarce and quasi-unique. This is in part because land is limited by regulation or geography. In addition, specific building land properties, such as ocean views or distance to the city center, cannot be changed by the land developers. Scarcity of these land plots allows land developers to exert market power:

Assumption 2. *The housing market is imperfect. Consumers need to pay a price equal to their reservation price in a competitive market ψ plus a mark-up δ.*

$$p = \psi + \delta \tag{4}$$

The idea of market power in the housing market was first discussed by Spengler (1946), and has been formalized to some extent by Martínez (1992).

To keep our exposition stylized and general, we deliberately do not model the underlying oligopolistic structure or monopolistic competition, but merely work with the resulting markup function.[2] Building on the central effect of imperfect competition, we assume that market power decreases with increasing numbers of competitors:

Assumption 3. *The markup that land developers can charge increases with the units of land that are not suitable for development at a given distance from the city center, hence we assume:*

$$\frac{\partial \delta(g)}{\partial g} > 0 \tag{5}$$

Using these assumptions, we first derive the reservation price on the demand side and then analyze the supply of housing. We use a comparative statics analysis to yield predictions about how geographical constraints affect building height and crowding, two of the components of urban density.

2.1.1 Demand Side

Households receive an income y, live in different rings with distance x from the city center, and pay a transport cost τ to get to their jobs there. They derive utility from the numeraire consumption good c and housing q, which is measured in square meters and costs the rental price p.[3] We further assume that every dwelling comes with a unique vector of properties B, which can be amenities for households, like having a view, or indirect costs, such as a steep incline leading up to the property. These positive and negative properties summarized in B might affect the rental price households are willing to pay.

[2]Note that this might also be the outcome of an underlying search model in the housing market as discussed by Duranton and Puga (2015). Explicitly developing such a model is beyond the scope of our primarily empirical paper. As mentioned by Duranton and Puga (2015), p.24, "[...] to our knowledge, no one has uncovered the implications of housing search for land use."

[3]At this stage, adding the markup that we assume exists in imperfect housing markets would make notation more tedious but would not change the result.

Households first choose consumption c and housing q to maximize their utility, and they then search for the housing that maximizes their overall utility given the land-specific properties B and their own preferences ϵ. Household utility can then be expressed as

$$v(q, c, B, \epsilon) = u, \tag{6}$$

subject to the budget constraint

$$y = t \cdot x + p \cdot q + c \cdot 1. \tag{7}$$

Housing goes to the highest bidder. The maximum price a resident is willing to pay while enjoying a utility u for a location with properties B at a distance x from the city center, is ψ.

$$\begin{aligned} \psi &= \max_{q,c}\Big\{p \mid v(q, c, B, \epsilon) = u, \;\; y = t \cdot x + p \cdot q + c\Big\} && (8) \\ &= \max_{q}\Big\{\frac{y - t \cdot x - c(q, B, \epsilon, u)}{q}\Big\} && (9) \end{aligned}$$

eq. 9 is obtained by replacing c with the restricted Hicksian demand for the numeraire $c(q, B, \epsilon, u)$. Hence, for a given level of utility u the reservation price ψ is a function of housing demand and housing characteristics x and B.

2.1.2 Supply Side

Building firms use land L and capital K to build houses with a concave production function H that is homogeneous of degree one. Concavity $\frac{\partial^2 H(L,K)}{\partial K^2} < 0$ implies that higher buildings are increasingly more expensive to build. As in the standard model, we normalize by dividing by L and will work with $h = \frac{H}{L}$.[4] The capital-land-ratio $S = \frac{K}{L}$ is an "index for building height" (Brueckner, 1987). As usual, capital is rented at an exogenously given rate i.

[4] Note that this means that "developers are indifferent to the value of L; the size of housing complexes is indeterminate" (Brueckner, 1983, p.219).

To keep the analysis simple we assume that building firms own the land and face opportunity costs of r when using the land for housing. Firms' profit is then given by

$$\Pi = p \cdot H - i \cdot K - r \cdot L = L \cdot \Big(p \cdot h(S) - i \cdot S - r\Big) \tag{10}$$

Making use of Assumption 2 and eq. 9 we get:

$$\Pi \;\; = \;\; L \cdot \Big([\psi(q, x, B) + \delta(g)] \cdot h(S) - i \cdot S - r\Big) \tag{11}$$

Firms determine the capital-land-ratio S, our index for building height, to maximize their profit:

$$\frac{\partial \Pi}{\partial S} = (\psi(q, x, B) + \delta(g)) \cdot \frac{\partial h}{\partial S} - i = 0 \tag{12}$$

eq. 12 gives the optimal S as a function of the reservation price ψ and geographical constraints g: $S^*(\psi, g)$

2.1.3 Model Predictions

Combining the demand and the supply sides, we can derive the implicit equilibrium and perform a comparative static analysis. In particular, we can analyze the effect of ring-level geographical constraints g on two components of urban density, building height, and crowding:

Proposition 1. *In the stylized model, the effects of an increase in geographical constraints g in a certain ring of a city on urban density in this ring are as follows:*

(a) Building height S increases: $\frac{\partial S}{\partial g} > 0$

(b) Crowding $1/q$ increases: $\frac{\partial q}{\partial g} < 0 \longrightarrow \frac{\partial 1/q}{\partial g} > 0$

Proof: See Online Appendix A

Note that the effect of g is a pure supply-side effect that is independent from local land properties consumers might value via B.

In Online Appendix A, we also derive further results: As in the classical Alonso-Muth-Mills model, our model predicts that buildings get shorter, and crowding decreases with increasing distance x to the city center. Moreover, we analyze the effect of the local vector B of housing properties on building height and crowding; we find the effect to be ambiguous. Only if households are willing to trade off consumption with specific attributes of a dwelling so that $\frac{\partial C}{\partial B}$ is negative, will building heights increase with an increase in these attributes. For example, if consumers unambiguously value open space, building height will decrease with increasing distance to open space. However, if closeness to open space also correlates with distance to local economic centers like shopping areas, which consumers appreciate, the effect of distance to open space might be ambiguous. In general, making predictions on the effects of local land properties on urban development is difficult, and would require many assumptions on preferences. This is not the case when considering citywide geography g outside of the living areas of consumers. The implicit assumption behind our model is that consumers value natural amenities such as lakes only if they are nearby. Yet, a lake at the other side of the city might decrease suitable land for development, pushing up the markup for building land, and thereby affecting house prices and density. This is precisely the effect of g contained in Proposition 1.

To make a prediction for the total effect of g on urban density, we have to identify the effect on the third component, residential coverage. Our model does not directly allow us to make such a prediction. Empirically, the urban region consists of building footprints; public recreational areas such as parks;, private recreational areas such as yards; and roads and walkways, among other things. Making a priori assumptions of this feature for modeling purposing is nontrivial. The relation between building footprints and private yard space might be complex, for example. Brueckner (1983) examines yard space and its relationship to other goods (such as apartment size) in more detail in an extension of the Alonso-Muth-Mills model. Even in the absence of market power and building land limitations, Brueckner (1983) shows that model mechanics depend crucially on various assumptions such as the elasticity of substitution between floor space and yard space, or how the costs of yard space are shared. Adding the consumption of yard space to our stylized model would most likely not lead to unambiguous predictions on the effect of building land scarcity. Therefore, we remain agnostic on the effect of building land limitations on residential coverage, and the overall effect on urban density. In the case of an increase in residential coverage resulting from geographical constraints, all three components of urban density would be increasing. This would be a special case in which the total effect of geographical constraints on urban density would be unambiguously positive.

We have to keep in mind that our model is very simple and stylized because it has been designed to guide our empirical analysis of geographical heterogeneity and urban density. While such Alonso-Muth-Mills-style models are known to capture various features of real-life cities (Brueckner, 1987), they necessarily neglect a number of components compared to more sophisticated urban economics models such as Turner (2005), Ahlfeldt et al. (2015) and Murphy (2018). For example, there is no income heterogeneity in our model. Income is known to be correlated with desirable geographical amenities (Brueckner et al., 1999, Lee and Lin, 2018), and therefore might affect our results. In the empirical analysis, we take this into account by using mean neighborhood income as well as other sociodemographic variables as controls. Moreover, our model neglects the overall city-level effects. A reduction in available building land commonly increases urban density in the entire city, as shown by Saiz (2010). Our model deliberately abstracts from the effect that the distribution of geography in one ring has on the overall land available in the city, and the subsequent influence on the rental price level across the city. Again, this is done with a view to the empirical analysis, where includes *kommune*-level, and city-level fixed effects to account for political economy issues. Because these fixed effects combine to absorb the overall city-level effects, we do not study them from a theoretical perspective.

2.2 Empirical Strategy

Based on our considerations so far, we propose an empirical strategy for estimating the effect of geography-induced building land limitations on urban density. At the neighborhood level, we run regressions of the general form:

$$density = \beta_1 \cdot geo\_ring + \beta_2 \cdot x + \beta_3 \cdot geo\_local + \beta_4 \cdot controls + FE + \epsilon \quad (13)$$

The dependent variable *density* is neighborhood-level urban density or, in turn, its components: crowding, building height, and residential coverage. *geo_ring* measures the amount of land in a given ring that is unsuitable for development because of its geographical features, corresponding to g in our theoretical model. In all specifications, we include distance to the city center x, as well as local geographical features *geo_local* (corresponding to B in the model). Including local geography ensures that our effect is driven by overall scarcity of land plots with the given characteristics, rather than nearby land unsuitable for development. One *control* variable is the size of the rings; this accounts for the fact that rings mechanically increase in size with distance to the city center. Some specifications will involve additional *controls*. We employ sociodemographic and specific geographical variables, such as ocean view and sunshine hours, to capture a possible geographical effect on density that does not work through building land limitations but instead surfaces through the amenity aspects brought about by geographical features. Sociodemographic controls, such as income, age and the population composition, take care of the empirical correlation between income, life cycle, and desirable geographical amenities.

Most of the regulation in Norway happens either on the city or *kommune* level (Kommunal- og Moderniseringsdepartementet, 2008). Neighborhood residents have only a very limited scope to influence new development. Most indirect effects of regulation should therefore be captured by the *kommune*- and city -level *FEs*, which we include. The latter also allow us to account for different levels of urban density across urban clusters of different size. We are then able to separate the effect of ring geography from the overall effect that comes with a different geography across the entire city.

Overall, our theoretical considerations suggest the following main hypotheses:

Hypothesis 1. *More ring-level geographical constraints geo_ring in eq. 13 that limit building land*

- *increase crowding at the neighborhood level:* $\beta_1 > 0$ *when "density" captures crowding and*
- *increase building heights at the neighborhood level:* $\beta_1 > 0$ *when "density" captures building heights.*

If residential coverage also increases at the neighborhood level ($\beta_1 > 0$ *when "density" captures residential coverage), urban density increases at the neighborhood level (*$\beta_1 > 0$ *when "density" captures urban density).*

With this empirical strategy in mind, we proceed to the construction of the geo-spatial data set that puts it into action.

3 Data

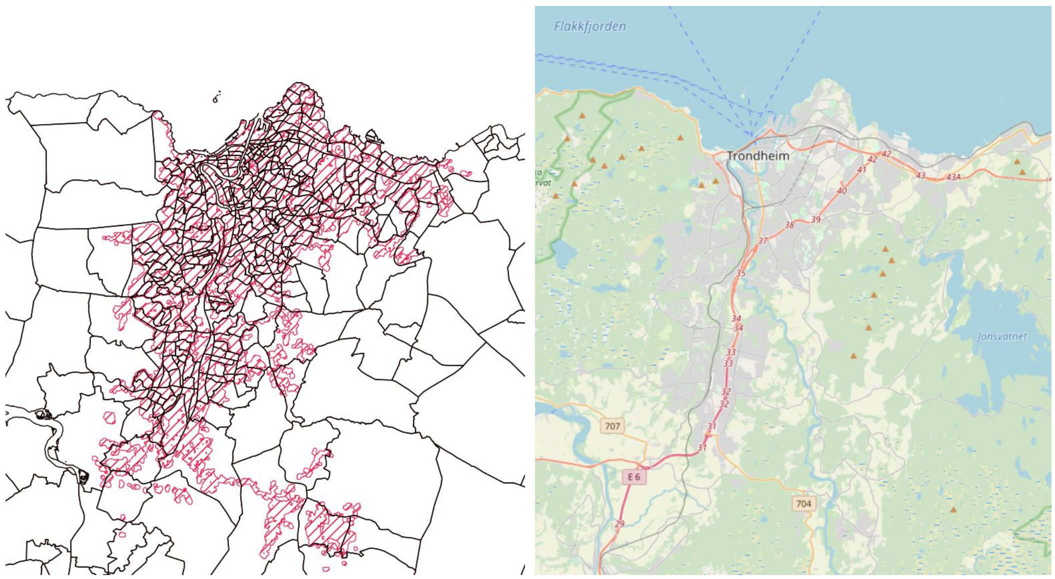
We conduct our analysis with Norwegian data for three main reasons: (i) We have high-resolution data to calculate density, its components, and geography, and to link these to socioeconomic characteristics at the neighborhood level. In particular, we can obtain neighborhood-level average pretax yearly income as well as demographic information from the population and income register, using data from 2013. (ii) The regulation influencing urban built-up is decided on the next higher administrative level, the *kommune* (Kommunal- og Moderniseringsdepartementet, 2008). In our study, this allows us to account for a large proportion of omitted variables related to the political economy of development regulation, whose importance has been shown in other studies (Duranton and Puga, 2015, Hilber and Vermeulen, 2016). (iii) Norwegian cities have a unique inner-city variation in geography, therefore providing an excellent testing ground for our hypothesis of building land limitations on density. At the same time, their natural shape with coasts, mountain slopes, and islands makes Norwegian cities particularly complex from the point of view of simple circular and monocentric urban economics models. If we can empirically confirm key model predictions in such a setting, it bodes well for other cities.

To be able to run regressions in the vein of eq. 13, we construct a novel data set with various high-resolution geo-spatial variables from a number of sources. We combine data on geographical features and ground elevation with building footprints and height, as well as administrative data on income and socioeconomic characteristics. In the following sections, we briefly define the neighborhood as unit of observation (Section 3.1), and describe the density measures (Section 3.2), the ring-based structure around the identified central business district (Section 3.3), and the geographical variables at the ring and local levels (Section 3.4). More details on the data and the process of data preparation are contained in Online Appendix B.

3.1 Unit of Observation: Neighborhood

In Norway, the smallest administrative unit is the *grunnkrets*, of which there are approximately 14,000. We define our unit of observation, the neighborhood, as the *consecutive residential built-up area of an urban grunnkrets*. We combine the information on continuous built-up areas from the European Settlement Map (ESM) with urban classifications from the Global Human Settlement Layers (GHSL) of 2015. Figure 1 shows the *grunnkrets* borders in black, and the urban residential built-up areas in red (on the left), compared to the area of Trondheim in the OpenStreetMap project (on the right).

Figure 1: Neighborhoods in Trondheim



Note: The figure shows the *grunnkrets* borders in black, and the urban residential built-up areas in red (on the left), compared to the area of Trondheim in the OpenStreetMap project (on the right).

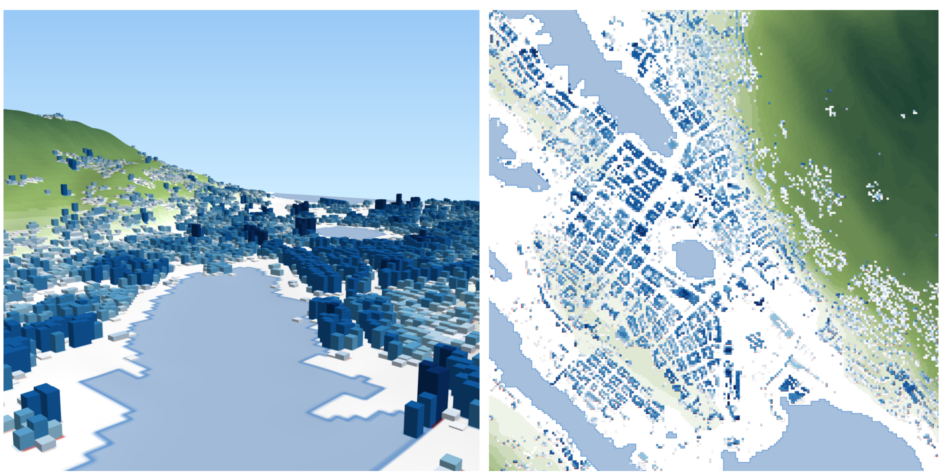
3.2 Urban Density and Its Three Components

Urban density, our main outcome variable, is calculated as the number of people per square kilometer of the urban, residential area.

3.2.1 Building Height and Footprint

For urban building footprint and height, we rely on the ESM data and high-resolution laser telemetry data from the National Detailed Altitude Model project provided by the Norwegian mapping authority. The data were collected from 2014 to 2016 by, for example, aircraft-mounted laser scanners. The vertical resolution is 10 m $\times$ 10 m; the horizontal resolution lies in the realm of centimeters. The output is the Norwegian Digital Surface Model (DSM), which includes all elevations, both natural and man-made. In addition, the Norwegian mapping authority also provides the so-called Digital Terrain Model (DTM) which reflects only ground elevation. Our approach is to take the difference between DTM and DSM data to yield non-ground elevation, including the height of man-made objects, such as houses, and natural objects, such as trees. We require the features to have a minimum height of 1 meter and to be marked as residential built-up in the ESM data, ending up with a 10 m $\times$ 10 m raster reflecting building heights for all of Norway. Defining a building footprint as an area these measurements indicate a positive building height, we construct the final building footprint map. To illustrate our approach, Figure 2 shows the 3D view of the old port of Bergen (Brugen) from the sea (on the left), and a "bird's eye view" of the city center (on the right). In both figures, blue indicates developed areas, with a darker blue indicating higher buildings.

Figure 2: Building Height and Footprint in Bergen



Note: The figure shows the 3D view of the old port of Bergen (Brugen) from the sea (on the left), and a "bird's eye view" of the city center (on the right). In both figures, blue indicates developed areas, with a darker blue indicating higher buildings.

3.2.2 Crowding and Residential Coverage

According to eq. 1, crowding is given by the number of people by the floor area in square meters. We extract the number of people residing in a neighborhood from Norwegian Register Data. We infer the floor area by the building volume divided by 3m (assumed to be the average floor height). The building volume is, in turn, calculated as the product of the building height and the building footprint:

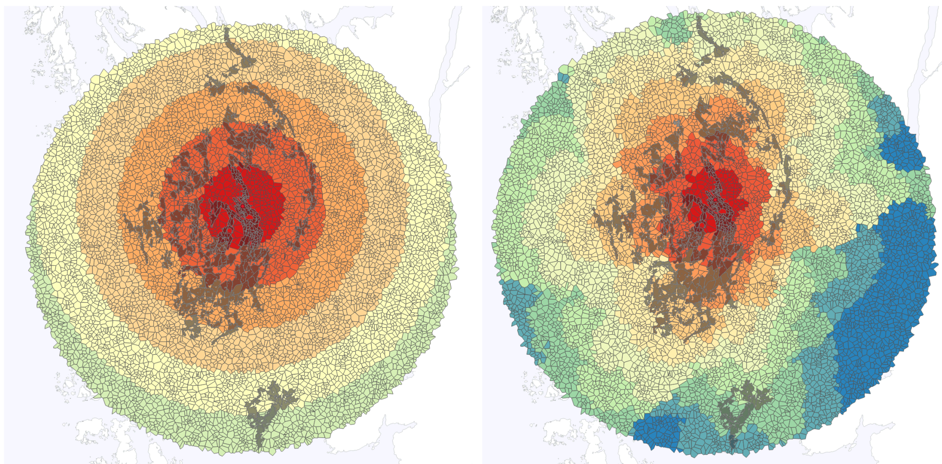
$$\text{Crowding} = \frac{\text{Pop}}{\text{Floor Area in } m^2} = \frac{\text{Pop}}{\frac{1}{3} \cdot \text{Building Height} \cdot \text{Footprint}}. \tag{14}$$

Residential coverage, the final component in eq. 1, is given by the building footprint divided by the urban, residential area. This means that a neighborhood with more parks, streets and/or private yards will have a lower residential coverage than a neighborhood where buildings are tightly packed next to each other.

3.3 Ring-Based City Structure Around the Central Business District

Distance to the city center is a key determinant of urban density in the literature because of commuting costs for households (Brueckner, 1987, Davies, 1974). In our setup we look at distance to the central busines district as a property of land that can be scarce due to city-wide building land limitations. By imposing building land limitations, geography might also affect travel costs. To separate both components, we classify neighborhoods into rings independent of geography based on their Euclidean distance to the city center in 1 km intervals. In our regression framework eq. 13, we include distance to the city center, and we calculate the geography-based shortest travel path to it (see Appendix Online Appendix B for more detail). We abstain from using actual travel distances on existing roads due to a policy bias. The comparison of the shortest travel path distance (right) with the Euclidean distance (left) in Figure 3 for the different rings around the city center of Bergen shows that controlling for the impact of geography on commuting distances looks relevant.

Figure 3: Bergen: Distance from the Rings to the City Center



Note: The figure shows neighborhoods within the circumference of the metropolitan area of Bergen. Color from red to blue indicates in increasing order the distance to the central business districts in 5km intervals. On the left: Euclidean distances. On the right: Distances based on the shortest path given the terrain. Gray borders indicate neighborhoods with urban development.

In our main specification, we will use the density of cafés recorded in the OpenStreetMaps data as a proxy for the central business district. Assuming that where people work they have to consume food and beverages, implies that a high density of cafés signals high levels of business activity. This is also in line with recent work linking cafés and restaurants as endogenous amenities to the city center (Aguiar and Bils, 2015, Baum-Snow and Hartley, 2017). As a robustness check, we create an alternative measure for the city center based on ports. In Norway, ports are natural harbors, and in an economy strongly driven by fishing, sea trade and more recently oil, they correlate strongly with historical city centers (Helle et al., 2006); see Online Appendix B for more details.

3.4 Geography

3.4.1 Land that is unsuitable for development

Our main explanatory variable is supposed to measure how geographical constraints within a ring of a city limit the areas that can be developed. We base this measure on several indicators linked to development costs, and expect the following variables to affect the extent to which building can take place within a given location:[5]

(i) **Slope mean**, the mean slope within a neighborhood measured in degrees. Higher slopes are known to increase building costs; Saiz (2010) finds that inclines of more than 15% are unsuitable as building sites. Nevertheless, a subset of slightly less than 10% of all neighborhoods in our data set has been developed, even on slopes with inclines greater than 15%; thus, we use this 15% slope as a cutoff value.

(ii) **Slope COV**, the coefficient of variation of the slope between 100m $\times$ 100m grid cells. It captures the irregularity of the terrain, which makes construction particularly difficult. Less than 10% of developed neighborhoods in Norway have a slope coefficient of variation higher than 0.6938003, so this will be our cutoff in this category.

(iii) **Elevation mean**, the mean elevation of a neighborhood. Higher altitudes increase development costs because raw materials have to be transported further up. Less than 10% of built-up neighborhoods in Norway are higher than 173.455m, which will serve as our cutoff value for land suitability.

(iv) **Ocean**, classified as every bit of land below the mean sea level. Building on or close to water is particularly challenging in the Norwegian fjords, where the sea beds become deep very quickly. We assume that areas on water are unsuitable for development.

[5]Note: All indicators are calculated from the 10m $\times$ 10m laser telemetry data from the National Detailed Altitude Model at the neighborhood or grid level.

We define areas as unsuitable for development as those that have at least one of the four characteristics above the cutoff value:

Assumption 4. *An area of land is unsuitable for development if* $\lambda = 1$ *where:*

$$\lambda = \begin{cases} 1 & slope\, mean > 8.5308 \cup slope\, COV > 0.6938003 \\ & \cup\, elevation\, mean > 173.455 \cup ocean > 0 \\ 0 & else. \end{cases} \tag{15}$$

In Figure 4 we compare the neighborhoods in Bergen that have developed urban areas (on the left) with those that are suitable for this by our definition (on the right). There is a strong overlap of our measure of suitability with the location of the areas that have actually been developed. Yet, at the city center, there are developed areas that our algorithm would declare as unsuitable, while at the outskirts the opposite is the case. This is well in line with our theoretical framework: Higher rental prices in the city core make it attractive to build even if building costs are higher than at alternative plots outside of the city.

Figure 4: Bergen Observed Urban Area vs Potential Land

Note: The figure shows neighborhoods within the circumference of the metropolitan area of Bergen. On the left, areas shown black indicate developed urban neighborhoods. On the right, areas in black indicate neighborhoods with a geography that is on average suitable for such development.

3.4.2 Ring Geography

Having established how we measure the unsuitability of land for development, we now apply this indicator to the ring level to calculate scarcity. The ring structure leads to a mechanical increase in land for development by $\pi \cdot (r^2 - (r-1)^2)$ when moving outwards from the city center – unless geography induces limitations. To calculate the area suitable for development as a measure of scarcity, we apply Assumption 4 to existing neighborhoods and artificial neighborhoods outside of the original neighborhoods. The artificial neighborhoods allow us to account for building land availability and geography outside of areas that have been developed.[6] Our measure for building land limitations within the rings is thus purely based on geography, and independent of the existence of the actual development.

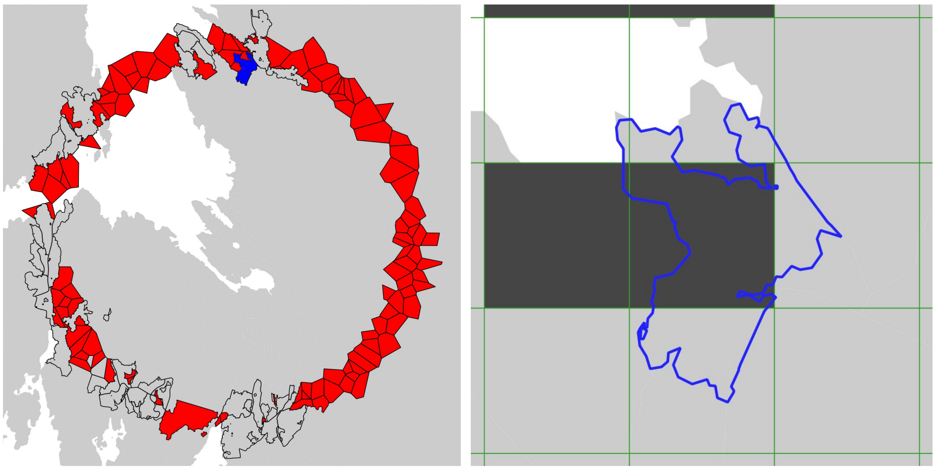
We calculate the land that is unsuitable for built-up within a ring of the city, referred to as **geo_ring** in our empirical analysis, as

$$geo\_ring_{rck} = \sum_{i \in r} \lambda_{irck} \cdot area_{irck}, \tag{16}$$

where $area_{irck}$ is the area of a neighborhood i in ring r in *kommune* k located in city c. Figure 5 (left panel) illustrates our approach. In red are neighborhoods classified as unsuitable for building development within ring 6 of Bergen (5-6 km from the city center). The sum of all red areas is our measure for geography-induced building land limitations in this ring. Note that we will control for the overall area of the ring.

[6] To generate artificial neighborhoods outside of the original neighborhoods, we randomly locate points within the circumference of the developed urban residential areas, and we generate Voronoi polygons with similar geometric properties as the actual neighborhoods (see Online Appendix B for an example). Note that we only use artificial neighborhoods when measuring geography with rings neighborhoods, but we do not use them in our main empirical analysis as dependent variable.

Figure 5: Ring and Local Building Land Measures



Note: The left figure shows the boundaries of neighborhoods within the ring 6 (5-6 km to the city center) of Bergen with black lines. Neighborhoods classified as unsuitable for development by Assumption 4 are marked in red. In both figures the same neighborhood is marked in blue. In the right figure the boundaries of a grid of 0.5x 0.5km cells are marked in green; cells in dark gray are classified as unsuitable for development by Assumption 4.

3.4.3 Local Geography

Our main channel of interest works through the of scarcity of lands with certain properties, such as distance to the city center, which is why we consider land suitable for development at the ring level. The most important control we need is the availability of building land within the vicinity of a neighborhood. To account for this local effect of building land restrictions we calculate two indicators, both based on a 0.5×0.5 km grid that classifies land as unsuitable for development based on Assumption 4:[7] (i) **geo_local_dist**, distance from a neighborhood to the nearest grid cell classified as unsuitable for development. (ii) **geo_local_area**, a proxy for the average area in square kilometers within

[7]At the local level we work with grid data for two reasons: (i) It ensures that the shape of neighborhoods and its surrounding neighborhoods does not influence the measures; think of a neighborhood and its adjacent smaller or larger neighborhoods. Note that for ring geography such problems are quantitatively much less of an issue than at the local level. (ii) With grid data, we can roughly control for an area around a neighborhood equal to the ring spacing we use.

0.8 km of a neighborhood that is classified as unsuitable for development. For each cell, we calculate the number of adjacent cells classified as undeveloped. We calculate the average of this number for a neighborhood and multiply it with the size of the cell.

Figure 5 (right panel) illustrates our approach. For the neighborhood marked in blue, the left panel shows the geography-induced building land limitations at the ring level in red. The right panel zooms in on the local level with boundaries of our 0.5 $\times$ 0.5 km grid marked in green. Cells suitable for development are marked in dark gray; land area is shown in light gray. For the cell at the center of the neighborhood, we see that only one of the surrounding cells is suitable for development, while seven are not, leading to an area of land unsuitable for development of 1.75 km^2. As the cell covers most of the neighborhood, the value for **geo_local_area** will be close to 1.75. As the center of the neighborhood is roughly in the middle of the central cell, the distance to the nearest cell that is unsuitable for development, **geo_local_dist**, will be around 0.5km.

The geography surrounding a neighborhood is likely to affect urban density indirectly through other channels as well. Mountains affect the sunniness of a neighborhood, the view, and transport costs to the city center. To isolate these mechanisms from the effect of building land limitations, we measure these characteristics individually and include them as control variables in our regressions. In particular, we generate the variable **sun hours** as the sunshine hours at equinox based on the surrounding terrain and longitude and latitude. Sunshine is an important amenity in the cross-city literature (Albouy and Lue, 2015), while, for example, data from New Zealand have shown that an extra daily hour of sunlight raises house prices by 2.3% (Fleming et al., 2018). In Norway, light in the winter is particularly precious, and our data reveal that in Norwegian cities some of the neighborhoods close to the cite center are literally on the dark side of town. This contrasts with the outskirts of cities, which have more sunny locations (see Online Appendix B). Moreover, we compute both **distance to the ocean** in *km* “as the crow flies”, as well as **ocean**

view, which is fulfilled, if more than 8 points on the ocean surface – approximately half a *sqkm* of ocean – are on average visible from the neighborhood. With these variables, we follow the real estate literature that has studied the effect of natural amenities on individual house prices for a long time (Davies, 1974, Nelson, 1972); see for instance Benson et al. (1998) and Bourassa et al. (2004) on ocean view, and Lee and Lin (2018) and Carlito and Saiz (2019) on proximity to the ocean.[8] Our data show that close proximity to the ocean does not always secure a view of the ocean (see Online Appendix B).

4 Descriptive Statistics

Having gathered all the data, we examine some statistics from our final data set. The summary statistics in Table 1 are calculated across the 3,478 neighborhoods in our sample. These are located in 13 urban clusters and 66 different *kommuner*. Lillehammer is the smallest urban cluster with around 14,000 inhabitants, one central business district, and 30 neighborhoods in one *kommune*. The largest cluster is Oslo with around 1,400,000 inhabitants, 10 central business districts, and 2,020 neighborhoods in 34 *kommuner* (for more details see Table C-1 in Online Appendix C). The average neighborhood has a mean of 665 inhabitants, reflecting the fine-grained nature of our analysis. Even the largest neighborhood, Skadberg in Stavanger, has only 5,725 inhabitants. The residential area of the average neighborhood is 0.27 sqkm.

Urban density exhibits strong variation. The average neighborhood has an urban density of 0.0041 people per square meter – or 41 people per hectare. The most densely populated neighborhood (Kampen Rode 5, close to the main port of Oslo) has 10 times as many people. The average crowding is 0.011 people per square meter of floorspace, the largest crowding implies an apartment size of 20 square meters per person (Lysskar in Haugesund). Residential cover-

[8]Hypothetically, an ocean view is one reason why hilly neighborhoods are empirically correlated with high incomes in many cities, the so-called "Beverly Hills effect" (see for instance Ye and Becker (2019)).

Table 1: Neighborhood Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Units
population	666.1668	491.4203	101	5725	pop
area	271861.7	270942.9	15031.62	2607329	m^2
footprint	45589.39	40044.42	1200	411400	m^2
			Density		
urban_density	0.0041124	0.0046471	0.0001419	0.0405212	$\frac{pop}{m^2}$
crowding	0.0111146	0.0070651	0.001698	0.0562575	$\frac{pop}{m^2}$
resid_cover	0.2062212	0.1086111	0.0300691	0.6561644	$share$
building_height	1.801583	0.762991	0.93041	6.160101	$floors$
			Geography and Distance to the CBD		
geo_ring	23.88457	20.26001	0.6444227	132.8266	km^2
geo_ring_share	0.6480632	0.1599635	0.2257895	1	$share$
dist_cbt	10.08044	11.66965	0.0996686	87.69476	km
geo_local_area	0.570633	0.3821387	0.0044402	2.315181	km^2
			Additional Local Geographic Controls		
elev_mean	74.1542	59.4953	1.771931	451.5524	m
slope_mean	4.495504	3.170848	0.0567857	28.58431	$degrees$
slope_cov	0.4248221	0.1960841	0.0012988	2.112248	$degrees$
sun hours	10.49466	0.889166	6.052083	12	$hours$
dist_ocean	6.576141	20.70945	0.0341827	135.6913	km
ocen_view	0.7113283	0.4532101	0	1	$binary$
			Socio-Demographic Controls		
income_pc	7.418064	1.717234	2.337588	20.25347	$\frac{10.000}{pop}\$$
income_pc_cov	0.8949535	0.4573723	0.358167	12.44372	$\frac{10.000}{pop}\$$
age	39.71693	5.496662	23.74138	82.91525	$years$
age_cov	0.5624322	0.0563508	0.1334791	0.7497294	$years$
retired	0.1869775	0.0975148	0	0.9322034	$share$
kid	0.2003951	0.0658677	0	0.4419831	$share$
migrant	0.1747338	0.1216314	0	0.8385461	$share$
sick leave	1.075057	0.2748867	0.1228861	2.361702	$share$

Note: Descriptive statistics are based on the final sample of 3,478 neighborhoods located within a 25km radius to the nearest city center. There are 13 urban clusters, 25 city centers, and 66 *kommuner*.

age shows the extent to which the area is covered by the footprint of buildings. Such residential coverage is 20.6% in the average neighborhood, it goes from a mere 3.0% (Torgård just on the outskirts of Trondheim) to 65.6% (Uranienborg Rode 6 in the center of Oslo). The average building height in the average neighborhood is 1.80 floors, but the neighborhood with the highest average building height is Solfjellet in Oslo with 6.16 floors. We also note a huge heterogeneity between the components of urban density: Neighborhoods with many high-rises may have a lot of parks and, hence, a low residential coverage (such as Solfjellet), or alternatively a high level of residential coverage (such as Kampen Rode 5) but only average crowding. Crowding might be high in family-friendly suburbs with small detached houses and many green spaces (Lysskar). In fact, the correlations between urban density and its components range from .76 to .02 (for details see Table C-2 in Online Appendix C). The descriptive statistics therefore indicate the need to study not just urban density but also its components, which can deviate from one another to a significant degree.

Our main explanatory variable, *geo_ring*, shows that on average, 23 km^2, of the land in a ring are unsuitable for development because of geography, which corresponds to around 64.8% of the ring area. In some rings these constraints correspond only to 22.6% of the land area, but in others it reaches the full 100%. On average, our neighborhoods are located 10.9 km away from their city centers, measured in terrain-based travel distance. At the local level, based on surrounding neighborhoods, 0.57 km^2 of the land is unsuitable for development (*geo_local*).

Looking at the additional local geographical variables, we see that mean elevation of the average neighborhood is 74.2m, with the mean slope varying considerably across neighborhoods (from 0.1 degrees to 28.6 degrees). Equinox sunshine hours range from 6.05 to 12. We see the importance of the ocean for Norwegian settlement structures. The average distance to the ocean is 6.6 km, and 71.1% of neighborhoods have an ocean view.

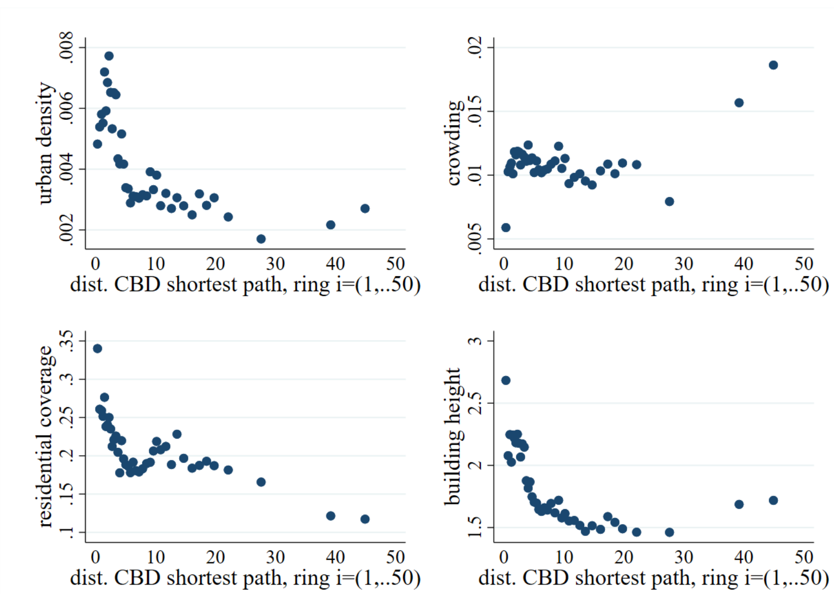
Finally, we turn to income (shown in US dollars), as well as other socioeconomic and demographic variables. The average neighborhood resident has a yearly income of $74,000, while in the wealthiest neighborhood is at more than $233,000 (Sentrum 3 Rode 4, the neighborhood closest to the yacht harbor in downtown Oslo). The poorest neighborhood is Hatleberget on the outskirts of Bergen with an average income per capita of $20,000. We also include the coefficient of variation of income as an inequality indicator. There is obviously a correlation between income and average age of the neighborhood inhabitants. Looking at further demographics, we see that the share of the retired population (aged 62 years and above) ranges from zero to 92.3%. The share of children and teenagers (under 18) is on average 20.0%, while the share of migrants (defined as those without Norwegian nationality, as well as Norwegian nationals born abroad) is on average 17.4%, but goes up to 83.9%. Finally, we include a health indicator, the number of yearly sick leave incidences per working population.

To gain further insights into the spatial distribution of the density, we plot the gradients of density and its components with distance to the central business district as bin scatter plots (Figure 6). Numerous empirical papers have confirmed the predictions of the Alonso-Muth-Mills model that population density is a downward-sloping function of distance to the city center (Batty and Longley, 1994, Bertaud and Malpezzi, 2014, Zielinski, 1980). Yet, to our knowledge, our paper conducts the first examination of such gradients by taking into account the three key density components: crowding, residential coverage, and building height.[9] For overall density, we observe an exponential decay pattern in line with the literature. Interestingly, this pattern appears to be mostly driven by the building-height component (lower right panel), which decays notably in a similar way with distance to the central business district. In terms of crowding (upper right panel), however, the pattern is less clear. There might be a slight downward slope up to the 30th ring around the central business district, while the few observations farther away do not support this hypothesis, and, instead, point toward an increase in crowding. Finally, for

[9] Ahlfeldt and Barr (2020) provide downward-sloping, building-height gradients for New York City and Chicago based on high-rise data from the Emporis database.

residential coverage (lower left panel), we again find a downward slope, which, however, does not appear to be monotonous. We conclude that urban density and most of its components decrease with distance to the central business district, but that this relationship is not uniform; factors other than distance might play a role. This leads us to our empirical analysis about building land limitations induced by geography.

Figure 6: Distance Gradients



Note: The figure displays the bin scatter plot of urban density (without controls) and the distance to the city center measured by the shortest path, given the terrain.

5 Results

5.1 Main results

Given the data described in Section 3, we concretize our estimation equation to:

$$ln(\mathbf{\Gamma}_{irck}) = \beta_1 \cdot ln(geo\_ring_{rck}) + \zeta_1 \cdot \mathbf{Z}_{irck} + controls + \kappa_k + \chi_c + \epsilon_{irck}, \quad (17)$$

where $ln(\mathbf{\Gamma}_{irck})$ is the logarithm of the vector of urban density measures discussed in Section 3.2 in neighborhood i, ring r (in Euclidean 1 km spacing), *kommune* k and city c. $ln(g_{rck})$ is our measure of geographical constraints in ring r as discussed in Section 3.4. $\mathbf{Z}_{irck}$ is the vector of standard controls that include all the log distance to the city center ($dist\_cbd_{irck}$) as described in Section 3.3; our measures for local land scarcity ($geo\_local\_dist_{irck}$ and $geo\_local\_area_{irck}$) as described in Section 3.4; and the size of the ring ($area\_ring_{rck}$). The *controls* contain additional geography- and sociodemographic controls. κ_k is a *kommune* fixed effect; χ_c is a city fixed effect; and ϵ_{ij} is the error term.

Table 2 contains our main results: the effects of geographical building land constraints on urban density. In the most parsimonious specification (column (1)), we find a positive effect that is statistically significant at the 95% level. A 10% increase in the share of geographical constraints in a given ring raises urban density of neighborhoods located anywhere in that ring by 2.95%. This is in line with Hypothesis 1 and our conceptual framework. Our results show that this scarcity-induced effect works differently from the local geographical features of a neighborhood – for which we control via *geo_local_area* and *geo_local_dist*. More land area unsuitable for development in the surrounding cells of a neighborhood decreases urban density. This local effect subsumes the increased building costs as well as the amenity values of geographical features in the immediate surroundings. By controlling for these local effects, we are left with the impact of geography in the same ring but farther away. In other words, scarcity comes into play, meaning that a given city neighborhood will have a higher density if there is a lake or steep incline at another city location that is the same distance from (in the same ring surrounding) the central business district. We also see that the total area of a ring has a negative impact on urban density, reflecting the fact that rings increase mechanically in the land area they contain with increasing distance to the the city center. The presence of ring area also explains the statistical insignificance of distance to the city center, which captures a very similar effect. Also note that the combination of *geo_ring* in square kilometers with *area_ring* allows us to interpret our main effect as land scarcity in relative terms. The higher the *share* of land unsuitable for development, the higher the urban density in all neighborhoods within the same ring.

Columns (2) to (5) of Table 2 show that our main result is robust to various alternative specifications and sets of control variables. From column (2) onward, we include additional local geographical controls, such as slope, ocean view and sunshine hours, as discussed in Section 4. Column (3) uses a different ring width of 2.5 km instead of the 1 km from the main specification. The inclusion of sociodemographic controls (see Section 4) in Column (4) ensures that the results are robust to the known correlation between income and density. Finally, column (5) identifies the central business district (CDB) based not on the café density but based on ports instead (see Section 3.3). What stands out in the comparison of the five different specifications is the similarity of the results. In fact, the coefficient estimate of our main effect of *geo_ring* on urban density increases slightly and becomes even more strongly statistically significant. We conclude that there is robust evidence of geographical constraints driving up urban density. The extent to which our regression "fits" is high in comparison to that of the related literature. Even without additional controls, the combination of building land limitations at the ring and local level as well as fixed effects can explain 43.8% of the neighborhood-level variations in urban density. When one takes into account additional geographic and sociodemographic controls, the effect is even stronger, rising to 63.1%.

Table 2: Urban Density and Land Development Limitations

	(1)	(2)	(3)	(4)	(5)
Dep.Variable:			log_urban_density		
log_geo_ring	0.295**	0.311***	0.453***	0.311***	0.323**
	(0.141)	(0.104)	(0.142)	(0.103)	(0.160)
log_area_ring	-0.760***	-0.731***	-0.781***	-0.673***	-0.494***
	(0.218)	(0.156)	(0.182)	(0.150)	(0.162)
log_dist_cbd	0.040	0.056	-0.083	0.029	-0.185***
	(0.045)	(0.043)	(0.051)	(0.030)	(0.055)
log_geo_local_area	-0.231*	-0.204**	-0.192**	-0.154**	-0.184*
	(0.119)	(0.086)	(0.079)	(0.065)	(0.100)
log_geo_local_dist	-0.003	-0.062**	-0.054**	-0.060***	-0.066***
	(0.030)	(0.027)	(0.026)	(0.022)	(0.024)
Add. Geo Controls	NO	YES	YES	YES	YES
Socio-Dem Controls	NO	NO	NO	YES	NO
Ring Width	1 km	1 km	2.5km	1 km	1 km
CBD Def	Cafés	Cafés	Cafés	Cafés	Ports
Observations	3,478	3,478	3,478	3,478	3,311
R-squared	0.438	0.512	0.508	0.631	0.506

Note: The table reports regression results of eq. 17 using log urban density as the dependent variable. For variable definitions, including the list of additional geographical and socioeconomic controls, see Table 1 in Section 4. All regressions include fixed effects at the city and *kommune* level. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city centers = 25, and the number of *kommune* = 66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

In Table 3 we look at the three components of urban density: crowding, residential coverage, and building height. We use the specification from Table 2, column (2), including the additional specific, local geographic controls. We reproduce the effects on total density in column (1) for comparison. We see that the positive effect of geographical constraints on urban density is almost exclusively driven by the responses in building heights. A doubling of geographical constraints leads to a 8.7% increase in average building height (which at the mean would be 0.2 floors, or around half a meter). The response of residential coverage is only statistically significant at the 90% level; the response of crowding is statistically insignificant. Still, all the three coefficients are positive, which is in line with Hypothesis 1.

Looking at the other variables in Table 3, we note that distance to the city center has a very different effect on the three components. Building height decreases with distance to the city center, in line with theory and our observed gradients in Figure 6. We also note a highly statistically significant decrease in residential coverage. Yet, there is a strong increase in crowding with distance to the city center, which drives down the overall effect of density.[10] This finding parallels the assertions put forward in Brueckner (1983), who argues that crowding and residential coverage might move into opposite directions if households consider apartment size and yard space as substitutes.[11] Table 3 also reveals which of the local geographic control variables has the strongest effects on the density components: Elevation has a negative effect on building height. Yet, it is slope rather than elevation – and, in particular, the coefficient of variation of slope – that has a strong and negative effect on urban density and all of its complements. This is arguably due to building costs. Neighborhoods where the terrain is very uneven have less crowding, less res-

[10] This effect holds regardless of whether the ring area or ring FEs are taken into account.

[11] Brueckner (1983) writes, "Under the Cobb-Douglas assumptions, yard space per dwelling is always increasing in x, while floor space per dwelling may be increasing, constant, or decreasing in x depending on the relationship between production and utility function parameters. Note that since intuition suggests that floor and yard space will in fact be substitutes rather than complements, the type of peculiar attribute behavior found in this example is a conceivable outcome in real-world cities."

Table 3: Urban Density Components and Land Development Limitations

Depend.Var:	(1) ln(urban density)	(2) ln(crowding)	(3) ln(residential coverage)	(4) ln(building height)
log_geo_ring	0.311***	0.052	0.171*	0.087**
	(0.104)	(0.107)	(0.098)	(0.038)
log_area_ring	-0.731***	-0.214	-0.325***	-0.192***
	(0.156)	(0.145)	(0.105)	(0.046)
log_dist_cbd	0.056	0.251***	-0.143***	-0.053**
	(0.043)	(0.035)	(0.027)	(0.023)
log_geo_local_area	-0.204**	-0.055*	-0.097**	-0.052
	(0.086)	(0.031)	(0.037)	(0.051)
log_geo_local_dist	-0.062**	-0.048**	-0.016	0.002
	(0.027)	(0.021)	(0.015)	(0.011)
log_elev_mean	-0.005	0.068**	0.039	-0.113***
	(0.049)	(0.031)	(0.030)	(0.027)
log_slope_mean	-0.076**	-0.069***	0.024	-0.031
	(0.035)	(0.023)	(0.023)	(0.020)
log_slope_cov	-0.411***	-0.191***	-0.151***	-0.069***
	(0.037)	(0.030)	(0.019)	(0.023)
log_sun_hours	0.387	-0.654***	1.138***	-0.097
	(0.521)	(0.216)	(0.326)	(0.161)
log_dist_ocean	0.044	0.029	-0.023	0.038**
	(0.040)	(0.019)	(0.020)	(0.019)
ocean_view	0.004	-0.033	0.016	0.021
	(0.042)	(0.039)	(0.039)	(0.023)
Observations	3,478	3,478	3,478	3,478
R-squared	0.512	0.310	0.544	0.551

Note: The table reports regression results of eq. 17, where the dependent variable is, in turn, urban density and its components: crowding, residential coverage, and building height. All regressions include fixed effects at the city and *kommune* levels. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city centers, and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

idential coverage, and shorter buildings. As regards the amenities, sunshine hours decrease crowding – possibly an income effect – and increase residential coverage. Distance to the ocean increases building height. However, after controlling for other variables, we find that an ocean view itself has no significant effect on density. Also note that the R^2 varies across the three components. The building height component can be explained very well (R^2 of 55.1%). By contrast, for crowding other factors seem to play a part (R^2 of 31.0%).

In Online Appendix D, we conduct a set of further robustness tests. First, we show that using the spatial standard errors by Conley (1999) does not alter our results. As Conley standard errors are typically smaller rather than larger, our coefficients remain significant at the same or at an even higher level of statistical significance. Next, we rerun the regressions on the density components from Table 3, under the following conditions: (i) when rings have a width of 2.5 km rather than 1 km (Table D-3); (ii) when the city center is defined based on ports rather than on the café density (Table D-4); (iii) by leaving out the outermost neighborhoods that are farther than 10 km from the central business district (Table D-5); (iv) by leaving out the innermost neighborhoods that are closer than 5km to the central businesss district (Table D-6); and (v) by merging neighborhoods from the same *kommune* in the same ring (Table D-7). Our main results hold across all specifications. Indeed, the results increase in magnitude in some instances.[12] Note that the last three specifications come with a sizable reduction in the number of observations, which makes it all the more remarkable that our main coefficient estimates stay strongly statistically significant. Also, the relative importance of the components of urban density remains, with the effects on total density driven by building height.[13] All these alternative specifications ensure us that our results are not driven by specifics of the city center or the outskirts, or by the administrative processes behind the definition of a *grunnkrets* that underlies our neighborhood data.

[12]This holds particularly when excluding the city core in (iv). This specification mitigates concerns that our results could have been influenced by specifics of the city core, such as the height of historical buildings, or the mixture between office and residential dwellings.

[13]The only exception to this is the specification with a 2.5km ring spacing, where the density effect is instead driven by crowding.

We conclude our analysis of the different specifications by taking a step back. Arguing that our effect of building land restrictions works through scarcity of neighborhoods with the same property, we have until now focused on one particular property: distance to the central business district. For this reason we have worked with ring-based geography. But one can also classify neighborhoods according to a different property. In Table D-8 we split up the neighborhoods of a city based on their average hours of sunshine. We find that the presence of more available plots for a given sunshine duration at the city level decreases urban density, underlining the scarcity mechanism.

5.2 Implications

Having established the effect of geography-induced building land restrictions on density and its components, we next set our results into a broader context. Urban density is thought to affect a number of socioeconomic outcomes (see for example Brownstone and Thomas, 2013, Ciccone and Hall, 1996, Larsson, 2014). The meta-study by Ahlfeldt and Pietrostefani (2019) provides elasticities of cross-city density and various outcome variables. For example, density is associated with higher wages (elasticity of 4%), higher wage inequality (elasticity of 3.5%), a higher mortality risk (elasticity of 9%), and higher subjective well-being (elasticity of 0.4%). With our neighborhood-level data, we are in a position to study the association of inner-city density with various outcomes that we can also observe at the neighborhood level. This allows us to investigate to what extent the cross-city patterns of density and its covariates hold within cities. When looking at the following results, one should be careful not to interpret the associations as causal effects; rather, they should be seen as associations in the vein of Ahlfeldt and Pietrostefani (2019). To keep estimates simple and comparable to those of the literature, we estimate elasticities without any other controls other than the *kommune* fixed effects.

In Table 4 we see that urban density is associated with lower per capita income (elasticity of 6.9%). This contrasts with the findings of previous literature showing a positive elasticity between density and wages in the cross-city setting. Panel B reveals that this result is driven by crowding and building height, which both have a highly statistically significant and negative association with income per capita. Similarly, we find a negative elasticity between urban density and income inequality of 10.8%. Again, this differs from the cross-city literature, which has concluded that the elasticity between urban density and income inequality is positive. These findings from our more granular analysis suggest that different economic mechanisms are at play in the inner city than at the cross-city level.

While an in-depth analysis is beyond the scope this study, the productivity-enhancing effects of density (Ciccone and Hall, 1996, Rosenthal and Strange, 2004) can be thought to play a larger role at the city level. Moreover, the analysis demonstrates that neighborhood-level density is also influenced by sorting and residential choice (Albouy and Lue, 2015, Kuminoff et al., 2013).

We examine further variables, finding that age has a negative association with the average crowding of a neighborhood, and that overall density has a negative elasticity with the age covariance. This suggests that in dense neighborhoods – particularly those with high building heights – inhabitants are, ceteris paribus, of similar age. Life-cycle based housing decisions, with families with children moving to less dense suburbs, might matter here (Andersen, 2011, Kim et al., 2005). We also note a strongly significant and positive elasticity of 18.1% between urban density and the migrant share, which again is driven by building height. Finally, we look at health outcomes. The literature points to a positive elasticity between cross-city density and mortality. We look at the issue by analyzing instances of sick leave per working population at the neighborhood level. The elasticity between density and sick notes is nearly zero (see column 6), but the individual density components reveal two highly significant and opposite effects. Residential coverage is negatively associated with the number of sick notes, but crowding exhibits a strongly positive elasticity (9.5%). Infectious diseases might play a role here, along the lines of Rocklöv and Sjödin (2020), who link the spread of COVID-19 to urban density.

Table 4: Elasticities of Inner-City Density and Its Components with Outcomes

Depend.Var:	(1) ln(income p.c.)	(2) ln(income p.c. cov)	(3) ln(age)	(4) ln(age cov)	(5) ln(migrant share)	(6) ln(sick notes)
Panel A: Urban density						
ln(urban density)	-0.069***	-0.108***	-0.006	-0.032***	0.181***	-0.000
	(0.008)	(0.019)	(0.010)	(0.009)	(0.028)	(0.026)
constant	1.576***	-0.807***	3.636***	-0.771***	-0.899***	0.039
	(0.048)	(0.113)	(0.056)	(0.049)	(0.167)	(0.150)
R^2	0.386	0.142	0.113	0.091	0.261	0.179
Panel B: The components of urban density						
ln(crowding)	-0.091***	-0.172***	-0.025***	0.011*	0.051	0.095***
	(0.020)	(0.032)	(0.009)	(0.006)	(0.042)	(0.028)
ln(residential cover.)	0.047**	0.060***	-0.023**	-0.000	-0.004	-0.105***
	(0.021)	(0.022)	(0.009)	(0.006)	(0.090)	(0.027)
ln(building height)	-0.251***	-0.298***	0.065	-0.189***	0.819***	0.004
	(0.019)	(0.033)	(0.041)	(0.009)	(0.102)	(0.068)
Constant	1.770***	-0.721***	3.485***	-0.432***	-2.154***	0.297***
	(0.064)	(0.120)	(0.033)	(0.028)	(0.172)	(0.107)
R^2	0.477	0.217	0.139	0.277	0.343	0.249
Observations	3,506	3,506	3,506	3,506	3,506	3,506
Kommune FE	YES	YES	YES	YES	YES	YES

Note: The table reports regression results of outcome variables on, respectively, density (Panel A) or its individual components (Panel B). Standard errors are clustered at the *kommune* level. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Taken together, the elements of our elasticity analysis show that understanding urban density and its effects is important for policymakers. Density might have different associations with socioeconomic outcome variables at the neighborhood than at the cross-city level, and these might be driven by particular density components. Our paper sheds light into how building land limitations and the distance to the city center determine density. Policymakers who are aware of these underlying mechanisms can shape urban density with a view toward influencing socioeconomic structures.

6 Conclusion

Urban density varies strongly within cities. The theoretical and empirical literature has mostly focused on distance to the central business district as the main explanatory factor of this variation. By contrast, we examine the role of local geography and its implication for available land upon which to construct buildings and develop cities. Exploiting fine-grained geo-spatial data at the neighborhood level from Norway, we are able to show a positive effect of geographical constraints on urban density. Crucially, this effect is driven by scarcity in a way that is independent from local, neighborhood-level geographical features. This result is robust to various different specifications and supported by a theoretical framework as a motivation.

To the best of our knowledge our paper is the first to examine urban density by overall density, but also its three key components – crowding, building height, and residential coverage – at the neighborhood level across cities. Our analysis does this by combining geographical data with building footprints and high-resolution elevation data. We provide evidence that all three components increase in response to geographical constraints, with the effect on building height the strongest. In addition, we analyze how the density components behave as a function of distance to the central business district. The findings suggest that building height and residential coverage react in a more uniform way to geographical constraints than crowding. The crowding response may be explained in part by the trade-off between apartment size and yard space, as discussed by Brueckner (1983) in his theoretical model. This finding calls for further empirical research in this direction to gain further insights into this relationship.

From a policy perspective, our findings for the first time make it possible to predict and gauge how building land restrictions affect urban density and its components. Our study overcomes the bias that results from political economic factors that have already influenced existing urban density. We overcome this by using the high exogenous variation in geography that limits development in Norway, and fine-grained data that allow us to control for regulation that is set at a higher administrative level than our unit of observation. Our findings indicate that if policy makers aim to increase urban density in parts of a city they can do so by using regulations to establish and expand the presence of open public spaces – for example, by dedicating space to parks. [14] Importantly, our results show that by changing the availability of land with certain development properties, such policy levers might have effects on both the surrounding neighborhoods and on the urban density of neighborhoods in other parts of the city.

Proost and Thisse (2019, p.615) have expressed surprise that so few papers have examined building heights, "given the importance of the subject matter." We hope that our approach of deriving high-resolution building-height data will open the door to many more applications on urban density – leading us to better understand its components, effects, and determinants in cities around the world.

[14] Note that for US cities there is evidence that parks can become a "public bad" in the presence of high levels of crime (Albouy et al., 2020). If such effects persist over a long period, they might alter the effect of open space on urban density.

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A Theory Appendix

A.1 Proof of Proposition 1

Here we provide the proof of Proposition 1 about the positive effect of geographical restrictions g on both building height S and crowding $1/q$.

We derive the effect of g on building height S by taking the total differential of eq. 12 with respect to g, making use of the assumption of decreasing productivity of capital and Assumption 3 to obtain:

$$\frac{\partial \frac{\partial \Pi}{\partial S}}{\partial g} = \frac{\partial \delta(g)}{\partial g} \cdot \frac{\partial h}{\partial S} + (\psi + \delta(g)) \cdot \frac{\partial^2 h}{\partial S^2} \cdot \frac{\partial S}{\partial g} = 0, \quad \text{((A-1))}$$

$$\frac{\partial S}{\partial g} = -\underbrace{\frac{\partial \delta(g)}{\partial g}}_{>0} \cdot \underbrace{\frac{\partial h}{\partial S}}_{>0} \cdot \Big(\underbrace{\psi + \delta(g)}_{>0}\Big)^{-1} \cdot \Big(\underbrace{\frac{\partial^2 h}{\partial S^2}}_{<0}\Big)^{-1} > 0. \quad \text{((A-2))}$$

We find that buildings are higher in rings with more geographical constraints. Note that this is a pure supply-side effect that is independent from local land properties consumers might value via B.

As regards the effect of g on crowding $1/q$, let us consider apartment size q. In equilibrium, we have demand and supply of housing equal to $q^* = q(p^*)$ where $p^* = \psi(x, B) + \delta(g)$. We can take the total derivative of q^* forward g while making use of Assumption 3 to get:

$$\frac{\partial q^*}{\partial g} = \frac{\partial q}{\partial p} \cdot \frac{\partial \delta}{\partial g} < 0. \quad \text{((A-3))}$$

The model therefore predicts crowding $1/q$ to increase with an increasing number of land plots being not suitable for development because of geographical obstacles. This completes the proof.

A.2 Additional Comparative Static Results

Here we provide additional comparative static results of our stylized model. In particular, we first analyze the effects of distance to the city center x and then of local building land properties B.

Making use the envelope theorem, the derivative of the reservation price ψ with respect to distance x can be obtained from eq. 9:

$$\frac{\partial \psi}{\partial x} = -\frac{t}{q} < 0. \tag{(A-4)}$$

We see that willingness to pay for rents unambiguously decreases with distance to the city center. Note that this is the same expression as in the standard Alonso-Muth-Mills model.[1]

In equilibrium, we have demand and supply of housing equal to $q^* = q(p^*)$ where $p^* = \psi(x, B) + \delta(g)$. Taking the total derivative of q^* forward x and making use of eq. (A-4) and the standard assumption that price negatively influences housing consumption ($\frac{\partial q^*}{\partial p} < 0$) we get:

$$\frac{\partial q^*}{\partial x} = \frac{\partial q}{\partial p} \cdot \frac{\partial \psi}{\partial x} > 0. \tag{(A-5)}$$

As crowding is defined as $\frac{1}{q}$, the model predicts crowding to decrease with distance to the city center.

Let us look at the effect of x on building height S. We start by taking the total differential of eq. 12 with respect to x, making use of the assumption of decreasing productivity of capital and eq. (A-4) to obtain:

[1] Note that we do not let properties B systematically depend on x. If this were the case, we would obtain the expression from Brueckner et al. (1999) with amenities, which contains an additional term for that.

$$\frac{\partial \frac{\partial \Pi}{\partial S}}{\partial x} = \frac{\partial \psi}{\partial x} \cdot \frac{\partial h}{\partial S} + (\psi + \delta(g)) \cdot \frac{\partial^2 h}{\partial S^2} \cdot \frac{\partial S}{\partial x} = 0, \qquad \text{((A-6))}$$

$$\frac{\partial S}{\partial x} = \underbrace{\frac{t}{q}}_{>0} \cdot \underbrace{\frac{\partial h}{\partial S}}_{>0} \cdot \Big(\underbrace{\psi + \delta(g)}_{>0}\Big)^{-1} \cdot \Big(\underbrace{\frac{\partial^2 h}{\partial S^2}}_{<0}\Big)^{-1} < 0. \qquad \text{((A-7))}$$

Like in the standard model, we obtain the result that buildings get shorter with distance to the city center.

Finally, turning to the vector of housing properties B, we can compute the partial derivative of the reservation price ψ with respect to B based on eq. 9:

$$\frac{\partial \psi}{\partial B} = -\frac{1}{q} \frac{\partial c}{\partial B}. \qquad \text{((A-8))}$$

If households are willing to trade off consumption with specific attributes of a dwelling so that $\frac{\partial C}{\partial B}$ is negative, the whole expression in eq. (A-8) is positive. This would for example imply that consumers are willing to pay higher rental prices in areas with more desirable local amenities. Making use of this, we get from the total derivative of q^* forward B:

$$\frac{\partial q^*}{\partial B} = -\frac{\partial q}{\partial p} \cdot \frac{\partial c}{\partial B}. \qquad \text{((A-9))}$$

Hence, if there is reason to believe that a specific attribute of a dwelling is desirable so that $\frac{\partial c}{\partial B} < 0$, then crowding will increase with an increase in this attribute. For example, if consumers unambiguously value open space, crowding will decrease with increasing distance from open space.

We can derive the effect of local land properties on building height S by taking the total differential of eq. 12 with respect to B making use of the assumption of decreasing productivity of capital and eq. (A-8) to obtain:

$$\frac{\partial \frac{\partial \Pi}{\partial S}}{\partial B} = \frac{\partial \psi}{\partial B} \cdot \frac{\partial h}{\partial S} + (\psi + \delta(g)) \cdot \frac{\partial^2 h}{\partial S^2} \cdot \frac{\partial S}{\partial B} = 0, \tag{(A-10)}$$

$$\frac{\partial S}{\partial B} = \frac{1}{q} \frac{\partial c}{\partial B} \cdot \underbrace{\frac{\partial h}{\partial S}}_{>0} \cdot \Big(\underbrace{\psi + \delta(g)}_{>0}\Big)^{-1} \cdot \Big(\underbrace{\frac{\partial^2 h}{\partial S^2}}_{<0}\Big)^{-1}. \tag{(A-11)}$$

If households are willing to trade off amenities against consumption so that c depends negatively on B, the first term in eq. (A-11) is positive, and the expression becomes positive. To stay with our example, if consumers values closeness to open space, building height will decrease with increasing distance to open space. If closeness to open space, however, also correlates with distance to local economic centers like shopping areas and consumers appreciate this, the effect of distance to open space might be ambiguous. By contrast, the effect of ring-level geography g is always positive, because it works through the scarcity channel and has nothing to do with consumers' valuation of local attributes.

B Data Appendix

This data appendix complements Section 3 in the paper by providing more detail on the data and the process of data preparation, including additional illustrations.

B.1 Unit of Observation: Neighborhood

We define our unit of observation, the neighborhood, as the *residential development area of an urban grunnkrets*. The administrative boundaries of the *grunnkretser* reflect the status in 2013. Our measure of residential development area is based on high resolution remote sensing data (10m $\times$ 10m) indicating residential development which we extract from the European Settlement Map (ESM) of 2015.[2] We calculate a buffer with a radius of 50m around all areas with residential development (DN=255). To distinguish between consumption and production, we deliberately do not account for development that is clearly industrial and hence labeled with DN=250 in the ESM data. We drop all non-contiguous areas where the ratio of development area to urban area is less than one to ten. The latter step removes small standalone housing settlements far away from the agglomeration. We do so because *grunnkretser* at the fringe of urban agglomerations are typically more extended than in the core and might include very small remote house groups that we do not think belong to the urban agglomeration.

To identify urban residential areas we match the residential development area with Global Human Settlement Settlement Model (GHS-SMOD) grid data from 2015. The GHS-SMOD data indicates on a 1 km $\times$ 1 km grid level the 'degree of urbanization' as defined by EUROSTAT. We keep all residential development areas that are within or adjacent to areas that are classified as urban in the GHS-SMOD data (DN>20). This includes the urban core but

[2] ESM data is derived via machine learning applied to the Copernicus VHR_IMAGE_2015 data set based on the satellite images from Pleiades, Deimos-02, WorldView-2, WorldView-3, GeoEye-01 and Spot 6/7 ranging from 2014 to 2016.

also urban peripheral areas like suburbs.

This way, we arrive at the 3478 neighborhoods to be included in our final sample. At the *grunnkrets* level, we also have access to the number of residents and their average socioeconomic characteristics. We extract this data from the Population and Income Register of Norway. It contains information on the average pretax yearly income of all residents of all *grunnkretser* that have more than 100 inhabitants in the year 2013. The minimum restriction is imposed by the authorities to secure privacy regulations. It does not constitute a problem for our analysis because it only leads to the loss of a handful of *grunnkretser* in the Northern Finnmark region which are far from any urban area and therefore not in our sample.

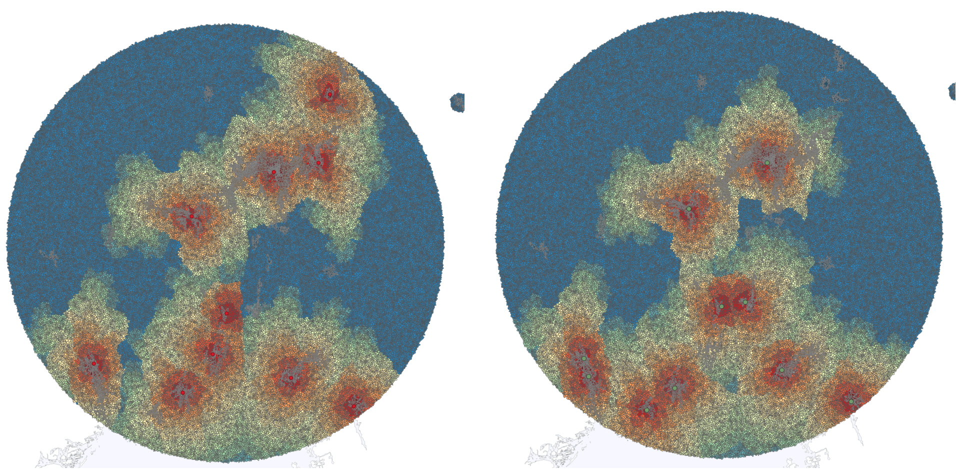
B.2 Distance to the City Center

Here we provide more information on the calculation of distance based on the shortest path through the terrain, as well as the definition of the city center. To calculate the shortest path, we assume that transport costs are equal to the incline of the terrain and that traveling over water has a cost equal to a 10 degree incline in a 100m $\times$ 100m raster. Comparing actual road data and shortest paths reveals that overground roads are often very close to shortest paths. Larger deviations are often associated with the extent of tunnels.

As regards the city center, the definition for our main analysis is based on the density of cafés. Using the Open Street Map data on the location of cafés, we define the gravitational center of consecutive areas that are larger than half a sqkm and have a café density of more than 5 cafés per sqkm to be a city center. This definition allows us to define at least one city center in all except three clusters of urban areas classified by the ESM data and our development data. In the cases of Halden, Haugesund and Kristiansund we had to reduce the cafe density cutoff to obtain at least one city center. In downtown Oslo we merged the city centers that had less than 5km distance to one another. In this way, we obtain a total of 25 city centers in all urban areas in Norway in our final sample. Most urban areas only have one city center, but some have more and, formidably, the metropolitan area of Oslo has 10 city centers.

For a robustness check, we define the city center based on ports, using data on the size of ports from the World Port Index. As the coordinates of the ports reported in the World Port Index are in some cases on land and in others on water, we unify locations using daylight satellite images by hand. Moreover, we compare pre-industrial-revolution maps of Norway with the location of ports in urban areas to prove that they are highly correlated. Hence, the location of ports captures historical - and still modern-day - city centers. Based on the port location, we obtain 19 city centers for all urban areas in Norway in our final sample. Most urban areas only have one city center, but some have more and the metropolitan area of Oslo has 9 city centers. Figure B-1 compares the two definitions of the city center for Oslo.

Figure B-1: Oslo City Centers



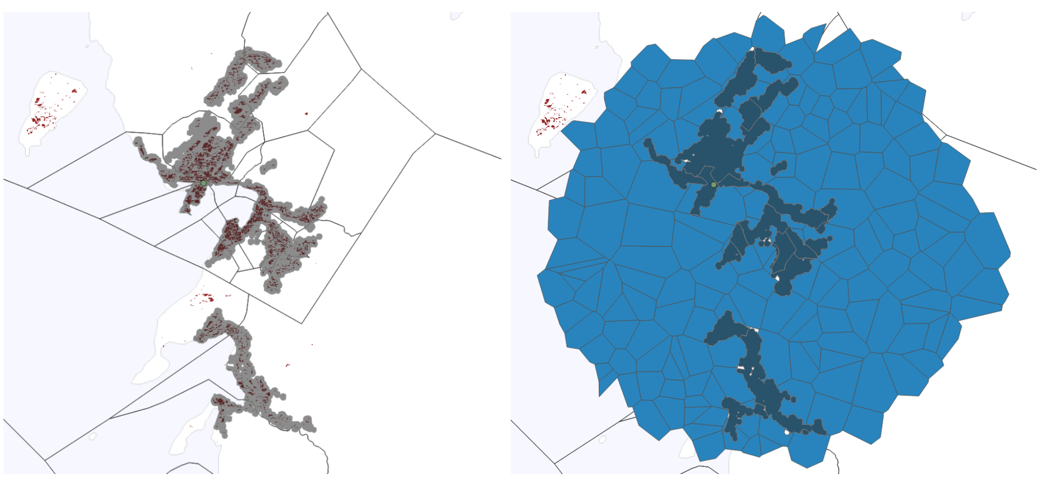
Note: The figure shows neighborhoods within the circumference of the metropolitan area of Oslo. Color from red to blue indicates in increasing order the distance to the city centers measured by the shortest path. On the left, city centers are defined by café density; on the right based on port locations. Gray borders indicate neighborhoods with urban development.

B.3 Geography

When analyzing the suitability of a certain neighborhood for development, we have to avoid the circulatory argument of looking only at developed areas. In the construction of *geo_ring*, we therefore work with both the original neighborhoods and artificial neighborhoods outside of the original neighborhoods. For this, we randomly locate points within the circumference of the urban residential development areas and generate Voronoi polygons with similar geometric properties as the actual neighborhoods.

To illustrate our approach, Figure B-2 presents the case of Hammerfest (though not part of the final data set because it is not classified as urban agglomeration). On the left, the urban residential development areas (gray) and development (red) are displayed; on the right, one can see the artificial Voronoi neighborhoods.

Figure B-2: Hammerfest Neighbourhoods and Artificial Neighborhoods



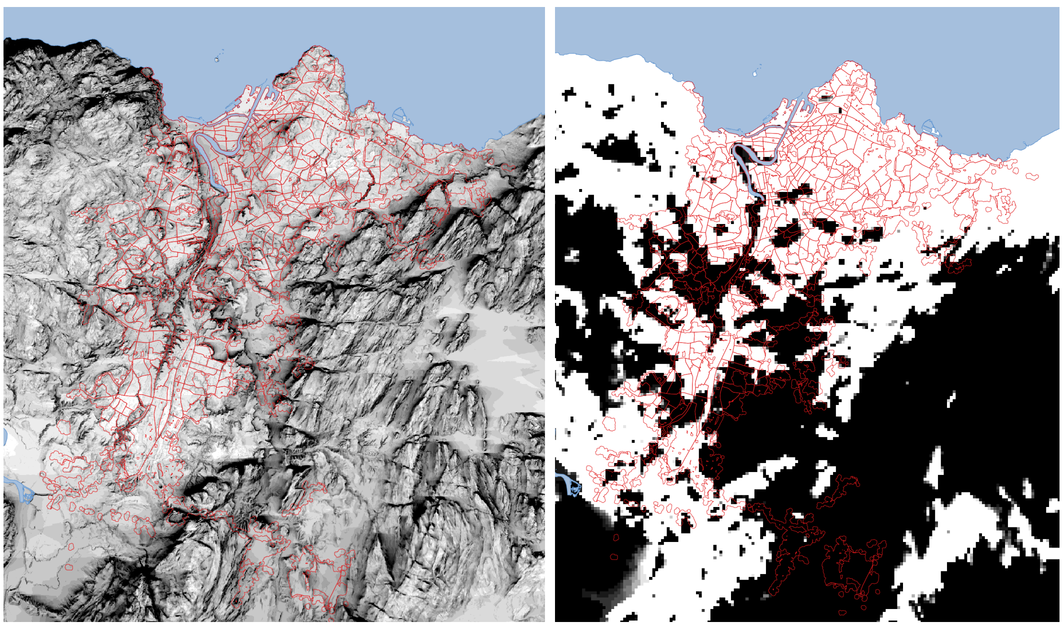
Note: The figure shows neighborhoods within the circumference of the small town of Hammerfest. On the left, the black lines indicate original *grunnkrets* borders, gray areas urban development areas and red areas actual development. The picture on the right displays the artificial Voronoi neighborhoods in blue and the actual neighborhoods defined by the urban development areas of the *grunnkrets* in gray.

In the following, we present illustrations of the *sun hours*, *distance to the ocean* and *ocean view* variables, which we include as additional local geographic controls in our regression.

Sun hours are calculated as the sunshine hours at equinox based on the surrounding terrain and longitude and latitude. The left panel of Figure B-3 shows the sunshine hours for Trondheim on a black-white scale ranging from areas with less than 5 hours (black) to those with full 12 hours (white). We can see the strong inner-city variation in sunshine determined by the terrain.

We measure *distance to the ocean* in *km* as the crow flies. Furthermore, we calculate the mean number of points located on the ocean surface with a spacing of 500m that are directly visible from the neighborhood, given the topography on the way to the ocean. We say that a neighborhood has ocean view if more than 8 points on the ocean surface (approximately half a sqkm of ocean) are on average visible from the neighborhood. We illustrate this approach for Trondheim in the right panel of Figure B-3, with white denoting ocean view and black the lack of ocean view. Comparing this figure with the left panel shows that ocean view and hours of sunshine vary considerably, given the direction of mountain lines. Moreover, close proximity to the ocean is sufficient for securing an ocean view.

Figure B-3: Sunshine Hours and Ocean View in Trondheim



Note: The figures show, respectively, sunshine hours and ocean view in Trondheim. Neighborhoods with urban development figure in red, blue areas are ocean. Left: Areas in pure black have less then 5 hours of sunshine, those in pure white 12 hours. Right: Black areas have no view of the ocean, while white areas do.

C Supplementary Descriptive Statistics

Here we supplement the descriptive analysis from the main text (Section 4) with an overview over the urban clusters as well as correlations between the variables.

Table C-1: Descriptive Statistics on Urban Clusters

	(1)	(2)	(3)	(4)
Cluster name	Total pop	# neighborhoods	# Centers (cafe)	#*kommuner*
Lillehammer	14018	30	1	1
Kristiansund	17588	34	1	1
Molde	18531	26	1	1
Bodø	21233	49	1	1
Tromsø	23971	34	1	1
Haugesund	40389	92	1	2
Ålesund	43802	54	1	2
Hamar	44107	104	1	4
Kristiansand	98208	150	4	4
Trondheim	168957	312	1	3
Stavanger	211837	255	1	6
Bergen	283934	347	1	6
Oslo	1344126	2020	10	34

Table C-2: Correlations of Urban Density and its Components

	(1) urban density	(2) residential coverage	(3) building height	(4) crowding
urban density	1.0000			
residential coverage	0.6269	1.0000		
building height	0.7553	0.4451	1.0000	
crowding	0.2296	-0.2999	0.0205	1.0000

D Additional Results

In this section, we repeat the regression from Table 3 for the effects of building land limitations on urban density and its components under slightly altered specifications. We first rerun Table 2 and Table 3 with Conley standard errors that account for spatial autocorrelation. As Table D-1 and Table D-2 show, these standard errors are typically smaller so that the coefficient estimates remain statistically significant at the same or even at a higher level of significance. Hence, our results are robust to the choice of standard errors.

In Table D-3, we repeat the analysis from Table 3 when using rings of 2.5 km rather than 1 km width. The overall effect remains, but it is now driven by crowding rather than building height (which has become statistically insignificant).

In Table D-4 we repeat the analysis from Table 3 when the city center is identified based on ports rather than the café density. The results are very similar to our baseline case.

In Table D-5 we exclude neighborhoods in rings that are further than 10 km away from the city center. The number of observations drops from 3478 to 2798 but the coefficients remain very close to the original ones (compare 0.281 to 0.311 for the main effect of building land limitations on urban density).

By contrast, in Table D-6 we exclude the innermost rather than the outermost neighborhoods. This ensures that our results are not driven by specifics of the city core, such as the height of historical buildings or the mixture between office and residential dwellings. It reduces the number of observations by nearly one half, but preserves the signs and magnitudes of our main estimation results. The positive effect of geography on density becomes even larger.

Table D-7 repeats the regression when neighborhoods from the same *kommune* and the same ring are merged. This is a robustness check against the administrative processes behind the definition of a *grunnkrets* which underlies our neighborhood unit. Although this leaves us with only 384 observations, we can replicate our main results of building land restrictions on density with similar magnitude and similar levels of significance. For distance, we again observe a strongly negative effect on density, with one source of inner-city heterogeneity reduced.

Finally, we investigate the scarcity channel with a different specification. We have argued that geographical obstacles such as a lake at the other side of the city affect urban density in a other neighborhoods within the same ring, because there is less available building land for all neighborhood which share the property of the same distance to the city center. But this scarcity effect also works with other properties. Instead of focusing on neighborhoods with the same distance to the city center (and thereby rings), we now classify the neighborhoods of a city according to their average sunshine hours. We use classes of 0.5 hours, ranging from 6 to 12 hours. To see how land scarcity for a given sunshine class affects density and its components, we have to modify eq. 17 to

$$ln(\mathbf{\Gamma}_{isck}) = \beta_1 \cdot ln(sun\_area_{sck}) + \zeta_1 \cdot \mathbf{Z}_{irck} + controls + \kappa_k + \chi_c + \epsilon_{isck}, \quad \text{((D-1))}$$

where $ln(\mathbf{\Gamma}_{irck})$ is the logarithm of the vector of urban density measures discussed in Section 3.2 in neighborhood i, *kommune* k and city c; $ln(sun\_area_{sck})$ measures the available land area for a sunshine class s, $\mathbf{Z}_{irck}$ is the vector of standard controls that includes the log distance to the city center ($dist\_citycenter_{irck}$) as described in Section 3.3, our measure for local land scarcity ($geo\_local\_dist_{irck}$ and $geo\_local\_area_{irck}$) as described in Section 3.4, $controls$ contain additional geography- and socio-demographic controls, κ_k is a *kommune* fixed effect, χ_c is a city fixed effect and ϵ_{ij} is the error term.

Note that when we group neighborhoods by sunshine hours, we do not need to account for a mechanical increases in group size as in the cases of grouping in rings around the city center. We therefore can directly estimate the effect of more available building land within a given group of neighborhoods. Hence, instead of using geography-based *limitations* we now focus on the *available* land area with a given property - sunshine - so that the expected sign of β_1 is negative. This indeed turns out to be the case, as Table D-8 shows: Both urban density (columns 1-3) and its three components (columns 4-6) decrease when more land area of a given sunshine class is available.

Table D-1: Urban Density and Land Development Limitations - Conley Standard Errors

	(1)	(2)	(3)	(4)	(5)
Dep.Variable:			log_urban_density		
log_geo_ring	0.295***	0.311***	0.453***	0.311***	0.323***
	(0.111)	(0.093)	(0.139)	(0.078)	(0.111)
log_area_ring	-0.760***	-0.731***	-0.781***	-0.673***	-0.494***
	(0.146)	(0.114)	(0.161)	(0.097)	(0.115)
log_dist_cbd	0.040	0.056*	-0.083**	0.029	-0.185***
	(0.036)	(0.032)	(0.037)	(0.028)	(0.052)
log_geo_local_area	-0.231***	-0.204***	-0.192***	-0.154***	-0.184**
	(0.078)	(0.060)	(0.060)	(0.039)	(0.072)
log_geo_local_dist	-0.003	-0.062***	-0.054***	-0.060***	-0.066***
	(0.023)	(0.021)	(0.020)	(0.017)	(0.020)
Add. Geo Controls	NO	YES	YES	YES	YES
Socio-Dem Controls	NO	NO	NO	YES	NO
Ring Width	1 km	1 km	2.5km	1 km	1 km
CBD Def	Cafés	Cafés	Cafés	Cafés	Ports
Observations	3,478	3,478	3,478	3,478	3,311
R-squared	0.163	0.273	0.268	0.451	0.275

Note: The table reports regression results of eq. 17 using log urban density as the dependent variable. The difference to Table 2 is that Conley standard errors are reported. All regressions include fixed effects at the city and *kommune* level. The number of urban clusters = 13, the number of city centers=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table D-2: Urban Density Components and Land Development Limitations - Conley Standard Errors

Depend.Var:	(1) ln(urban density)	(2) ln(crowding)	(3) ln(residential coverage)	(4) ln(building height)
log_geo_ring	0.311***	0.052	0.171***	0.087**
	(0.093)	(0.081)	(0.058)	(0.039)
log_area_ring	-0.731***	-0.214**	-0.325***	-0.192***
	(0.114)	(0.100)	(0.066)	(0.046)
log_dist_cbd	0.056*	0.251***	-0.143***	-0.053***
	(0.032)	(0.032)	(0.026)	(0.018)
log_geo_local_area	-0.204***	-0.055	-0.097***	-0.052
	(0.060)	(0.044)	(0.037)	(0.033)
log_geo_local_dist	-0.062***	-0.048**	-0.016	0.002
	(0.021)	(0.019)	(0.014)	(0.009)
log_elev_mean	-0.005	0.068**	0.039	-0.113***
	(0.042)	(0.032)	(0.027)	(0.020)
log_slope_mean	-0.076**	-0.069***	0.024	-0.031*
	(0.033)	(0.025)	(0.020)	(0.018)
log_slope_cov	-0.411***	-0.191***	-0.151***	-0.069***
	(0.030)	(0.026)	(0.015)	(0.014)
log_sun_hours	0.387	-0.654***	1.138***	-0.097
	(0.339)	(0.208)	(0.214)	(0.144)
log_dist_ocean	0.044	0.029	-0.023	0.038***
	(0.030)	(0.025)	(0.020)	(0.015)
ocean_view	0.004	-0.033	0.016	0.021
	(0.043)	(0.039)	(0.029)	(0.022)
Observations	3,478	3,478	3,478	3,478
R-squared	0.273	0.110	0.281	0.309

Note: The table reports regression results of eq. 17, where the dependent variable is in turn urban density and its components crowding, residential coverage, and building height. The difference to Table 3 is that Conley standard errors are reported. All regressions include fixed effects at the city and *kommune* level. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city centers=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table D-3: Urban Density Components and Land Development Limitations - Different Ring Width

Depend.Var:	(1) ln(urban density)	(2) ln(crowding)	(3) ln(residential coverage)	(4) ln(building height)
log_geo_ring_2_5km	0.438***	0.257**	0.163	0.018
	(0.147)	(0.108)	(0.115)	(0.066)
log_area_ring_2_5km	-0.760***	-0.446***	-0.232**	-0.082
	(0.186)	(0.134)	(0.116)	(0.064)
log_geo_local_area_5x5	-0.196**	-0.051	-0.107***	-0.038
	(0.080)	(0.033)	(0.034)	(0.046)
log_geo_local_dist	-0.052**	-0.047**	-0.009	0.003
	(0.026)	(0.021)	(0.016)	(0.010)
log_dist_cbt_curent_spa	-0.085	0.221***	-0.215***	-0.091***
	(0.051)	(0.030)	(0.031)	(0.022)
log_elev_mean	-0.001	0.067*	0.050	-0.118***
	(0.049)	(0.034)	(0.032)	(0.024)
log_slop100_mean	-0.109***	-0.030	-0.054***	-0.025
	(0.020)	(0.027)	(0.016)	(0.017)
log_slop100_cov	-0.411***	-0.180***	-0.163***	-0.068***
	(0.034)	(0.029)	(0.016)	(0.021)
log_dist_o	0.035	0.029	-0.034*	0.040**
	(0.041)	(0.020)	(0.019)	(0.019)
ocen_view_dum	-0.004	-0.048	0.023	0.021
	(0.040)	(0.038)	(0.038)	(0.020)
Observations	3,478	3,478	3,478	3,478
R-squared	0.512	0.310	0.544	0.551

Note: The table reports regression results of eq. 17, where the dependent variable is in turn urban density and its components crowding, residential coverage, and building height. In contrast to Table 3, the ring width is 2.5 km rather than 1 km. All regressions include fixed effects at the city and *kommune* level. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city center=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table D-4: Urban Density Components and Land Development Limitations - City Center based on Ports

Depend.Var:	(1) ln(urban density)	(2) ln(crowding)	(3) ln(residential coverage)	(4) ln(building height)
log_geo_ring_port	0.320**	0.080	0.125	0.115**
	(0.159)	(0.123)	(0.078)	(0.051)
log_area_ring_port	-0.488***	-0.101	-0.208***	-0.179***
	(0.163)	(0.111)	(0.076)	(0.060)
log_geo_local_area_5x5	-0.189*	-0.029	-0.112***	-0.047
	(0.101)	(0.039)	(0.039)	(0.055)
log_geo_local_dist	-0.064**	-0.040*	-0.019	-0.004
	(0.024)	(0.022)	(0.015)	(0.011)
log_dist_cbt_port_euc	-0.188***	0.088	-0.186***	-0.090***
	(0.056)	(0.064)	(0.043)	(0.022)
log_elev_mean	0.020	0.060**	0.067	-0.107***
	(0.057)	(0.030)	(0.040)	(0.025)
log_slop100_mean	-0.138***	-0.020	-0.078***	-0.040***
	(0.024)	(0.024)	(0.017)	(0.014)
log_slop100_cov	-0.426***	-0.181***	-0.168***	-0.077***
	(0.041)	(0.032)	(0.018)	(0.023)
log_dist_o	0.035	0.039*	-0.042	0.037*
	(0.044)	(0.021)	(0.026)	(0.021)
ocen_view_dum	0.015	-0.042	0.031	0.026
	(0.046)	(0.037)	(0.042)	(0.023)
Observations	3,478	3,478	3,478	3,478
R-squared	0.512	0.310	0.544	0.551

Note: The table reports regression results of eq. 17, where the dependent variable is in turn urban density and its components crowding, residential coverage, and building height. In contrast to Table 3, the city center is based on ports rather than café density, see Section 3 for details. All regressions include fixed effects at the city and *kommune* level. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city centers=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table D-5: Urban Density Components and Land Development Limitations - Without the Outermost Rings

Depend.Var:	(1) ln(urban density)	(2) ln(crowding)	(3) ln(residential coverage)	(4) ln(building height)
log_geo_ring	0.281**	0.057	0.141	0.083**
	(0.105)	(0.106)	(0.097)	(0.039)
log_area_ring	-0.686***	-0.230	-0.278**	-0.178***
	(0.153)	(0.141)	(0.109)	(0.050)
log_geo_local_area	-0.247***	-0.047	-0.120***	-0.081
	(0.092)	(0.035)	(0.038)	(0.053)
log_geo_local_dist	-0.064**	-0.028	-0.036***	-0.000
	(0.029)	(0.022)	(0.011)	(0.012)
log_dist_cbd	0.060	0.273***	-0.152***	-0.061**
	(0.040)	(0.038)	(0.028)	(0.024)
log_elev_mean	-0.020	0.081*	0.021	-0.121***
	(0.056)	(0.041)	(0.033)	(0.029)
log_slope_mean	-0.083**	-0.084***	0.027	-0.027
	(0.038)	(0.028)	(0.024)	(0.022)
log_slope_cov	-0.392***	-0.170***	-0.153***	-0.069***
	(0.040)	(0.028)	(0.021)	(0.025)
log_sun_hours	0.546	-0.694***	1.237***	0.003
	(0.482)	(0.152)	(0.345)	(0.187)
log_dist_ocean	0.059	0.022	-0.008	0.045**
	(0.043)	(0.028)	(0.021)	(0.021)
ocean_view	0.018	-0.020	0.024	0.015
	(0.045)	(0.040)	(0.049)	(0.024)
Observations	2,798	2,798	2,798	2,798
R-squared	0.518	0.263	0.536	0.573

Note: The table reports regression results of eq. 17, where the dependent variable is in turn urban density and its components crowding, residential coverage, and building height. In contrast to Table 3, all neighborhoods lying in rings that are father away than 10 km from the city center are excluded. All regressions include fixed effects at the city and *kommune* level. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city centers=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table D-6: Urban Density Components and Land Development Limitations - Without the City Core

Depend.Var:	(1) ln(urban density)	(2) ln(crowding)	(3) ln(residential coverage)	(4) ln(building height)
log_geo_ring	0.718***	0.435***	0.105	0.178***
	(0.159)	(0.149)	(0.192)	(0.044)
log_area_ring	-1.028***	-0.504*	-0.244	-0.280***
	(0.381)	(0.266)	(0.222)	(0.084)
log_geo_local_area	-0.105*	-0.073	-0.056	0.024
	(0.057)	(0.050)	(0.046)	(0.018)
log_geo_local_dist	-0.057*	-0.039	-0.018	0.000
	(0.033)	(0.028)	(0.026)	(0.013)
log_dist_cbd	-0.040	0.114	-0.146*	-0.008
	(0.086)	(0.097)	(0.076)	(0.036)
log_elev_mean	0.115**	0.077**	0.096**	-0.059***
	(0.051)	(0.033)	(0.043)	(0.021)
log_slope	-0.088*	-0.034	-0.005	-0.050***
	(0.046)	(0.033)	(0.034)	(0.018)
log_slope_cov	-0.410***	-0.230***	-0.127***	-0.053***
	(0.045)	(0.039)	(0.021)	(0.020)
log_sun_hours	0.200	-0.405	0.845**	-0.240*
	(0.493)	(0.267)	(0.357)	(0.133)
log_dist_ocean	-0.001	0.017	-0.048**	0.030
	(0.033)	(0.018)	(0.022)	(0.020)
ocean_view	-0.030	-0.074*	0.019	0.025
	(0.039)	(0.044)	(0.035)	(0.025)
Observations	1,954	1,954	1,954	1,954
R-squared	0.367	0.363	0.511	0.271

Note: The table reports regression results of eq. 17, where the dependent variable is in turn urban density and its components crowding, residential coverage, and building height. In contrast to Table 3, all neighborhoods lying in rings that are closer than 5 km to the city center are excluded. All regressions include fixed effects at the city and *kommune* level. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city centers=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table D-7: Urban Density Components and Land Development Limitations - Merged Within *Kommuner* and Rings

Depend.Var:	(1) ln(urban density)	(2) ln(crowding)	(3) ln(residential coverage)	(4) ln(building height)
log_geo_ring	0.489***	0.198	0.158	0.134**
	(0.168)	(0.125)	(0.110)	(0.051)
log_area_ring	-0.755***	-0.203	-0.301*	-0.251***
	(0.182)	(0.163)	(0.160)	(0.060)
log_geo_local_area	0.102	0.098	0.003	0.002
	(0.162)	(0.113)	(0.095)	(0.046)
log_geo_local_dist	-0.036	-0.006	-0.027	-0.004
	(0.093)	(0.072)	(0.050)	(0.018)
log_dist_cbd	-0.054	0.073	-0.087	-0.040
	(0.066)	(0.063)	(0.091)	(0.026)
log_elev_mean	0.247**	0.232***	0.068	-0.053
	(0.104)	(0.077)	(0.073)	(0.038)
log_slope_mean	-0.285***	-0.139	-0.138**	-0.007
	(0.087)	(0.088)	(0.068)	(0.033)
log_slope_cov	-0.623***	-0.325***	-0.313***	0.015
	(0.138)	(0.091)	(0.087)	(0.044)
log_sun_hours	-0.430	-0.529	0.022	0.077
	(1.010)	(0.713)	(0.686)	(0.248)
log_dist_ocean	-0.087	-0.073	-0.026	0.012
	(0.074)	(0.064)	(0.047)	(0.023)
ocean_view	0.017	-0.017	0.007	0.027
	(0.111)	(0.096)	(0.078)	(0.039)
Observations	384	384	384	384
R-squared	0.658	0.675	0.771	0.727

Note: The table reports regression results of eq. 17, where the dependent variable is in turn urban density and its components crowding, residential coverage, and building height. In contrast to Table 3, neighborhoods from the same *kommune* in the same ring are merged. All regressions include fixed effects at the city and *kommune* level. Robust standard errors are clustered on the *kommune* level. The number of urban clusters = 13, the number of city center=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Table D-8: Urban Density Components and Land Availability - Neighborhoods Classified by Sunshine rather than Distance to City Ccenter

Variables	(1)	(2) log_urban_density	(3)	(4) log_crowding	(5) log_resid_cover	(6) log_building_height
log_sun_area	-0.080***	-0.068***	-0.056***	-0.011	-0.032***	-0.025***
	(0.020)	(0.019)	(0.016)	(0.014)	(0.012)	(0.010)
log_sun_h_mean	1.052***	0.879**	0.851**	-0.623**	1.401***	0.102
	(0.298)	(0.384)	(0.334)	(0.273)	(0.254)	(0.172)
log_dist_cbd	-0.291***	-0.231***	-0.203***	0.136***	-0.244***	-0.123***
	(0.042)	(0.037)	(0.038)	(0.023)	(0.019)	(0.013)
log_geo_local_area	-0.185**	-0.181**	-0.122***	-0.053	-0.083**	-0.045
	(0.090)	(0.070)	(0.047)	(0.045)	(0.039)	(0.034)
log_geo_local_dist	-0.003	-0.057***	-0.055***	-0.049**	-0.013	0.004
	(0.024)	(0.021)	(0.018)	(0.019)	(0.014)	(0.009)
Add. Geo Controls	NO	YES	YES	YES	YE	YES S
Socio-Dem Controls	NO	NO	NO	NO	NO	NO
Ring Width	1 km	1 km	1 km	1 km	1 km	1 km
CBD Def	Cafés	Cafés	Cafés	Cafés	Cafés	Cafés
Observations	3,476	3,476	3,476	3,476	3,476	3,476
R-squared	0.132	0.246	0.430	0.102	0.272	0.300

Note: The table reports regression results of eq. (D-1), where the dependent variable is in turn urban density and its components crowding, residential coverage, and building height. Conley standard errors are in parentheses. All regressions include fixed effects at the city and *kommune* level. The number of urban clusters = 13, the number of city centers=25 and the number of *kommune*=66. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.