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The Economic Effects of Density: A Synthesis

Abstract

This paper synthesises the state of knowledge on the economic effects of density. We consider 15 outcome categories and 209 estimates of density elasticities from 103 studies. More than 50% of these estimates have not been previously published and have been provided by authors on request or inferred from published results in auxiliary analyses. We contribute own estimates of density elasticities of 16 distinct outcome variables that belong to categories where the evidence base is thin, inconsistent or non-existent. Along with a critical discussion of the quality and the quantity of the evidence base we present a set of recommended elasticities. Applying them to a scenario that roughly corresponds to an average high-income city, we find that a 1% increase in density implies positive per capita net present values of wage and rent effects of \$280 and \$485. The decrease in real wage net of taxes of \$342 is partially compensated for by an aggregate amenity effect of \$221 and there is a positive external welfare effect of \$52. Density has important positive amenity and resource implications, but also appears to create a scarcity rent, which harms renters and first-time buyers.

JEL-Codes: R380, R520, R580.

Keywords: compact, city, density, meta-analysis, elasticity, net present value.

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1 Introduction

An urban area, most generally defined, is an area that exceeds its surroundings in terms of economic density. The degree of concentration of economic activity in urban areas is striking as they host more than 50% of the world's population (United Nations 2014) on only an approximate 2.7% of the world's land (GRUMP 2010; Liu et al. 2014).[1] This concentration will likely increase as the share of urban areas at the world pollution is predicated to reach 70% globally by 2050 and 86% within OECD countries (OECD 2010), reflecting the growing demand for density. While the average density of economic activity in urban areas is impressive, the variation in density across urban areas is equivalently striking. Although definitions of urban areas vary, they are often characterised as having a population density of at least 400 residents per square kilometre, but some urban areas have densities that exceed this threshold by a factor of 100 (United Nations 2005).

While the degree of spatial concentration of economic activity in urban areas is already high, there is a consensus among planners and policymakers in the global policy debate that, on average, even higher densities within cities and urban areas are desirable (Boyko & Cooper 2011; OECD 2012). The increasingly popular "compact city" concept idealises a city that is distinctively urban in very general terms of density, but also in more specific terms such as a contiguous building structure, interconnected streets, mixed land uses, and the way people travel within the city (walking, cycling, public transit). As a policy agenda, the compact city is directly concerned with promoting the most "urban" externalities, i.e. those that originate from density and accessibility, the quintessence of cities. The positive effects ascribed to density include increases in productivity due to agglomeration economies, travel time savings due to shorter trips or a smaller ecological footprint due to lower energy and land consumption, among others.

Nowadays most countries pursue policies that implicitly or explicitly aim at promoting "compact urban form", reflecting the concern that unregulated economic markets will fail to deliver allocations of uses and infrastructures that are efficient and equitable (IAU-IDF 2012; Holman et al. 2014). Popular policies to promote density include urban containment, transit-oriented development, minimum density requirement and regenerating existing residential areas (OECD 2012). Implicit to the wide support the concept receives in the urban policy debate, is the

[1] The estimates of the global urban land reported in the literature vary widely, from less than 0.3 to 3% primarily because of the different definitions of urban land and data used (night light data, Landsat data etc.) (Angel et al. 2005; GRUMP 2010; Liu et al. 2014). In 2010, the global urban land was close to 3%, while the global built-up area was approximately 0.65%.

agreement that, for the most part, the returns to density and compactness exceed the cost which can come in the form of reduced affordability, traffic congestions, a high concentration of pollution, and a loss of open and recreational spaces.

It is difficult to ascertain, however, to what extent this normative statement prevailing in the policy debate can be substantiated by evidence (Neuman 2005). Cheshire (2006) warns of the dangers of advocating policies, such as densification, without the clear evidence base needed. For sure, some effects of density are well-understood. As an example, the urban economics and economic geography literature has in recent decades produced robust evidence that density has positive effects on productivity (e.g. Ciccone & Hall 1996; Ahlfeldt et al. 2015; Combes et al. 2012).[2] Similarly, it has been well-documented in a more planning-orientated literature that density makes cities less car-dependent (Ewing & Cervero 2010). For most other areas, the evidence is much scarcer, inconclusive, or both. Moreover, the evidence is scattered across various separate literatures in different disciplines and is therefore difficult to access. To our knowledge, no attempt has been made to synthesise the evidence on the economic effects of density and to compare the variety of costs and benefits across a comprehensive range of outcome categories. It seems fair to state that the dominating "compact city" policy paradigm, which aims at shaping the habitat of the urban population over the decades to come, is not evidence-based. We make four contributions to address this notable gap in the literature.

Our first contribution is to provide a unique summary of the quantitative literature on the economic effects of density. Our evidence base contains 209 estimates (from 103 studies) of the effects of density on a wide range of outcomes including accessibility (job accessibility, accessibility of private and public services), various economic outcomes (productivity, innovation, value of space), various environmental outcomes (open space preservation and biodiversity, pollution reduction, energy efficiency), efficiency of public service delivery, health, safety, social equity, transport (ease of traffic flow, sustainable mode choice), and subjective well-being. The analyses covered in this paper are a subset of the broader evidence base studied in a companion paper (Ahlfeldt & Pietrostefani 2017) in which we summarise qualitative results on the effects of a variety of compact city characteristics (including morphological features and land use mix). To facilitate a quantitative comparison, we restrict the analysis to results that can be expressed as an elasticity of an outcome with respect to density. For about half of the cases the elasticity estimates are reported in the reviewed publications. For the remaining fraction, we conduct back-of-the-envelope calculations to convert the results into a singular metric or obtain results that had not previously been published from the relevant authors. Borrowing techniques from meta-analytic research, we analyse within-category heterogeneity with respect to studying

[2] See Melo et al. (2009) for a meta-analysis.

characteristics such as the type of methods used, the citations adjusted for years since publication, or the geographic setting of the analysis. In some instances, we make admittedly ambitious assumptions to translate results published in fields such as engineering and medical research into a format that is compatible with the conventions in economics and related disciplines.

Our second contribution is to provide own elasticity estimates where the evidence base is thin or inconsistent. We provide transparent density elasticity estimates based on a consistent econometric framework and OECD data that refer to 16 distinct outcome variables (from 10 outcome categories). For some outcomes, such as the elasticity of preserved green space with respect to density, our estimates are without precedent. We provide an estimate of the elasticity of density with respect to city size, which facilitates a better comparison of the results from studies analysing the effects of density and city size. To reconcile the evidence on the effects of density on wages, rents, and various (dis)amenities, we also provide novel estimates of the elasticity of construction costs with respect to density.

Our third contribution is to condense this broad evidence base into a set of 15 category-specific density elasticities. Specific to each category, we either recommend the weighted (by adjusted citations) mean across the elasticities in our evidence base, the result of a dedicated meta-analysis, an estimate from a high-quality original research paper or one of our own estimates. Along with the recommended elasticities, we provide a critical discussion of the quality and the quantity of the evidence base, highlighting priority areas for further research. The compact presentation of a variety of density elasticities in a consistent format is unique in terms of accessibility and coverage and represents a convenient source for research engaging with the quantitative interpretation of density effects.

Our fourth contribution is to monetise the economic effects of density. For each of the 15 outcome categories, we compute the per capita net present value (NPV) of the effect of a 1% increase in density assuming a 5% discount rate for a scenario that roughly corresponds to an average metropolitan area in a developed country. For this purpose, we combine our recommended density elasticities with several valuations of non-marketed goods such as time, crime and mortality risk, or pollution, among many others. The monetary equivalents allow for a novel accounting of the costs and benefits of density and how the net effect of density across a broad range of amenity and dis-amenity categories aligns with estimates of quality of life based on cost-earning differentials.[3]

[3] The indirect inference of quality of life from relative wages goes back to the work pioneered by Rosen (1979) and Roback (1982) has spurred a growing literature (see Albouy & Lue 2015 for a review).

Our analysis reveals sizable benefits and costs of density. Density is associated with (recommended elasticities in parentheses) higher wages (4%), patent activity (19%), consumption variety value (12%), the preservation of green spaces (23%), use of non-car modes (7%) as well as lower average vehicle mileage (8.5%), energy consumption (7%), pollution density (8%), crime (8.5%), and costs of providing local public services (14.4%). Density, however, is also associated with higher rents (21%), construction costs (5.5%), inter-quartile wage gaps (3.5%), mortality risk (9%) as well as lower average speed (12%) and subjective well-being (0.4%). Studies that are more frequently cited, or use more rigorous methods, find significantly less positive density effects (in a normative sense), suggesting a role for the quality of evidence.

In our illustrative scenario, a 1% increase in density leads to an increase in the per capita NPV of wages of $280 per capita ($143 after taxes) and a respective increase in rent of $485. Summing up the monetary equivalents of all amenity and dis-amenity categories we find a clearly positive value, which is, however, not as large as the "compensating differential" (rent effect – after-tax wage effect). While density seems to be a net amenity, our admittedly imperfect accounting also suggests that part of the rent increase is attributable to the higher cost of providing space and is not exclusive to enjoyable amenities.[4] This is in line with a scarcity rent that harms renters and first-time buyers.

Our analysis unifies important strands in the economics literature on the spatial organisation of economic activity. We provide an explicit comparison of the magnitude of agglomeration benefits on the production (e.g. Combes et al. 2012) and consumption side (e.g. Couture 2016), the effects of urban form on innovation (e.g. Carlino et al. 2007), housing rent (e.g. Combes et al. 2016), quality of life (e.g. Albouy & Lue 2015), driving distances (Duranton & Turner 2015), road speeds (Couture et al. 2016), public spending reduction (e.g. Hortas-Rico & Sole-Olle 2010), energy consumption (Glaeser & Kahn 2010) and subjective well-being (Glaeser et al. 2016), in addition to a range of density effects on outcomes that have remained under-researched in the economics literature. Our findings also have important policy implications as they suggest that densification policies are likely efficient but not necessarily equitable.

Some words are due on the limitations of this ambitious synthesis. Given the nature of the evidence reviewed here, the quantitative results should be interpreted as associations as they exist in the world today. They cannot generally be interpreted as causal evidence and are not suitable for making predictions regarding the short-run effects of policies that promote density. At best, they allow for an evaluation of the likely effects of such policies in the long run.

[4] To be theoretically consistent this interpretation requires that residents are not fully mobile (e.g. because they have location-specific preferences).

Compared to wages and mode choice, the evidence base for the other outcomes is generally underdeveloped. While for some categories singular high-quality contributions are available, the nature of the evidence is at best preliminary for others. Significant uncertainty surrounds any quantitative interpretation in the categories urban green, income inequality, pollution, health, and well-being. We view these outcomes as priority areas for further research into the effects of density. In general, the extant evidence base consists of point estimates, so that heterogeneity in density effects across contexts and the density distribution remains a key subject for future original research and reviews.

The remainder of this paper is organised as follows. In section 2 we lay out how the evidence base was collected and classified. Section 3 summarises the evidence by outcomes and attributes. Section 4 presents a discussion of our own density elasticity estimates. Section 5 condenses the evidence (including our own estimates) to 15 outcome-specific density elasticities. Section 6 discusses the monetary equivalents of an increase in density. The final section (7) concludes. We also provide an extensive technical appendix with additional results and explanations, which is essential reading for those wishing to use our quantitative results in further research (recommended elasticities and monetary equivalents).

2 The evidence base

2.1 Collection

The evidence base considered in this paper includes a subset of analyses reviewed in a companion paper (Ahlfeldt & Pietrostefani 2017). In that paper, we collect an evidence base that covers, as broadly as possible, the theoretically relevant links between the same 15 outcome categories considered here and various compact city characteristics. We do not impose any geographical restrictions (with respect to the study area) and consider various geographic layers (from micro-geographic scale to cross-region comparisons). In line with standard best-practice approaches of meta-analytic research, as reviewed by Stanley (2001), the literature search is carried out in several stages.[5]

First, we conduct 260 separate searches for various combinations of category-specific keywords (combinations of outcomes and empirically observed variables) in academic databases (EconLit, Web of Science, and Google Scholar) and specialist research institute working paper series (NBER, CEPR, CESIfo, and IZA). Second, we expand on relevant research strands by conducting

[5] Recent examples of classic meta-analyses in economics include studies by Eckel and Füllbrunn (2015), Melo et al. (2009), and Nitsch (2005).

an analysis of citation trees. Third, we ask colleges in our research networks to recommend relevant research (by personal mail and a call circulated in social media) and add studies that were previously known to us or came up in discretionary searches.[6] We keep track of the stage at which the evidence is added to control for a bias due to a potentially selective research network. To prevent publication bias, we explicitly consider studies that were published as edited book chapters, in refereed journals or in academic working paper series (we were also open to other types of publications). This process, which is described in more detail in the appendix to this paper and in Ahlfeldt & Pietrostefani (2017), results in 190 relevant studies, which include 328 conceptually distinct analyses. We typically keep multiple estimates (analyses) from the same study if they refer to different dependent variables.

In the companion paper, we analyse the full evidence base focussing on various compact city characteristics including economic density, morphological features (building height, floor area ratios, street connectivity, etc.), and land use mix. We focus on the qualitative result (whether compactness has positive, negative or insignificant effects) as the lowest common denominator in that paper. In this paper, we are interested in the quantitative effects of density. Thus, we restrict the analysis to results that can be expressed as a density elasticity of an outcome. Since elasticity is unit-free, it is the natural way to express marginal effects to allow for a comparison across a heterogeneous evidence base. A restriction to elasticity estimates that are explicitly reported in publications shrinks the sample by about 70% to 90 analyses in 60 studies. We make some effort, however, to increase the evidence base.

We infer density elasticities from reported city size elasticities using the elasticity of city size with respect to density, which we estimate in section 2.3. We convert reported marginal effects in levels or reported semi-elasticities into density elasticities (at the mean of a distribution) using descriptive statistics reported in the studies. Where necessary, we conduct auxiliary research into the institutional setting to facilitate such conversions (e.g. to infer mean density). For studies from disciplines that are remote to economics (e.g. engineering and medical research), additional steps are often necessary to infer density elasticity estimates because the results are reported not as marginal density effects but as predicted values by density category (e.g. energy consumption or adjusted premature mortality rates). In such instances, we extract the predicted values (if necessary by the visual inspection of graphs) and approximate the implied density elasticity by regressing the natural logarithm of an outcome value against the natural logarithm of the midpoint of the density interval. Finally, some authors kindly provided

[6] At this stage, we were pointed to a literature on urban scaling in which city size is related to a variety of outcomes (CITE). This literature is not part of this review, because unlike with the bulk of the evidence base, the analysis is purely descriptive and not concerned with density (Gomez-Lievano et al. 2012; Bettencourt & Lobo 2016).

density elasticity estimates on request, which were not reported in their papers (e.g. Couture 2016; Tang 2015). This way, we increase the quantitative evidence base by more than 100% to 209 analyses in 103 studies. The final quantitative sample is comparable to the full sample (328 analyses from 190 studies) across a range of characteristics that we introduce in the next subsections (see appendix section 2).

We also note that we make some adjustments to allow for a consistent interpretation within categories. As an example, we convert the density elasticities of land prices into density elasticities of housing rents assuming a Cobb-Douglas housing production function (Epple et al. 2010) and a land share of 0.25 (Combes et al. 2016; Ahlfeldt et al. 2015). A more complete discussion of the various adjustments made to ensure comparability of the evidence is in appendix section 2. A complete list of studies along with the encoded attributes introduced in the following sections is provided in a separate appendix to this paper.

2.2 Attributes

We choose a quantitative approach to synthesise our broad and diverse evidence base. Our aim is to provide an accessible synthesis of the evidence on the economic effects of density across various outcome categories. As with most quantitative literature reviews we use statistical approaches to test whether existing empirical findings vary systematically in the selected attributes of the studies, such as the geographic context, the data or the methods used. Therefore, we encode the results and the various attributes of the reviewed studies into variables that can be analysed using statistical methods.

The typical approach in meta-analytic research is to analyse the findings in a very specific literature strand. The results that are subjected to a meta-analysis are normally directly comparable, and are often parameters that have been estimated in an econometric analysis. In such instances, it is useful to collect specific information concerning the econometric setup. In contrast, the scope of our analysis is much broader. Our aim is to synthesise the evidence on the economic effects of density across a range of outcome categories. We consider studies from separate literature strands that naturally use very different empirical approaches. The information we collect is, therefore, somewhat more generic and includes the following attributes:

i) The outcome category, one for the 15 categories (see Table A1 for details, appendix section 1)
ii) The dependent variable, e.g. wages, land value, crime rate
iii) The study area, including the continent and the country
iv) The publication venue, e.g. academic journal, working paper, book chapter, report
v) The disciplinary background, e.g. economics, regional sciences, planning, etc.
vi) The stage (1–3) at which an analysis is added to the evidence base (see Table A4)
vii) The period of analysis
viii) The spatial scale of the analysis, i.e. within-city vs. between-city
ix) The quality of evidence as defined by the Scientific Maryland Scale (SMS) used by the What Works Centre for Local Economic Growth (2016)
The quality can take the following values:
    0. Exploratory analyses (e.g. charts). This score is not part of the original SMS
    1. Unconditional correlations and OLS with limited controls
    2. Cross-sectional analysis with appropriate controls
    3. Good use of spatiotemporal variation controlling for period and individual effects, e.g. difference-in-differences or panel methods
    4. Exploiting plausibly exogenous variation, e.g. by use of instrumental variables, discontinuity designs or natural experiments
    5. Reserved to randomised control trials (not in the evidence base)
x) The cumulated number of citations, adjusted for the years since publication, which we generate using yearly citations counts per study from Scopus. For non-journal publications, we impute the citation index using data from Google Scholar. Expectedly, our study-based index is closely correlated with journal quality as measured by the SNIP (Source Normalized Impact per Paper) score (Scopus 2016) and the SCImago Journal Rank (Scimago 2017). A detailed discussion is in appendix 1.2.

In Table 1 we tabulate the distribution of analyses included in this review by selected attributes (as discussed above, one study can include several analyses). While our evidence base to some extent covers most world regions, including the global south, there is a strong concentration of studies from high-income countries and, in particular, from North America. The clear majority of studies have been published in academic journals. The evidence base is diverse with respect to disciplinary background, with economics as the most frequent discipline, accounting for a share of about 30%.

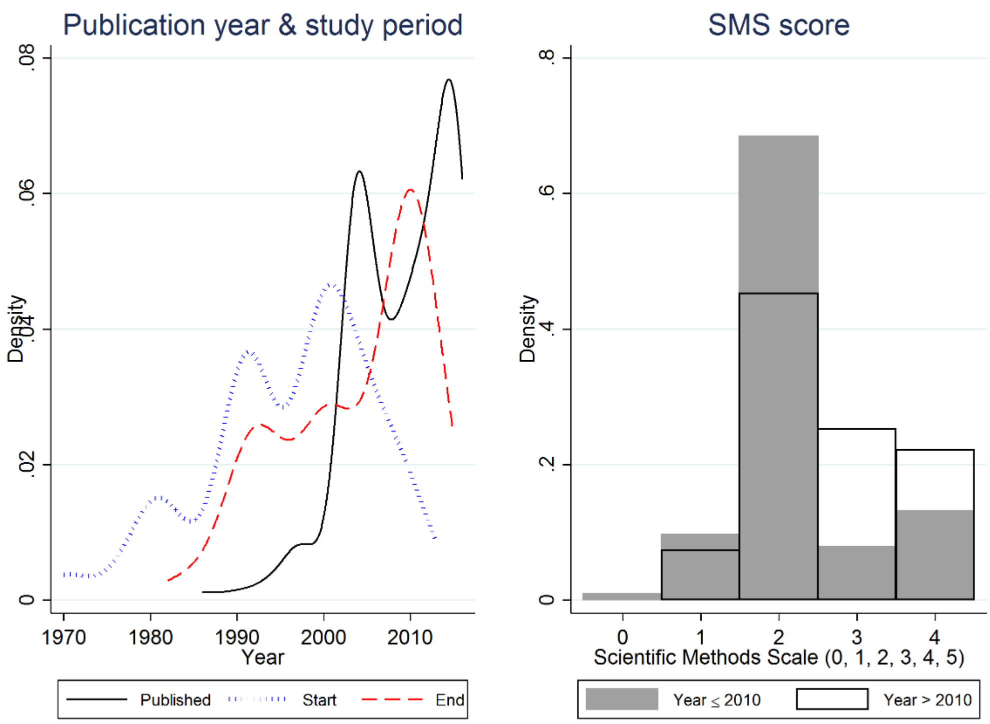
In Figure 1, we illustrate the distribution of publication years, the study period, and the quality of evidence according to the SMS. The evidence, overall, is very recent, with the great majority of studies having been published within the last 15 years, reflecting the growing academic interest in the topic. Most studies use data from the 1980s onwards. A clear majority of studies score two or more on the SMS, which means there is usually at least some attempt to disentangle density effects from other effects, often including unobserved fixed effects and period effects. Distinguishing between studies published before or after the median year of publication (2010) reveals a progression towards more rigorous methods that score three or four on the SMS.

Tab. 1. Distribution of analyses by attributes I

World region		Publication		Discipline	
North America	108	Academic Journal	176	Economics	59
Europe	60	Working Paper	32	Planning	43
Asia	26	Book chapter	1	Urban Studies	35
World	4	-	-	Transport	18
non-OECD	3	-	-	Other	16
OECD	3	-	-	Regional Studies	16
South America	3	-	-	Health	10
Oceania	1	-	-	Economic Geography	8
Africa	1	-	-	Energy	4

Notes: Assignment to disciplines based on publication venues. Studies contain multiple analyses if density effects refer to multiple outcomes.

Fig. 1. Distribution of study period and quality of evidence



Notes: Kernel in the left panel is Gaussian. 2010 is the median year of publication. Scientific Methods Scale (SMS) defined above (higher values indicate more rigorous methods).

2.3 Density and city size

Before we proceed to the analysis of our evidence base, a note is due on the relationship between city size and density. We retrieve two key parameters that help us in the interpretation of the evidence base: The city size (population), elasticity of (population) density and the density elasticity of construction costs.

The literature sometimes refers to actual density, e.g. the population normalised by the geographic size of a city and city size, e.g. the total population, interchangeably. Faberman &

Freedman (2016), just to mention a recent example of a rigorous analysis of agglomeration effects, estimate what they refer to as *density premium* using city *population* as a density measure.[7]

This ambiguity is not necessarily surprising because the workhorse tools in urban economics, such as the monocentric city model and its many derivatives, predict that an increase in city population results in an increase in density. Yet some researchers have attempted to disentangle the effects of density and city size (Cheshire & Magrini 2009). At the heart of such a separation is the idea that different types of agglomeration economies operate at different spatial resolutions (Andersson et al. 2016, p.1093). Separating the effects of city size and density corresponds to separating the effects of different agglomeration economies (and diseconomies), some of which operate over large distances (such that city size matters), while others are more localised (such that density matters). While separating the effects of density and city size is interesting, it is also challenging because the geographic size of an integrated urban area cannot grow infinitely, which implies that density and city size cannot vary independently. Our reading of the literature is that in most studies identifying density effects from between-city (as opposed to within-city) comparisons, city population implicitly changes as city density changes (and vice versa). The results discussed here should be interpreted in that light because the implications may be different from a scenario in which policymakers seek to change density while keeping population constant.

For the comparison of results across studies analysing the effects of city size and density, it is useful to know how the two variables are functionally related, at least on average. We therefore estimate the elasticity of (population) density with respect to city size (population) using OECD metropolitan functional economic area data (OECD 2016) and the following specification:

$$\ln\left(\frac{P_i}{A_i}\right) = \alpha \ln(P_i) + \mu_c + \varepsilon_{ic} \tag{1}$$

, where P_i is the population of city i, A_i is the respective land area, and μ_c is a country fixed effect. We address the mechanical endogeneity problem arising from the fact that population shows up on both sides of the equation using the (ln) rank a city occupies in the distribution of cities within a country as an instrument for population. Our preferred elasticity estimate is 43%, i.e. we expect elasticities with respect to density to be slightly more than twice as large as elasticities with respect to population if the underlying economic mechanisms are the same. We note that our elasticity estimate is broadly consistent with the elasticity of land area with respect

[7] The authors analyse the density effects using a panel framework. If the geographic area was inelastic in the short run, population would indeed be a density measure in an area fixed effect model.

to a population of 0.7 estimated by Combes et al (2016) for French cities, which implies an elasticity of density with respect to a city size of 0.3. Details related to the estimation of equation (1), the estimation results, and the various transformations used to standardise the results reported in the literature are reported in section 2 of the appendix.

The positive city size elasticity of density results from an interplay of the demand side and the supply side of the urban economy. Transport costs within cities imply that there are limits to horizontal urban expansion. Urban growth, therefore, drives up the average rent in a city, leading to lower use of space and a substitution effect on the consumption side. Since building taller becomes profitable, higher rents lead to densification due to a more intense use of land and a substitution effect on the supply side. Higher densities, in turn, imply that it is more expensive to provide space, pushing rents up. Larger cities are therefore theoretically expected to be denser and have higher rents, with the latter being the cause and effect of higher construction costs.

The empirical evidence is generally in line with these expectations. Helsley and Strange (2008) provide anecdotal evidence of larger cities having taller buildings. Gyourko and Saiz (2006) show that constructing a standard home is more expensive in denser areas, even after controlling for differences in geography (high hills and mountains), regulatory regimes (housing permits, regulatory chatter), and labour market conditions (e.g. wages, unionisation). According to Ellis (2004), midrise stacked flats are twice as expensive to construct as single-family detached housing. Ahlfeldt & McMillen (2017) estimate a height elasticity of construction cost of 0.25 for small structures (five stories and below), and even higher elasticities for taller structures. However, estimates of the effect of density on construction cost that capture the changes in the composition of building types (a structure effect) as well as changes in the cost of building equivalent units (a location effect) to our knowledge do not exist to date.

To substantiate the interpretation of our evidence base, we therefore provide novel estimates of the elasticity of density with respect to construction costs. We combine a micro-data set on building constructions from Emporis with census tract level population and area data from the 2010 US Census and the American Community Survey (ACS). In an alternative approach, we create a construction cost index using structure-type-specific construction cost estimates from Ellis (2004) and information on the structure-type composition from the ACS (Ruggles et al. 2017). This index exclusively captures variation in construction costs due to the composition of structure types (the structure effect). The density elasticity of this index can be combined with the density elasticity of the cost of a standard home (the location effect) estimated by Gyourko and Saiz (2006) to give the overall density effect.

From the results of both analyses, we conclude that 4–7% represent a conservative range for the density elasticity of construction cost in the US. This estimate is a gross estimate that includes all structure effects and location effects that are associated with density (including differences in regulation, geology and labour market conditions that may be cause or effects of density). A detailed discussion of the effects of density on construction cost is in appendix 2.2. We will return to this parameter when reviewing the evidence on the effects of density on rents, wages and amenities.

3 Density elasticities in the literature

3.1 Results by outcome category

In Table 2 we summarise the quantitative results in our evidence base. We made an effort to condense the elasticity estimates into a limited number of outcome groups. Because of the great variety of outcomes in the evidence base we frequently report more than one elasticity per outcome category to which we will refer to in the remainder of the paper (indicated by ID). Throughout this paper, all outcomes are expressed such that positive elasticities imply economic effects that are typically considered to be positive in the relevant literatures.

Given the variety of outcomes we do not discuss each result here, but leave it to the interested reader to pick their finding of relevance. We note, however, that there is significant variation in the quantity of the evidence base (N) and the quality of the underlying evidence (as well as other attributes) and we urge these differences to be taken into account when considering the evidence. Caution is warranted, not only when the evidence base is quantitatively small (small N), but also when it is inconsistent. A useful indicator is a standard deviation (SD) that is large compared to the mean, like, for example, pollution reduction. For a selected set of outcome groups (one per category) we provide a critical discussion of the quantity and the quality of the evidence in section 4 of the appendix. We report the mean elasticity weighted by our citation index in Table 2. The interested reader will find results using alternative weighting schemes in section 2 of the appendix.

Tab. 2. Outcome elasticities with respect to density

ID	Elasticity of outcome with respect to density	N	Proportion Poor[a]	Acad.	Econ.	With.	Med. year[b]	Mean SMS[c]	Elasticity[d] Mean	S.D.
1	Wages	22	0.18	0.95	0.64	0.14	2010	3.23	0.04	0.03
1	Total factor productivity	6	0.00	1.00	0.83	0.33	2009	2.83	0.06	0.03
2	Patents p.c.	2	0.00	1.00	0.50	0.00	2009	4.00	0.19	0.06
3	Rental value	9	0.00	0.78	0.56	0.56	2012	2.56	0.13	0.11
4	Commuting reduction	8	0.13	0.63	0.25	0.38	2009	2.25	0.06	0.18
4	Non-work trip reduction	2	0.00	1.00	0.00	0.50	2000	2.00	0.08	0.08
5	Metro rail density	3	0.00	1.00	0.00	1.00	2010	3.33	0.01	0.02
5	Quality of life	7	0.43	0.86	1.00	0.14	2015	2.86	0.04	0.08
5	Variety (consumption amenities)	1	0.00	1.00	0.00	0.00	2015	4.00	0.19	-
5	Variety price reduction	2	0.00	0.00	1.00	1.00	2016	4.00	0.12	0.06
6	Public spending reduction	20	0.00	1.00	0.05	0.00	2007	2.00	0.17	0.25
7	90th–10th pct. wage gap reduction	1	0.00	1.00	0.00	0.00	2004	4.00	0.17	-
7	Black-white wage gap reduction	1	0.00	0.00	1.00	0.00	2013	2.00	0.00	-
7	Dissimilariy index reduction	3	0.00	1.00	0.33	0.00	2009	3.33	0.66	0.94
7	Gini coef. reduction	1	0.00	1.00	0.00	0.00	2010	4.00	4.56	-
8	Crime rate reduction	12	0.00	0.67	0.17	1.00	2015	2.50	0.46	0.22
9	Foilage projection cover	1	0.00	1.00	0.00	1.00	2015	1.00	-0.06	0.00
10	Noise reduction	1	0.00	1.00	0.00	0.00	2012	1.00	0.04	-
10	Pollution reduction	12	0.67	0.42	0.08	0.58	2013	2.42	0.08	0.60
11	Energy reduction: Domestic & driving	19	0.11	0.95	0.42	0.26	2010	1.74	0.07	0.09
11	Energy reduction: Public transit	1	0.00	1.00	1.00	0.00	2010	1.00	-0.37	-
12	Speed	2	0.00	0.00	1.00	0.00	2016	4.00	-0.12	0.01
13	Car usage (incl. shared) reduction	21	0.00	0.95	0.00	0.86	2003	2.00	0.07	0.06
13	Non-car use	28	0.14	0.89	0.00	0.93	2007	2.07	0.16	0.27
14	Serious disease reduction	5	0.00	1.00	0.00	0.60	2000	2.40	-0.33	0.20
14	KSI & casualty reduction	4	0.00	1.00	0.00	0.00	2003	2.00	0.01	0.61
14	Mental health	1	0.00	1.00	0.00	1.00	2015	2.00	0.01	-
14	Mortality reduction	3	0.00	1.00	0.00	0.00	2010	2.00	-0.36	0.17
15	Reported health	3	0.00	1.00	0.00	0.00	2013	1.00	-0.27	0.11
15	Reported safety	1	0.00	1.00	0.00	1.00	2015	2.00	0.07	0.00
15	Reported social interaction	6	0.00	0.17	0.83	0.00	2007	3.50	-0.13	0.19
15	Reported wellbeing	1	0.00	1.00	1.00	0.00	2016	3.00	0.00	-
	Sum	209								

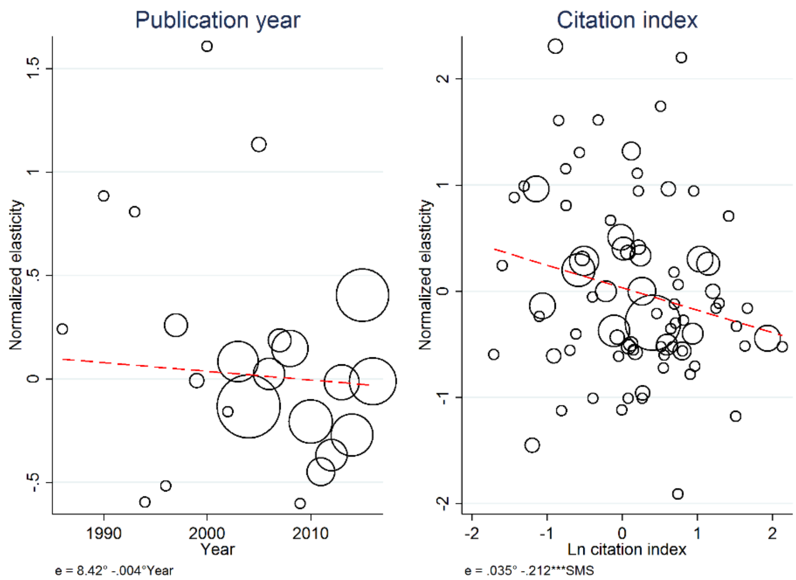
Notes: [a] Poor countries include low-income and median-income countries according to the World Bank definition. [b] Year of publication. [c] Scientific Methods Scale (SMS) defined in section 2.2 (higher values indicate more robust methods). 1: Productivity; 2: Innovation: 3: Value of space; 4: Job accessibility; 5: Services access; 6: Efficiency of public services delivery; 7: Social equity; 8: Safety; 9: Open space preservation and biodiversity; 10: Pollution reduction; 11: Energy efficiency; 12: Traffic flow: 13: Sustainable mode choice; 14: Health; 15: Well-being. [d] Weighted by the citation index introduced in section 2.2 and appendix section 1.2.

3.2 Results by attributes

It is common for meta-analytic research to investigate the sources of heterogeneity in the evidence base. To this end researchers often collect a large number of estimates of the same parameter (normally several from the same study) and subject the evidence base to a multivariate analysis to uncover how specifics of the data and the empirical design are correlated with the result (Melo et al. 2009; Stanley 2001; Disdier & Head 2008). In contrast, we collect evidence on a variety of different parameters, which comes at the expense of having a smaller number of estimates of the same parameters. This is because instead of collecting all the estimates of the same parameter from each individual study, we only collect the baseline estimate of a parameter of interest provided in a study. Due to the relatively small number of observations per outcome elasticity category it is difficult to analyse the distribution of elasticity estimates by category. For a graphical inspection, we therefore pool all the elasticity estimates, normalising them to have a zero mean and a unit standard deviation within the outcome groups listed in Table 2.

Figure 2 plots the normalised elasticity estimates against the year of publication and the quality of the evidence (proxied by the citation index). While there is little evidence of a time trend, normalised elasticities tend to decrease significantly in quality. The results of the bivariate regressions reported at the bottom of the panels confirm the visual impression.

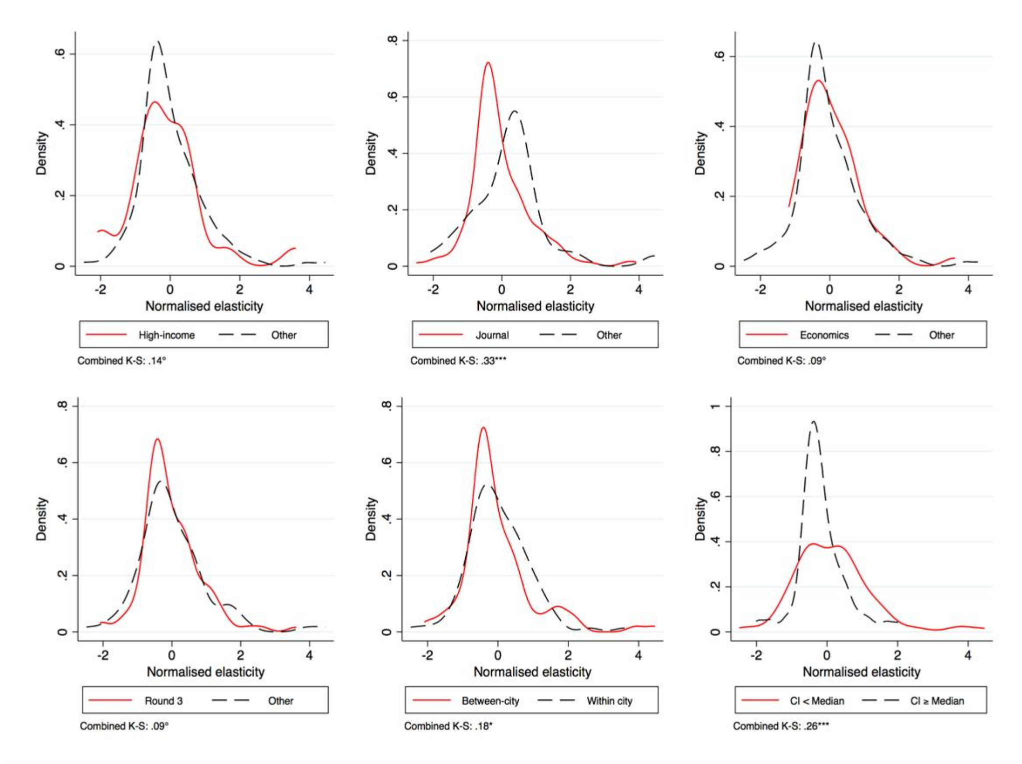
Fig. 2. Normalised elasticities vs. publication year and quality of evidence



Notes: Elasticities normalised within outcome elasticity groups (listed in Table 2) to have a mean of zero and a standard deviation of one. Citation index defined in section 2.2. Marker size proportionate to number of observations. Linear fits (dashed lines, parametric results at the bottom) are frequency weighted by observations. °/*/**/*** indicates insignificant/significant at the 10%/5%/1% level (robust standard errors).

In Figure 3 we illustrate how the distribution of normalised elasticities varies in selected attributes. At the bottom of each panel we report (two-sided) Kolmogorov-Smirnov test statistics and significance levels. We find statistically significant differences in the distributions with respect to publication venue (smaller elasticities in journals) and quality of evidence (smaller elasticities for higher quality). As the effects of journal publication and citation index (CI) are in the same direction it is difficult to conclude whether the former represents publication bias or quality of peer review.

Fig. 3. Distribution of normalised elasticities by attributes



Notes: Elasticities normalised within outcome elasticity groups (listed in Table 2) to have a mean of zero and a standard deviation of one. Non-high-income include low-income and median-income countries according to the World Bank definition. The citation index (CI) defined in section 2.2. °/*/**/*** indicates insignificant/significant at the 10%/5%/1% level based on a two-sample Kolmogorov-Smirnov test for equality of distribution functions.

Table 3 presents the results of a multivariate analysis simultaneously controlling for all attributes considered in Figure 3. We first run the regression by inserting the normalised citation index and the SMS score independently in columns (1) and (2) and then inserting both into regression (3). A one-standard deviation increase in the citation index results in a 0.17 standard deviation reduction in the elasticity, and conditional on the citation effect, the SMS score decreases the elasticity by a 0.355 standard deviation. To obtain the effect on an outcome elasticity the coefficients should be multiplied by the standard deviations reported in Table 2. For example, rigorous methods (SMS>=3) reduce the wage elasticity by 0.01 (0.03 x 0.35). The effect of the quality measures is not reduced when estimated conditional on each other. This is in line with the two measures being virtually uncorrelated (see appendix 1.2), suggesting that they capture different aspects of quality. Given we do not find robust effects for any of the other considered attributes, evidence quality seems to be an important determinant of the estimated density elasticities in absolute and relative terms.

Tab. 3. Multivariate analysis of density elasticities

	(1)		(2)		(3)	
	Normalised (by outcome group mean and s.d.) density elasticity of outcome					
Non-high-income country	-0.149	(0.23)	-0.063	(0.26)	-0.102	(0.23)
Academic journal	-0.164	(0.23)	-0.351*	(0.21)	-0.249	(0.20)
Economics	0.140	(0.17)	0.147	(0.19)	0.293	(0.18)
Round 3	-0.064	(0.15)	-0.099	(0.15)	-0.085	(0.15)
Within-city variation	-0.032	(0.16)	-0.028	(0.17)	-0.011	(0.17)
Citation index normalised by s.d.	-0.153***	(0.05)			-0.170***	(0.05)
SMS >=3			-0.317*	(0.16)	-0.355**	(0.15)
Constant	0.332	(0.28)	0.429	(0.27)	0.491*	(0.27)
N	199		199		199	
r2	0.036		0.033		0.060	

Notes: Normalised elasticities are normalised within outcome groups to have a zero mean and a unity standard deviation. Citation index normalised by the global standard deviation. All other explanatory variables are dummy variables taking the value of one if the condition is true and zero otherwise. 10 observations drop out due to normalisation within categories with singular observations. Non-high-income countries include low-income and median-income countries according to the World Bank definition. Standard errors (in parentheses) are clustered on studies (one study can contain multiple analyses, the unit of observation).* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4 Own density elasticity estimates

While the evidence base on the quantitative effects of density summarised above is rich and reasonably consistent for outcomes like productivity or mode choice, it is thinner and less consistent for many other outcomes. To enrich the evidence base in some of the less-developed categories, we contribute some transparent elasticity estimates using data from the OECD functional economic areas and regional statistics database and the following regression model:

$$\ln(Y_i) = \beta \ln\left(\frac{P_i}{A_i}\right) + \tau \ln\left(\frac{G_i}{P_i}\right) + \mu_c + \epsilon_{ic} \tag{2}$$

, where i indexes cities, Y_i is an outcome, P_i, A_i, μ_c are population, geographic area, and country fixed effects as in equation (1), and G_i is GDP. The coefficient of interest is β, which gives the elasticity of an outcome with respect to population density controlling for GDP per capita and unobserved cross-country heterogeneity. Where either population or area forms part of the dependent variable, we instrument population density using the (ln) rank within the national population density distribution as an instrument. Table 4 summarises the key results. Full estimation results, in each case for a greater variety of model specifications, are in the appendix (section 3).

We find a negative association between well-being and density, which seems to be more pronounced across countries than within. Still, the results support the singular comparable result found in the literature (Glaeser et al. 2016). Our results further support the average findings in the evidence base, in that innovation (number of patents) increases in density and crime rates, energy use (carbon emissions), and average road speeds decrease in density.

Conflicting with the mean elasticities in the evidence base reported in Table 2, we find that pollution concentrations are higher in denser cities and that the mortality rate is lower. Furthermore, our results consistently suggest that income inequality increases in density. This is in line with the typical finding in urban economics research that the high-skilled disproportionately benefit from agglomeration (Glaeser & Resseger 2010). But there is some contrast to the reviewed literature that has found mixed results, with many studies pointing to lower inequalities at higher levels of economic density. To reconcile the evidence base with our own findings, we note that the evidence base contains several case studies on a within-city scale, but our comparison is across economic areas. It seems plausible that the mechanisms affecting equity dimensions are different on a within-city (segregation) and a between-city (skill complementarity) scale, but further research is required to substantiate this intuition.

Our estimates of the relationship between green coverage and population density are without precedent. The elasticity of green density with respect to population density qualitatively depends on the spatial layer of analysis. At regional level (administrative boundaries) the spatial units cover both urban and rural areas. The negative elasticity likely reflects that an increase in population implies a larger share of urban, at the expense of non-urban land. Functional economic areas are designed to cover exclusively urban areas. The positive elasticity likely reflects that within an urbanised area, increasing population density preserves space for urban parks and suburban forests. Because we focus on the effects of urban form in this paper, the latter is our preferred estimate. We note that the relatively large elasticity estimated conditional on country fixed effects is driven by a suspiciously large elasticity across US cities (>1.4), whereas the within-country elasticity for the rest of the world is in line with the baseline elasticity from the cross-sectional model excluding fixed effects. Therefore, in this case we prefer the conservative non-fixed effects model. The elasticity of per capita green area with respect to population is negative, as expected. Our preferred elasticity estimate (-0.283) is of roughly the same magnitude as the elasticity of green space value with respect to population density of 0.3 (Brander & Koetse 2011) suggesting that congestion (number of users) and the value of green space increase at roughly the same rate.

Tab. 4. Own elasticity estimates

	Ln patents p.c.[a]		Ln broadband p.c.[b]		Ln income quintile ratio[b]		Ln Gini coefficient [b]	
Ln dens.	0.349^{***}	0.129^{*}	0.034^{***}	0.01	0.024	0.035^{**}	-0.007	0.025^{***}
FE	-	Yes	-	Yes	-	Yes	-	Yes
IV	-	Yes	-	Yes	-	-	-	-
	Ln poverty rate[b]		Ln homicides p.c.[b]		Ln green density[b] (administrative)		Ln urban green density[a] (functional economic)	
Ln dens.	-0.013	0.032	-0.166^{***}	-0.048	-0.267^{***}	-0.245^{***}	0.283^{**}	0.761^{*}
FE	-	Yes	-	Yes	-	Yes	-	Yes
IV	-	Yes	-	Yes	-	Yes	-	Yes
							Ln speed[a,d]	
	Ln green p.c.[c]		Ln pollution (PM2.5)[b]		Ln CO2 p.c.[b]		freeway	arterial
Ln dens.	-0.717^{***}	-0.239	0.220^{***}	0.124^{***}	-0.224^{***}	-0.173^{***}	-0.008	-0.063^{***}
FE	-	Yes	-	Yes	-	Yes	-	-
IV	-	Yes	-	-	-	Yes	-	-
	Ln mortality rate[b]		Ln mortality rate: transport[b]		Ln life expectancy at birth[b]		Ln subjective well-being[b]	
Ln dens.	-0.046^{***}	-0.017	-0.150^{***}	-0.099^{***}	0.013^{***}	0.007^{*}	-0.023^{***}	-0.007^{**}
FE	-	Yes	-	Yes	-	Yes	-	Yes
IV	-	Yes	-	Yes	-	-	-	-

Notes: Density (dens.) is population density (population / area). All models control for ln GDP p.c. Fixed effects (FE) are by country. IV is rank of a city in the population density distribution within a country.[a] Data from OECD.Stat functional economic areas.[b] Data from OECD.Stat administrative boundaries (large regions).[c] Data from OECD.Stat administrative boundaries (small regions, excluding GDP control due to unavailability of data for the US) [d] Speed data from Lomax et al (2010). Poverty line is 60% of the national median income. Speeds are measured during peak time. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, with standard errors clustered on FE where applicable.

5 Recommended elasticities

In Table 5 we condense the quantitative evidence, including our own estimates, into recommended density elasticities which we provide for each outcome category. Specific to each category, we either recommend a mean across the elasticities in our evidence base as reported in Table 2, the result of a dedicated meta-analysis, an estimate from a high-quality original research paper or one of our own estimates. In general, we prefer the results of good expert meta-analyses over our own summary of the evidence base as well as estimates from dedicated high-quality original research papers over our own estimates. We also prefer estimates from dedicated high-quality papers over the weighted means in the evidence base if the evidence base is thin or inconsistent or inclusive.

Our aim is to provide a compact and accessible comparison of density effects across categories. We are aware and wish to remind the reader that this comes at a cost of ignoring substantial context-specific heterogeneity. Moreover, the quality and quantity of the evidence base is highly heterogeneous across categories. We strongly advise to consult section 4 in the appendix, which provides a discussion of the origin of each of the recommended elasticities against the quality and quantity of the evidence base, before applying any of the elasticities reported in Table 5 in further research. We stress that significant uncertainty surrounds the effects of density on income inequality, urban green, pollution concentration, health, and subjective well-being.

There is an important additional elasticity that is implicitly determined by the elasticities reported in Table 5. Assuming perfect mobility and competition in all markets, all benefits and costs in urban area offers must be compensated by wages and rents (Rosen 1979; Roback 1982). The relative quality of life of a place can be inferred from the relative real wage (income after taxes and housing expenditures) residents are willing to give up to enjoy living there, i.e. $\mathrm{dln}\, Q = \rho\, \mathrm{dln}\, r - T\, \mathrm{dln}\, w$, where $\mathrm{dln}\, Q$, $\mathrm{dln}\, r$,and $\mathrm{dln}\, w$ are differentials in quality of life, rents, and wages (in natural logs), ρ is the housing expenditure share and T is one minus the tax rate. The elasticity of quality of life with respect to density can be expressed as: $\frac{\mathrm{dln}\, Q}{\mathrm{dln}(P/A)} = \rho \frac{\mathrm{dln}\, r}{\mathrm{dln}(P/A)} - T \frac{\mathrm{dln}\, w}{\mathrm{dln}(P/A)}$.

Applying conventional values of $\rho = 1/3$ and $T = 0.51$ (Albouy & Lue 2015) and the elasticities reported in Table 5, the resulting quality-of-life elasticity at 5% is close to the citation-weighted mean elasticity from the evidence base (4%). However, we must note that there is considerable variation in the collected quality-of-life elasticities including both negative (Chauvin et al. 2016) and positive effects (Albouy & Lue 2015).

Tab. 5. Recommended elasticities by category

ID	Elasticity	Value	Source
1	Wage	4%	Median elasticity in review, roughly in line with Combes et al. (2016) and Melo et al. (2009)
2	Patent intensity	19%	Mean elasticity in review, in line with own analysis of OECD data
3	Rent	21%	Dedicated high-quality paper (Combes et al. 2016)
4	Vehicle miles travelled (VMT) reduction	8.5%	Dedicated high-quality paper (Duranton & Turner 2015), between mean and median elasticity in review
5	Variety value (price index reduction)	12%	Dedicated analysis on request (Couture 2016), in line with Ahlfeldt et al. (2015)
6	Local public spending	14.4%	Dedicated high-quality paper (Carruthers & Ulfarsson 2003)
7	Wage gap[a] reduction	-3.5%	Own analysis of OECD data (evidence base thin and inconsistent)
8	Crime rate reduction	8.5%	Dedicated analysis on request (Tang 2015)
9	Green density	29%	Own analysis of OECD data (evidence base non-existent)
10	Pollution reduction	8%	Mean elasticity in review
11	Energy use reduction	7%	Mean elasticity in review
12	Average speed	-11%	Mean of two high-quality papers (Duranton & Turner 2015; Couture et al. 2016)
13	Non-car mode choice	7%	Meta-analysis by Ewing & Cervero (2010)
14	Mortality rate reduction	-9%	Dedicated paper (Reijneveld et al. 1999)
15	Subjective well-being	-0.37%	Only direct estimate in literature (Glaeser et al. 2016)

Notes: [a] 80^{th} vs. 20^{th} percentile. 1: Productivity; 2: Innovation: 3: Value of space; 4: Job accessibility; 5: Services access; 6: Efficiency of public services delivery; 7: Social equity; 8: Safety; 9: Open space preservation and biodiversity; 10: Pollution reduction; 11: Energy efficiency; 12: Traffic flow: 13: Sustainable mode choice; 14: Health; 15: Well-being. See appendix section 4 for a critical discussion of the evidence base by category.

6 Monetary equivalents

While the elasticities reported in Table 5 are all in the same unit-free dimension, the implied effects of density are still difficult to compare as they materialise in very different metrics. To allow for a better comparison, we conduct a series of back-of-the-envelope calculations to express the effects that would result from a 1% increase in density as per capita NPV dollar effects, assuming a conventional 5% discount rate (de Rus 2010), . We summarise the results in Table 6. Because most of the parameters used in the back-of-the envelope calculations are context-dependent, the table is designed to allow for straightforward adjustments. The monetary effect in the last column (8) is simply the product over the elasticity (3), the base value (5), the unit value (7), the 5% discount rate and a 1% increase in density (e.g. 4% × \$35,000 × 1 × 1% for the wage effect × 5%). By changing any of the factors a context-specific monetary equivalent can be immediately calculated.

Table 6, to our knowledge, represents an unprecedented attempt to condense the state of empirical knowledge on a great variety of density effects into a compact, accessible and quantitative format. This is an ambitious exercise and there are some limitations. First, to monetise the effects of density on the various outcomes we make admittedly heroic assumptions, which are laid out in detail in the appendix (section 5). As a result, the monetary equivalents are best understood as illustrative examples that refer to an average person in an average metropolitan area in a high-income country. In drawing conclusions for a specific institutional context, we strongly advise that the assumptions made in appendix section 5 are evaluated with respect to their applicability.

Second, the results in Table 6 correspond to a comparison of an actual situation to a hypothetical counterfactual with a 1% lower density assuming an overall adjustment to density that corresponds to the average in the data (i.e. no specific policies). This is not necessarily the same as increasing the density of a given city by 1%. As an example, a denser city, ceteris paribus, will in general have more preserved green space compared to the counterfactual because its economic activity is concentrated on a smaller developed area. However, increasing the density of a city is unlikely to result in the increase in green density that is implied by the elasticity. Instead, the increase in density may lead to a higher green density in the future compared to a counterfactual of urban growth at a lower density.

Third, the reported elasticities typically refer to the means of distributions observed in the data. They represent less plausible approximations for extreme scenarios (e.g. places with very high or low values of an outcome or density). Also, the effects implied by the elasticities apply to marginal changes only, i.e. they should not be used to evaluate the likely effects of extreme changes (e.g. a 100% increase in density) in particular settings.

Fourth, as already discussed in the previous section, the evidence base from which the outcome elasticities are inferred is more mature for some categories than for others. Section 5 in the appendix provides a more detailed discussion of the evidence base that should be consulted before there is any further use of the suggested monetary equivalents in Table 6. Given the quantity and the quality of the evidence base, we consider the results in the categories urban green, income inequality, pollution, health, and well-being as, at best, preliminary.

Tab. 6. Net present value[a] of a 1% increase in density I: Category-specific effects

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Category			Quantity, p.c., year		Unit value		NPV of 1%
ID	Outcome	Elast.	Variable	Value	Unit	Value	dens. incr.
1	Wage	4%	Income ($)	35,000	-	1	280
2	Patent intensity	19%	Patents (#)	2.06E-04	Patent value ($/#)	793K	6
3	Rent	21%	Income ($)	35,000	Expenditure share	0.33	485
4	VMT[b] reduction	8.5%	VMT[b] (mile)	10,658	Priv. cost $/mile	0.83	151
5	Variety value[c]	12%[b]	Income ($)	35,000	Expenditure share[d]	0.14	115
6	Local public spending	14.4%	Total spending ($)	1,463	-	1	42
7	Wage gap[e] reduction	-3.5%	Income ($)	35,000	Inequality premium	0.048	-12
8	Crime rate[f] reduction	8.5%	Crimes (#)	0.29	Full cost ($/#)	3,224	16
9	Green density	23%	Green area (p.c., m^2)	540	Park value ($/$m^2$)	0.3	82
10	Pollution reduction	8%	Rent ($)	11,550	Rent-poll. elasticity	0.3	55
11	Energy use reduction	7%	Energy (1M BTU)	121.85	Cost ($/1M BTU)	18.7	32
	(private and social effects)	7%	CO_2 emissions (t)	25	Social cost ($/t)	43	15
12	Average speed	-12%	Driving time (h)	274	VOT ($/h)	10.75	-71
13	Non-car mode choice	7%	VMT[b]	10,658	Social cost ($/mile)[g]	0.016	2
14	Health	-9%	Mortality risk (#)	5.08E-04	Value of life ($/#)[h]	7M	-64
15	Subjective well-being[j]	-0.4%	Income ($)	35,000	Inc.-happ. elasticity	2	-52

Notes: [a] The per capita net present value at a 5% discount rate. [b]Vehicle miles travelled. [c]Reduction in price index of consumption varieties. [d] Local non-tradeables: home, entertainment, and apparel and services. [e]80th vs. 20th percentile. [f]All crimes against individual and households, [g]Emissions externality [h]Statistical value of life. [i]Pre-mature (> 70) mortality rate. [j] Self-reported subjective well-being. See appendix section 5 for a discussion of the assumptions on quantities and unit values by category.

Despite these limitations, Table 6 offers novel insights into the direction and the relative importance of density effects. The density effect on wages, which has been thoroughly investigated in the agglomerations literature, is large, but not as large as the effect on rents, on average.[8] Density generates costs in the form of higher congestion and lower average road speeds, which are, however, more than compensated for by the cost reductions due to shorter trips. Agglomeration benefits on the consumption side due to larger and more accessible consumption variety are quantitatively important and amount to more than one-third of agglomeration benefits on the production side (wages). Other quantitatively relevant benefits arising from the density include cost savings in the provision of local public services, preserved

[8] The results by Combes at al. (2016) suggest that this result may not apply to small cities as the rent elasticity increases in city size.

green spaces, and reduced energy use, which creates a sizable social benefit (reduced carbon emissions) in addition to private cost savings. Other benefits relate to lower crime rates and lower pollution externalities. Besides the aforementioned congestion effects, the cost of density comes in the form of increased inequality, adverse health effects and reduced well-being.

Given that we have gone a long way in computing category-specific measures of costs and benefits that are comparable across categories, a natural question arises: Do the benefits of density exceed the costs and, if so, by how much? To address this question, we conduct a simple accounting exercise in Table 7. We distinguish between private (columns 1–5) and external (column 6) costs and benefits, which residents do not directly experience and likely do not pay for via rents (such as reductions in carbon emissions that have global rather than local effects). To avoid double-counting, we exclude gasoline costs in computing the benefits of shorter average trips (category 4) as this cost-saving is already accounted for by reduced energy consumption (category 11). Also, we correct consumption benefits (category 5) to reflect the pure gains from variety and not savings due to shorter car trips, which are already itemised in category (4). The external effect from sustainable mode choice (13) is already itemised in the external benefit of reduced energy use (11) and is thus not counted separately.

The standard urban economics framework builds on the spatial equilibrium assumption, which implies that individuals are fully mobile and competition in all markets is perfect. In this framework, rents reflect the capitalised values of productivity and utility so that the sum over rents and wages (column 1) amounting to close to $800, p.c. can be interpreted as a welfare gain. Depending on whether the items in columns (6) are expected to capitalise into rents (e.g. if local public services are financed through local taxes) or not (e.g. if local public services are financed through national taxes) they can be added to the welfare balance. The spatial equilibrium framework is also the theoretical fundament for the economic quality-of-life literature mentioned above, which infers place-specific amenity values from compensating differentials. The implication is that an increase in rent that exceeds an increase in disposable income reflects a positive quality-of-life effect.

An alternative theoretical view is that increases in rents at least partially reflect the costs of economic frictions. If mobility is not perfect and/or there is heterogeneity in the preference for locations, rents will not only reflect demand-side conditions (here, amenities), but also supply-side conditions (Arnott & Stiglitz 1979). Density – or the policies that enforce density – can then increase rents because of the restricted supply of space, in which case the rent effect can be suggestive of deadweight loss (Hilber & Vermeulen 2016; Cheshire & Hilber 2008). Distinguishing these scenarios is notoriously difficult, but it is informative to compare the quality-of-life effect inferred from wages and rents to the aggregate amenity effects across categories. If the accounting was precise and complete and there were no frictions, we would expect the aggregate amenity effect to equal the quality-of-life effect.

The amenity effect reported in column (3) with an NPV of $221 per capita, is substantial, but less than two-thirds of the compensating differential (about $342) in column (2), suggesting a role for the supply side (as long as demand is locally downward-sloping). The role of subjective well-being is controversial as it is regarded either as a proxy for individual utility (Layard et al. 2008) or as a component in the utility function that is traded against the consumption of goods and amenities (Glaeser et al. 2016). However, excluding the well-being effect as a (dis)amenity category is not sufficient to align the amenity effect with the quality-of-life effect. Likewise, treating local public services as fully locally financed, which implies that the savings are passed on to individuals and are capitalised into rents, leaves a sizable difference between the quality-of-life effect and the amenity effect. Even if we ignore the well-being effect and assume locally financed public services, there remains a notable gap ($300 vs. $273).

To assess the potential relevance of density effects on rents that originate from the supply side, we assume a share of structural value in housing of 75% (Ahlfeldt et al. 2015; Combes et al. 2016) and compute a range for the monetary equivalent of the effect of a 1% density increase on construction cost as 4–7% (density elasticity of construction cost, see section 2.3) x $35k (income) x 75% (share of structure value) x 33% (expenditure share on housing) x 1% (change in density) = $70–120. This is close to the $79 (locally financed public services) to $121 (state-financed public services) gap between the quality-of-life effect of density (Table 7, column 2) and the aggregated density effect of all (dis)amenities (Table 7, column 3), suggesting a role for the supply side. A complementary channel that strengthens the supply-side argument is a scarcity land rent that results from policies that restrict the amount of usable land to increase density (Gyourko et al. 2008; Mayer & Somerville 2000). A detailed discussion of the effects of density on construction costs is in appendix section2.2.

In columns (4) and (5) we change the perspective and ask how a marginal increase in the density of a city would affect residents in the long run (compared to the counterfactual of having no increase). Because costs and benefits of density capitalise into rents, the individual net-benefit depends on housing tenure. Given the positive amenity affect from column (5) it is immediate that homeowners gain, on average, as they receive an amenity benefit without having to pay a higher rent. If they were moving to another area they would leave the amenity gain behind, but would benefit from a higher housing value. Renters would be negatively compensated for the amenity gain by higher rents, making the implications more ambiguous (Ahlfeldt & Maennig 2015). The net benefit to homeowners is positive with a combined amenity and wage effect of $364 or more (if there are tax savings or we abstract from the well-being effect). There is a net cost to renters of up to $121 if we include well-being effects and assume that there are no tax effects due to savings in public services. Even if we exclude the well-being effect and allow for cost savings in public services to be passed on to renters via lower taxes, the net benefit remains negative.

Overall, the evidence suggests that density is a net amenity. However, this does not imply that everybody is a net beneficiary from increases in density. Renters may be net losers of densification because of rent effects that exceed amenity benefits. The negative net-effect is consistent with a negative density effect on well-being if individuals are attached to some areas more than others. If one is willing to believe that there are strong forces that prevent renters from moving, a supply constraining effect of density can shift renters to a lower utility level, consistent with a negative effect on well-being (or happiness). This is, however, an ambitious interpretation of the evidence as it is impossible to claim full coverage and perfect measurement of amenity effects. It is important to acknowledge that the difference between the amenity effect (in column 3) and the quality-of-life effect (in column 2) of density could simply be due to measurement error (e.g. missing items column 3). Research into the well-being effects of density differentiated by tenure would be informative, but to our knowledge, such research has yet to be conducted.

Tab. 7. Net present value[a] effects of a 1% increase in density II: Accounting

ID	Outcome Category	(1) Factor Incomes	(2) Quality of life	(3) Amenity value	(4) Effect on Owner	(5) Renter	(6) External welfare
1	Wage	280	-143	0	143	143	0
2	Innovation	0	0	0	0	0	6
3	Value of space	485	485	0	0	-485	0
4	Job accessibility	0	0	124[b]	124[b]	124[b]	0
5	Services access	0	0	99[c]	99[c]	99[c]	0
6	Eff. of pub. services delivery	0	0	0	0	0	42
7	Social equity	0	0	0	0	0	-12
8	Safety	0	0	16	16	16	0
9	Urban green	0	0	82	82	82	0
10	Pollution reduction	0	0	55	55	55	0
11	Energy efficiency	0	0	32	32	32	0
12	Traffic flow	0	0	-71	-71	-71	0
13	Sustainable mode choice	0	0	0	0	0	0[d]
14	Health	0	0	-64	-64	-64	0
15	Subjective well-being	0	0	-52	-52	-52	0
	Sum	765	342	221	364	-121	52
	Excl. subj. well-being	-	-	273	416	-69	51
	Locally financed pubic services	-	300		406	-79	
	Factor incomes and externality	817	-	-	-	-	-
	Locally financed pubic services	775	-	-	-	-	-

Notes: [a] The net present value per capita at a 5% discount rate. All values in $. [b] Excludes $27.18 of driving energy cost ($0.15/mile gasoline cost) discounted at 5%, which are itemised in 1 [c] Assumes a 10.2% elasticity to avoid double-counting of road trips already included in 4. [d] Set to zero to avoid double counting with 11. Numbers reported in the "Locally financed pubic services" row assume that cost savings in local public services are fully passed on to residents via lower taxes.

7 Conclusion

We provide the first quantitative evidence review of the effects of density on a broad range of outcomes. We collect 209 density elasticity estimates that we group into 15 outcome categories. These elasticities express the effect of density on an outcome in unit-free percentage terms and are thus suitable for comparisons across empirical studies analysing data in different contexts and geographies. More than half of these estimates have not been previously published and are provided by the authors on request or inferred from existing estimates in auxiliary analyses. In addition, we contribute density elasticity estimates for 15 outcome variables that belong to outcome categories for which the evidence base is thin, inconsistent or non-existent.

The most notable insights of the analysis of within-category heterogeneity in the evidence base is that studies that are more frequently cited or employ more robust methods, tend to find less positive density effects. The effects are quantitatively large, highlighting the importance of considering the quality of evidence when interpreting density effects. There is no similarly robust effect for any of the other considered attributes.

One of our main contributions is to condense the evidence base to a set of recommended elasticities (one for each outcome category), selecting either the mean result from our evidence base, a result from an existing dedicated meta-analysis or original research piece, or an own estimate if the quantitative evidence is thin or inconclusive. Density is associated with (recommended elasticities in parentheses) higher wages (4%), patent activity (19%), consumption variety value (12%), preservation of open spaces (23%), use of non-car modes (7%) as well as lower average vehicle mileage (8.5%), energy consumption (7%), pollution density (8%), crime (8.5%), and the costs of providing local public services (14.4%). Density, however, is also associated with higher rents (21%), inter-quartile wage gaps (3.5%), mortality risk (9%), lower average speed (12%) and subjective well-being (0.4%).

Using these elasticities and an illustrative scenario that roughly corresponds to an average individual in an average city in a high-income country in terms of per capita wages, rents, amenities and other characteristics, we compute the per capita NPV of a 1% increase in density for each of the 15 categories. Given the assumptions made, we find that a 1% increase in density leads to an increase in wages of $280 per capita and year ($143 after taxes) and a respective increase in rent of $485. We find economically sizable effects of shorter trip lengths ($151) that more than compensate for the cost of lower average road speeds ($71). Consumption benefits (greater and more accessible variety, $115), reductions in local public spending per capital ($42), lower crime rates ($16), preserved green space ($82), lower levels of pollution ($55), and energy consumption ($32 private benefits due to lower energy cost plus $15 external benefit due to lower carbon emissions) also have sizable positive effects. Besides lower average road speeds, significant monetised costs come in the form of larger income inequality ($12), adverse health effects ($64), and lower subjective well-being ($52).

Summing up the monetary equivalents of all amenity categories and avoiding double-counting, we find a positive amenity value, which is, however, not as large as the "compensating differential" (rent effect – disposable income effect). While density seems to be a net amenity, our admittedly imperfect accounting also suggests that part of the rent increase is attributable to the higher cost of providing space and not exclusively to enjoyable amenities.[9] This is in line with our novel estimates of the density elasticity of construction cost of 4–7%. Policies aiming at increasing density and making cities more compact are likely to benefit homeowners, but are potentially harmful to renters and first-time buyers. To avoid such inefficient and unequitable effects it is important to ensure that compactness is not achieved at the cost of excessively constraining the supply of space. As an example, restrictions of developable land (e.g. due to

[9] To be theoretically consistent this interpretation requires that residents are not fully mobile (e.g. because they have location-specific preferences).

urban growth boundaries) should not be coupled with binding height constraints as this would lead to a rent increase due to a shortage of space, a so-called "regulatory tax" (Cheshire & Hilber 2008), and not (only) due to increased productivity or amenity.

These results are our best attempt at condensing a heterogeneous literature on heterogeneous effects into a compact and accessible quantitative format. It is important to acknowledge that the interpretations made are ambitious given the quantity and the quality of the evidence. Researchers wishing to apply our quantitative results in further research are advised to consult sections 4 and 5 in the technical appendix for a critical assessment of the evidence base and an evaluation of the transferability of the assumptions made.

A final word concerns future research in this area. In general, much work lies ahead of the related research fields to consistently bring the evidence base to the quantity and quality levels of the outcome categories productivity and mode choice. For all other categories, more research is required – even if selected high-quality evidence exists – to substantiate the recommended elasticities. At this stage, significant uncertainty surrounds any quantitative interpretation in the categories urban green, income inequality, pollution, health, and well-being.

As research progresses and the quantity of the evidence base increases, evidence reviews and meta-analyses become a more important aspect of knowledge generation. Regrettably, the scope of this review was constrained because it was frequently not possible to translate results into a comparable metric. To increase the scope of future reviews and meta-analyses, we encourage researchers to complement the presentation of their preferred results by density elasticity estimates that are comparable to those collected here. Minimally, complete summary statistics need to be provided to allow for a conversion of reported marginal effects. Another feature that hinders comparisons across studies is the common practice of analysing more than one aspect of urban form at once, i.e. simultaneously using multiple spatial variables such as population density, building density and job centrality. Disentangling the sources of the effects of compact urban form is important. But it is difficult to compare such conditional marginal effects estimated under the ceteris paribus condition across studies if the measures of urban form co-vary in reality because they are simultaneously determined. To facilitate future reviews and meta-analyses we encourage researchers to complement their differentiated analyses with simple models that exclusively consider the most conventional measure of urban form, which is density.

A fundamental limitation of the evidence base across all outcome categories is that the best studies usually focus on obtaining well-identified point estimates of density effects. While the evidence summarised here suggests that increasing the density of an average large city in the developed world is likely associated with net benefits, this implication does not necessarily generalise to all cities. An important challenge that lies ahead of the research community is to generate a deeper understanding of heterogeneity in density effects across contexts and the density distribution itself, a necessary condition for inference on optimal levels of density.

Literature

Ahlfeldt, G.M. & Maennig, W., 2015. Homevoters vs. leasevoters: A spatial analysis of airport effects. *Journal of Urban Economics*, 87.

Ahlfeldt, G.M. & McMillen, D.P., 2017. Tall buildings and land values: Height and construction cost elasticities in Chicago, 1870-2010. *CEPR DP 12351*.

Ahlfeldt, G.M. & Pietrostefani, E., 2017. The compact city in empirical research: A quantitative literature review. *SERC discussion paper 215*.

Ahlfeldt, G.M., Redding, S.J., Sturm, D.M. & Wolf, N., 2015. The Economics of Density: Evidence from the Berlin Wall. *Econometrica*, 83(6), pp.2127–2189.

Albouy, D. & Lue, B., 2015. Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life. *Journal of Urban Economics*, 89, pp.74–92.

Andersson, M., Klaesson, J. & Larsson, J.P., 2016. How Local are Spatial Density Externalities? Neighbourhood Effects in Agglomeration Economies. *Regional Studies*, 50(6), pp.1082–1095.

Angel, S., Sheppard, S.C., Civco, D.L., Buckley, R., Chabaeva, A., Gitlin, L., Kraley, A., Parent, J. & Perlin, M., 2005. *The Dynamics of Global Urban Expansion*, Washington D.C.

Arnott, R.J. & Stiglitz, J.E., 1979. Aggregate Land Rents, Expenditure on Public Goods, and Optimal City Size. *The Quarterly Journal of Economics*, 93(4), pp.471–500.

Bettencourt, L.M.A. & Lobo, J., 2016. Urban scaling in Europe. *Journal of The Royal Society Interface*, 13, pp.1–14.

Boyko, C.T. & Cooper, R., 2011. Clarifying and re-conceptualising density. *Progress in Planning*, 76(1), pp.1–61.

Brander, L.M. & Koetse, M.J., 2011. The value of urban open space: Meta-analyses of contingent valuation and hedonic pricing results. *Journal of Environmental Management*, 92, pp.2763–2773.

Carlino, G.A., Chatterjee, S. & Hunt, R.M., 2007. Urban density and the rate of invention. *Journal of Urban Economics*, 61(3), pp.389–419.

Carruthers, J.I. & Ulfarsson, G.F., 2003. Urban sprawl and the cost of public services. *Environment and Planning B: Planning and Design*, 30(4), pp.503–522.

Chauvin, J.P., Glaeser, E.L., Ma, Y. & Tobio, K., 2016. What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States. *Journal of Urban Economics*, pp.1–33.

Cheshire, P. & Magrini, S., 2009. Urban growth drivers in a Europe of sticky people and implicit boundaries. *Journal of Economic Geography*, 9(1), pp.85–115.

Cheshire, P.C., 2006. Resurgent Cities, Urban Myths and Policy Hubris: What We Need to Know. *Urban Studies*, 43(8), pp.1231–1246.

Cheshire, P.C. & Hilber, C.A.L., 2008. Office Space Supply Restrictions in Britain: The Political Economy of Market Revenge*. *The Economic Journal*, 118(529), pp.F185–F221.

Ciccone, A. & Hall, R.E., 1996. Productivity and the Density of Economic Activity Productivity and the Density of Economic Activity. *The American Economic Review*, 86(1), pp.54–70.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D. & Roux, S., 2012. The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection. *Econometrica*, 80(6), pp.2543–2594.

Combes, P., Duranton, G. & Gobillon, L., 2016. The Costs of Agglomeration: Land Prices in French Cities. *Working Paper*, (7027).

Couture, V., 2016. Valuing the Consumption Benefits of Urban Density. *Working Paper: Univeristy of California, Berkeley*, (September).

Couture, V., Duranton, G. & Turner, M.A., 2016. Speed. *Working Paper*.

Disdier, A.-C. & Head, K., 2008. The Puzzling Persistence of the Distance Effect on Bilateral Trade. *Review of Economics and Statistics*, 90(1), pp.37–48.

Duranton, G. & Turner, M.A., 2015. Urban form and driving: Evidence from US cities. *Working Paper*.

Eckel, C.C. & Füllbrunn, S.C., 2015. Thar SHE Blows? Gender, Competition, and Bubbles in Experimental Asset Markets. *American Economic Review*, 105(2), pp.906–920.

Ellis, J.G., 2004. Explaning Residential Density. *Places*, 16(2).

Epple, D., Gordon, B. & Sieg, H., 2010. American Economic Association A New Approach to Estimating the Production Function for Housing. *American Economic Review*, 100(3), pp.905–924.

Ewing, R. & Cervero, R., 2010. Travel and the Built Environment: A Synthesis. *Journal of the American Planning Association*, 76(3), pp.265–294.

Faberman, R.J. & Freedman, M., 2016. The urban density premium across establishments. *Journal of Urban Economics*, 93, pp.71–84.

Glaeser, E.L., Gottlieb, J.D. & Ziv, O., 2016. Unhappy Cities. *Journal of Labor Economics*, 34(2), pp.S129–S182.

Glaeser, E.L. & Kahn, M.E., 2010. The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics*, 67(3), pp.404–418.

Glaeser, E.L. & Resseger, M.G., 2010. The complementarity between cities and skills. *Journal of Regional Science*, 50(1), pp.221–244.

Gomez-Lievano, A., Youn, H.J. & Bettencourt, L.M.A., 2012. The statistics of urban scaling and their connection to Zipf's law. *PLoS ONE*, 7(7), p.e40393.

GRUMP, 2010. Columbia University Socioeconomic Data and Applications Center Gridded Population of the World and the Global Rural-Urban Mapping Project. Available at: http://sedac.ciesin.columbia.edu/data/collection/gpw-v4 [Accessed January 7, 2017].

Gyourko, J. & Saiz, A., 2006. Construction costs and the supply of housing structure. *Journal of Regional Science*, 46(4), pp.661–680.

Gyourko, J., Saiz, A. & Summers, A., 2008. A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies*, 45(3), pp.693–729.

Helsley, R.W. & Strange, W.C., 2008. A game-theoretic analysis of skyscrapers. *Journal of Urban Economics*, 64(1), pp.49–64.

Hilber, C.A.L. & Vermeulen, W., 2016. The Impact of Supply Constraints on House Prices in England. *The Economic Journal*, 126(591), pp.358–405.

Holman, N., Mace, A., Paccoud, A. & Sundaresan, J., 2014. Coordinating density; working through conviction, suspicion and pragmatism. *Progress in Planning*, 101, pp.1–38.

Hortas-Rico, M. & Sole-Olle, A., 2010. Does Urban Sprawl Increase the Costs of Providing Local Public Services? Evidence from Spanish Municipalities. *Urban Studies*, 47(7), pp.1513–1540.

IAU-IDF, 2012. *Document d'orientations stratégiques pour le fret en Ile-de-France à l'horizon 2025*, Direction régionale et interdépartementale de l'Équipement et de l'Aménagement d'Île-de-France: Paris.

Layard, R., Mayraz, G. & Nickell, S., 2008. The marginal utility of income. *Journal of Public Economics*, 92(8–9), pp.1846–1857.

Liu, Z., He, C., Zhou, Y. & Wu, J., 2014. How much of the world's land has been urbanized, really? A hierarchical framework for avoiding confusion. *Landscape Ecology*, 29(5), pp.763–771.

Lomax, T., Schrank, D., Turner, S., Geng, L., Li, Y. & Koncz, N., 2010. *Real-Timing the 2010 Urban Mobility Report*,

Mayer, C.J. & Somerville, C.T., 2000. Land use regulation and new construction. *Regional Science and Urban Economics*, 30(6), pp.639–662.

Melo, P.C., Graham, D.J. & Noland, R.B., 2009. A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, 39(3), pp.332–342.

Neuman, M., 2005. The Compact City Fallacy. *Journal of Planning Education and Research*, 25(1), pp.11–26.

Nitsch, V., 2005. Zipf zipped. *Journal of Urban Economics*, 57(1), pp.86–100.

OECD, 2010. *Cities and Climate Change*, OECD Publishing.

OECD, 2012. *Compact City Policies: A Comparative Assessment*, OECD Green Growth Studies, OECD Publishing.

OECD, 2016. OECD Metropolitan area data.

Reijneveld, S.A., Verheij, R.A. & de Bakker, D.H., 1999. Relative importance of urbanicity, ethnicity and socioeconomic factors regarding area mortality differences. *Journal of epidemiology and community health*, 53(7), pp.444–5.

Roback, J., 1982. Wages, Rents, and the Quality of Life. *Journal of Political Economy*, 90, pp.1257–1278.

Rosen, S., 1979. Wages-based Indexes of Urban Quality of Life. In P. Mieszkowski & M. Straszheim, eds. *Current Issues in Urban Economics*. Baltimore: John Hopkins Univ. Press.

Ruggles, S., Genadek, K., Goeken, R., Grover, J. & Sobek, M., 2017. Integrated Public Use Microdata Series: Version 7.0 [dataset].

de Rus, G., 2010. *Introduction to cost-benefit analysis : looking for reasonable shortcuts*, Cheltenham, UK; Northampton, MA: Edward Elgar.

Scimago, 2017. SJR: Scientific Journal Rankings. Available at: http://www.scimagojr.com/journalrank.php [Accessed September 14, 2017].

Scopus, 2016. Journal Metrics. Available at: https://journalmetrics.scopus.com/ [Accessed September 14, 2017].

Stanley, T.D., 2001. Wheat From Chaff: Meta-Analysis As Quantitative Literature Review. *Journal of Economic Perspectives*, 15(3), pp.131–150.

Tang, C.K., 2015. Urban Structure and Crime. *Working Paper*.

United Nations, 2005. Definition of "Urban." In *Demographic Yearbook 2005*.

United Nations, 2014. *World Urbanization Prospects: The 2014 Revision*, New York.

What Works Centre for Local Economic Growth (WWC), 2016. *Guide to scoring evidence using the Maryland Scientific Methods Scale*, London, UK.

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Appendix to
The economic effects of density: A synthesis

Version: October 2017

Introduction

This appendix complements the main paper by providing additional detail not reported in the main paper for brevity. To improve the flow of the presentation it partially duplicates discussions in the main text. The appendix, however, is designed to complement, not replace the reading of the main paper.

1 Evidence base

1.1 Collecting the evidence

In order to determine the selection of keywords to collect our evidence base we developed a theory matrix through a transparent and theory-consistent literature search which can be found in a companion paper (Ahlfeldt & Pietrostefani 2017). The theory matrix establishes the economic channels connecting 15 outcome categories to three compact city characteristics. We use combinations of keywords that relate to each outcome and compact city characteristic. Where appropriate, we use empirically observed variables specified in the companion paper (Ahlfeldt & Pietrostefani 2017).

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Tab. A1. Organisation of keyword search

	Compact city effects	Compact city characteristics		
#	Outcome category	Residential and employment Density	Morphological Density	Mixed use
1	Productivity	density; productivity; wages; urban	-	-
		density; productivity; rent; urban	-	-
2	Innovation	density; innovation; patent; urban	-	-
		density; innovation; peer effects, urban	-	-
3	Value of space	density; land value; urban	building height; land value; urban	-
		density; rent; urban	building height; rent; urban	-
		density; prices; urban	building height; prices; urban	-
4	Job accessibility	density; commuting; urban	land border; commuting; urban	-
5	Services access	density; amenity; distance; urban	street; amenity; distance; urban	mixed use; amenity; distance; urban
		density; amenity; consumption; urban	street; amenity; consumption; urban	mixed use; amenity; consumption; urban
6	Eff. of public services	density; public transport delivery; urban	building height; public transport delivery; urban	-
		density; waste; urban	street; waste; urban	-
7	Social equity	density; real wages; urban	building height; real wages; urban	-
		density; segregation; urban	building height; segregation; urban	-
		density; “social mobility”; urban	street; “social mobility”; urban	-
8	Safety	density; crime; rate; urban	building height; crime; urban	-
		density; open; green; space; urban	land border; open; green; space; urban	-
9	Open space	density; green; space; biodiversity; urban	land border; green; space; biodiversity; urban	-
10	Pollution reduction	density; pollution; carbon; urban	building height; pollution; carbon; urban	mixed use; pollution; carbon; urban
		density; pollution; noise; urban	building height; pollution; noise; urban	mixed use; pollution; noise; urban
11	Energy efficiency	-	building height; energy; consumption; urban	mixed use; energy; consumption; urban
12	Traffic flow	density; congestion; road; urban	Street layout; congestion; road; urban	mixed use; congestion; road; urban
13	Mode choice	density; mode; walking; cycling; urban	street; mode; walking; cycling; urban	mixed use; mode; walking; cycling; urban
14	Health	density; health; risk; mortality; urban	-	-
15	Well-being	density; well-being; happiness; perception; urban	space; well-being; perception; urban	mixed use; well-being; perception; urban

Notes: Each outcome- characteristics cell contains one or more (if several rows) combinations of keywords each used in a separate search. In each cell we use a combination of keywords based on effects (related to the outcome category or typically observed variables) and characteristics (related to residential and employment density, morphological density or mixed use). Outcome-characteristics cells map directly to Table A1.

We usually use the term density in reference to economic density and a more specific term to capture the relevant aspect of morphological density. In several instances, we run more than one search for an outcome-characteristics combination to cover different empirically observed variables and, thus, maximise the evidence base. We note that because this way our search focuses directly on specific features that make cities "compact," we exclude the phrase 'compact city' itself in all searches. Adding related keywords did not improve the search outcome in several trials, which is intuitive given that, by itself, "compactness" is not an empirically observable variable. In total, we consider the 52 keyword combinations (for 32 theoretically relevant outcome-characteristic combinations) summarised in Table A1 which we apply to five databases, resulting in a total of 260 keyword searches. We note that Google Scholar, unlike the other databases, tends to return a vast number of documents, ordered by potential relevance. In several trials preceding the actual evidence collection, we found that the probability of a paper being relevant for our purposes was marginal after the 50th entry. Therefore, in an attempt to keep the literature search efficient, we generally did not consider documents beyond this threshold.

In a limited number of cases we reassign a paper returned in a search for a specific outcome category to another category if the fit is evidently better. Studies referring to economic density may thus have sometimes been found through searches focused on other compact city characteristics. Occasionally, a study contains evidence that is relevant to more than one category in which case it is assigned to multiple categories. We generally refer to such distinct pieces of evidence within our study as *analyses*. We do not double count any publication when reporting the total number of *studies* throughout the paper and the appendix.

Based on the evidence collected in step one, we then conduct an analysis of citation trees in the second step of our literature search. In particular, we select a random sample of studies within each category and evaluate to what extent these studies refer to empirically relevant work that was not picked up by our keyword search. For all but two categories, we find that the evidence is reasonably self-contained in the sense that the studies identified by the keyword search tend to cite each other but no other relevant work. Only for *health* and *well-being* did the analysis of citation trees point us to additional literature strands. This systematic literature search resulted in 285 studies. Upon inspection (excluding empirically irrelevant work, duplications of working papers, and journal articles, etc.) we were left with 135 studies and 201 analyses.

Up to this point, our evidence collection is unbiased in the sense that it mechanically follows from the theory matrix (Ahlfeldt & Pietrostefani 2017) and is not driven by our possibly selective knowledge of the literature, nor that of our research networks. For an admittedly imperfect approximation of the coverage we achieve with this approach we exploit the fact that the search for theoretical literature already revealed a number of empirically relevant studies that were not used in the compilation of the theory matrix unless they contained significant theoretical thought. From 19 empirically relevant papers known before the actual evidence collection, we find that step one (keyword search) and two (analysis of citation trees) identified six, i.e., 31%.

In the final step 3 of the evidence collection we add all relevant empirical studies known to us before the evidence collection as well as studies that were recommended to us by colleagues working in related fields. To collect recommendations, we reached out by circulating a call via social media (Twitter) and email (to researchers within and outside LSE). 22 colleagues contributed by suggesting relevant literature. This step increases the evidence base to 190 studies and 328 analyses. The evidence included at this stage may be selective due to particular views that prevail in our research community. However, recording the stage at which a study is added to the evidence base allows us to test for a potential selection effect.

Table A2 summarises the collection process of the evidence base. We present the number of studies found by category and the stage at which they were added to the evidence base. Table A3 summarises the distribution of analyses collected by outcome categories and compact city characteristics. The large majority of 263 out of 328 analyses are concerned with the effects of economic density, on which we focus in this paper. After restricting the sample to analyses for which we are able to infer a density elasticity estimate, this number is reduced to 209. Table A4 compares the subsample of analyses for which we were able to compute an outcome elasticity with respect to density to the universe of analyses, revealing only moderate differences. The analyses in the elasticity subsample have a slightly higher propensity of being added in the third evidence collection stage, a slightly higher mean SMS score (proxy for evidence quality), and a somewhat higher propensity of showing positive (qualitatively) results.

Tab. A2. Evidence base by collection stage and research topic

Panel 1

#	Outcome	Google Scholar	Web of Science	EconLit	CesIfo	Step 2	Step 3	Total
1	Productivity	11	3	5	0	3	10	32
2	Innovation	4	1	2	1	0	1	9
3	Value of space	6	1	6	1	1	7	22
4	Job accessibility	3	1	3	0	3	5	15
5	Services access	2	0	1	0	0	7	10
6	Efficiency of public services delivery	2	0	1	0	0	4	7
7	Social equity	3	1	0	0	4	1	9
8	Safety	2	3	0	0	3	2	10
9	Open space preservation and biodiversity	4	1	0	0	0	0	5
10	Pollution reduction	2	1	1	0	1	2	7
11	Energy efficiency	5	2	2	0	7	5	21
12	Traffic flow	2	0	1	0	1	1	5
13	Sustainable mode choice	7	2	1	0	8	4	22
14	Health	2	1	0	0	4	1	8
15	Well-being	2	0	1	0	0	5	8
	Total	57	17	24	2	35	55	190

Panel 2

	Compact city effects	Compact city characteristics			
#	Outcome category	Economic	Morph.	Mixed	Total
1	Productivity	35	-	-	35
2	Innovation	9	1	-	10
3	Value of space	14	8	2	24
4	Job accessibility	13	3	2	18
5	Services access	15	2	**0**	17
6	Efficiency of public services delivery	14	2	-	16
7	Social equity	17	**0**	-	17
8	Safety	18	4	-	22
9	Open space preservation and biodiversity	2	5	-	7
10	Pollution reduction	12	3	**0**	15
11	Energy efficiency	23	8	1	32
12	Traffic flow	4	2	1	7
13	Sustainable mode choice	60	10	6	76
14	Health	13	3	-	16
15	Well-being	14	2	**0**	16
	Total	263	53	12	328

Notes: Panel 1: Google Scholar, Web of Science, EconLit, CesIfo searches all part of evidence collection step one. Step 2 contains results from the analysis of evidence from step 1 and studies which were collected during step one but corresponded to a different outcome to the one suggested by the keyword search they were found with. Step 3 consists of previously known evidence and recommendations by colleagues. Evidence base by outcome category and compact city characteristic.

Panel 2: All numbers indicate the number of analyses collected within an outcome-characteristics cell. "**0**" indicates missing evidence in theoretically relevant outcome characteristic cell. "-" indicates missing evidence in theoretically irrelevant relevant outcome characteristic cell.

Tab. A3. All analyses vs. elasticity sample

	All analyses		Elasticity sample	
	Mean	S.D.	Mean	S.D.
Non-high-income country [a]	0.13	0.34	0.11	0.31
Academic journal	0.85	0.36	0.84	0.37
Economics	0.24	0.43	0.28	0.45
Within-city	0.46	0.50	0.45	0.50
Round 3	0.38	0.49	0.52	0.50
Year of publication	2008	8.40	2009	5.80
Citation index	1.60	1.80	1.60	1.40
SMS (methods score)	2.20	1.00	2.40	0.89
Positive & significant [b]	0.69	0.46	0.74	0.44
Insignificant [b]	0.06	0.25	0.043	0.20
Negative & significant [b]	0.25	0.43	0.22	0.41
Qualitative result score [c]	0.44	0.86	0.53	0.83
N	328		209	

Notes: Elasticity sample the sample of analyses from which a density elasticity could be inferred. [a] Non-high-income include low-income and median-income countries according to the World Bank definition. [b] Qualitative results (positive, insignificant, negative) is a category-characteristics specific and defined in Table A4. [c] Qualitative results scale takes the values of 1 / 0 / -1 for positive / insignificant / negative.

1.2 Citation weights

For the SMS-based quality measure, we use a mapping of methods to quality ranks. Although we closely follow an existing approach (What Works Centre for Local Economic Growth (WWC) 2016), the assignment of methods to quality scores involves individual judgement that is potentially controversial. Moreover, the method used is at best an imperfect measure of the quality of a research piece. Given these limitations, we develop, as an alternative, a citation-based quality measure that is objective in the sense that it avoids individual judgements. With this approach, we delegate the quality judgement to the wider research community, assuming that better papers receive more attention. Still, to obtain a measure that is comparable across papers we need to account for the obvious time trend in the probability of being cited. For this purpose, we recover a paper's cumulated citation count adjusted for the years since publication as the fixed effect component μ_p from the following regression:

$$\ln C_{pt} = f\left(YSP_p\right) + \mu_p + \varepsilon_{pt}$$

, where $C_{pt} = \sum_{z \leq t} c_{ptz}$, c_{ptz} is the number of citations of a paper p in year t, ε_{pt} is an idiosyncratic component, and $f\left(YSP_{pt}\right)$ is a function that describes how a paper's cumulative citation count increases in the years a paper has been out.

To allow for non-linearities, given the lack of theoretical priors identifying the functional form, we use a linear spline specification:

$$f(YSP_{pt}) = \alpha_1 YSP_{pt} + \sum_{n=2,5,10,20} \alpha_2 (YSP_{pt} - n) \times (YSP_{pt} - n > 0)$$

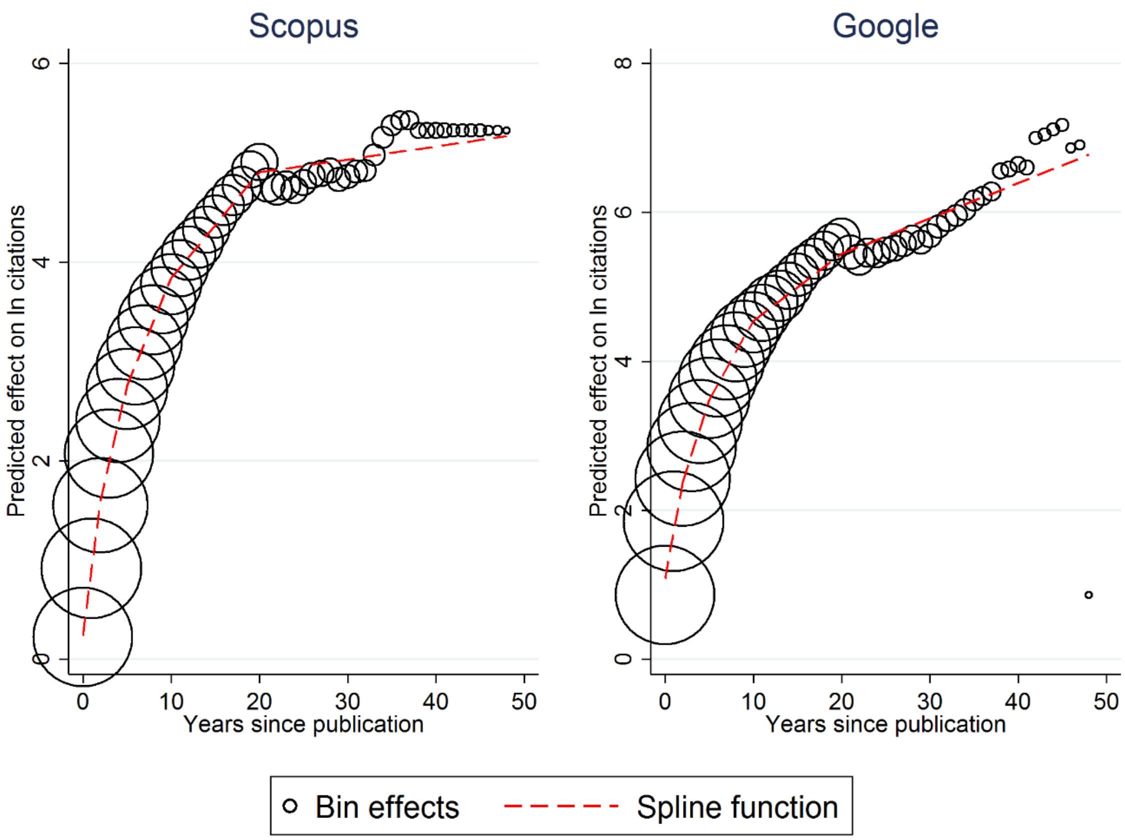
, where $(YSP_{pt} - n > 0)$ is a dummy variable that takes the value of one if the condition is true and zero otherwise. In the figure below, we compare the fit provided by a linear spline function allowing for changes in the marginal effect after 2, 5, 10, and 20 years since publications (dashed lines) to a more flexible semi-non-parametric function (black circles). In this alternative specification, we estimate a bin effect α_m for every group of papers with the same number of years since publication:

$$f(YSP_{pt}) = \sum_{m>0} \alpha_m (YSP_{pt} = m)$$

, where $(YSP_{pt} = m)$ is a dummy variable that is one if the condition is true, and zero otherwise. Figure A1 suggests that the spline function overall provides a reasonable fit to the data generating process. The bin effects are somewhat noisier for larger values of the year since publication because only a fraction of papers in our data base have been out for such a long time, introducing some selection effects. For this reason, we prefer the parametric spline function as a control for year-since-publication effects.

We collect citation counts from Google Scholar and Scopus. The data was collected from the summary tables of citation counts that both Google Scholar and Scopus provide starting from the year of publication to today. Total number of citations for each source was also collected. Figure A1 suggests that the rate at which citation counts increase in both data bases is roughly comparable, although Google counts tend to be larger on average and increase a bit faster over time for papers that have been out for a while.

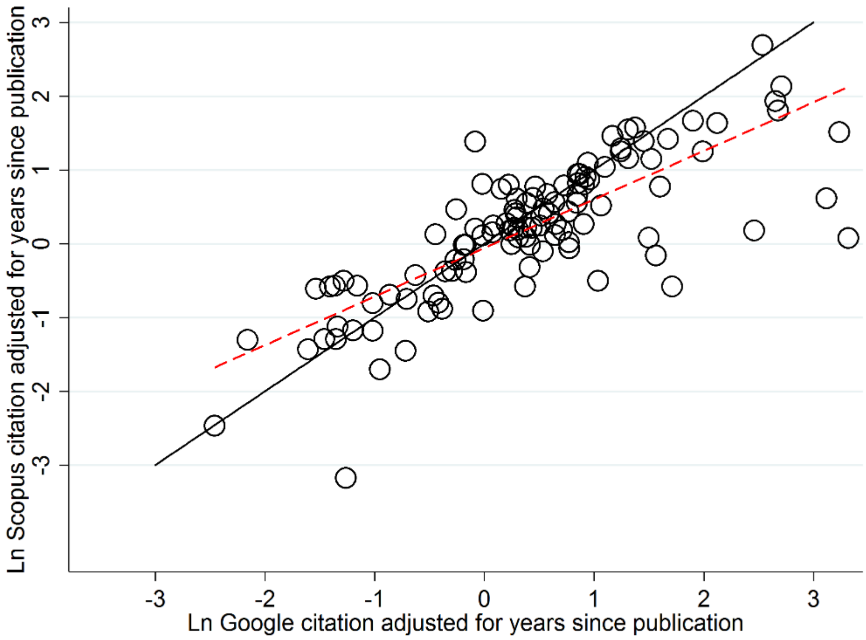
Fig. A1. Cumulated citation counts vs. years since publication (within-paper effects)



Notes: Predicted values (excluding fixed effects) from regressions of the cumulated citation count of a paper against bin effects and a spline function controlling for paper fixed effects. Dot size proportionate to the number of papers in a bin.

In Figure A2, we compare the fixed effects components recovered from the Google Scholar and the Scopus citation count regressions. The adjusted citation measures are highly correlated, which is reassuring given neither data base provides full citations coverage. We select Scopus as a baseline source because their counts are considered more reliable for a variety of reasons. Scopus only indexes articles published in journals affiliated with its databases, but is the largest abstract and citations database of peer-reviewed literature including research from science, social sciences, humanities and other fields (Guide 2016). It not only includes citations counts for journal articles but also trade publications, books and conference papers. Although Google Scholar is increasingly used as a tool to collect citation impact, it has been shown to inflate numbers of citations, be prone to double counting and does not have a clear indexing policy (Moed et al. 2016; Harzing & Alakangas 2016). To achieve full coverage, we impute 26 missing values in our Scopus-based adjusted citation measure using the Google-based adjusted citation measure. In particular, we use predicted values from regressions of the Scopus measure against the Google measure (corresponding to the dashed line in Figure A2).

Figure A2: Google Scholar vs. Scopus adjusted citation indices



Notes: Solid line is the 45-degree line. Dashed line is the linear fit. Sample restricted to observations with positive Google Scholar and Scopus citation counts.

In the table below, we correlate our adjusted citation index with the Source Normalised Impact per Paper (SNIP) published by Scopus. This is a citation-based journal quality measure and it should be positively correlated with our paper-based quality measure to the extent that our year-since-publication adjustment results in a sensible approximation of the long-run impact of a paper. Indeed, we find such a positive and statistically significant correlation. We also find that the there is a significant trend in our (adjusted) citation count measure. Controlling for year-since-publication effects, a paper published one year later attracts approximately 5% more citations.

The effects of the SNIP score and the publication year seem to be independent as the marginal effects remain within close range across columns (1-3). The effects also remain within close range if we control for differences in average number of citations across disciplines (4). Our adjusted citation index is also positively correlated with the SCImago Journal Rank (5-6)

Tab. A4. Adjusted citations by paper vs. Scopus journal measures

	(1) Ln Scopus citation adjusted for years since publication	(2) Ln Scopus citation adjusted for years since publication	(3) Ln Scopus citation adjusted for years since publication	(4) Ln Scopus citation adjusted for years since publication	(5) Ln Scopus citation adjusted for years since publication	(6) Ln Scopus citation adjusted for years since publication
Ln SNIP score	0.783***		0.788***	0.921***		
	(0.23)		(0.19)	(0.18)		
Year – 2000		0.051***	0.051***	0.054***		0.055***
		(0.01)	(0.01)	(0.01)		(0.01)
Ln SJR score					0.344***	0.501***
					(0.13)	(0.13)
Constant	-0.361**	-0.285**	-0.718***	-0.812***	-0.102	-0.564***
	(0.16)	(0.12)	(0.16)	(0.11)	(0.11)	(0.09)
Discipline effects	-	-	-	Yes	-	Yes
r2	0.091	0.184	0.276	0.367	0.050	0.345
N	169	169	169	169	169	169

Notes: Sample includes a subset of studies for which Scopus journal quality measures are available. Citation scores adjusted for years since publications (in columns 1 and 3) are the study fixed effects recovered from regressions of study-year Google citation counts against years since publication (a spline function) and study fixed effects. A small number of observations is imputed using an auxiliary regression of the Google-based citation measure against a similarly constructed Scopus-based measure. Citation scores adjusted for year of publication and discipline are the residuals from a regression of the measures used in columns (1) and (3) against discipline fixed effects and a yearly trend variable with a zero value in 2000. Disciplines are defined based on outlets (journals and working paper series). SNIP is the Source Normalised Impact per Paper and SJR is the SCImago Journal Rank, both published by Scopus. Scopus scores are averaged over 2011-2015. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Table A5, we compare our adjusted citation index to the SMS methods score. A one step increase on the SMS, on average, is associated with an increase in adjusted citations by some notable 14% (1). The effect becomes insignificant once we control for discipline fixed effects, but the point estimate increases (2). Once we control for the publication year trend, the positive association disappears (3), suggesting that the positive correlation in (1) is driven by a common time trend and that the two alternative quality measures are orthogonal to each other (in the cross-section). Similarly, the journal-based SNIP is unrelated to the methods that prevail in the published literature once we control for discipline effects (5-6).

Tab. A5. Citation measures vs. scientific methods scale

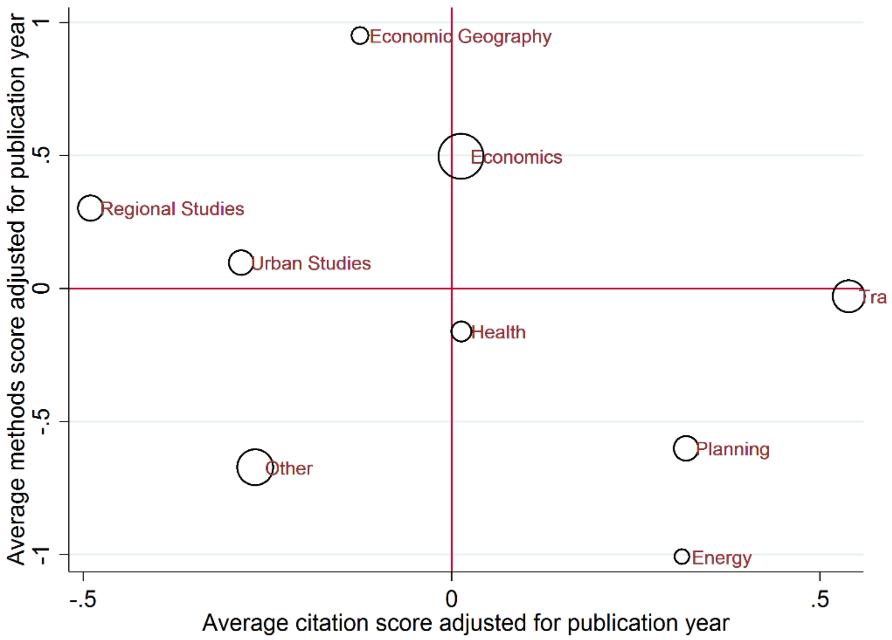
	(1) Ln Scopus citation adjusted for years since publication	(2) Ln Scopus citation adjusted for years since publication	(3) Ln Scopus citation adjusted for years since publication	(4) Ln SNIP score	(5) Ln SNIP score	(6) Ln SNIP score
Scientific methods scale score	0.130*	0.173	0.009	0.056**	-0.002	-0.003
	(0.07)	(0.12)	(0.11)	(0.03)	(0.05)	(0.03)
Year – 2000			0.049***			0.000
			(0.01)			(0.01)
Constant	-0.246	-0.341	-0.338	0.424***	0.552***	0.552***
	(0.20)	(0.26)	(0.23)	(0.06)	(0.10)	(0.10)
Discipline_FE	-	Yes	Yes	-	Yes	Yes
r2	0.019	0.096	0.252	0.022	0.217	0.217
N	190	190	190	169	169	169

Notes: Sample in columns (4-6) includes a subset of studies for which Scopus journal quality measures are available. Citation scores adjusted for years since publications are the study fixed effects recovered from regressions of study-year Google citation counts against years since publication (a spline function) and study fixed effects. A small number of observations is imputed using an auxiliary regression of the Google-based citation measure against a similarly constructed Scopus-based measure. Disciplines are defined based on outlets (journals and working paper series). SNIP is the 2011-2015 average over the Source Normalised Impact per Paper and SJR published by Scopus. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Figure A5, we compare adjusted citation scores to the SMS scores by discipline. The values plotted on the x-axis are the discipline fixed effects recovered from a regression of the Scopus citation count adjusted for years since publication effects against discipline effects and a publication year trend (the model from Table A5, column 3). The values on the y-axis are the discipline fixed effects from similar regressions using our SMS scores as a dependent variable. The figure suggests significant heterogeneity in the methods used as well as in the citation probabilities across disciplines, but no significant correlation between the two.

It is possible that differences in the average citation counts across disciplines reflect a tendency for researchers in some disciplines to cite relatively more frequently. This brings up the question of whether such differences should be controlled for in a citation-based quality measure. Controlling for discipline effects would impose the assumption that the average quality within disciplines is the same across disciplines. This is a strong assumption; especially given that we cover a potentially selective set of papers within each discipline. The high variation in the SMS score across disciplines is certainly not suggestive of a constant average quality. We, therefore, prefer not to control for cross-discipline differences in citation counts and, instead, assume that such differences are driven by differences in the quality of the papers.

Fig. A2. Quality measures: Methods-based vs. citation-based by discipline



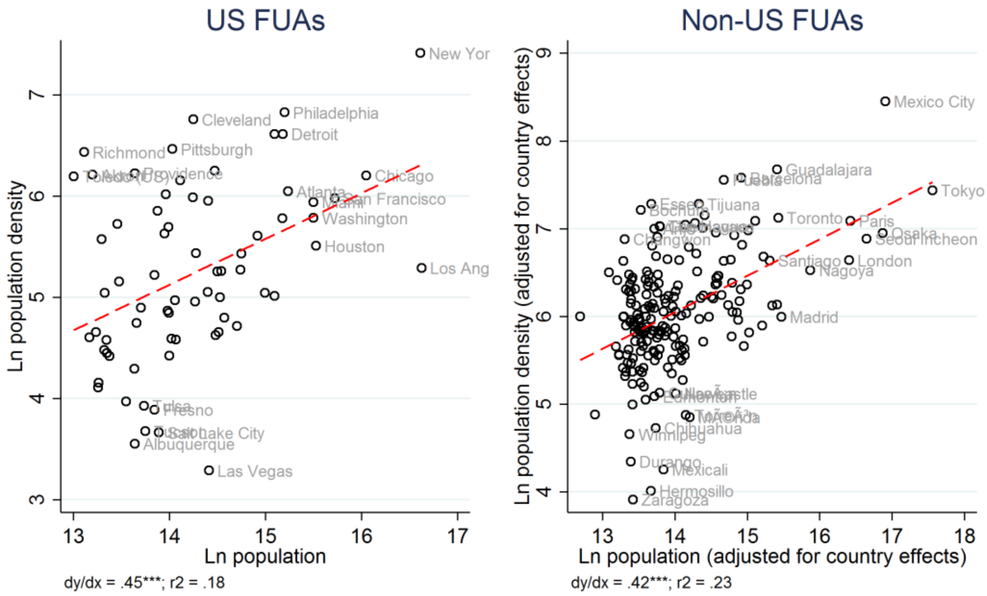
Notes: The values plotted on the x-axis are the discipline fixed effects recovered from regressions of the Google citation count adjusted for years since designation effects against discipline effects and a publication year trend (the model from TableA5, column 3). The values on the y-axis are the discipline fixed effects from similar regressions using our SMS scores as dependent variable.

2 Density elasticities in the literature

2.1 Elasticity of density with respect to city size

In Figure A3, we correlate city size proxied by population and density (population/area) across a sample of functional urban areas (FUA) as defined by the OECD. In keeping with theoretical predictions from standard models, there is a positive relationship between the two variables. The correlation is reasonably well defined and similar with the sub-samples of US and non-US FUAs.

Fig. A3. Population vs. population density



Notes: Dotted lines are the fitted lines from linear regressions. Non-US panel shows the partial correlation controlling for country effects. Afunctional urban area (FUA) is labelled if the population is among the ten largest or if it is an outlier. Outlies are below the 10th/5th or above the 90th/95th percentile in the US/Non-US residual distribution. *** indicates significance at the 1% level.

We estimate the elasticity of density with respect to population using the following straightforward econometric specification.

$$\ln\left(\frac{P_i}{A_i}\right) = \alpha \ln(P_i) + \mu_c + \varepsilon_{ic}$$

, where P_i is the population of city i, A_i is the respective land area, and μ_c is a country fixed effect. While the data theoretically allows us to estimate the elasticity from within-city variation over time, we are concerned about the very limited within-city variation in land area in the data. An imperfect measurement of changes in land area over time will lead to an upward bias in the elasticity. In the extreme case, where land area does not change at all over time, the elasticity would be mechanically one as the only variation on the left-hand side and the right-hand side originates from population. To mitigate this problem, we prefer to estimate the elasticity from cross-sectional between-city variation. Yet, there is still a potential mechanical endogeneity as population (left-hand side) is also a component of density (right-hand side) so that any measurement error in population will upward bias the elasticity. To address this problem, we exploit that, mechanically, there is a negative relationship between the population of a city and its rank in the population distribution within a city system. This negative relationship has been analysed in a vast literature on city size distributions (Nitsch 2005). The rank of a city in the distribution of a country city-size distribution is naturally a strong instrument. It is also a valid instrument in this particular context because it effectively removes the population level from the right-hand side of the estimation equation.

We note that it is straightforward to solve $\ln(P_i/A_i) = \alpha \ln(P_i)$ for $\ln(A_i) = (1-\alpha)\ln(P_i)$. Thus, the elasticity of density with respect to city size can also be estimated from a regression of the log of land area against the log of population, which avoids the mechanical endogeneity problem.

Our estimates of the elasticity of density with respect to city size are reported in Table A6. The elasticity increases significantly as the country fixed effects are added to the equation (from 1 to 2). As expected given the presumed absence of measurement error in population, using an IV for population hardly affects the results (3). The results from the alternative specification using the city log of area and log of population are identical to the baseline, as expected (4 and 5 vs. 1 and 2, resp. 3). Our preferred estimate of the elasticity of density with respect to city size is 0.43. The distribution of country-specific elasticities estimated by country using the same model as in Table A6, column (3) (excluding country fixed effects), is illustrated in Figure A2 and Table A7.

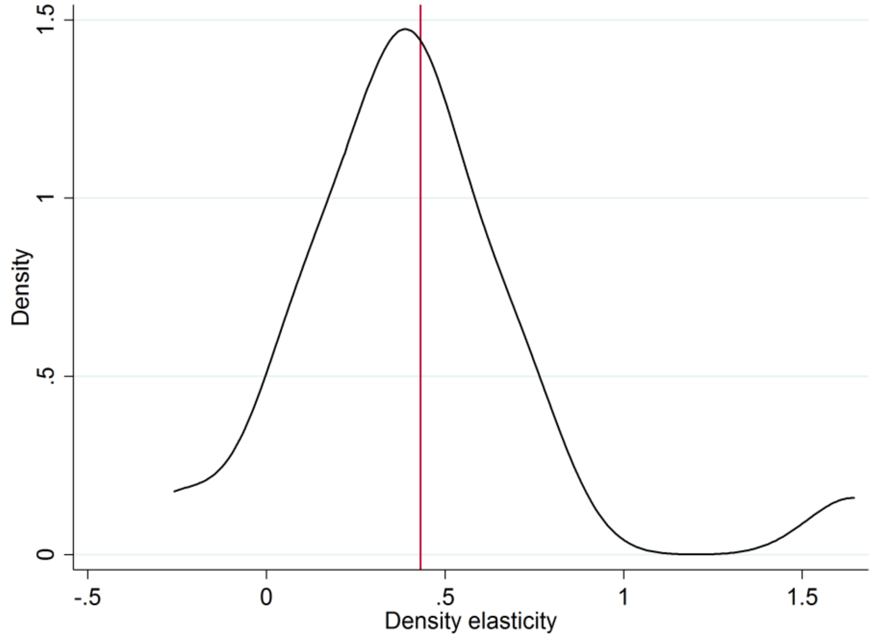
We note that our preferred estimate of the elasticity of density with respect to city size is within close range of Combes et al. (2016), who report an elasticity of land area with respect to population of approximately 0.7 for French cities, implying an elasticity of density with respect to city size of 0.3. Our results are also close to Rappaport (2008) who estimates an elasticity of 0.34 across US metropolitan areas.

Tab. A6. Elasticity of density with respect to population

	(1) Ln population density	(2) Ln population density	(3) Ln population density	(4) Ln geographic area	(5) Ln geographic area
Ln population	0.304^{***}	0.427^{***}	0.431^{***}	0.696^{***}	0.573^{***}
	(0.07)	(0.05)	(0.04)	(0.07)	(0.05)
Country effects	-	Yes	Yes	-	Yes
IV	-	-	Yes	-	-
Density elasticity	0.3	0.43	0.43	0.3	0.43
N	281	281	281	281	281
r2	0.057	0.614		0.239	0.689

Notes: Standard errors in parentheses. Population density and population are averages over the 2000–2014. IV is rank of a city in the population distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Fig. A4. Elasticity of density with respect to population: Distribution across countries



Notes: The vertical line represents the elasticity estimated in Table A6, column 2 model. The black curved line is the kernel density distribution across 19 countries with sufficient metropolitan areas estimated using Table A6, column 1 model by country.

Tab. A7. Elasticity of density with respect to population by country

Country code	N	Elasticity of density with respect to population	Standard error
AT	3	0.27	0.07
AU	6	0.06	0.15
BE	4	0.30	0.16
CA	9	0.74	0.39
CH	3	1.65	0.17
CL	3	0.55	0.15
CZ	3	-0.26	0.56
DE	24	0.08	0.18
ES	8	0.65	0.62
FR	15	0.39	0.17
IT	11	0.40	0.17
JP	36	0.40	0.10
KR	10	0.50	0.18
ME	33	0.71	0.25
NL	5	0.19	0.57
PL	8	0.43	0.28
SE	3	0.35	0.06
UK	15	0.11	0.17
US	70	0.43	0.13

Notes: Elasticity estimated for 19 countries with sufficient metropolitan areas estimated using Table A1, column 1 model by country.

2.2 The elasticity of construction cost with respect to density

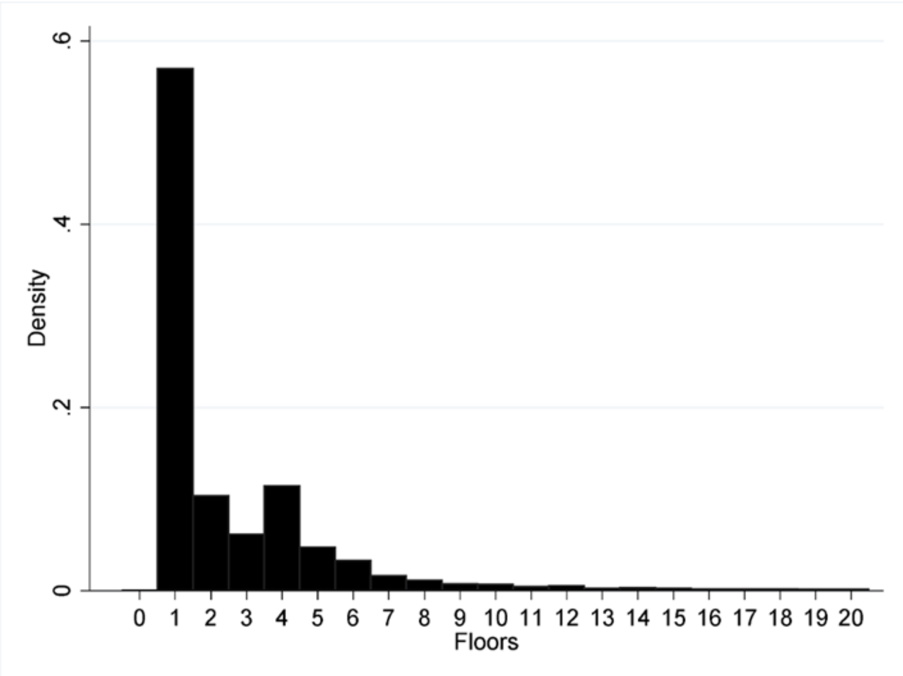
We assume that density impacts on construction costs through two principle channels. On the one hand, constructing a dwelling unit with exactly the same specification is likely more expensive in denser places because such places are usually more congested (higher cost of moving materials, less space for construction), have higher construction worker wages, and are more regulated (a location effect). On the other hand, while density can be achieved by reducing housing consumption and increasing building density, it at least in the limit also requires taller buildings, which are more expensive to construct (a structure effect). We are interested in the gross effect of density on construction cost and, thus, in an estimate of the density elasticity of construction cost that captures both location and the structure effects. To our knowledge, such an estimate does not exist to date. However, Gyourko and Saiz (2006) provide estimates of the density elasticity of construction cost using a construction cost index for a same-specification home, which reflects on the effects of location exclusively. Ellis (2004), in contrast, provides a construction cost index by dwelling type (various types of single-family and multifamily structures) that holds all locational effects constant. In the remainder of this section we provide two novel approaches to estimating the density elasticity of construction cost.

Frist, we make use of a micro-data set to compare how observed construction costs (excluding costs for land acquisition) vary in density within and across cities. This approach directly yields an estimate of the combined location and structure effect. Second, we create a construction cost index that captures variation in the average construction cost across locations due to differences in the structure composition, i.e. the structure effect. We then combine the estimated density elasticity of this index with density elasticity estimates inferred from Gyourko and Saiz (2006), which capture the locational effect, to obtain an estimate of the overall effect of density on construction cost.

2.2.1 Estimates using micro-data

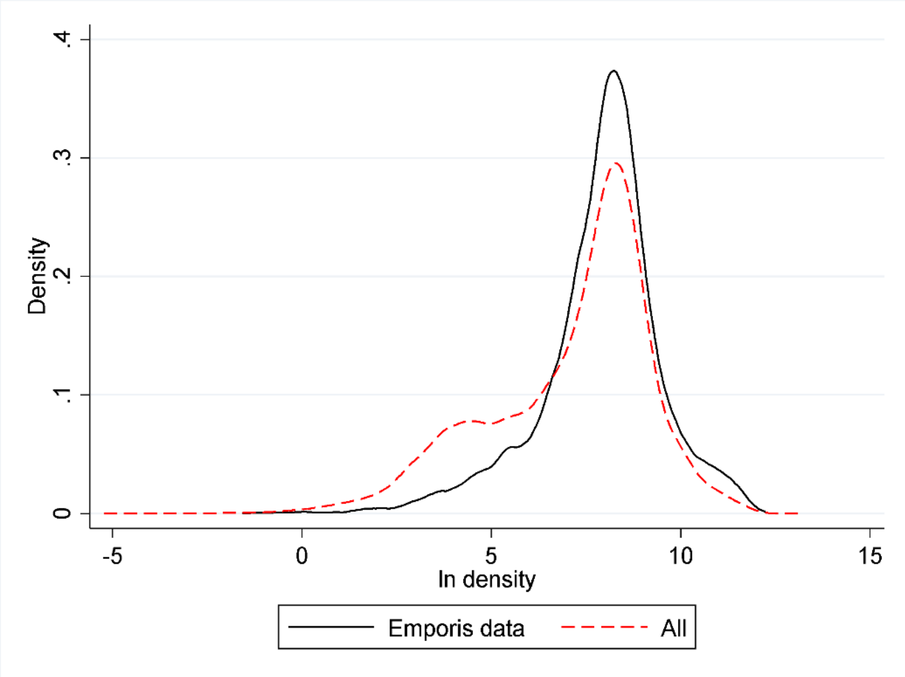
To our knowledge, no estimates of the effect of density on construction costs using actual construction cost data exist to date. To fill this gap, we make use of a commercial data set compiled by Emporis that has previously been used by Ahlfeldt & McMillen (2017). The data set contains information on the date of construction, the height, and the number of floors for a large number of buildings worldwide. Geo-information is provided in form of geographic coordinates so that the location can be merged with other spatial data in GIS. The data set contains additional building information, such as construction costs, use, or total floor space, however missing values are present for a substantial fraction of constructions. While the data set is a unique source of information on construction costs, its representativeness with respect to location and structure type is not guaranteed. The intuition is that taller buildings at denser places will be overrepresented in the data set as Emporis claims a nearly comprehensive coverage of tall buildings such as skyscrapers. Against this background, it is reassuring to see that within the US-sub-sample we use (containing information on construction cost and floor space, among other characteristics), a large share of observations refers to small structures which account for the majority of the building stock in US metropolitan areas (see also Figure A8). However, it is still notable from Figure A6 that low-density census tracts are underrepresented in the data set we analyse, suggesting that we obtain local elasticity estimates representative for above-average density areas. Within tracts with at least one Emporis observation, constructions are also more concentrated than population, as revealed by a more than twice as large Herfindahl index (0.0205% vs. 0.0097%).

Fig. A5. Distribution of buildings in micro-data by number of floor



Notes: Data from Emporis. Sample restricted to observations in the US with information on location, construction year, construction cost, building area, building height and the number of floors. Constructions exceeding 20 floors excluded in the graph to improve the presentation.

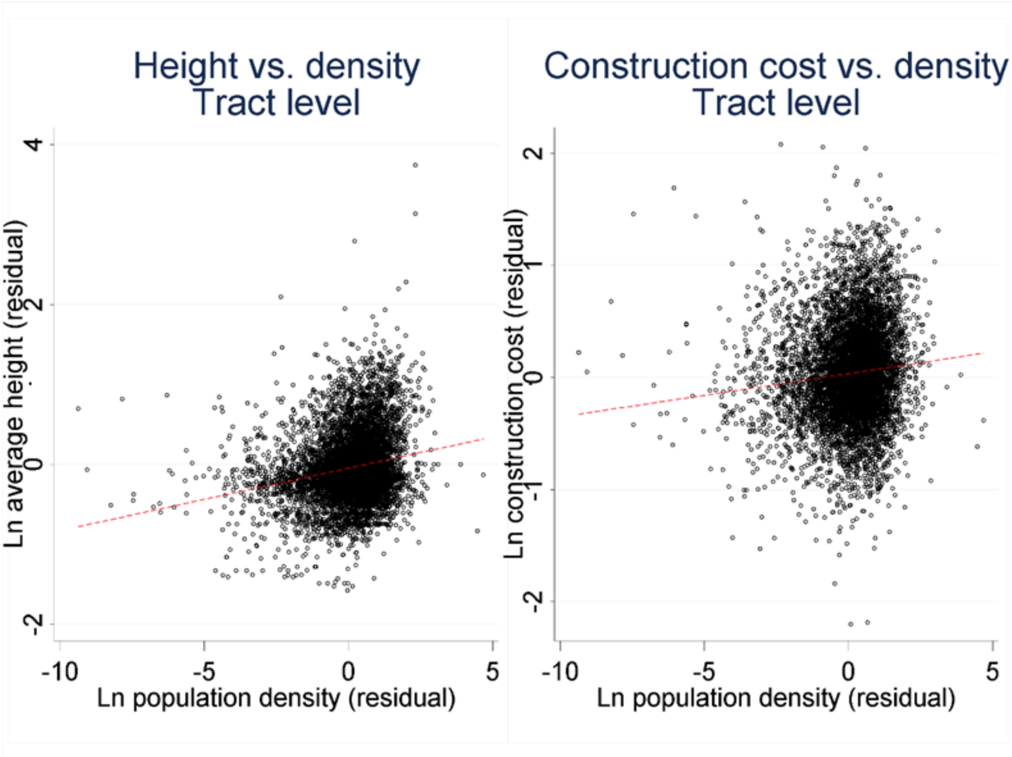
Fig. A6. Census tract population density distribution: Emporis sample vs. all tracts



Notes: Population density computed using census tract population from the US 2010 Census and tract perimeter data from the US 2010 Census with areas calculated on ARCGIS (US Census Bureau 2010). "Emporis data" is a subsample of "all" US census tracts that contain construction observations in the Emporis data set (observation with complete information used in Figure A5.

In keeping with intuition, Figure A7 shows a positive correlation between average building height and population density across census tracts, i.e. density is achieved at least to some extent by building taller (the other margins of adjustment being building density and per-capital consumption of floor space). Given that taller buildings are generally more expensive to construct (Ahlfeldt & McMillen 2017) and that the same building is more difficult to construct where density is higher (Gyourko & Saiz 2006), it is no surprise that floor space construction costs are also higher at denser places.

Fig. A7. Height, construction cost, and density within metropolitan areas



Notes: Residuals are from regressions of each variable against MSA x year effects. Building data from Emporis. Population density computed using population data and area data from the US 2010 Census.

In Table A8, column (1), we estimate the density elasticity of construction cost using variation within and across metropolitan areas. Because density is measured at the census-tract level we cluster standard errors at the same level. We exclude any control except for year effects, which control for the time trend in nominal construction costs. We find a density elasticity of construction cost of 7%. This estimate captures the effects of structure height due to expensive materials and engineering as well as locational effects originating from congestion (transport cost, space for construction), regulation (ease of obtaining planning permission), and labour market conditions (construction wages, unionisation) that vary within and across metropolitan areas. Besides the potential sample selection implying a local estimate that is likely valid for denser-than-average places, the main concern with this estimate is that density is correlated with structure quality conditional on height. As an example, renters and buyers in markets with different densities may demand buildings of more sophisticated materials and designs due to differences in tastes and incomes.

In column (2) we replace year effects with metro-year effects, which control for all such effects at the metropolitan level (core-based statistical areas) and also capture time trends that potentially vary across metropolitan areas. In column (3), in addition, we add a set of variables capturing non-height related features of the structure that are likely correlated with quality. Among these variables is the ratio of building height over the number of floors, which captures the effects of differences in ceiling height and decorative elements of the roof that primarily serve aesthetic purposes. The controls also include two sets of variables capturing the architectural design (e.g. modernism, postmodernism) and the structural material (e.g. wood, masonry). The density elasticity is reduced to 4.3% conditional on these feature controls and metro-year effects. With respect to the gross-density effect we aim to estimate, there is a concern of over-controlling (bad control problem (Angrist & Pischke 2009)). For one thing, metro-year effects could absorb effects related to density that vary primarily across metropolitan areas, such as labour market conditions and regulation. For another, design and, in particular, materials (e.g. concrete and steel) to some extent are endogenous to building height as taller buildings require different approaches to structural engineering. In light of these concerns (omitted variable bias vs. over-controlling) our preferred interpretation of the density elasticities reported in (1) and (3) is that of a range between an upper-bound and a lower-bound estimate.

The remaining columns in Table A8 are added to connect to the extant literature. In column (3), we estimate a (gross) height elasticity of construction cost of 25% for the US, which is close to the respective elasticity estimated by Ahlfeldt & McMillen (2017) from a global sample of small structures (up to five floors). In keeping with intuition, this elasticity decreases considerably to approximately 14% when controlling for metro-year effects and the building features introduced in column (3).

To our knowledge, Gyourko and Saiz (2006) provide the only explicit estimate of density effects on construction costs that exist thus far. The estimates of the specification they use, which is quadratic in density, imply a density elasticity of 2% at the mean of the density distribution across US metropolitan areas. As noted above, their estimate, by construction, excludes the structure effect as they use a construction cost index as dependent variable that refers to a same-specification home. Their estimate also excludes various locational effects because they control for labour market conditions and the regulatory environment. The bounds of the density effect reported in Table A8, columns (1) and (3), thus, expectedly exceed their estimates. In column (6), we expand the baseline model from column (1) by the feature controls from column (3) and a large set of 310 indicator variables capturing various aspects of the building, such as the type and the use of a building (e.g. single-family detached housing, mid-rise apartment building). We also control for building height. With this specification, we aim to control for the structure effect as comprehensively as the Emporis data allows to obtain a density effect on construction cost that approximates the location effect. The resulting 2.3% density elasticity is slightly larger than the implied 2% elasticity at the mean from Gyourko and Saiz (2006). This is the expected result, because unlike Gyourko and Saiz (2006) we estimate the gross location effect without controlling for regulation and labour market conditions. In the last column, we further add metro-year effects, which controls for regulation and labour market conditions as these vary mostly between metropolitan areas. Of course, metro-year effects also control for any other density effect originating from variation between metropolitan areas. Even conditional on these demanding controls, we still estimate a density elasticity of approximately 1%, which is highly statistically significant. It is no surprise that this estimate which captures only a fraction of the location effect of density is smaller than the estimates by Gyourko and Saiz (2006). We thus conclude that our estimate of the density effect on construction cost is novel, but consistent with the existing literature.

Tab. A8. Density elasticity of construction costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ln floor space construction cost						
Ln census tract population density	0.070^{***} (0.003)	0.053^{***} (0.004)	0.043^{***} (0.004)			0.023^{***} (0.002)	0.009^{***} (0.002)
Ln Building height				0.250^{***} (0.006)	0.137^{***} (0.008)	0.140^{***} (0.008)	0.094^{***} (0.008)
Year effects	Yes	-	-	Yes	-	Yes	-
Metro-year effects	-	Yes	Yes	-	Yes	-	Yes
Feature controls	-	-	Yes	-	Yes	Yes	Yes
Building type controls	-	-	-	-	-	Yes	Yes
N	30,048	30,048	30,048	30,048	30,048	30,048	30,048
r2	.202	.379	.435	.245	.438	.607	.699

Notes: Unit of analysis is construction. Construction data from Emporis. Census tract population density data from the US 2010 Census. Feature controls include the ratio of building height over the number of floors, a set of 18 dummy variables indicating architectural styles and a set of 19 dummy variables indicating structural materials. Building type controls are a set of 310 dummy variables indicating building types and uses. Standard errors clustered on census tracts. Standard errors (in parentheses) are robust or clustered on metro-year effects where applicable. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Since the unit of observation in Table A8 is a construction, the models are implicitly weighted by the number of constructions per tracts. This weighting scheme attaches greater importance to census tracts for which we have more construction cost information. In Table A9, we consider alternative weighting schemes. First, we re-estimate the models from columns (1) and (3) in Table A8, weighting each observation by the ratio of the population over the number of per-tract observations to instead obtain a density elasticity estimate that is more representative for an average household (columns 1-2). Then, we repeat the exercise using the inverse of the observation count (same weight to all tracts, columns 3-4) and the tract-population (lager weights to tracts with many constructions and large population) as weights. The density elasticity estimates reported in Table A8, columns (1) and (3) are roughly at the centre of the range of estimates we find in this sensitivity analysis.

Tab. A9. Density elasticity of construction costs

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln floor space construction cost					
Ln census tract population density	0.088*** (0.009)	0.057*** (0.008)	0.046*** (0.003)	0.025*** (0.004)	0.073*** (0.004)	0.044*** (0.004)
Year effects	Yes	-	Yes	-	Yes	-
Metro year effects	-	Yes	-	Yes	-	Yes
Feature controls	-	Yes	-	Yes	-	Yes
Building type controls	-	-	-	-	-	-
Weights	Tract population / Emporis count		1 / Emporis count		Tract population	
N	30,048	30,048	30,048	30,048	30,048	30,048
r2	.211	.441	.172	.443	.179	.412

Notes: Unit of analysis is construction. Construction data from Emporis. Census tract population density data from the US 2010 Census. Feature controls include the ratio of building height over the number of floors, a set of 18 dummy variables indicating architectural styles and a set of 19 dummy variables indicating structural materials. Building type controls are a set of 310 dummy variables indicating building types and uses. Standard errors clustered on census tracts. Standard errors (in parentheses) are robust or clustered on metro-year effects where applicable. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.2.2 Index-based estimates

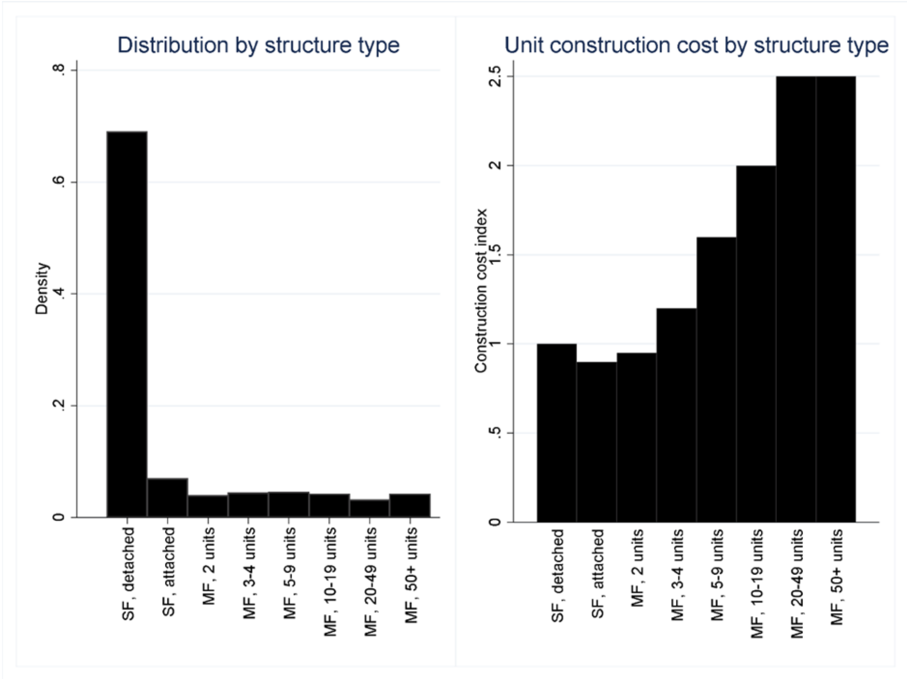
As noted, our primary concerns with the estimation of density effects using the Emporis data are the selectivity of the sample and an imperfect control for structural quality. These concerns motivate a complementary analysis in which we rely on engineering estimates of construction costs. This approach does not involve the arguably attractive use of actual micro data, but it largely avoids the aforementioned problems.

In what follows, our aim is to estimate the cost of providing a mix of structures required to accommodate higher density (essentially greater average building height), holding non-height related structure features constant. While the use of an engineering cost index as dependent variable is analogical to Gyourko and Saiz (2006), the density effect we estimate is not. Gyourko and Saiz (2006) estimate the density effect on the cost of a same-specification home, i.e. they hold the structure effect constant and estimate a location effect. In contrast, we focus exclusively on the effect of having taller same-quality structures at denser places, i.e. we hold the location effect constant and estimate the structure effect. We argue that combining both estimates yields a reasonable approximation of the gross density effect that can be compared to our micro-data estimates of the density elasticity.

For this exercise, we require the composition of dwelling units by structure type at a geographically disaggregated level. To approximate the shares of various structure types we make use of the American Community Survey (ACS). The data contains relatively rich information on the type structure a household lives in for a 1% sample of the total US population. To increase the number of observations we pool the 2010-2015 survey waves, weighting each observation by the sample weight reported in the data.

As expected, the left panel of Figure A8 reveals that the great majority of households live in single-family homes (left panel). To explore the relationship between construction cost and density, we merge a structure-type specific per-unit construction cost index to the data. Ellis (2004) provides same-quality per-dwelling-unit engineering estimates of relative construction cost for eight structure types, which roughly correspond to the eight structure types in the ACS data. According to the Ellis (2004) index illustrated in the right panel of Figure A8, same-quality-same-size units in large multi-family structures are more than twice as expensive to build as single-family homes because they require more expensive materials (e.g. brick), more sophisticated structural engineering (e.g. concrete frames), and facilities (e.g. elevators).

Fig. A8. Household accommodation by structure

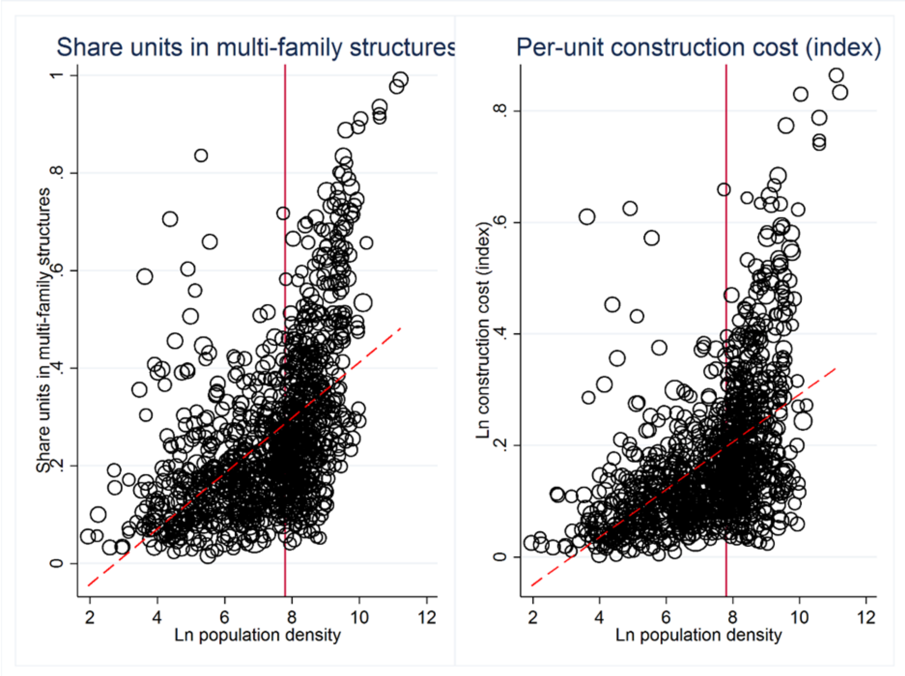


Notes: Left panel uses household-level data from American Community Survey (ACS), weighted by household weights. SF = single family house, MF = multi-family house (Ruggles et al. 2017). Right panel illustrates the construction cost index by Ellis (2004), mapping the closest of the eight categories in Ellis to each of the eight categories in IPUMS.

Having merged the Ellis index to the ACS data by structure type, it is straightforward to compute the weighted (by the household weight) mean structure replacement value within a public use microdata area (PUMA) – the smallest geographic identifier in the ACS data set – to which we refer to as construction cost for simplicity. To this PUMA level data set we merge population data from the ACS and the geographic area from the US Census to compute density (US Census Bureau 2010).

In the left panel of Figure A9, we examine the relationship between structure composition and density. In keeping with intuition, higher densities are associated with larger shares of units in multi-family buildings, i.e. density is correlated with height as already evident from Figure A7. The relationship seems to be non-linear. One interpretation is that at low levels of density, increases in density can be achieved by building single-family homes more densely. Beyond a certain level, however, higher densities require the construction of tall multi-family buildings. Expectedly, the positive non-linear correlation also exists between density and the mean construction cost (right panel).

Fig. A9. Density, dwelling type, and the cost of construction



Notes: Unit of analysis is PUMA. Ln population density rescaled to have a zero mean. Area-based construction cost index and share of dwelling in multi-family structures is computed as the mean over the construction cost by dwelling type provided by Ellis (2004), weighted by the dwelling-type shares in the IPUMS data (incorporating sample weights). Population density computed using population data and area data from the American Community Survey (ACS).

In the table below, we provide estimates of the density elasticity of our construction cost index at the PUMA level. To account for the non-linearity suggested by Figure A8, we experiment with a quadratic specification. We also add metro effects in some specifications and weight observations by PUMA population in others. The elasticity estimates (at the mean) range from 4.3-5.6%. As discussed above, these estimates capture the structure effect of density exclusively. Adding the 2% location effect estimated by Gyourko and Saiz (2006) (at the mean of the density distribution), we obtain a combined effect in the range of 6% to 7.5%, which is close to the upper bound of the density elasticity estimated from the micro-data. The quadratic specification from column (2) implies a spread of the marginal density effect of 3.8-6.6% from the 5th to the 95th percentile in the density distribution across PUMAs.

Tab. A10. Density elasticity of construction costs (index-based models)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln construction cost index					
Ln population density	0.043***	0.055***	0.043***	0.056***	0.043***	0.056***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.003)	(0.005)
Ln population density squared		0.011***		0.012***		0.012***
		(0.002)		(0.003)		(0.002)
CBSA effects	-	-	Yes	Yes	-	Yes
Weighted	-	-	-	-	By pop.	By pop.
N	1158	1158	1158	1158	1158	1158
r2	.259	.323	.357	.41	.263	.417

Notes: Unit of analysis is PUMA. Ln population density rescaled to have a zero mean. Area-based construction cost index is computed as the mean over the construction cost by dwelling type provided by Ellis (2004), weighted by the dwelling-type shares in the ACS data (incorporating sample weights). Population density computed using population data from ACS data and area data from US Census Bureau. Standard errors are robust or clustered on CBSAs where included. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.2.3 Summary

The micro-data analysis presented in this section yields a density elasticity of construction cost that is a composite of all structural effects (costs of building taller structures to achieve density) and locational effects (costs of building similar structures at denser locations). However, because of the potential selectivity of the Emporis data, the density estimate is potentially local and representative for above-average density locations. The estimates may also confound the effects of non-height-related structural characteristics (quality of design and materials) that are correlated with density. Our index-based estimates are likely robust to these problems because the composition of dwelling types in the ACS data is likely representative and the engineering cost index we use refers to constant-quality units. However, these estimates capture exclusively the structure effect of density, and not the location effect, for which we refer to Gyourko and Saiz (2006).

The combined structural and locational effect that results from summing our engineering estimate and Gyourko and Saiz (2006)'s estimate of the density elasticity still differs conceptually from the elasticity that results from the analysis of the micro-data. Gyourko and Saiz (2006) control for several locational attributes that are likely correlated with and potentially endogenous to density. If regulation was tighter in denser areas and had a positive effect on construction cost (Green et al. 2005; Saiz 2010; Gyourko & Saiz 2006), one would expect the density elasticity estimated from the micro-data to exceed the index-based elasticity (our engineering estimate, plus Gyourko and Saiz (2006) estimate). However, the index-based estimate is close to the upper-bound estimate from the micro-data, even though we suspect, if anything, an upward bias of the latter due to selection. This is consistent with a weakly negative correlation between the Wharton Regulatory Index and population density, which suggests that achieving density is not the primary motivation for more intense regulation in the US (Gyourko et al. 2007)

Based on the evidence presented in this section, we conclude that 4-7% is a conservative range for the density elasticity of construction cost. This estimate is a gross estimate that includes all structure effects and location effects that are associated with density (including differences in regulation, geology and labour market conditions may be cause or effects of density).

2.3 Converting marginal effects into elasticities

In this subsection we discuss how we adjust the density effects reported in the literature into a consistent format. Our aim is to express as many as possible estimates in terms of an elasticity of an outcome measure Y with respect to density P/A:

$$\beta = \frac{\frac{dY}{Y}}{\frac{d(P/A)}{(P/A)}}$$

, where P (population) and A (area) are defined as in the previous sub-section. Authors of the studies included in the evidence base frequently report marginal effects of the following forms:

Marginal effects in levels:

$$\gamma = \frac{dY}{d(P/A)}$$

Log-lin semi-elasticities estimated using log-lin models:

$$\delta = \frac{\frac{dY}{Y}}{d(P/A)}$$

Lin-log semi-elasticities estimated using lin-log models:

$$\vartheta = \frac{dY}{\frac{d\left(\frac{P}{A}\right)}{(P/A)}}$$

Hence, we can compute β at the mean of the distributions of Y and P (denoted by bars) from reported estimates of γ or δ or ϑ as follows:

$$\beta = \delta\left(\overline{P/A}\right)$$

$$\beta = \gamma \frac{\left(\overline{P/A}\right)}{\bar{Y}}$$

$$\beta = \vartheta \frac{1}{\bar{Y}}$$

We note that in some instances, a conversion into an elasticity requires further auxiliary steps such as removing a standardisation (normalisation by standard deviations) or the auxiliary estimation of elasticities based on results reported for discrete categories. In some cases, we infer a marginal effect from graphical illustrations (in particular in the health category).

2.4 Converting city size elasticities into density elasticities

In several instances the authors of the considered analyses use city population as a proxy of density. The elasticity of an outcome with respect to population (city size proxy) takes the following form (after the transformations described 2.2, if necessary):

$$\theta = \frac{\frac{dY}{Y}}{\frac{d(P)}{(P)}}$$

As we have shown in 2.1, the elasticity of density with respect to city size is not unity. It is therefore necessary to adjust the estimates in order to make them comparable to elasticities with respect to density. Given that we have an estimate of the elasticity of density with respect to city size

$$\alpha = \frac{\frac{d(P/A)}{(P/A)}}{\frac{dP}{P}}$$

we can easily compute the elasticity of an outcome with respect to density as:

$$\beta = \frac{\theta}{\alpha}$$

2.5 Converting density elasticities of land price into density elasticities of rent

Density effects on the value of real estate are often reported in terms of house price capitalisation, which is linearly related to rent capitalisation (assuming a constant discount factor). Sometimes, authors report the effects in terms of land price capitalisation. Land price elasticities are not directly comparable to house price elasticities because house prices generally move less than land prices due to factor substitution (developers substitute away from land as land prices increase).

To allow for a simple micro-founded translation of land price capitalisation effects into house price capitalisation effects, it is useful to assume a Cobb-Douglas housing production function and a competitive construction sector. Assume that housing services H are produced using the inputs capital K and land L as follows: $H = K^{\beth}L^{1-\beth}$. Housing space is rented out at bid-rent ψ while land is acquired at land rent Ω. From the first-order condition $K/L = \beth/(1-\beth)\ \Omega$ (the price of capital is the numeraire) and the non-profit condition $\psi H = K + \Omega L$, it is immediate that $\log(\psi) = (1-\beth)\log(\Omega) + c$, where c is a constant that cancels out in differences, i.e., $d\ln(\psi) = (1-\beth) d\ln(\Omega)$.

It is, therefore, possible to translate an elasticity of land price with respect to density into an elasticity of rent (house price) with respect to density as follows:

$$\frac{d\ln\psi}{d\ln\left(\frac{P}{A}\right)} = (1-\beth)\frac{d\ln\Omega}{d\ln\left(\frac{P}{A}\right)}$$

, where we set $(1-\beth) = 0.25$, following Ahlfeldt, Redding, et al. (2015).

2.6 Density elasticities: Weighted averages

In the table below we compare the mean elasticities within selected outcome categories to the respective means weighted by quality (SMS) and the inverse of the number of estimates added from a study. The latter is to ensure that studies (not estimates) receive the same weights, i.e., studies reporting various useful estimates are deflated. In the last column, we report the median for comparison.

Tab. A11. Weighted average density elasticities

		No weights		Method weights		Inv. frequency		
ID	Elasticity of outcome with respect to density	Mean	S.D.	Mean	S.D.	Mean	S.D.	Median
1	Labour productivity	0.05	0.04	0.05	0.04	0.05	0.03	0.04
1	Total factor productivity	0.08	0.04	0.07	0.03	0.08	0.04	0.07
2	Patents p.c.	0.13	0.11	0.13	0.11	0.13	0.11	0.13
3	Rent	0.11	0.11	0.09	0.11	0.11	0.11	0.07
4	Commuting reduction	0.07	0.14	0.07	0.14	0.04	0.14	0.10
4	Non-work trip reduction	0.15	0.12	0.15	0.12	0.18	0.11	0.15
5	Metro rail density	0.01	0.02	0.02	0.02	0.01	0.02	0.00
5	Quality of life	0.01	0.07	0.01	0.08	0.03	0.06	-0.01
5	Variety (consumption amenities)	0.19	-	0.19	-	0.19	-	0.19
5	Variety price reduction	0.12	0.06	0.12	0.06	0.12	0.06	0.12
6	Public spending reduction	0.16	0.31	0.16	0.31	0.19	0.33	0.14
7	90th-10th pct. wage gap reduction	0.17	-	0.17	-	0.17	-	0.17
7	Black-white wage gap reduction	0.00	-	0.00	-	0.00	-	0.00
7	Diss. index reduction	1.10	1.28	0.80	1.08	1.10	1.28	0.39
7	Gini coef. reduction	4.56	-	4.56	-	4.56	-	4.56
8	Crime rate reduction	0.43	0.23	0.41	0.23	0.36	0.24	0.41
9	Foliage projection cover	-0.06	-	-0.06	-	-0.06	-	-0.06
10	Noise reduction	0.04	-	0.04	-	0.04	-	0.04
10	Pollution reduction	0.04	0.90	0.02	1.00	-0.03	0.66	0.23
11	Energy consumption red.: Domestic & driving	0.10	0.12	0.12	0.13	0.14	0.13	0.07
11	Energy consumption reduction: Public transit	-0.37	-	-0.37	-	-0.37	-	-0.37
12	Speed	-0.12	0.01	-0.12	0.01	-0.12	0.01	-0.12
13	Car usage (incl. shared) reduction	0.07	0.09	0.07	0.09	0.20	0.19	0.04
13	Non-car use	0.21	0.41	0.20	0.40	0.21	0.42	0.10
14	Cancer & other serious disease reduction	-0.23	0.22	-0.28	0.22	-0.15	0.19	-0.19
14	KSI & casualty reduction	0.01	0.61	0.01	0.61	0.01	0.61	0.17
14	Mental-health	0.01	-	0.01	-	0.01	-	0.01
14	Mortality reduction	-0.29	0.20	-0.29	0.20	-0.24	0.21	-0.29
15	Reported health	-0.27	0.11	-0.27	0.11	-0.27	0.11	-0.32
15	Reported safety	0.07	-	0.07	-	0.07	-	0.07
15	Reported social interaction	-0.10	0.16	-0.05	0.10	-0.11	0.17	-0.03
15	Reported well-being	0.00	-	0.00	-	0.00	-	0.00

Notes: "Method" weights are SMS scores. Scientific Methods Scale (SMS) defined in section 2.2 of the main paper (higher values indicate more robust methods). "Inv. frequency" weights are one over the number of estimates included per study. 1: Productivity; 2: Innovation: 3: Value of space; 4: Job accessibility; 5: Services access; 6: Efficiency of public services delivery; 7: Social equity; 8: Safety; 9: Open space preservation and biodiversity; 10: Pollution reduction; 11: Energy efficiency; 12: Traffic flow: 13: Sustainable mode choice; 14: Health; 15: Well-being.

3 Own density elasticity estimates

In this section we complement the existing literature on the effect of density using OECD.Stat functional economic areas or regional statistics data and the following regression model:

$$\ln(Y_i) = \beta \ln\left(\frac{P_i}{A_i}\right) + \tau \ln\left(\frac{G_i}{P_i}\right) + \mu_c + \epsilon_{ic}$$

, where i indexes cities, Y_i is an outcome as defined in the table below, P_i, A_i, μ_c are population, geographic area, and country fixed effects, and G_i is GDP per capita. The coefficient of interest is β, which gives the elasticity of an outcome with respect to population density controlling for local GDP p.c. and unobserved cross-country heterogeneity. Where either population or area forms part of the dependent variable we instrument population density using the rank within the national population density distribution as an instrument. In the following subsections, we present estimates of this model including and excluding the GDP control and fixed effects, as well as with and without using the instrumental variable. Because the interpretation of the parameter on population density as an elasticity is straightforward, we generally present the results without further discussion. The exception is our estimate of the elasticity of speed with respect to density, which follows a slightly different structure.

3.1 Innovation

Tab. A12. Elasticity of patents per capita with respect to population density

	(1) Ln patents per capita	(2) Ln patents per capita	(3) Ln patents per capita	(4) Ln patents per capita	(5) Ln patents per capita	(6) Ln patents per capita
Ln population density	0.170	0.349^{***}	0.122^{**}	0.129^{*}	0.164^{*}	0.036
	(0.11)	(0.06)	(0.06)	(0.07)	(0.09)	(0.10)
Ln GDP per capita		2.953^{***}	1.426^{***}	1.425^{***}	2.028^{***}	1.053^{***}
		(0.11)	(0.21)	(0.39)	(0.34)	(0.35)
Country effects	-	-	Yes	Yes	-	Yes
Sample	Non-US	Non-US	Non-US	Non-US	US	Non-US
IV	-	-	-	Yes	Yes	Yes
N	218	218	218	218	70	148
r2	0.010	0.723	0.894		0.408	

Notes: Standard errors in parentheses. Unit of observation is functional economic area. All variables are averaged over 2000–2014. IV is rank of a city in the population density (and population where included) distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.2 Services access (broadband)

Tab. A13. Elasticity of broadband per capita with respect to population density

	(1) Ln broadband per capita	(2) Ln broadband per capita	(3) Ln broadband per capita	(4) Ln broadband per capita	(5) Ln broadband per capita	(6) Ln broadband per capita
Ln population density	0.033***	0.034***	0.011	0.010	-0.000	0.013
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Ln GDP per capita		0.474***	0.305***	0.306***	0.119	0.327***
		(0.04)	(0.06)	(0.06)	(0.07)	(0.06)
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	343	343	343	343	51	292
Sample	All	All	All	All	US	Non-US
r2	0.020	0.576	0.862		0.186	

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.3 Social equity

Tab. A14. Elasticity of income quintile ratio with respect to population density

	(1) Ln disposable income quintile ratio (pct. 80 vs 20)	(2) Ln disposable income quintile ratio (pct. 80 vs 20)	(3) Ln disposable income quintile ratio (pct. 80 vs 20)	(4) Ln disposable income quintile ratio (pct. 80 vs 20)	(5) Ln disposable income quintile ratio (pct. 80 vs 20)
Ln population density	0.023	0.024	0.035**	0.057***	0.032**
	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)
Ln GDP per capita		-0.233***	0.469	0.197*	0.503
		(0.09)	(0.29)	(0.11)	(0.32)
Country effects	-	-	Yes	-	Yes
IV	-	-	-	-	-
N	275	269	269	51	218
Sample	All	All	All	US	Non-US
r2	0.004	0.042	0.734	0.352	0.718

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tab. A15. Elasticity of Gini coefficient with respect to population density

	(1) Ln Gini coefficient	(2) Ln Gini coefficient	(3) Ln Gini coefficient	(4) Ln Gini coefficient	(5) Ln Gini coefficient
Ln population density	-0.007	-0.007	0.025***	0.020***	0.026***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ln GDP per capita		-0.133***	0.026	0.025	0.028
		(0.03)	(0.02)	(0.04)	(0.03)
Country effects	-	-	Yes	-	Yes
IV	-	-	-	-	-
N	275	269	269	51	218.
Sample	All	All	All	US	Non-US
r2	0.003	0.118	0.880	0.237	0.880

Notes: Unit of observation is large regions (OECD definition). Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tab. A16. Elasticity of poverty rate with respect to population density

	(1) Ln poverty rate (poverty line 60%)	(2) Ln poverty rate (poverty line 60%)	(3) Ln poverty rate (poverty line 60%)	(4) Ln poverty rate (poverty line 60%)	(5) Ln poverty rate (poverty line 60%)
Ln population density	-0.014	-0.013	0.032	0.034**	0.027
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Ln GDP per capita		-0.280***	-0.590***	-0.396**	-0.617***
		(0.05)	(0.11)	(0.18)	(0.13)
Country effects	-	-	Yes	-	Yes
IV	-	-	-	-	-
N	275	269	269	51	218
Sample	All	All	All	US	Non-US
r2	0.004	0.148	0.547	0.156	0.549

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.4 Safety

Tab. A17. Elasticity of homicides p.c. with respect to population density

	(1) Ln homicides p.c.	(2) Ln homicides p.c.	(3) Ln homicides p.c.	(4) Ln homicides p.c.	(5) Ln homicides p.c.	(6) Ln homicides p.c.
Ln population density	-0.204***	-0.166***	-0.033	-0.048	0.105**	-0.076**
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)
Ln GDP per capita		-0.918***	0.086	0.086	0.312	0.058
		(0.07)	(0.06)	(0.07)	(0.48)	(0.07)
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	481	474	474	474	51	423
Sample	All	All	All	All	US	Non-US
r2	0.088	0.393	0.879		0.139	

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.5 Urban green

Tab. A18. Elasticity of vegetation density with respect to population density

	(1) Ln vegetation density	(2) Ln vegetation density	(3) Ln vegetation density	(4) Ln vegetation density	(5) Ln vegetation density	(6) Ln vegetation density
Ln population density	-0.199***	-0.267***	-0.257***	-0.245***	0.034	-0.261***
	(0.02)	(0.02)	(0.04)	(0.05)	(0.10)	(0.05)
Ln GDP per capita		0.388***				
		(0.06)				
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	583	410	583	583	45	538
Sample	All	Non-US	All	All	US	Non-US
r2	0.142	0.262	0.381			

Notes: Standard errors in parentheses. Unit of observation is small regions (urban and intermediate, OECD definition). US GDP data not available at this scale. All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tab. A19. Elasticity of green area density with respect to population density

	(1) Ln green area density	(2) Ln green area density	(3) Ln green area density	(4) Ln green area density	(5) Ln green area density	(6) Ln green area density
Ln population density		0.283^{**}	0.683^{**}	0.761^{*}	1.446^{***}	0.197
		(0.14)	(0.31)	(0.40)	(0.38)	(0.43)
Ln GDP per capita		0.496^{**}	0.035	0.022	1.178	-0.857
		(0.23)	(0.94)	(0.86)	(0.96)	(0.69)
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	280	280	280	280	70	210
Sample	All	All	All	All	US	Non-US
r2	0.021	0.040	0.283		0.246	

Notes: Standard errors in parentheses. Unit of observation is functional economic area. All variables are averaged over 2000–2014. IV is rank of a city in the population density (and population where included) distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tab. A20. Elasticity of green area per capita with respect to population density

	(1) Ln green area per capita	(2) Ln green area per capita	(3) Ln green area per capita	(4) Ln green area per capita	(5) Ln green area per capita	(6) Ln green area per capita
Ln population density	-0.754^{***}	-0.717^{***}	-0.317	-0.239	0.446	-0.803^{*}
	(0.14)	(0.14)	(0.31)	(0.40)	(0.38)	(0.43)
Ln GDP per capita		0.496^{**}	0.035	0.022	1.178	-0.857
		(0.23)	(0.94)	(0.86)	(0.96)	(0.69)
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	280	280	280	280	70	210
Sample	All	All	All	All	US	Non-US
r2	0.170	0.186	0.392		0.027	

Notes: Standard errors in parentheses. Unit of observation is functional economic area. All variables are averaged over 2000–2014. IV is rank of a city in the population density (and population where included) distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.6 Pollution concentration

Tab. A21. Elasticity of air pollution concentration with respect to population density

	(1) Ln air pollution (level PM2.5)	(2) Ln air pollution (level PM2.5)	(3) Ln air pollution (level PM2.5)	(4) Ln air pollution (level PM2.5)	(5) Ln air pollution (level PM2.5)
Ln population density	0.221***	0.220***	0.124***	0.111***	0.128***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Ln GDP per capita		-0.208***	0.020	0.053	0.018
		(0.04)	(0.19)	(0.14)	(0.21)
Country effects	-	-	Yes	-	Yes
IV	-	-	-	-	-
N	343	343	343	51	292
Sample	All	All	All	US	Non-US
r2	0.407	0.456	0.708	0.247	0.720

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.7 Energy

Tab. A22. Elasticity of ln CO2 emissions p.c. with respect to population density

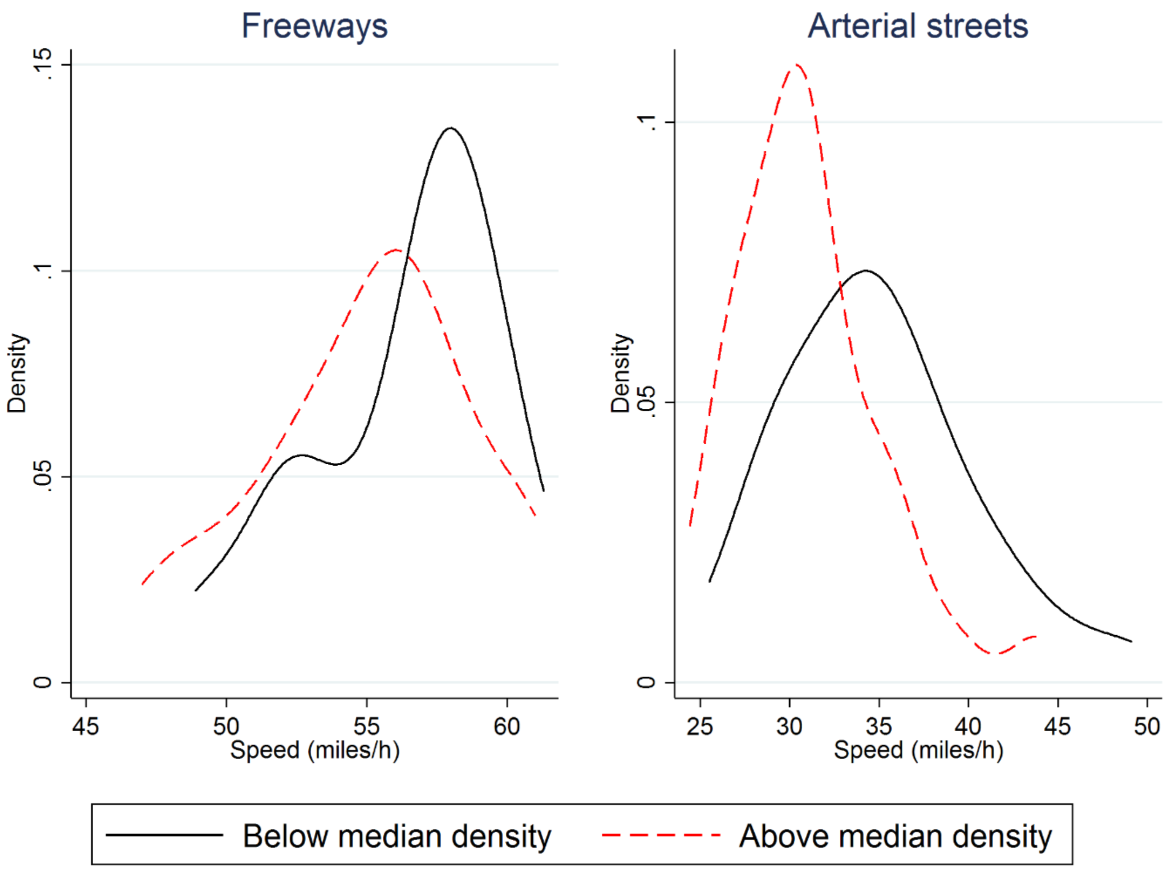
	(1) Ln CO2 emissions p.c.	(2) Ln CO2 emissions p.c.	(3) Ln CO2 emissions p.c.	(4) Ln CO2 emissions p.c.	(5) Ln CO2 emissions p.c.	(6) Ln CO2 emissions p.c.
Ln population density	-0.225***	-0.224***	-0.189***	-0.173***	-0.190***	-0.170***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)	(0.05)
Ln GDP per capita		0.503***	0.283***	0.282***	0.354	0.280***
		(0.04)	(0.08)	(0.07)	(0.27)	(0.07)
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	570	562	562	562	51	511
Sample	All	All	All	All	US	Non-US
r2	0.176	0.358	0.597		0.300	

Notes: Standard errors in parentheses. Unit of observation is large urban regions (OECD definition). All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.8 Traffic flow

In the figure below we compare the peak time (with congestion) speeds on freeways and arterial roads across metros that are above and below the median population density. Both distributions seem to suggest that metros with a higher population density have lower average speeds, which is in line with more congestion in denser cities.

Fig. A10. Distribution of peak time speeds by population density



Notes: Data from OECD (population density) and Lomax (2010).

However, regressing the freeway speed against population density does not yield a significant relationship during peak time (with congestion) or off-peak time (free flow). There is also no population density effect on congestions, i.e., on peak time speeds controlling for free-flow speeds. There is, however, a significantly negative effect of population size on congestion, suggesting that freeway congestion is determined by the size of the city and not its density.

Tab. A23. Elasticity of speed with respect to population density: Freeways

	(1) Ln freeway speed (miles/h): Peak time	(2) Ln freeway speed (miles/h): Peak time	(3) Ln freeway speed (miles/h): Free flow	(4) Ln freeway speed (miles/h): Free flow	(5) Ln freeway speed (miles/h): Peak time	(6) Ln freeway speed (miles/h): Peak time
Ln population density	-0.008	0.003	0.001	0.003	-0.001	0.011
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Ln GDP p.c.		-0.097***		-0.015	-0.078**	-0.037
		(0.03)		(0.02)	(0.03)	(0.03)
Ln freeway speed (miles/h): Free flow					1.312***	1.315***
					(0.18)	(0.16)
Ln population						-0.042***
						(0.01)
N	62	62	62	62	62	62
r2	0.012	0.113	0.001	0.013	0.420	0.630

Notes: Standard errors in parentheses. Data from OECD and Lomax (2010). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For arterial streets, in contrast we find a significant elasticity of peak time speed with respect to population density of -0.063. Interestingly, we find an elasticity within the same range for free-flow speeds. This suggests that the lower speed is primarily a morphological density effect. Street layouts in denser cities result in a generally lower speed, but not higher congestion. This effect is confirmed by the model controlling for free-flow speeds, which yields no significant congestion effect (on peak time speeds). As with freeway speeds, there is a significant population size effect, although it is relatively smaller.

Tab. A24. Elasticity of speed with respect to population density: Arterial streets

	(1) Ln arterial streets speed (miles/h): Peak time	(2) Ln arterial streets speed (miles/h): Peak time	(3) Ln arterial streets speed (miles/h): Free flow	(4) Ln arterial streets speed (miles/h): Free flow	(5) Ln arterial streets speed (miles/h): Peak time	(6) Ln arterial streets speed (miles/h): Peak time
Ln population density	-0.063***	-0.041**	-0.050***	-0.034**	-0.001	0.003
	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)
Ln GDP p.c.		-0.192***		-0.139***	-0.029	-0.018
		(0.06)		(0.05)	(0.02)	(0.02)
Ln arterial streets speed (miles/h): Free flow					1.182***	1.142***
					(0.03)	(0.03)
Ln population						-0.017***
						(0.00)
N	62	62	62	62	62	62
r2	0.138	0.217	0.130	0.192	0.966	0.972

Notes: Standard errors in parentheses. Data from OECD and Lomax et al. (2010). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.9 Health

Tab. A25. Elasticity of standardised mortality rate with respect to population density

	(1) Ln standardised mortality rate	(2) Ln standardised mortality rate	(3) Ln standardised mortality rate	(4) Ln standardised mortality rate	(5) Ln standardised mortality rate	(6) Ln standardised mortality rate
Ln population density	-0.056***	-0.046***	-0.015	-0.017	-0.005	-0.019
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ln GDP per capita		-0.140***	0.039	0.039*	-0.017	0.040
		(0.02)	(0.02)	(0.02)	(0.12)	(0.02)
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	528	528	528	528	51	477
Sample	All	All	All	All	US	Non-US
r2	0.107	0.223	0.882		.	

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tab. A26. Elasticity of life expectancy at birth with respect to population density

	(1) Ln life expectancy at birth	(2) Ln life expectancy at birth	(3) Ln life expectancy at birth	(4) Ln life expectancy at birth	(5) Ln life expectancy at birth
Ln population density	0.016***	0.013***	0.007**	-0.001	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln GDP per capita		0.055***	0.002	0.023	0.002
		(0.00)	(0.00)	(0.02)	(0.00)
Country effects	-	-	Yes	-	Yes
IV	-	-	-	-	-
N	496	496	496	51	445
Sample	All	All	All	US	Non-US
r2	0.157	0.496	0.922	0.065	0.931

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tab. A27. Elasticity of mortality in transport p.c. with respect to population density

	(1) Ln mortality in transport p.c.	(2) Ln mortality in transport p.c.	(3) Ln mortality in transport p.c.	(4) Ln mortality in transport p.c.	(5) Ln mortality in transport p.c.	(6) Ln mortality in transport p.c.
Ln population density	-0.162***	-0.150***	-0.103***	-0.099***	-0.119***	-0.093***
	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.03)
Ln GDP per capita		-0.278***	-0.111**	-0.110***	-0.484*	-0.087**
		(0.04)	(0.04)	(0.04)	(0.25)	(0.04)
Country effects	-	-	Yes	Yes	-	Yes
IV	-	-	-	Yes	Yes	Yes
N	420	414	414	414	51	363
Sample	All	All	All	All	US	Non-US
r2	0.260	0.375	0.819		0.534	

Notes: Standard errors in parentheses. Unit of observation is large regions (OECD definition). All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * p < 0.1, ** p < 0.05, *** p < 0.01

3.10 Well-being

Tab. A28. Elasticity of subjective well-being with respect to population density

	(1) Ln subjective life satisfaction	(2) Ln subjective life satisfaction	(3) Ln subjective life satisfaction	(4) Ln subjective life satisfaction	(5) Ln subjective life satisfaction
Ln population density	-0.021***	-0.023***	-0.007**	-0.001	-0.008**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Ln GDP per capita		0.114***	0.069***	0.012	0.074***
		(0.01)	(0.01)	(0.04)	(0.01)
Country effects	-	-	Yes	-	Yes
IV	-	-	-	-	-
N	339	339	339	51	288
Sample	All	All	All	US	Non-US
r2	0.073	0.410	0.850	0.003	0.859

Notes: Standard errors in parentheses. All variables are averaged over 2000–2014. IV is rank of a city in the population density distribution within a country. * p < 0.1, ** p < 0.05, *** p < 0.01

4 Recommended elasticities

This section provides a justification of the recommended elasticities reported in Table 5 in the main paper alongside a critical discussion of the quality and the quantity of the evidence base. We strongly advise consulting the relevant subsections below before applying one of the recommended elasticities in further research.

4.1 Wage elasticity

The literature reports both wage and TFP elasticities with respect to density, the former being the by far most frequently reported parameter. While we find a significant difference between the wage and the TFP elasticity in our review, it is notable that good work analysing both wage and TFP within a consistent framework does not support the existence of such a difference (Combes et al. 2010). We choose the median value of the wage elasticities in our sample of 4%, which is close to the results from recent high-quality work (Combes et al. 2012) and meta-analysis (Melo et al. 2009). We do note, however, that there is a tendency for within-city analyses (Ahlfeldt et al. 2015) and TFP analyses to yield larger estimated elasticities, but we recommend further work to substantiate this impression.

4.2 Patents

While there is a sizable literature engaged with the effects of urban form on innovation, we only found two studies that provided estimates that either directly corresponded to or could be converted into an elasticity of patents with respect to density (Carlino et al. 2007; Echeverri-Carroll & Ayala 2011). Some studies report marginal effects that cannot be converted into elasticities due to missing descriptive statistics. Our ancillary analysis of OECD functional economic area data suggests that the elasticity of patents with respect to density is around 20% for the US, which is thus in line with Carlino et al. (2007) and the quality-weighted mean across the two analyses found. The consistency of our own estimates and the estimates in the literature is reassuring. However, the evidence base is very thin and our own elasticity estimates for the world-wide sample at 12.9% are somewhat smaller than the recommended elasticity from US data. More work aiming at comparable elasticity estimates would clearly be desirable.

4.3 Rents

Our recommended rent elasticity of 21% is from Combes et al. (2013), a dedicated high-quality paper. While the estimate is specific to France, other good work shows that the magnitude generalises to the US (Albouy & Lue 2015). The estimate is also within the range of the works that we consider good and relevant. We are thus reasonably confident in recommending this elasticity even though the evidence base is not as well developed as it is, e.g., for wages. It should be noted, however, that there is evidence suggesting that the elasticity increases in city size (Combes et al. 2016).

4.4 Vehicle miles travelled

Our recommended elasticity of driving distance reductions with respect to a density of 8.5% is from Duranton & Turner (2015), a dedicated high-quality paper. The estimate is within the range of the mean and the median elasticities found in our review. We are, thus, reasonably confident in recommending this elasticity even though the evidence base is not as well developed as it is, e.g., for wages.

4.5 Variety benefits

The literature on consumption benefits arising from agglomeration is underdeveloped relative to the production side. However, there are some good papers which suggest a sizable effect. Victor Couture kindly provided estimates of the elasticity of restaurant price indices with respect to population density not reported in his paper (Couture 2016). Expressed in terms of price reductions (gains from variety) the elasticities take the values of 0.08 for driving and 0.16 for walking. These elasticities roughly generalise when estimated exploiting between-city variation (0.05–0.11 and 0.1–0.22). We recommend the naïve average of the two elasticities (12%), stressing that the exact elasticity will depend on the relative importance of the two modes in a setting. In support of the recommended elasticity we highlight that other good work has pointed to a positive impact of density on consumption variety (Schiff 2015) and that Couture's result is close to the elasticity of urban amenity value with respect to density provided by Ahlfeldt et al. (2015). The recommended elasticity is based on a small sample of high-quality evidence. More research is required to substantiate the findings.

4.6 Local public spending

The recommended elasticity of total local public spending reduction with respect to density of 14.4% is from a good analysis (Carruthers & Ulfarsson 2003). It is within close range of the mean across all estimates (for all spending types) in our review. Many of these estimates are from Carruthers & Ulfarsson (2003). Few other studies have contributed comparable results and the variance of the findings across these studies is significant. Overall, the evidence base is relatively thin and is not entirely consistent. More research is required in this area.

4.7 Income inequality

The literature on the effects of density on inequality is relatively inconsistent in the sense that a small number of studies use different inequality measures (e.g., dissimilarity index, wage gaps, Gini coefficient), different geographic scales (within-city, between-city) and different density measures (e.g., population density, relative centralisation, clustering). The results are, therefore hard to compare and are also qualitatively inconsistent. Our analysis of OECD regional data suggests that inequality increases in density, irrespective of the inequality measure we use (Gini, poverty ratio, interquartile wage gap). This finding is consistent with broader evidence in urban economics suggesting that the highly skilled (high-wage earners) benefit relatively more from agglomeration benefits. We acknowledge that we may be capturing different phenomena than studies that find a negative association between density and inequality at a within-city scale (Galster & Cutsinger 2007). However, we believe that our own estimates are closer to the thought experiment conducted here, which refers to an increase in overall urban density. Therefore, we choose the -3.5% elasticity of the income quintile wage gap reduction with respect to density from Table 4 in the main paper as the basis for a monetary quantification described in the next section. Of course, we must stress that this estimate should be considered preliminary as a sizable evidence base with comparable results has yet to be developed.

4.8 Crime rate reduction

The literature of the effects of urban form on crime rates is small, but consistently points to a positive effect of compactness on crime rates (crimes, p.c. as opposed to crimes per area) of sizable magnitudes. The interpretation of the results is somewhat complicated as authors typically consider various dimensions of compact urban forms at the same time. While separating the effects of different shades of compactness is interesting, it also complicates the evaluation of an overall density effect as any dimension can only be varied under the ceteris paribus condition (while most measures effectively change at the same time). Our recommended elasticity, therefore, is from Cheng Keat Tang, who kindly provided estimates of the elasticity of crime rates with respect to population density (without controlling for other dimensions of urban form) not reported in his paper (Tang 2015). Reassuringly, the elasticities implied from his estimates (level-level model) are almost identical for crimes against persons and property. While we consider the recommended elasticity to be a good estimate suitable for our purposes, more comparable evidence is required to substantiate the estimate.

4.9 Urban green

As discussed in the context of the presentation of our own results in the main paper quantitative evidence suitable for our purposes is essentially non-existent. We are thus left with no choice but to recommend our own elasticity of green space density with respect to population density of 29%. Of course, we must stress that this estimate should be considered preliminary as a sizable evidence base with comparable results has yet to be developed.

4.10 Pollution reduction

The literature on the effects of density on pollution concentrations is small. Moreover, the quantitative results prevailing in the literature are highly inconsistent as reflected by a standard deviation of 90% relative to a weighted mean elasticity of pollution reduction with respect to a density of 8%. Given that the literature is small, it is difficult to identify common features that explain the large differences. Our own cross-sectional estimate of approximately -12% (using OECD data) is close to the elasticity reported by Albouy & Stuart (2014) and roughly within the range of the cross-sectional estimates by Hilber & Palmer (2014). Their panel fixed effects results, which should come with improved identification, however, take the opposite sign and are even larger in terms of magnitude, with similarly large variation. Sarzynski (2012) finds results that are similar to Hilber and Palmer's panel-fixed effects estimates using a cross-sectional research design, suggesting that the estimation method cannot account for the inconsistency of the evidence base. Given that it is not possible to identify any consensus estimate we use the mean elasticity across the reviewed studies. But we stress that, to date, the evidence base is highly unsatisfactory, and we caution against an uncritical application of the chosen elasticity. More research is required to allow for a better understanding of the inconsistency in the existing estimates and to settle on a consensus estimate.

4.11 Energy consumption

We interpret CO2 emissions as reflecting energy usage, assuming that the elasticity of energy mix with respect to density is zero. CO2's social cost is primarily incurred through global warming. This is different from the pollutants considered in category 10, which have much more localised effects. The literature on the effects of density on energy consumption is relatively well developed and reasonably consistent, both qualitatively and quantitatively. We therefore choose the weighted mean elasticity of energy use reduction with respect to density across the reviewed analyses of 7% as a recommended elasticity. We note that the respective elasticity of public transport seems to be negative (meaning more energy is consumed) and large (-37%), which is consistent with higher transit usage in denser cities (see category 13). Given the relatively small proportion of overall energy consumption, the effects on aggregate outcomes are limited.

4.12 Traffic flow

The quantitative literature on the effects of density on average speed is surprisingly small. Most related analyses focus on the effects of road usage on speed on individual road segments. We found only two studies providing estimates of the elasticity of speed with respect to density, both of which, however, are of high quality (Couture et al. 2016; Duranton & Turner 2015). They yield very similar elasticities with a mean of -12%. Because the evidence base is quantitatively thin we contribute an own analysis using OECD functional urban area (density) and speed data from Lomax et al. (2010). We find no effect of urban density on speeds on highways where the metropolitan population is the more important predictor. This is intuitive because highways represent a transport system which is used to overcome relatively large distances and which is separate from the local street network. As long as the length of the highway network grows with the population in the metro area, flows on highways are not necessarily determined by population density. In contrast, for the arterial road network, density is predicted to be a more explicit determinant of flow as more people per area are expected to congest local roads as it is more difficult to increase the overall road density proportionately in population density. In line with these expectations, we find an elasticity of speed with respect to population density of -6.3%, which is at least roughly in line with Couture et al. (2016). Given the consistency of the estimates we are reasonably confident in recommending the -11% elasticity from the small literature. More research, however, is required to substantiate the evidence and to allow for us to differentiate by road types and geographies. In particular, evidence from outside the US is desirable.

4.13 Mode choice

The literature on the effects of urban form on mode choice is quantitatively well developed, although there is significant variability in the methodological approaches, which complicates the comparability of results across studies. Our recommended elasticity of non-car mode choice with respect to density is from a dedicated meta-analysis from experts in the field (Ewing & Cervero 2010). They find that the elasticity of walking and public transit use with respect to density is 7% in each case. We note that this elasticity of non-car usage with respect to density is consistent with the elasticity of car usage reduction of 7% we find in our evidence review if car trips account for roughly 50% of overall trips. The elasticity of non-car use with respect to density of 21%, in contrast, is consistent with our 7% car usage reduction elasticity if automobile trips account for more than 50%. We note that the relatively large mean elasticity of non-car use with respect to density of 21% across the reviewed studies is driven by outliers. The median value is 10%. We are therefore confident in recommending Ewing & Cervero's estimates. We further note that the authors provide a range of elasticities with respect to other dimensions of compact urban form such as diversity or design, which may well be more appropriate in particular contexts and are worth considering.

4.14 Health

The evidence base on the effects of density on health is small and difficult to interpret. The results are mostly published in the field of medicine with a presentation that differs significantly from social sciences. None of the considered studies estimates marginal effects with respect to density. Instead, adjusted (by individual characteristics) rates (e.g., pre-mature mortality or mortality by disease) are reported by density categories. In some instances, such categories refer to density terciles or quintiles, which are not specified further so that admittedly heroic assumptions have to be made regarding density distributions in a study setting. In other instances, rates are only reported graphically and numeric values must be entered after a visual inspection. We conduct ambitious back-of-the-envelope calculations to compute marginal effects, which can be converted into elasticities with respect to density as otherwise we would virtually be left without any evidence base. The nature of this evidence base needs to be critically acknowledged when working with the results. In particular, because the relatively large negative effects of density on health are not confirmed by our own analysis of OECD regional data. In our preferred specification, we do not find a significant effect of density on overall mortality rates. If anything, the effect is negative (meaning, positive health effects) as we find significantly negative effects in simpler specifications that do not control for cross-country heterogeneity. Moreover, there is a robust negative effect of density on mortality in transport rates and a robust positive association between density and life expectancy at birth. Following our rule, that we generally prefer evidence from the literature over our own estimates – unless the evidence is highly inconsistent or inconclusive – we use the elasticity of mortality rate reduction with respect to density, implied by Reijneveld et al.'s (1999) findings in the further calculations: their research focuses specifically on density and the overall mortality rate is particularly amenable to back-of-the-envelope calculations using the statistical value of life (see next section). We note however, that the evidence base is not sufficiently developed to allow for a confident recommendation of a consensus estimate. More research is required, ideally research using methods that are closer to the conventions in economics to allow for a more immediate cross-category comparison.

4.15 Well-being

Except for reported safety (in line with the evidence reviewed in category 8), the literature finds a negative association between reported satisfaction indicators and density, including reported satisfaction with social contacts, health (consistent with 14) and healthy environment (inconsistent with 9, but consistent with 10). Our evidence base contains surprisingly few analyses of the relationship between life satisfaction (subjective well-being or happiness) and density. For one of the few analyses in the evidence base, we were not able to convert the presented results into an elasticity of well-being with respect to happiness (Brown et al. 2015). We found one estimate which we were able to convert (from a lin-log semi-elasticity) in Glaeser et al. (2016). This estimate referred to city size instead of density and we converted it using the elasticity of density with respect to city size estimated in section 2.1. The resulting elasticity of reported life satisfaction with respect to density is -0.37%, which is roughly within the range of our own analysis of OECD data of -0.7%. While we proceed using -0.37% elasticity implied by Glaeser et al.'s (2016) analysis, we caution against uncritical application of this elasticity unless further research substantiates our quantitative interpretation.

5 Monetary equivalents

This section lays out the assumptions on quantities and unit values on which we base the calculation of monetary equivalents of density increases reported in Table 6 in the main paper. We strongly advise to consider the relevant subsection before applying the monetary equivalents to specific contexts as the assumptions may not be transferrable. All monetary equivalents are expressed in per capita and year Dollar terms. Some of the quantities and unit values borrowed from the literature are in other currencies. To convert Pound and Euro values into Dollar values we apply the average exchange rates over the 2000–2016 (October) period (1.64 and 1.22).

5.1 Productivity

A value of $35,000 is set as the worker wage, which is slightly below the US real disposable household income during 2010 (US Bureau of Economic Analysis 2016), but above the level of most high-income countries.

5.2 Innovation

We use the mean number of patents per year and 10,000 of population over 1990–1999 (2.057) as reported by Carlino et al. (2007). Valuing patents is difficult because prices are not usually directly observed. To analyse the distribution of patent values, the literature uses patent renewal data (Pakes 1986), event studies (Austin 1993), inventor surveys (Giuri et al. 2007), and census data (Balasubramanian & Sivadasan 2010), typically facing a trade-off between representativeness and identification. Recent estimates of an average patent value range from a simple average of transaction prices of patents of $288K ($233K median) to well-identified but much more specific estimates of $20M–30M inferred from the economic success of start-ups (Gaulé 2016). A common theme emerging from the literature is that the distribution of patent values is skewed, i.e., the majority of patents have low values, while a small number of patents achieve extremely high values. Given these challenges, our preferred approximation of the value of a representative patent is a reservation price (the price at which inventors report being willing to sell their patent) of $793,000 (€650,000) from Giuri et al. (2007). This value is in the middle of the median category (300K–1M) of reported patent reservation prices and the broader distribution of patent value estimates in the literature. We prefer self-reported reservation prices to observed transaction prices because the latter subsample is likely prone to adverse selection due to severe information asymmetries.

5.3 Value of space

We assume that the expenditure share on housing is one-third, which is in line with empirical evidence (Combes et al. 2016) and conventional assumptions made in urban economics (Chauvin et al. 2016; Albouy & Lue 2015). The total rent paid per year thus corresponds to one-fourth of the disposable income. This expenditure share is an average and seems to increase in city size (Combes et al. 2016).

5.4 Job accessibility

Total vehicle miles p.c. are taken from the American Driving Survey (Triplett et al. 2015). The total (private) per mile driving costs are from the American Automobile Association (2015).

5.5 Amenity access

Assuming that similar gains from variety arise in the consumption of other non-tradeables, we apply the density elasticity of the restaurant variety price index to household expenditures (see 5.5 for a discussion) in food away from home, entertainment, and apparel and services (based on shares reported in the 2015 Consumer Expenditure Survey) (Bureau of Labour Statistics 2015). In Table 5 in the main paper we use an adjusted elasticity to avoid a double counting of reduced costs of road trips that are already itemised in category 4. Couture reports that approximately

56% from the gains are pure gains from variety, with the remaining share result from travel cost reductions. Since the overall reduction in vehicle miles travelled is already accounted for in 4, we multiply the car elasticity by 0.56 to capture purely the gains from variety, resulting in an elasticity of 0.045. Assuming that each of the modes accounts for half of the restaurant trips made, we use the naïve average over the adjusted car and the walking elasticity in our calculations.

5.6 Efficiency of public services

The per capita expenditures on local public services are from Carruthers & Ulfarsson (2003).

5.7 Social equity

Valuing income inequality is even more challenging than measuring income inequality. To value income equality as it arises from density we compute the premium an individual would be willing to pay to insure themselves against uncertain realisations of incomes. In doing so we assume a concave relationship between utility and income that implies certain outcomes are preferred over uncertain outcomes, which is in line with risk-aversion. We compute the difference between the expected income E and the certainty equivalent (which a risk-averse individual would accept to avoid uncertainty) across the 20th (I^{20pct}) vs. the 80th (I^{80pct}) percentiles in the income distribution after taxes. The expected income is simply the mean across the two potential outcomes.

$$E = \frac{1}{2} I^{20pct} + \frac{1}{2} I^{80pct}$$

The certainty equivalent is computed as,

$$CE = U^{-1} \left[\frac{1}{2} U(I^{20pct}) + \frac{1}{2} U(I^{20pct}) \right]$$

where $U(I) = I^{\aleph}$ is the utility function in which $\aleph$ determines the degree of concavity. We set $\aleph = 0.5$, which is in the middle of the range of the elasticity of happiness (viewed as a proxy for utility) with respect to income estimates reported by Layard, Mayraz, & Nickell (2008). We use the distribution of incomes after taxes of the UK, a country that is arguably neither among the most equal nor unequal countries in the world (HM Revenue & Customs 2016). In dollar terms, the resulting inequality premium corresponds to $CE - E = \$1{,}793$ or $(E - CE)/CE = 4.8\%$. To analyse the effects of density on inequality we apply the elasticity of the interquartile wage gap with respect to density to the product of the percentage uncertainty premium and the disposable income in our scenario.

5.8 Safety

The average crime rate (p.c.) as well as the estimated cost of crime are from Brand & Price (2000).

5.9 Urban green

The green area p.c. of 540 m^2 we use is the mean across functional economic areas in the OECD.Stat data. The value of a m^2 green area per year is based the meta-analysis of contingent valuation estimates by Brander & Koetse (2011). Based on the reported meta-analysis coefficients we compute the average per m^2 and year value of a park in a functional economic area with a population density and a per capita GDP that corresponds to the mean in the OECD.Stat data.

5.10 Pollution concentration

We use an elasticity of rent with respect to density of 0.25, which is in the middle of the range of estimates reported by Chay & Greenstone (2005) with respect to the total suspended particles (TSPs).

5.11 Energy reduction

The total energy consumption per year is from the US Energy Information Administration (2012). We consider residential and transport energy consumption, which corresponds to 40% of all energy consumed according to Glaeser & Kahn (2010). To compute the p.c., annual consumption, we normalise by the total US population (320M). This results in a p.c. energy consumption of 121M BTU. We use an average over the price of all individual energy sources of $18.7 per 1M BTU from the U.S. Energy Information Administration (2012). To compute the corresponding CO2 emissions, we first convert p.c. energy consumption into KWH, to which we apply a factor of 25T/KWH and a social cost of $43/T (Glaeser & Kahn 2010).

5.12 Traffic flow

We obtain the total travel time p.c. per year by multiplying the average daily car trip length of 45 minutes (Triplett et al. 2015) by 365. The value of time is set to 50% of the average hourly wage of $21.5 as in Anderson (2014).

5.13 Sustainable mode choice

In computing the economic benefits of changes in mode we operate under the assumption that the marginal user is indifferent between modes, thus, there are no private costs and benefits to be considered above and beyond those already considered in categories 4, 5, and 12. However, a switch in mode may be associated with external benefits. Since the effects on congestion are already captured by the outcome category 12, we focus exclusively on the emission externalities. To compute the average emissions economised by switches away from car trips we proceed as follows. First, we compute the average energy consumed per passenger km by mode across the US, EU, high-income Asian, and Latin American countries. Weighted by the average modal split the average energy consumed per passenger km corresponds 0.49 MJ/km for non-car trips and 3.73 MJ/km for a car trip (Bohler-Baedeker & Huging 2012). These figures can be converted into KWH/mile, CO2/mile, and eventually $/mile using the same conversation rates as in 11.

5.14 Health

The premature mortality risk refers to OECD countries and is taken from OECD (2011). The statistical value of life is to $7,000,000 according to Viscusi & Aldy (2003) and confirmed in later studies (Hammitt & Haninger 2010; Viscusi 2010).

5.15 Wellbeing

We use an elasticity of self-reported well-being with respect to income of 0.5, which in the middle of the range reported by Layard et al. (2008) who estimate this elasticity through survey data on both happiness and life satisfaction from a wide range of geographical locations (US, Europe, and worldwide). Due to the concavity of the happiness function in income a 2% change in income is required to trigger a 1% change in happiness.

6 References

Ahlfeldt, G.M. & McMillen, D.P., 2017. Tall buildings and land values: Height and construction cost elasticities in Chicago, 1870-2010. *CEPR DP 12351*.

Ahlfeldt, G.M. & Pietrostefani, E., 2017. The compact city in empirical research: A quantitative literature review. *SERC discussion paper 215*.

Ahlfeldt, G.M., Redding, S.J., Sturm, D.M. & Wolf, N., 2015. The Economics of Density: Evidence from the Berlin Wall. *Econometrica*, 83(6), pp.2127–2189. Available at: http://www.princeton.edu/~reddings/papers/cepdp1154.pdf.

Albouy, D. & Lue, B., 2015. Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life. *Journal of Urban Economics*, 89, pp.74–92. Available at: http://dx.doi.org/10.1016/j.jue.2015.03.003.

Albouy, D. & Stuart, B., 2014. Urban Population and Amenities. *National Bureau of Economic Research, Inc. NBER Working Papers: 19919*. Available at: http://web.b.ebscohost.com/ehost/detail/detail?vid=12&sid=4da8fd9f-ac71-4e15-bc39-

f8f1d02573d1%40sessionmgr102&hid=128&bdata=JnNpdGU9ZWhvc3QtbGl2ZQ%3D%3D#AN=1439924&db=ecn.

American Automobile Association, 2015. Your driving costs. Available at: http://newsroom.aaa.com/2015/04/annual-cost-operate-vehicle-falls-8698-finds-aaa-ar [Accessed October 27, 2016].

Anderson, M.L., 2014. Subways, Strikes, and Slowdowns: The Impacts of Public Transit on Traffic Congestion. *American Economic Review*, 104(9), pp.2763–2796. Available at: http://www.aeaweb.org/articles?id=10.1257/aer.104.9.2763.

Angrist, J.D. & Pischke, J.-S., 2009. *Mostly Harmless Econometrics: An Empiricist's Companion* Princeton University Press, ed., Princeton & Oxford.

Austin, D.H., 1993. An Event-Study Approach to Measuring Innovative Output: The Case of Biotechnology. *The American Economic Review*, 83(2), pp.253–258. Available at: http://www.jstor.org/stable/2117673.

Balasubramanian, N. & Sivadasan, J., 2010. What Happens When Firms Patent? New Evidence from U.S. Economic Census Data. *Review of Economics and Statistics*, 93(1), pp.126–146. Available at: http://dx.doi.org/10.1162/REST_a_00058.

Bohler-Baedeker, S. & Huging, H., 2012. *Urban Transport and Energy Efficiency. Module 5h. Sustainable Transport: A Sourcebook for Policy-makers in Developing Cities*, Federal Ministry for Economic Cooperation and Development (BMZ). Available at: http://www2.giz.de/wbf/4tDx9kw63gma/SUT_module5h.pdf [Accessed November 1, 2016].

Brand, S. & Price, R., 2000. The economic and social costs of crime. *Home Office Research Study 217*. Available at: http://webarchive.nationalarchives.gov.uk/20110218135832/rds.homeoffice.gov.uk/rds/pdfs/hors217.pdf [Accessed November 1, 2016].

Brander, L.M. & Koetse, M.J., 2011. The value of urban open space : Meta-analyses of contingent valuation and hedonic pricing results. *Journal of Environmental Management*, 92, pp.2763–2773.

Brown, Z.S., Oueslati, W. & Silva, J., 2015. Exploring the Effect of Urban Structure on Individual Well-Being. *OECD Environment working papers*, (95), p.35.

Bureau of Labor Statistics, 2015. Consumer Expenditure Survey. Available at: http://www.bls.gov/cex/ [Accessed November 11, 2016].

Carlino, G.A., Chatterjee, S. & Hunt, R.M., 2007. Urban density and the rate of invention. *Journal of Urban Economics*, 61(3), pp.389–419.

Carruthers, J.I. & Ulfarsson, G.F., 2003. Urban sprawl and the cost of public services. *Environment and Planning B: Planning and Design*, 30(4), pp.503–522.

Chauvin, J.P., Glaeser, E.L., Ma, Y. & Tobio, K., 2016. What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States. *Journal of Urban Economics*, pp.1–33.

Chay, K. & Greenstone, M., 2005. Does Air Quality Matter? Evidence from the Housing Market. *Journal of Political Economy*, 113(2), pp.376–424. Available at: http://www.jstor.org/stable/10.1086/427462.

Combes, G., Duranton, P.-P., Gobillon, L. & Roux, S., 2010. Estimating Agglomeration Economies with History, Geology, and Worker Effects. In E. L. Glaeser, ed. *Agglomeration Economics*. Chicago: Chicago University Press., pp. 15–66.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D. & Roux, S., 2012. The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection. *Econometrica*, 80(6), pp.2543–2594.

Combes, P., Duranton, G. & Gobillon, L., 2016. The Costs of Agglomeration : Land Prices in French Cities. *Working Paper*, (7027).

Couture, V., 2016. Valuing the Consumption Benefits of Urban Density. *Working Paper: Univeristy of California, Berkeley*, (September).

Couture, V., Duranton, G. & Turner, M.A., 2016. Speed. *Working Paper*.

Duranton, G. & Turner, M.A., 2015. Urban form and driving: Evidence from US cities. *Working Paper*.

Echeverri-Carroll, E.L. & Ayala, S.G., 2011. Urban Wages : Does City Size Matter ? *Urban Studies*, 48(2), pp.253–271.

Ellis, J.G., 2004. Explaning Residential Density. *Places*, 16(2).

Ewing, R. & Cervero, R., 2010. Travel and the Built Environment: A Synthesis. *Journal of the American Planning Association*, 76(3), pp.265–294. Available at: http://trrjournalonline.trb.org/doi/abs/10.3141/1780-10%5Cnhttp://dx.doi.org/10.3141/1780-10.

Galster, G. & Cutsinger, J., 2007. Racial Settlement and Metropolitan Land-Use Patterns: Does Sprawl Abet Black-White segregation? *Urban Geography*, 28(6), pp.516–553.

Gaulé, P., 2016. Patents and the Success of Venture-Capital Backed Startups : Using Examiner Assignment to Estimate Causal Effects. *Working Paper*, pp.1–42.

Giuri, P., Mariani, M., Brusonib, S., Crespic, G., Francozd, D., Gambardellae, A., Garcia-Fontes, W., Geunac, A., Gonzalesf, R., Harhoff, D., Hoislg, K., Le Bash, C., Luzzii, A., Magazzinia, L., Nestac, L., Nomalerj, O., Palomerasi, N., Patel, P., Romanellik, M. & Verspagenj, B., 2007. Inventors and invention processes in Europe: Results from the PatVal-EU survey. *Research Policy*, 36(8), pp.1107–1127.

Glaeser, E.L., Gottlieb, J.D. & Ziv, O., 2016. Unhappy Cities. *Journal of Labor Economics*, 34(2), pp.S129–S182.

Glaeser, E.L. & Kahn, M.E., 2010. The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics*, 67(3), pp.404–418. Available at: http://dx.doi.org/10.1016/j.jue.2009.11.006.

Green, R.K., Malpezzi, S. & Mayo, S.K., 2005. Metropolitan-specific estimates of the price elasticity of supply of housing, and their sources. *American Economic Review*, 95(2), pp.334–339.

Guide, C.C., 2016. *Scopus: Content Coverage Guide*,

Gyourko, J. & Saiz, A., 2006. Construction costs and the supply of housing structure. *Journal of Regional Science*, 46(4), pp.661–680.

Gyourko, J., Saiz, A. & Summers, A., 2007. A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index. *Working Paper*.

Hammitt, J.K. & Haninger, K., 2010. Valuing fatal risks to children and adults: Effects of disease, latency, and risk aversion. *Journal of Risk and Uncertainty*, 40(1), pp.57–83.

Harzing, A.W. & Alakangas, S., 2016. Google Scholar, Scopus and the Web of Science: a longitudinal and cross-disciplinary comparison. *Scientometrics*, 106(2), pp.787–804.

Hilber, C.A.L. & Palmer, C., 2014. Urban Development and Air Pollution: Evidence from a Global Panel of Cities. *SSRN Electronic Journal*, (175). Available at: http://papers.ssrn.com/abstract=2541387.

HM Revenue & Customs, 2016. *Personal Incomes Statistics 2013-2014*, London, UK.

Layard, R., Mayraz, G. & Nickell, S., 2008. The marginal utility of income. *Journal of Public Economics*, 92(8–9), pp.1846–1857. Available at: http://www.sciencedirect.com/science/article/pii/S0047272708000248.

Lomax, T., Schrank, D., Turner, S., Geng, L., Li, Y. & Koncz, N., 2010. *Real-Timing the 2010 Urban Mobility Report*, Available at: http://utcm.tamu.edu/publications/final_reports/Lomax_10-65-55.pdf [Accessed November 1, 2016].

Melo, P.C., Graham, D.J. & Noland, R.B., 2009. A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, 39(3), pp.332–342. Available at: http://dx.doi.org/10.1016/j.regsciurbeco.2008.12.002.

Moed, H.F., Bar-Ilan, J. & Halevi, G., 2016. A new methodology for comparing Google Scholar and Scopus. *Journal of Informetrics*, 10(2), pp.533–551. Available at: http://dx.doi.org/10.1016/j.joi.2016.04.017.

Nitsch, V., 2005. Zipf zipped. *Journal of Urban Economics*, 57(1), pp.86–100.

OECD, 2011. *Premature mortality, in Health at a Glance 2011: OECD Indicators*, Paris: OECD Publishing.

Pakes, A., 1986. Patents as Options: Some Estimates of the Value of Holding European Patent Stocks. *Econometrica*, 54(4), pp.755–784. Available at: http://www.jstor.org/stable/1912835.

Rappaport, J., 2008. Consumption amenities and city population density. *Regional Science and Urban Economics*, 38, pp.533–552.

Reijneveld, S.A., Verheij, R.A. & de Bakker, D.H., 1999. Relative importance of urbanicity, ethnicity and socioeconomic factors regarding area mortality differences. *Journal of epidemiology and community health*, 53(7), pp.444–5. Available at: http://www.ncbi.nlm.nih.gov/pubmed/10492743%5Cnhttp://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC1756932.

Ruggles, S., Genadek, K., Goeken, R., Grover, J. & Sobek, M., 2017. Integrated Public Use Microdata Series: Version 7.0 [dataset].

Saiz, A., 2010. The Geographic Determinants of Housing Supply. *Quarterly Journal of Economics*, 125(3), pp.1253–1296. Available at: http://qje.oxfordjournals.org/lookup/doi/10.1162/qjec.2010.125.3.1253.

Sarzynski, A., 2012. Bigger Is Not Always Better: A Comparative Analysis of Cities and their Air Pollution Impact. *Urban Studies*, 49(14), pp.3121–3138.

Schiff, N., 2015. Cities and product variety: Evidence from restaurants*. *Journal of Economic Geography*, 15(6), pp.1085–1123.

Tang, C.K., 2015. Urban Structure and Crime. *Working Paper*.

Triplett, T., Santos, R. & Rosenbloom, S., 2015. *American Driving Survey: Methodology and Year 1 Results, May 2013 – May 2014*, Washington D.C. Available at: http://newsroom.aaa.com/wp-content/uploads/2015/04/REPORT_American_Driving_Survey_Methodology_and_year_1_results_May_2013_to_May_2014.pdf.

U.S. Energy Information Administration, 2012. *Annual Energy Review 2011*, Washington D.C. Available at: https://www.eia.gov/totalenergy/data/annual/pdf/aer.pdf [Accessed November 1, 2016].

US. Bureau of Economic Analysis, 2016. *Real Disposable Personal Income: Per Capita, retrieved from FRED, Federal Reserve Bank of St. Louis*, Available at: https://fred.stlouisfed.org/series/A229RX0 [Accessed October 27, 2016].

US Census Bureau, 2010. Cartographic Boundary Shapefiles - Census Tracts [dataset]. Available at: https://www.census.gov/geo/maps-data/data/cbf/cbf_tracts.html [Accessed August 9, 2017].

Viscusi, W.K., 2010. The heterogeneity of the value of statistical life: Introduction and overview. *Journal of Risk and Uncertainty*, 40(1), pp.1–13.

Viscusi, W.K. & Aldy, J.E., 2003. The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World. *Journal of Risk and Uncertainty*, 27(1), pp.5–76. Available at: http://dx.doi.org/10.1023/A:1025598106257.

What Works Centre for Local Economic Growth (WWC), 2016. *Guide to scoring evidence using the Maryland Scientific Methods Scale*, London, UK.

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Studies reviewed in The economic effects of density

Version: October 2017

Summary of study attributes

ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
P1	Abel et al.	2012	1	Labour productivity	PD	US	OLS IV	4	1.96	3.00%
P2	Andersson et al.	2014	1	Wages	ED	Sweden	panel FE	3	1.08	1.00%
P3	Andersson et al.	2016	1	Wages	ED	Sweden	panel	3	1.08	3.00%
P4	Barde	2010	1	Wages	ED	France	CrossSec, IV	4	0.54	3.50%
P5	Ciccone	2002	1	Labour productivity	ED	Europe	FE, IV	4	3.49	4.50%
P6	Ciccone & Hall	1996	1	Total factor productivity	ED	US	OLS IV	3	5.13	6.00%
P7	Combes et al.	2008	1	Wages	ED	France	panel IV	4	8.43	3.00%
P8	Dekle & Eaton	1999	1	Wages	ED	Japan	panel FE	3	0.68	1.00%
P9	Echeverri-Carroll & Ayala	2011	1	Wages	PD	US	OLS IV	4	0.40	3.05%
P10	Graham	2007	1	Labour productivity	ED	UK	GLS CONTR	2	2.27	4.02%
P11	Graham et al.	2010	1	Labour productivity	ED	UK	panel GMM	3	1.24	9.05%
P12	Larsson	2014	1	Wages	ED	Sweden	panel IV	3	1.31	1.00%
P13	Rosenthal & Strange	2008	1	Wages	ED	US	OLS, GMM, IV	4	5.30	4.50%
P14	Morikawa	2011	1	Total factor productivity	PD	Japan	panel	2	0.86	11.00%
P15	Tabuchi	1986	1	Labour productivity	PD	Japan	CrossSec IV	4	0.20	6.15%
P16	Faberman & Freedman	2016	1	Wages	PD	US	panel IV	3	0.56	6.98%

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ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
P17	Barufi et al.	2016	1	Wages	ED	Brazil	panel IV	3	0.56	7.30%
P18	Ahlfeldt et al.	2015	1	Total factor productivity	ED	Germany	DID, GMM	4	1.85	8.00%
P19	Ahlfeldt & Feddersen	2015	1	Labour productivity	ED	Germany	DID IV	4	4.58	3.80%
P20	Combes et al.	2012	1	Total factor productivity	ED	France	panel IV	4	8.43	3.20%
P21	Ahlfeldt & Wendland	2013	1	Total factor productivity	SPP	Germany	panel FE	3	0.94	5.90%
P22	Fu	2007	1	Wages	ED	US	CrossSec FE	2	1.92	3.70%
P23	Rappaport	2008	1	Total factor productivity	PD	US	CGEM	1	0.73	15.00%
P24	Chauvin et al.	2016	1	Wages	PD	US	panel IV	3	0.56	5.00%
P25	Chauvin et al.	2016	1	Wages	PD	Brazil	panel IV	3	0.56	2.60%
P26	Chauvin et al.	2016	1	Wages	PD	China	panel IV	3	0.56	20.00%
P27	Chauvin et al.	2016	1	Wages	PD	India	panel IV	3	0.56	7.50%
P28	Albouy & Lue	2015	1	Wages	PD	US	OLS CONTR	2	0.98	9.80%
I1	Carlino et al.	2007	2	Patents/capita	ED	US	OLS IV	4	4.13	20.00%
I2	Echeverri-Carroll & Ayala	2011	2	Patents/capita	PD	US	OLS IV	4	0.40	5.04%
VS1	Kholodilin & Ulbricht	2015	3	House prices	PD	Europe	OLS QR	2	0.57	25.00%
VS2	Lynch & Rasmussen	2004	3	House prices	PD	US	OLS CONTR	2	0.45	-1.79%
VS3	Palm et al.	2014	3	Rent	PD	US	OLS FE	2	0.50	4.50%
VS4	Combes et al.	2013	3	House prices	PD	France	OLS IV	2	2.60	21.00%
VS5	Ahlfeldt, Moeller, et al.	2015	3	House prices	PD	Germany	SPVAR IV	4	0.98	4.65%
VS6	Song & Knaap	2004	3	House prices	PD	US	OLS IV	4	0.99	-1.70%
VS7	Ahlfeldt & Wendland	2013	3	Rent	SPP	Germany	panel FE	3	0.94	7.00%
VS8	Liu et al.	2016	3	Rent	ED	US	OLS FE	2	0.67	10.00%
VS9	Albouy & Lue	2015	3	House prices	PD	US	OLS CONTR	2	0.98	26.80%
JA1	Veneri	2010	4	Av. Commuting time	PD	Italy	OLS, ML	2	0.96	-2.12%
JA2	Yang et al.	2012	4	Commuting time reduction	PD	China	OLS CONTR	2	2.10	-20.85%
JA3	Pouyanne	2004	4	Commuting length reduction	PD	France	OLS, LOGIT	2	0.32	20.65%
JA4	Pouyanne	2004	4	Commuting length reduction	ED	France	OLS, LOGIT	2	0.32	11.04%
JA5	Chatman	2003	4	Commercial trip length red.	ED	US	LOGIT, TOBIT	2	0.41	23.27%
JA6	Duranton & Turner	2015	4	VKT	PD	US	panel IV	4	1.24	8.50%
JA7	Albouy & Lue	2015	4	Commuting cost red.	PD	US	LPROB	2	0.98	-0.40%
JA8	Cervero & Kockelman	1997	4	VMT	ED	US	LOGIT	2	3.15	24.70%

ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
JA9	Cervero & Kockelman	1997	4	VMT (non-work trip)	ED	US	LOGIT	2	3.15	6.30%
JA10	Brownstone & Thomas	2013	4	Red. total vehicle mileage/year	HD	US	OLS	2	1.08	12.22%
SA1	Ahlfeldt, Redding, et al.	2015	5	Quality of life	ED	Germany	DID, GMM	4	1.85	15.00%
SA2	Schiff	2015	5	Cuisine variety	PD	US	OLS IV	4	0.85	18.50%
SA3	Couture	2016	5	Restaurant prices	PD	US	OLS LOGIT IV	4	3.35	8.00%
SA4	Couture	2016	5	Restaurant prices	PD	US	OLS LOGIT IV	4	3.35	16.00%
SA5	Albouy	2008	5	Quality of life	PD	US	OLS FE	2	2.00	2.00%
SA6	Albouy & Lue	2015	5	Quality of life	PD	US	OLS CONTR	2	0.98	3.10%
SA7	Chauvin et al.	2016	5	Real wages	PD	US	panel IV	3	0.56	-2.00%
SA8	Chauvin et al.	2016	5	Real wages	PD	Brazil	panel IV	3	0.56	-1.00%
SA9	Chauvin et al.	2016	5	Real wages	PD	China	panel IV	3	0.56	-5.20%
SA10	Chauvin et al.	2016	5	Real wages	PD	India	panel IV	3	0.56	-6.90%
SA11	Levinson	2008	5	Rail station density	PD	UK	panel	3	1.19	0.23%
SA12	Levinson	2008	5	Underground station density	PD	UK	panel	3	1.19	0.27%
SA13	Ahlfeldt et al.	2015	5	Underground station density	PD	Germany	SPVAR IV	4	0.98	3.50%
PS1	Carruthers & Ulfarsson	2003	6	Red. total spending	PD	US	CrossSec FE	2	0.90	14.40%
PS2	Carruthers & Ulfarsson	2003	6	Red. spending capital	PD	US	CrossSec FE	2	0.90	14.40%
PS3	Carruthers & Ulfarsson	2003	6	Red. spending roadways	PD	US	CrossSec FE	2	0.90	28.80%
PS4	Carruthers & Ulfarsson	2003	6	Red. spending transport	PD	US	CrossSec FE	2	0.90	-48.00%
PS5	Carruthers & Ulfarsson	2003	6	Red. spending sewerage	PD	US	CrossSec FE	2	0.90	-14.40%
PS6	Carruthers & Ulfarsson	2003	6	Red. spending trash	PD	US	CrossSec FE	2	0.90	9.60%
PS7	Carruthers & Ulfarsson	2003	6	Red. spending police	PD	US	CrossSec FE	2	0.90	9.60%
PS8	Carruthers & Ulfarsson	2003	6	Red. spending education	PD	US	CrossSec FE	2	0.90	19.20%
PS9	Carruthers & Ulfarsson	2003	6	Red. total spending	GAR	US	CrossSec FE	2	0.90	1.95%
PS10	Ladd	1994	6	Change per capita spending	PD	US	CrossSec FE	2	0.18	-3.02%
PS11	Prieto et al.	2015	6	Water supply cost per capita	PD	Spain	LOGIT	2	1.13	39.70%
PS12	Prieto et al.	2015	6	Sewage cost per capita	PD	Spain	LOGIT	2	1.13	50.70%
PS13	Prieto et al.	2015	6	Paving cost per capita	PD	Spain	LOGIT	2	1.13	81.20%
PS14	Hortas-Rico & Sole-Olle	2010	6	Red. total spending	UL	Spain	OLS CONTR	2	1.30	10.58%
PS15	Hortas-Rico & Sole-Olle	2010	6	Red. spending trash	UL	Spain	OLS CONTR	2	1.30	30.58%

ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
PS16	Hortas-Rico & Sole-Olle	2010	6	Red. community facilities per capita	UL	Spain	OLS CONTR	2	1.30	10.69%
PS17	Hortas-Rico & Sole-Olle	2010	6	Red. spending police	UL	Spain	OLS CONTR	2	1.30	9.20%
PS18	Hortas-Rico & Sole-Olle	2010	6	Red. housing and community development per capita	UL	Spain	OLS CONTR	2	1.30	7.53%
PS19	Hortas-Rico & Sole-Olle	2010	6	Red. culture and sports per capita	UL	Spain	OLS CONTR	2	1.30	15.09%
PS20	Hortas-Rico & Sole-Olle	2010	6	general administration spending per capita	UL	Spain	OLS CONTR	2	1.30	10.75%
SE1	Ananat et al.	2013	7	Red. in black-white wage gap	ED	US	OLS FE	2	0.88	-0.33%
SE2	Galster & Cutsinger	2007	7	Dissimilarity index	PD	US	OLS CONTR	2	0.47	256.75%
SE3	Rothwell	2011	7	Dissimilarity index	PD	US	CrossSec IV	4	1.17	39.20%
SE4	Rothwell & Massey	2010	7	Red. Gini coefficient	PD	US	CrossSec IV	4	1.24	456.35%
SE5	Rothwell & Massey	2009	7	Dissimilarity index	PD	US	CrossSec IV	4	1.75	32.61%
SE6	Wheeler	2004	7	Red. 90th vs. 10th decile	PD	US	GLS IV	4	0.33	17.00%
SF7	Raleigh & Galster	2015	8	Red. assault	PD	US	OLS CONTR	2	0.60	35.62%
SF8	Raleigh & Galster	2015	8	Red. robbery	PD	US	OLS CONTR	2	0.60	82.88%
SF9	Raleigh & Galster	2015	8	Red. violence	PD	US	OLS CONTR	2	0.60	52.34%
SF10	Raleigh & Galster	2015	8	Red. burglary	PD	US	OLS CONTR	2	0.60	34.17%
SF11	Raleigh & Galster	2015	8	Red. vandalism	PD	US	OLS CONTR	2	0.60	35.62%
SF12	Raleigh & Galster	2015	8	Red. narcotics	PD	US	OLS CONTR	2	0.60	81.42%
SF13	Raleigh & Galster	2015	8	Vehicle theft	PD	US	OLS CONTR	2	0.60	27.63%
SF14	Raleigh & Galster	2015	8	Property theft	PD	US	OLS CONTR	2	0.60	45.80%
SF15	Tang	2015	8	Red. assault	PD	UK	panel	3	0.30	8.45%
SF16	Tang	2015	8	Property theft	PD	UK	panel	3	0.30	9.02%
SF17	Twinam	2016	8	Red. robbery	PD	US	panel IV	4	0.59	46.79%
SF18	Twinam	2016	8	Red. assault	PD	US	panel IV	4	0.59	53.14%
OG1	Lin et al.	2015	9	Foliage Projection Cover	HD	Australia	OLS	1	0.80	-6.00%
PO1	Tang & Wang	2007	10	Red. CO2 concentration	HD	China	CORR	1	2.03	-23.00%
PO2	Salomons & Berghauser Pont	2012	10	Red. Noise	PD	Netherlands	CORR	1	2.16	4.00%
PO3	Albouy & Stuart	2014	10	Red. Pollution (particulates)	PD	US	NLLS CONTR	2	1.59	-15.00%

ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
PO4	Sarzynski	2012	10	Red. Nox m. metric tons	PD	World	CrossSec	2	1.28	43.80%
PO5	Sarzynski	2012	10	Red. VOCs m. metric tons	PD	World	CrossSec	2	1.28	33.00%
PO6	Sarzynski	2012	10	Red. CO m. metric tons	PD	World	CrossSec	2	1.28	22.80%
PO7	Sarzynski	2012	10	Red. SO2 m. metric tons	PD	World	CrossSec	2	1.28	37.60%
PO8	Hilber & Palmer	2014	10	Red. NOx μg/m3	PD	OECD	panel FE	3	0.35	23.82%
PO9	Hilber & Palmer	2014	10	Red. SOx μg/m3	PD	OECD	panel FE	3	0.35	200.80%
PO10	Hilber & Palmer	2014	10	Red. PM10 μg/m3	PD	OECD	panel FE	3	0.35	-47.40%
PO11	Hilber & Palmer	2014	10	Red. NOx μg/m3	PD	non-OECD	panel FE	3	0.35	-78.16%
PO12	Hilber & Palmer	2014	10	Red. SOx μg/m3	PD	non-OECD	panel FE	3	0.35	-183.67%
PO13	Hilber & Palmer	2014	10	Red. PM10 μg/m3	PD	non-OECD	panel FE	3	0.35	34.82%
EN1	Norman et al.	2006	11	Red. CO2 emissions	HD	Canada	CORR	1	3.63	8.90%
EN2	Hong & Shen	2013	11	Red. CO2 transport	PD	US	OLS IV	4	1.67	31.00%
EN3	Barter	2000	11	Red. Emission/capita	PD	Eastern Asia	DESC	0	0.43	29.40%
EN4	Su	2011	11	Gasoline consumption	FSDI	US	OLS CONTR	2	1.32	-9.20%
EN5	Su	2011	11	Gasoline consumption	PD	US	OLS CONTR	2	1.32	6.80%
EN6	Travisi et al.	2010	11	Env. impact reduction	PD	Italy	pooled WLS	3	2.47	0.92%
EN7	Cirilli & Veneri	2014	11	CO2 emissions commutes	PD	Italy	OLS IV	4	1.23	23.46%
EN8	Holden & Norland	2005	11	Red. domestic energy	HD	Norway	OLS	2	2.11	11.00%
EN9	Osman et al.	2016	11	Red. gasoline consumption	PD	Egypt	OLS	1	2.24	3.54%
EN10	Muñiz & Galindo	2005	11	Red. ecological footprint	PD	Spain	OLS	2	2.20	36.48%
EN11	Brownstone & Thomas	2013	11	Red. gasoline consumption	HD	US	OLS	2	1.08	14.40%
EN12	Larson et al.	2012	11	Red. residential energy	FACAP	US	OLS	2	1.09	3.38%
EN13	Larson et al.	2012	11	Red. residential energy	FACAP	US	OLS	2	1.09	4.67%
EN14	Glaeser & Kahn	2010	11	Red. gasoline consumption	PD	US	CORR	1	6.91	3.20%
EN15	Glaeser & Kahn	2010	11	Red. gasoline consumption	PD	US	CORR	1	6.91	9.74%
EN16	Glaeser & Kahn	2010	11	CO2 private driving	PD	US	CORR	1	6.91	8.21%
EN17	Glaeser & Kahn	2010	11	CO2 public transport	PD	US	CORR	1	6.91	-36.85%
EN18	Glaeser & Kahn	2010	11	CO2 heating	PD	US	CORR	1	6.91	-3.39%
EN19	Glaeser & Kahn	2010	11	CO2 electricity	PD	US	CORR	1	6.91	6.82%
EN20	Glaeser & Kahn	2010	11	CO2 Total	PD	US	CORR	1	6.91	5.27%

ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
C1	Duranton & Turner	2015	12	Travel speed	PD	US	panel IV	4	1.24	-11.00%
C2	Couture	2016	12	Travel speed	PD	US	OLS IV	4	2.63	-13.00%
MC1	Chatman	2003	13	Driving choice	ED	US	LOGIT TOBIT	2	0.41	43.73%
MC2	de Sa & Ardern	2014	13	Walking/cycling choice	PD	Canada	LOGIT	2	0.33	10.93%
MC3	Frank et al.	2008	13	Transit choice (work trip)	PD	US	LOGIT	2	2.82	26.00%
MC4	Frank et al.	2008	13	Cycle choice (work trip)	PD	US	LOGIT	2	2.82	84.00%
MC5	Frank et al.	2008	13	Walk choice (work trip)	PD	US	LOGIT	2	2.82	43.00%
MC6	Frank et al.	2008	13	Transit choice (non-work trip)	PD	US	LOGIT	2	2.82	24.00%
MC7	Frank et al.	2008	13	Cycle choice (non-work trip)	PD	US	LOGIT	2	2.82	-8.00%
MC8	Frank et al.	2008	13	Walk choice (non-work trip)	PD	US	LOGIT	2	2.82	28.00%
MC9	Nielsen et al.	2013	13	Cycle distance	PD	Denmark	Heckman	4	1.74	-8.70%
MC10	Zhao	2014	13	Walking choice	PD	China	LOGIT	2	2.56	0.13%
MC11	Zhao	2014	13	Cycling choice	PD	China	LOGIT	2	2.56	0.34%
MC12	Zhao	2014	13	Walking choice	ED	China	LOGIT	2	2.56	4.18%
MC13	Zhao	2014	13	Cycling choice	ED	China	LOGIT	2	2.56	12.65%
MC14	Pouyanne	2004	13	Car share rate	PD	France	OLS, LOGIT	2	0.32	-2.10%
MC15	Pouyanne	2004	13	Public transport choice	PD	France	OLS, LOGIT	2	0.32	42.03%
MC16	Pouyanne	2004	13	Walking choice	PD	France	OLS, LOGIT	2	0.32	43.90%
MC17	Pouyanne	2004	13	Cycling choice	PD	France	OLS, LOGIT	2	0.32	201.43%
MC18	Chao & Qing	2011	13	Walking choice	PD	US	OLS CONTR	2	2.00	15.73%
MC19	Zhang	2004	13	Transit choice (work trip)	PD	US	LOGIT	2	1.50	11.80%
MC20	Zhang	2004	13	Walk choice (work trip)	PD	US	LOGIT	2	1.50	10.50%
MC21	Zhang	2004	13	Driving choice (work trip)	PD	US	LOGIT	2	1.50	4.40%
MC22	Zhang	2004	13	Car share (work trip)	PD	US	LOGIT	2	1.50	7.10%
MC23	Zhang	2004	13	Public transport choice	PD	US	LOGIT	2	1.50	12.60%
MC24	Zhang	2004	13	Driving choice	PD	US	LOGIT	2	1.50	4.00%
MC25	Zhang	2004	13	Walking/cycling choice	PD	US	LOGIT	2	1.50	6.00%
MC26	Zhang	2004	13	Car share red.	PD	US	LOGIT	2	1.50	3.30%
MC27	Zhang	2004	13	Transit choice (work trip)	ED	US	LOGIT	2	1.50	9.00%
MC28	Zhang	2004	13	Driving choice (work trip)	ED	US	LOGIT	2	1.50	3.10%

ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
MC29	Zhang	2004	13	Walking/cycling (work trip)	ED	US	LOGIT	2	1.50	2.60%
MC30	Zhang	2004	13	Car share red. (work trip)	ED	US	LOGIT	2	1.50	4.40%
MC31	Zhang	2004	13	Public transport choice	ED	US	LOGIT	2	1.50	0.40%
MC32	Zhang	2004	13	Driving choice	ED	US	LOGIT	2	1.50	0.10%
MC33	Zhang	2004	13	Walking/cycling choice	ED	US	LOGIT	2	1.50	0.40%
MC34	Zhang	2004	13	Car share red.	ED	US	LOGIT	2	1.50	0.30%
MC35	Zhang	2004	13	Transit choice (work trip)	PD	Hong Kong	LOGIT	2	1.50	0.50%
MC36	Zhang	2004	13	Driving choice (work trip)	PD	Hong Kong	LOGIT	2	1.50	3.90%
MC37	Zhang	2004	13	Taxi red.	PD	Hong Kong	LOGIT	2	1.50	2.60%
MC38	Zhang	2004	13	Public transport choice	PD	Hong Kong	LOGIT	2	1.50	1.40%
MC39	Zhang	2004	13	Driving choice red.	PD	Hong Kong	LOGIT	2	1.50	11.00%
MC40	Zhang	2004	13	Taxi red.	PD	Hong Kong	LOGIT	2	1.50	12.80%
MC41	Zhang	2004	13	Transit choice (work trip)	ED	Hong Kong	LOGIT	2	1.50	1.10%
MC42	Zhang	2004	13	Driving choice (work trip)	ED	Hong Kong	LOGIT	2	1.50	7.70%
MC43	Zhang	2004	13	Taxi red.	ED	Hong Kong	LOGIT	2	1.50	11.80%
MC44	Zhang	2004	13	Public transport choice	ED	Hong Kong	LOGIT	2	1.50	0.60%
MC45	Zhang	2004	13	Driving choice	ED	Hong Kong	LOGIT	2	1.50	7.00%
MC46	Zhang	2004	13	Taxi red.	ED	Hong Kong	LOGIT	2	1.50	2.40%
MC47	Cervero & Kockelman	1997	13	Non-personal vehicle	ED	US	LOGIT	2	3.15	9.80%
MC48	Cervero & Kockelman	1997	13	Non-pers. vehicle (non work)	ED	US	LOGIT	2	3.15	8.40%
MC49	Cervero & Kockelman	1997	13	Non-pers. vehicle (work trip)	ED	US	LOGIT	2	3.15	11.30%
H1	Chaix et al.	2006	14	IHD risk red.	PD	Sweden	Panel LOGIT	3	2.22	-29.86%
H2	Chaix et al.	2006	14	Lung cancer risk red.	PD	Sweden	Panel LOGIT	3	2.22	-19.49%
H3	Chaix et al.	2006	14	Pulmonary disease red.	PD	Sweden	Panel LOGIT	3	2.22	-57.79%
H4	Fecht et al.	2016	14	Premature mortalities	PD	UK	CrossSec	2	1.12	-29.00%
H5	Fecht et al.	2016	14	Premature mortalities	SDI	UK	CrossSec	2	1.12	-50.00%
H6	Melis et al.	2015	14	Red. metal health prescriptions	PD	Italy	OLS, panel	2	1.42	1.27%
H7	Graham & Glaister	2003	14	Pedestrian casualty red.	PD	UK	LOGLIN	2	0.81	52.90%
H8	Graham & Glaister	2003	14	Pedestrian casualty red.	ED	UK	LOGLIN	2	0.81	-82.60%
H9	Graham & Glaister	2003	14	KSI reduction	PD	UK	LOGLIN	2	0.81	39.90%
H10	Graham & Glaister	2003	14	KSI reduction	ED	UK	LOGLIN	2	0.81	-5.10%

ID	Author	Year	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
H11	Howe et al.	1993	14	Red. all cancer rate	PD	US	COR	1	0.47	-5.50%
H12	Mahoney et al.	1990	14	Mortality red. (all cancers)	PD	US	LOGIT	2	0.24	-3.80%
H13	Reijneveld et al.	1999	14	Mortality red.	PD	Netherlands	LOGLIN	2	0.27	-9.06%
WB1	Brueckner & Largey	2006	15	Social contacts	PD	US	PROBIT IV	4	1.02	-1.59%
WB2	Brueckner & Largey	2006	15	Visit neighbour/week	PD	US	PROBIT IV	4	1.02	-4.46%
WB3	Brueckner & Largey	2006	15	# people can confide in	PD	US	PROBIT IV	4	1.02	-0.56%
WB4	Brueckner & Largey	2006	15	# close friends	PD	US	PROBIT IV	4	1.02	-0.81%
WB5	Brueckner & Largey	2006	15	# times attends club meeting	PD	US	PROBIT IV	4	1.02	-7.96%
WB6	Harvey et al.	2015	15	Perceived safety	FAR	US	OLS, LOGIT	2	0.98	6.90%
WB7	Fassio et al.	2013	15	Self-rep. social satisfaction	PD	Italy	COR	1	1.82	-42.32%
WB8	Fassio et al.	2013	15	Self-rep. env. health	PD	Italy	COR	1	1.82	-33.84%
WB9	Fassio et al.	2013	15	Self-rep. physical health	PD	Italy	COR	1	1.82	-13.80%
WB10	Fassio et al.	2013	15	Self-rep. psychological status	PD	Italy	COR	1	1.82	-31.89%
WB11	Glaeser et al.	2016	15	Self-rep. well-being	PD	US	panel	3	1.19	-0.37%

Legend

Category		Density		Maryland Scientific Method Scale[a]		CI[b]
1	Productivity	PD	Population density	0	Descriptive data	Citation Index
2	Innovation	ED	Employment or other economic density	1	Correlations, cross-sectional no control variables	
3	Value of space	SPP	Spillover / market potential	2	Cross-sectional, adequate control variables	
4	Job accessibility	HD	Development density	3	Panel data methods	
5	Services access	FACAP	Floor area per capita	4	Instrumental variables, RDD	
6	Efficiency of public services delivery	GAR	Geographic area reduction	5	Randomised control trials	
7	Social equity	FAR	Floor area ration and related measures			
8	Safety	FSDI	Freeway density			
9	Open space preservation and biodiversity					
10	Pollution reduction					
11	Energy efficiency					
12	Traffic flow					
13	Sustainable mode choice					
14	Health					
15	Wellbeing					

[a] As applied by the What Works Centre for Local Economic Growth (2016).
[b] Citations (in Scopus) adjusted for years since publication as discussed in section 1.2 of the appendix.

Full Bibliography

Abel, J.R., Dey, I. & Gabe, T.M., 2012. Productivity and the density of Human Capital. *Journal of Regional Science*, 52(4), pp.562–586.
Ahlfeldt, G.M., Redding, S.J., et al., 2015. The Economics of Density: Evidence from the Berlin Wall. *Econometrica*, 83(6), pp.2127–2189.
Ahlfeldt, G.M. & Feddersen, A., 2015. From Periphery to Core : Measuring Agglomeration Effects Using High-Speed Rail. *Working Paper*.
Ahlfeldt, G.M., Moeller, K. & Wendland, N., 2015. Chicken or egg? The PVAR econometrics of transportation. *Journal of Economic Geography*, 15(6), pp.1169–1193.
Ahlfeldt, G.M. & Wendland, N., 2013. How polycentric is a monocentric city ? Centers, spillovers and hysteresis. *Journal of Economic Geography*, 13(September 2012), pp.53–83.
Albouy, D., 2008. Are Big Cities Bad Places to Live? Estimating Quality of Life across Metropolitan Areas. *National Bureau of Economic Research Working Paper Series*, No. 14472.
Albouy, D. & Lue, B., 2015. Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life. *Journal of Urban Economics*, 89, pp.74–92.
Albouy, D. & Stuart, B., 2014. Urban Population and Amenities. *National Bureau of Economic Research, Inc. NBER Working Papers: 19919*.
Ananat, E., Fu, S. & Ross, S.L., 2013. Race-Specific Agglomeration Economies: Social Distance and the Black-White Wage Gap. *NBER Working Paper 18933 (National Bureau of Economic Research)*, pp.13–24.
Andersson, M., Klaesson, J. & Larsson, J.P., 2016. How Local are Spatial Density Externalities ? Neighbourhood Effects in Agglomeration Economies. *Regional Studies*, 50(6), pp.1082–1095.
Andersson, M., Klaesson, J. & Larsson, J.P., 2014. The sources of the urban wage premium by worker skills : Spatial sorting or agglomeration economies ? *Papers in Regional Science*, 93(4), pp.727–747.
Barde, S., 2010. Increasing Returns and the Spatial Structure of French Wages. *Spatial Economic Analysis*, 5(1), p.73.
Barter, P.A., 2000. Transport Dilemmas in Dense Urban Areas: Examples from Eastern Asia. In *Compact Cities: Sustainable Urban Forms for Developing Countries*. London & New York: SPON Press.
Barufi, A.M.B., Haddad, E.A. & Nijkamp, P., 2016. Industrial scope of agglomeration economies in Brazil. *Annals of Regional Science*, 56(3), pp.707–755.
Brownstone, D. & Thomas, F.G., 2013. The impact of residential density on vehicle usage and fuel consumption: Evidence from national samples. *Energy Economics*, 40(1), pp.196–206.
Brueckner, J.K. & Largey, A.G., 2006. Social interaction and urban sprawl. *CESifo WP*, 1843(1), pp.18–34.
Carlino, G.A., Chatterjee, S. & Hunt, R.M., 2007. Urban density and the rate of invention. *Journal of Urban Economics*, 61(3), pp.389–419.
Carruthers, J.I. & Ulfarsson, G.F., 2003. Urban sprawl and the cost of public services. *Environment and Planning B: Planning and Design*, 30(4), pp.503–522.
Cervero, R. & Kockelman, K., 1997. Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and Environment*, 2(3), pp.199–219.
Chaix, B. et al., 2006. Disentangling contextual effects on cause-specific mortality in a longitudinal 23-year follow-up study: Impact of population density or socioeconomic environment? *International Journal of Epidemiology*, 35(3), pp.633–643.
Chao, L. & Qing, S., 2011. An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers, Environment and Urban Systems*, 35(5), pp.347–357.
Chatman, D., 2003. How Density and Mixed Uses at the Workplace Affect Personal Commercial Travel and Commute Mode Choice. *Transportation Research Record*, 1831(3), pp.193–201.
Chauvin, J.P. et al., 2016. What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States. *Journal of Urban Economics*, pp.1–33.
Ciccone, A., 2002. Agglomeration effects in Europe. *European Economic Review*, 46(2), pp.213–227.
Ciccone, A. & Hall, R.E., 1996. Productivity and the Density of Economic Activity Productivity and the Density of Economic Activity. *The American Economic Review*, 86(1), pp.54–70.
Cirilli, A. & Veneri, P., 2014. Spatial Structure and Carbon Dioxide (CO2) Emissions Due to Commuting: An Analysis of Italian Urban Areas. *Regional Studies*, 48(12), pp.1993–2005.
Combes, P.-P. et al., 2012. The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection. *Econometrica*, 80(6), pp.2543–2594.
Combes, P.-P., Duranton, G. & Gobillon, L., 2008. Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, 63(2), pp.723–742.
Combes, P., Duranton, G. & Gobillon, L., 2016. The Costs of Agglomeration : Land Prices in French Cities. *Working Paper*, (7027).
Couture, V., 2016. Valuing the Consumption Benefits of Urban Density. *Working Paper: Univeristy of California, Berkeley*, (September).
Dekle, R. & Eaton, J., 1999. Agglomeration and Land Rents: Evidence from the Prefectures. *Journal of Urban Economics*, 46(2), pp.200–214.

Duranton, G. & Turner, M.A., 2015. Urban form and driving: Evidence from US cities. *Working Paper*.

Echeverri-Carroll, E.L. & Ayala, S.G., 2011. Urban Wages : Does City Size Matter ? *Urban Studies*, 48(2), pp.253–271.

Faberman, R.J. & Freedman, M., 2016. The urban density premium across establishments. *Journal of Urban Economics*, 93, pp.71–84.

Fassio, O., Rollero, C. & De Piccoli, N., 2013. Health, Quality of Life and Population Density: A Preliminary Study on "Contextualized" Quality of Life. *Social Indicators Research*, 110(2), pp.479–488.

Fecht, D. et al., 2016. Associations between urban metrics and mortality rates in England. *Environmental health : a global access science source*, 15 Suppl 1(Suppl 1), p.34.

Frank, L. et al., 2008. Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, 35(1), pp.37–54.

Fu, S., 2007. Smart Café Cities: Testing human capital externalities in the Boston metropolitan area. *Journal of Urban Economics*, 61(1), pp.86–111.

Galster, G. & Cutsinger, J., 2007. Racial Settlement and Metropolitan Land-Use Patterns: Does Sprawl Abet Black-White segregation? *Urban Geography*, 28(6), pp.516–553.

Glaeser, E.L., Gottlieb, J.D. & Ziv, O., 2016. Unhappy Cities. *Journal of Labor Economics*, 34(2), pp.S129–S182.

Glaeser, E.L. & Kahn, M.E., 2010. The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics*, 67(3), pp.404–418.

Graham, D.J., 2007. Agglomeration, productivity and transport investment. *Journal of Transport Economics and Policy*, 41(3), pp.317–343.

Graham, D.J. et al., 2010. Testing for causality between productivity and agglomeration economies. *Journal of Regional Science*, 50(5), pp.935–951.

Harvey, C. et al., 2015. Effects of skeletal streetscape design on perceived safety. *Landscape and Urban Planning*, 142, pp.18–28.

Hilber, C.A.L. & Palmer, C., 2014. Urban Development and Air Pollution: Evidence from a Global Panel of Cities. *SSRN Electronic Journal*, (175).

Holden, E. & Norland, I., 2005. Three challenges for the compact city as a sustainable urban form: Household consumption of energy and transport in eight residential areas in the greater Oslo Region. *Urban Studies*, 42(12), pp.2145–2166.

Hong, J. & Shen, Q., 2013. Residential density and transportation emissions : Examining the connection by addressing spatial autocorrelation and self-selection. *Transportation Research Part D*, 22, pp.75–79.

Hortas-Rico, M. & Sole-Olle, A., 2010. Does Urban Sprawl Increase the Costs of Providing Local Public Services? Evidence from Spanish Municipalities. *Urban Studies*, 47(7), pp.1513–1540.

Howe, H.L., Keller, J.E. & Lehnherr, M., 1993. Relation between Population Density and Cancer Incidence, Illinois, 1986-1990. *American Journal of Epidemiology*, 138(1), pp.29–36.

Kholodilin, K.A. & Ulbricht, D., 2015. Urban house prices: A tale of 48 cities. *Economics*, 9.

Ladd, H.F., 1994. Fiscal impacts of local population growth: A conceptual and empirical analysis. *Regional Science and Urban Economics*, 24(6), pp.661–686.

Larson, W., Liu, F. & Yezer, A., 2012. Energy footprint of the city: Effects of urban land use and transportation policies. *Journal of Urban Economics*, 72(2–3), pp.147–159.

Larsson, J.P., 2014. The neighborhood or the region? Reassessing the density-wage relationship using geocoded data. *Annals of Regional Science*, 52(2), pp.367–384.

Levinson, D., 2008. Density and dispersion: The co-development of land use and rail in London. *Journal of Economic Geography*, 8(1), pp.55–77.

Lin, B., Meyers, J. & Barnett, G., 2015. Understanding the potential loss and inequities of green space distribution with urban densification. *Urban Forestry and Urban Greening*, 14(4), pp.952–958.

Liu, C.H., Rosenthal, S.S. & Strange, W.C., 2016. *The Vertical City: Rent Gradients and Spatial Structure*,

Lynch, A.K. & Rasmussen, D.W., 2004. Proximity, Neighbourhood and the Efficacy of Exclusion. *Urban Studies*, 41(2), pp.285–98.

Mahoney, M.C. et al., 1990. Population density and cancer incidence differentials in New York State, 1978-82. *International Journal of Epidemiology*, 19(3), pp.483–490.

Melis, G. et al., 2015. The effects of the urban built environment on mental health: A cohort study in a large northern Italian city. *International Journal of Environmental Research and Public Health*, 12(11), pp.14898–14915.

Morikawa, M., 2011. Economies of Density and Productivity in Service Industries: An Analysis of Personal Service Industries Based on Establishment-Level Data. *Review of Economics and Statistics*, 93(1), pp.179–192.

Muñiz, I. & Galindo, A., 2005. Urban form and the ecological footprint of commuting. The case of Barcelona. *Ecological Economics*, 55(4), pp.499–514.

Nielsen, T.A.S. et al., 2013. Environmental correlates of cycling: Evaluating urban form and location effects based on Danish micro-data. *Transportation Research Part D: Transport and Environment*, 22, p.4044.

Norman, J., MacLean, H. & Kennedy, C., 2006. Comparing high and low residential density: life-cycle analysis of energy use and greenhouse gas emissions. *J Urban Plann Dev*, 132(1), pp.10–21.

Osman, T., Divigalpitiya, P. & Osman, M.M., 2016. The impact of Built Environment Characteristics on Metropolitans Energy Consumption: An Example of Greater Cairo Metropolitan Region. *Buildings*, 6(2), p.12.

Palm, M. et al., 2014. The trade-offs between population density and households' transportation-housing costs. *Transport Policy*, 36, pp.160–172.

Pouyanne, G., 2004. Urban Form and Travel Patterns. *Working Paper*, pp.1–39.
Prieto, Á.M., Zofío, J.L. & Álvarez, I., 2015. Cost economies, urban patterns and population density: The case of public infrastructure for basic utilities. *Papers in Regional Science*, 94(4), pp.795–816.
Raleigh, E. & Galster, G., 2015. Neighborhood Disinvestment, Abandonment, And Crime Dynamics. *Journal of Urban Affairs*, 37(4), pp.367–396.
Rappaport, J., 2008. A productivity model of city crowdedness. *Journal of Urban Economics*, 63(2), pp.715–722.
Reijneveld, S.A., Verheij, R.A. & de Bakker, D.H., 1999. Relative importance of urbanicity, ethnicity and socioeconomic factors regarding area mortality differences. *Journal of epidemiology and community health*, 53(7), pp.444–5.
Rosenthal, S.S. & Strange, W.C., 2008. The attenuation of human capital spillovers. *Journal of Urban Economics*, 64(2), pp.373–389.
Rothwell, J. & Massey, D.S., 2009. The Effect of Density Zoning on Racial Segregation in U.S. Urban Areas. *Urban Affairs Review*, 44(6), pp.779–806.
Rothwell, J.T., 2011. Racial enclaves and density zoning: The institutionalized segregation of racial minorities in the United States. *American Law and Economics Review*, 13(1), pp.290–358.
de Sa, E. & Ardern, C.I., 2014. Associations between the built environment, total, recreational, and transit-related physical activity. *BMC public health*, 14(1), p.693.
Salomons, E.M. & Berghauser Pont, M., 2012. Urban traffic noise and the relation to urban density, form, and traffic elasticity. *Landscape and Urban Planning*, 108(1), pp.2–16.
Sarzynski, A., 2012. Bigger Is Not Always Better: A Comparative Analysis of Cities and their Air Pollution Impact. *Urban Studies*, 49(14), pp.3121–3138.
Schiff, N., 2015. Cities and product variety: Evidence from restaurants*. *Journal of Economic Geography*, 15(6), pp.1085–1123.
Song, Y. & Knaap, G.J., 2004. Measuring the effects of mixed land uses on housing values. *Regional Science and Urban Economics*, 34(6), pp.663–680.
Su, Q., 2011. The effect of population density, road network density, and congestion on household gasoline consumption in U.S. urban areas. *Energy Economics*, 33(3), pp.445–452.
Tabuchi, T., 1986. Urban agglomeration, capital augmenting technology, and labor market equilibrium. *Journal of Urban Economics*, 20(2), pp.211–228.
Tang, C.K., 2015. Urban Structure and Crime. *Working Paper*.
Tang, U.W. & Wang, Z.S., 2007. Influences of urban forms on traffic-induced noise and air pollution: Results from a modelling system. *Environmental Modelling and Software*, 22(12), pp.1750–1764.
Travisi, C.M., Camagni, R. & Nijkamp, P., 2010. Impacts of urban sprawl and commuting: a modelling study for Italy. *Journal of Transport Geography*, 18(3), pp.382–392.
Twinam, T., 2016. *Danger Zone: Local government Land use Regulation and Neighbourhood Crime*,
Veneri, P., 2010. Urban polycentricity and the costs of commuting: Evidence from Italian metropolitan areas. *Growth and Change*, 41(3), pp.403–429.
Wheeler, C.H., 2004. Wage inequality and urban density. *Journal of Economic Geography*, 4(4), pp.421–437.
Yang, J. et al., 2012. Transport Impacts of Clustered Development in Beijing: Compact Development versus Overconcentration. *Urban Studies*, 49(5), pp.1315–1331.
Zhang, M., 2004. The role of land use in travel mode choice - Evidence from Boston and Hong kong. *Journal of the American Planning Association*, 70(3), pp.344–360.
Zhao, P., 2014. The Impact of the Built Environment on Bicycle Commuting: Evidence from Beijing. *Urban Studies*, 51(5), pp.1019–1037.