Gabriel M. Ahlfeldt[♣], Elisabetta Pietrostefani[♠]

The economic effects of density: A synthesis[*]

Abstract: This paper synthesises the state of knowledge on the economic effects of density. We consider 347 estimates of density elasticities of a broad range of outcomes ranging from wages, innovation, rents, various amenities, the cost of providing public services, transport- and environment-related outcomes to health and wellbeing. More than 100 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 original 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 density seems to be a net-amenity that is associated with positive external welfare effects. Densification policies may be welfare enhancing, but the distributional effects may be regressive, especially if residents are immobile and housing supply is inelastic.

Key words: Compact, city, density, meta-analysis, elasticity, present value

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♣ London School of Economics and Political Sciences (LSE) and Centre for Economic Policy Research (CEPR), Houghton Street, London WC2A 2AE, g.ahlfeldt@lse.ac.uk, www.ahlfeldt.com

♠ London School of Economics and Political Sciences (LSE).

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1 Introduction

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] There is a consensus among planners and policymakers, however, that even higher densities within cities and urban areas are desirable, at least on average (Boyko & Cooper 2011; OECD 2012). 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 infrastructure that are efficient and equitable (IAU-IDF 2012; Holman et al. 2014). It is difficult to ascertain, however, to what extent this normative statement prevailing in the policy debate can be substantiated by evidence (Neuman 2005).

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 well-grounded in evidence. 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 347 estimates (from 180 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 self-reported well-being.

While the evidence base is shared with a companion paper (Ahlfeldt & Pietrostefani 2017), the results presented in the two papers are mutually exclusive. In the companion paper, we analyse the effects of a variety of compact city characteristics (including morphological features and land use mix), restricting the interpretation to qualitative results in order to explore the full evidence base. In this paper, we focus on a quantitative comparison, and, therefore, restrict the analysis to results that can be expressed as density elasticity estimates. For more than 100 cases, we

[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%.

conduct back-of-the-envelope calculations to convert the results into a comparable 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 characteristics such as the 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 original 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 density elasticity of preserved green space, 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 density elasticity of construction costs.

Our third contribution is to condense this broad evidence base into a set of 15 category-specific density elasticity estimates. Specific to each category, we either recommend the weighted (by adjusted citations) mean across the elasticity estimates in our evidence base, an estimate from a high-quality original research paper or one of our original 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 elasticity estimates 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 present value (PV, at a 5% discount rate) of the effect of a 1% increase in density for a scenario that roughly corresponds to an average metropolitan area in a developed country. For this purpose, we combine our recommended density elasticity estimates 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.[2]

Our analysis reveals sizeable benefits and costs of density. A log-point increase in density leads to (log-point effects in parenthesis) higher wages (0.04), higher rent (0.15) and lower average vehicle mileage (0.06), but also higher pollution concentration (0.13) and lower average speed (0.12). For other outcomes, existing estimates are better interpreted as associations in the data since the causal interpretation would rest on the strong assumption that differences in density are historically determined by factors that have no contemporaneous effects on outcomes. A log-point increase in density is associated with (log-point effects in parenthesis) higher patent activity (0.21), consumption variety value (0.12), preservation of green spaces (0.28), as well as lower car use (0.05), energy consumption (0.07), crime (0.085), and costs of providing local public services (0.17). Density, however, is also associated with higher construction costs (0.55), skill wage gaps (0.035), mortality risk (0.09) as well as lower self-reported well-being (0.004).

Studies that are more frequently cited, or use more rigorous methods, find less positive density effects (in a normative sense). The estimates also become less positive over time, possibly reflecting a trend towards the application of more rigorous methods. Although more evidence would be desirable to substantiate our findings, our analysis reveals some insights into geographic heterogeneity in density elasticity estimates. For non-high-income countries, the estimated density elasticity of wages, at 0.08, is twice as large for high-income countries, on average. Mode choice is less likely to change with density, whereas the gains from density in terms of domestic energy consumption appear to be larger. Compared to other developed countries, density in the US is associated with larger skill wage gaps and higher rather than lower crime rates. Our review of the literature also suggests that the effect of density on rents may not be log-linear. Estimates of the density elasticity of rent increase by 0.063 for every increase in population density by 1000 inhabitants per square kilometre. We do not find a similar non-linearity in the estimated effects of density on wages, suggesting that convex costs lead to a bell-shaped net-agglomeration benefits curve (Henderson 1974).

In our illustrative scenario, a 1% increase in density leads to an increase in the per capita present value (infinite horizon, 5% discount rate) of wages and rents of $280 ($190 after taxes) and $347. 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

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

imperfect accounting also suggests that part of the rent increase may be attributable to the higher cost of providing space in addition to enjoyable amenities. Policy-induced densification may lead to aggregate welfare gains. However, there may be a collateral net-cost to renters and first-time buyers.[3] This effect adds to a potentially regressive distributional impact due to a widening skill wage gap.

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. 2018), quality of life (e.g. Albouy & Lue 2015), driving distances (Duranton & Turner 2018), road speeds (Couture et al. 2018), public spending reduction (e.g. Hortas-Rico & Sole-Olle 2010), energy consumption (Glaeser & Kahn 2010), skill-wage gaps (Baum-Snow & Pavan 2012) and self-reported 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. The fundamental challenge the literature faces is to separate the effects of density from unobserved factors that determine density. As mentioned above, a causal interpretation often requires the strong identifying assumption that contemporary density is not endogenous to factors that have direct effects on outcomes. Moreover, for individual-, firm-, and unit-based outcomes (e.g. wages, innovation, rent, wellbeing), the collected density elasticity estimates often capture composition effects. In general, the quantitative results are best suited for an evaluation of the effects of densification policies applied to individual cities (as opposed to all cities in a country) in the long run. Compared to wages and mode choice, the evidence base for the other outcomes is generally underdeveloped. While for some categories selected 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, 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.

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

The remainder of this paper is organised as follows. In section 2, we provide an introduction into the origins of density and some ancillary estimates that help with the interpretation of density effects. In section 3, we lay out how the evidence base was collected and classified. Section 4 summarises the evidence by outcomes and attributes. Section 5 presents a discussion of our original density elasticity estimates. Section 6 condenses the evidence (including our original estimates) to 15 outcome-specific density elasticity estimates. Section 7 discusses the monetary equivalents of an increase in density. The final section (8) 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 Background

In this section, we provide some theoretical background and ancillary empirical analyses that will guide the interpretation of the evidence base.

2.1 Origins of density

The first columns of Table 1 summarise the distribution of population density by OECD functional urban areas (FUA), comparing the US to the rest of the world. While, on average, density in US cities is relatively low, the variation, at a coefficient of variation of about one, is similarly striking in both samples. Another notable insight from Table 1 is that the variation in density within US FUAs is about two and a half times the variation across FUAs.

Tab. 1. Variation in density

	(1) FUA, Non-US		(2) FUA, US		(3) FUA, US		(4) Census tract, US	
	OECD data		OECD data		Census data		Census data	
	Pop. Density		Pop. density		Pop. Density (PD)		Tract PD - FUA mean	
	Level	Ln	Level	Ln	Level	Ln	Level	Ln
Min	36	3.58	27	3.29	34	3.54	-1,947	-10.99
p1	55	4.01	27	3.29	34	3.54	-1,201	-3.18
p25	330	5.80	100	4.60	163	5.10	369	0.57
p50	580	6.36	179	5.19	371	5.92	1,295	1.44
p75	994	6.90	386	5.96	648	6.47	2,831	2.37
p99	4,652	8.44	1,661	7.42	1,947	7.57	31,388	4.28
Max	4,851	8.49	1,661	7.42	1,947	7.57	209,187	5.87
Mean	814	6.33	274	5.23	451	5.76	2,907	1.36
SD[1]	798	0.90	268	0.89	370	0.90	5,890	1.49
CV[2]	98.03%	-	97.81%	-	82.06%	-	202.58%	-
N	211		70		70		34,123	

Notes: Population density in inhabitants per square kilometre. Functional urban area (FUA) data from OECD (Columns 1 and 2). Census data matched to FUA shapefiles on GIS, aggregated to FUA (Columns 3 and 4) – data includes only core FUA, excluding the commuting zones around them. City cores are defined using the population grid from the global dataset Landscan (2000). [1] Standard Deviation. [2] Coefficient of variation.

Economic theory offers a range of explanations for this large variation in density. In a world without internal or external scale economies, density naturally results from the fundamental productivity and amenity value of a location. Exogenous geographic features such as fertile soil, moderate climate, or access to navigable rivers attract economic activity, leading to growing cities. Classic urban economics models predict that larger cities will be denser since positive within-city transport costs limit horizontal urban expansion (Brueckner 1987). 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. Within cities, densities are higher close to desirable locations (such as the CBD) where rents are particularly high to offset for transport cost. Transport innovations (e.g. mass-produced cars) allow for horizontal expansion and, ceteris paribus, reduce urban density.

Reflecting the shift towards knowledge-based urban economies (Michaels et al. 2018), recent models feature agglomeration externalities (Lucas & Rossi-Hansberg 2002; Ahlfeldt et al. 2015) making density a cause and an effect of productivity and utility. This class of models features multiple equilibria so that cities may be dense and monocentric or polycentric and dispersed. Yet, due to agglomeration-induced path dependency, contemporary economic geography often follows features that were important in the past, e.g. agricultural land suitability (Henderson et al. 2018) or portage sites (Bleakley & Lin 2012). Similarly, the compact monocentric city structure that is characteristic for historic cities has been argued to be more resilient to shocks (e.g. natural disasters, or transport innovations) in cities that were already large about a century ago, the time when external returns and mass-produced cars presumably started to become increasingly important (Ahlfeldt & Wendland 2013).

In practice, and at the heart of the policy dimension of this paper, density is also determined by various land use regulations, such as urban growth boundaries, preservation policies, as well as height, floor area ratio, and lot size regulations, which often have their origins in history (McMillen & McDonald 2002; Siodla 2015). For a comprehensive review of the role of history in urban economics research, see Hanlon & Heblich (2018).

Given the endogeneity of density, separating the effects of density on an economic outcome from the effects of location fundamentals represents an identification challenge. Natural experiments such as the division of a city due to exogenous political reasons (Ahlfeldt et al. 2015) are rare. Plausible instruments for density are often difficult to find, although some researchers have exploited geology as a factor that likely impacts on the distribution of economic activity, but not on an economic outcome of interest (Combes et al. 2010). Our reading is that, for the most part, the literature implicitly exploits the idea that much of the spatial variation in density is rooted in history. Many of the results summarised below are informative to the extent that density is determined by factors that were relevant in the past and have a limited direct effect on economic outcomes today.

2.2 Density and city size

The relationship between city size and density is critical to the interpretation of our evidence base. Given the theoretical link discussed above, it is perhaps not surprising that the literature refers to actual density, the population normalised by the geographic size of a city, and city size, the total population, interchangeably.

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 (Rosenthal & Strange 2001). 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 evidence from between-city comparisons reviewed here should be interpreted in that light, since compact-city policies aiming at changing density while keeping population constant may result in smaller effects, if there is a genuine city-size effect that is independent from density. As an example, if productivity gains from labour market pooling operated at the city scale over relatively large commuting distances without spatial decay, increasing density while holding population constant would not increase productivity. Reassuringly, the estimates from between-city and within-city studies (which hold population constant) tend to be quite similar conditional on us making the following adjustment.

To translate estimated city size elasticities from the literature into density elasticity estimates, we use an estimate of the elasticity of (population) density with respect to city size (population) derived from a multi-country FUA-level data set (OECD 2016) and the following empirical specification:

$$\ln\left(A_{i,c}\right) = a\ln(P_i) + \mu_c + \varepsilon_{i,c}, \tag{1}$$

where $A_{i,c}$ is the geographic area of FUA i in country c, P_i is the land area of the FUA, and μ_c is a country fixed effect. The city size elasticity of density is implicitly determined as $d\ln(P_i/A_i)$ / $d\ln(P_i) = \alpha = 1 - a$. Compared to using the log of density as dependent variable, this estimation strategy avoids the mechanical endogeneity problem that arises if population shows up on both sides of the equation. Our preferred estimate of a is 0.57, which implies a city size elasticity of density of $\alpha = 0.43$. Therefore, we expect density elasticity estimates to be slightly more than twice as large as population elasticity estimates if the underlying economic mechanisms are the same. We note that our estimate of a is broadly consistent with the 0.7 estimate for French cities by Combes et al (2018). 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.

2.3 Density and the supply side

As discussed above, the positive city size elasticity of density results from an interplay of the demand side and the supply side of the urban economy. Higher rents in larger cities lead to higher densities. 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 (2018) 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 density elasticity of (per-unit) 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 estimated density elasticity of this index can be combined with the estimated density elasticity of the cost of a standard home (the location effect) from Gyourko and Saiz (2006) to give an estimate of the gross density effect.

From the results of both analyses, we conclude that 0.04–0.07 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 The evidence base

3.1 Collection

In line with standard best-practice approaches of meta-analytic research, as reviewed by Stanley (2001), our literature search is carried out in several stages.[4] 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).

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

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 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.[5] 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, PhD theses, reports, 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 268 relevant studies, which include 473 conceptually distinct analyses. We typically keep multiple estimates (analyses) from the same study if they refer to different dependent variables or geographic areas.

A restriction to elasticity estimates that are explicitly reported in publications shrinks the sample by about 50% to 242 analyses in 127 studies. We make some effort, however, to increase the evidence base. We infer density elasticity estimates from reported city size elasticity estimates using the estimated elasticity of city size with respect to density discussed above. Similarly, we conduct back-of-the-envelope calculations to approximate density elasticity estimates if results are reported as estimated marginal effects in levels, semi-elasticities, or in graphical illustrations. We also make some adjustments to allow for a consistent interpretation within categories. As an example, we convert estimates of the density elasticity of land price into estimates of the density elasticity of housing rent assuming a Cobb-Douglas housing production function (Epple et al. 2010) and a land share of 0.25 (Combes et al. 2018; Ahlfeldt et al. 2015). Finally, some authors kindly provided density elasticity estimates on request, which were not reported in their papers (e.g. Couture 2016; Tang 2015; Albouy 2008). This way, we increase the quantitative evidence base by more than 100 estimates to 347 analyses in 180 studies. The final quantitative sample is comparable to the full sample (473 analyses from 268 studies) across a range of characteristics that we introduce in the next subsections (see appendix section 2).

[5] At this stage, we were pointed to a literature on urban scaling in which city size is related to a variety of outcomes. 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 (Bettencourt & Lobo 2016; Batty 2008; Bettencourt 2013).

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.

3.2 Attributes

We choose a quantitative approach to synthesise our broad and diverse evidence base. 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 often parameters that have been estimated in relatively similar econometric analyses. 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 A2)
vii) The period of analysis
viii) The spatial scale of the analysis, i.e. within-city vs. between-city
ix) The methodological approach as defined by the Scientific Maryland Scale (SMS) used by the What Works Centre for Local Economic Growth (2016)
The variable 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 comprehensive 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 Normalised Impact per Paper) score (Scopus 2016) and the SCImago Journal Rank (Scimago 2017). A detailed discussion is in appendix 1.2.

It is worth pointing out that, in the present context, a higher SMS score does not necessarily imply a higher quality of the evidence. While exploiting plausibly exogenous variation (SMS 4) is certainly desirable to separate the effects of density from unobserved location fundamentals, it is less clear that having a greater set of covariates (SMS 2) improves the analysis if the controls are potentially endogenous. One example frequently found in the literature that gives cause for concerns is the inclusion of multiple variables that capture different shades of urban compactness such as population density, building density and job centrality. Similarly, the inclusion of spatial fixed effects (SMS 3) does not improve the identification if the fraction of the variation in density that is most likely exogenous is cross-sectional, because it is determined by history (see discussion in section 2.1). Given these ambiguities, our preferred measure for weighting the elasticities in the evidence base is the citation index, which captures the impact an analysis has had within the research community.

In Table 2 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%.

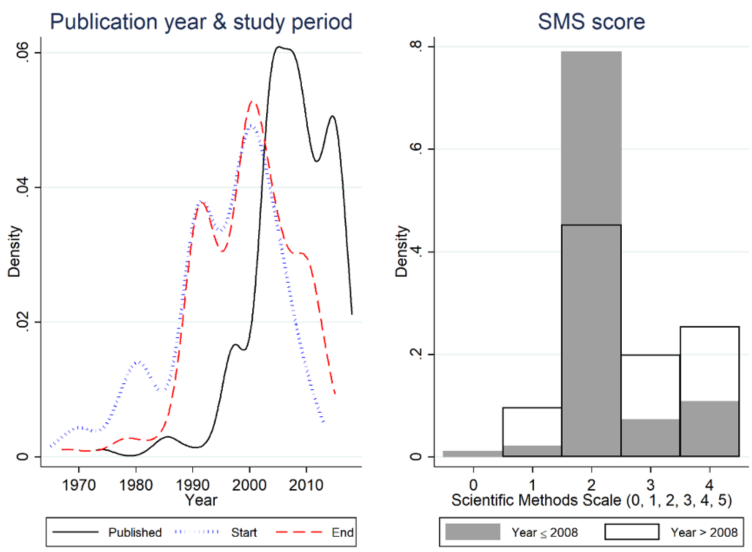
In Figure 1, we illustrate the distribution of publication years, the study period, and the type of methods used, according to the SMS. The evidence, overall, is very recent, with the great majority of studies having been published within the last 15 years, reflecting the growing academic interest in 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 (2008) reveals a progression towards more rigorous methods that score three or four on the SMS.

Tab. 2. Distribution of analyses by attributes I

World region		Publication		Discipline	
North America	208	Academic Journal	266	Economics	100
Europe	86	Working Paper	62	Transport	72
Asia	34	Report	14	Planning	48
South America	7	PhD	4	Urban Studies	42
World	4	Book chapter	1	Other	34
OECD	3	-	-	Regional Studies	24
non-OECD	3	-	-	Health	14
Oceania	1	-	-	Economic Geography	9
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. 2008 is the median year of publication. Scientific Methods Scale (SMS) defined above (higher values indicate more rigorous methods).

4 Density elasticity estimates in the literature

4.1 Results by outcome category

In Table 3 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 values imply economic effects that are typically considered to be positive in a normative sense 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. We also note that the results summarized in Table 3 cannot generally be interpreted as causal estimates since the estimated density effects, in many cases, may capture the effects of correlated location fundamentals. 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 3. The interested reader will find results using alternative weighting schemes in section 2 of the appendix.

Tab. 3. Density elasticity estimates in the literature

ID	Elasticity of outcome with respect to density	N	Proportion Poor[a]	Ac.[b]	Econ.[c]	With.[d]	Med. Year[e]	Mean SMS[f]	Elasticity[g] Mean	S.D.
1	Labour productivity	47	0.19	0.79	0.74	0.06	2007	3.02	0.04	0.04
1	Total factor productivity	15	0.13	0.87	0.80	0.20	2004	2.80	0.06	0.03
2	Patents p.c.	7	0.00	1.00	0.14	0.00	2006	2.86	0.21	0.11
3	Rent	13	0.00	0.69	0.62	0.62	2013	3.00	0.15	0.13
4	Commuting reduction	36	0.03	0.56	0.08	0.56	2005	2.17	0.06	0.12
4	Non-work trip reduction	7	0.00	0.71	0.00	0.86	2005	2.00	-0.20	0.44
5	Metro rail density	3	0.00	1.00	0.00	1.00	2010	3.33	0.01	0.02
5	Quality of life	8	0.38	0.88	1.00	0.13	2014	3.00	0.03	0.07
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	Diss. 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	-
7	High-low skill wage gap reduction	3	0.00	0.67	1.00	0.00	2013	4.00	-0.13	0.07
8	Crime rate reduction	13	0.00	0.69	0.15	0.92	2014	2.54	0.24	0.47
9	foliage projection cover	1	0.00	1.00	0.00	1.00	2015	1.00	-0.06	-
10	Noise reduction	1	0.00	1.00	0.00	0.00	2012	1.00	0.04	-
10	Pollution reduction	18	0.44	0.33	0.33	0.39	2014	2.83	0.04	0.47
11	Energy reduction: Domestic & driving	21	0.10	0.90	0.38	0.24	2010	1.81	0.07	0.10
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	22	0.00	0.95	0.00	0.95	2004	2.00	0.05	0.07
13	Non-car use	76	0.05	0.79	0.00	0.86	2006	2.03	0.16	0.24
14	Cancer & other 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	-
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	347								

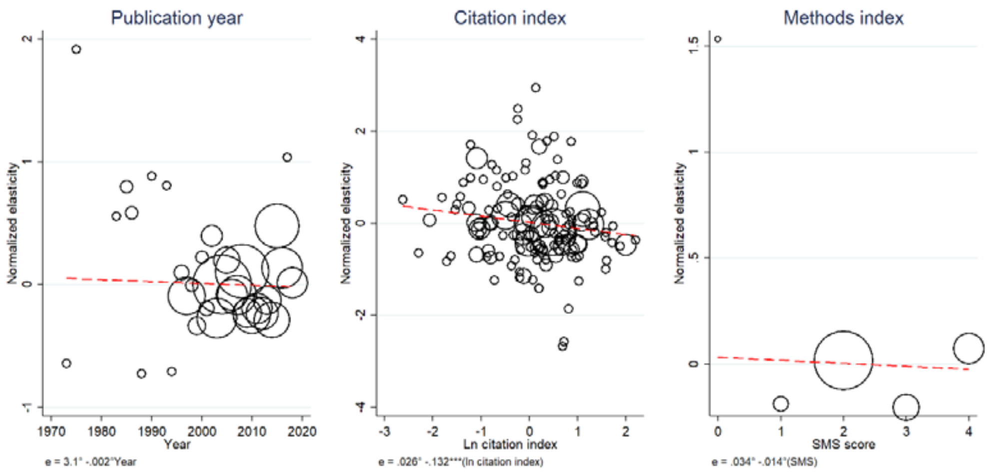
Notes: [a] Poor countries include low-income and median-income countries according to the World Bank definition. [b] Published in academic journal. [c] Belongs to the economics discipline. [d] Exploits within-city variation. [e] Year of publication. [f] Scientific Methods Scale (SMS) defined in section 3.2 (higher values indicate more robust methods). [g] Weighted by the citation index introduced in section 3.2 and appendix section 1.2. Outcome categories correspond to ID as follows: 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.

4.2 Results by attributes

For a pooled analysis of the sources of heterogeneity in the evidence base, we normalise category-specific elasticity estimates so that they have a zero mean and a unit standard deviation within the outcome groups listed in Table 3. Figure 2 reveals that density elasticity estimates tend to decline in the year of publication, the citation index, and the SMS score. This pattern is in line with the increasing popularity of more rigorous methods displayed in Figure 1.

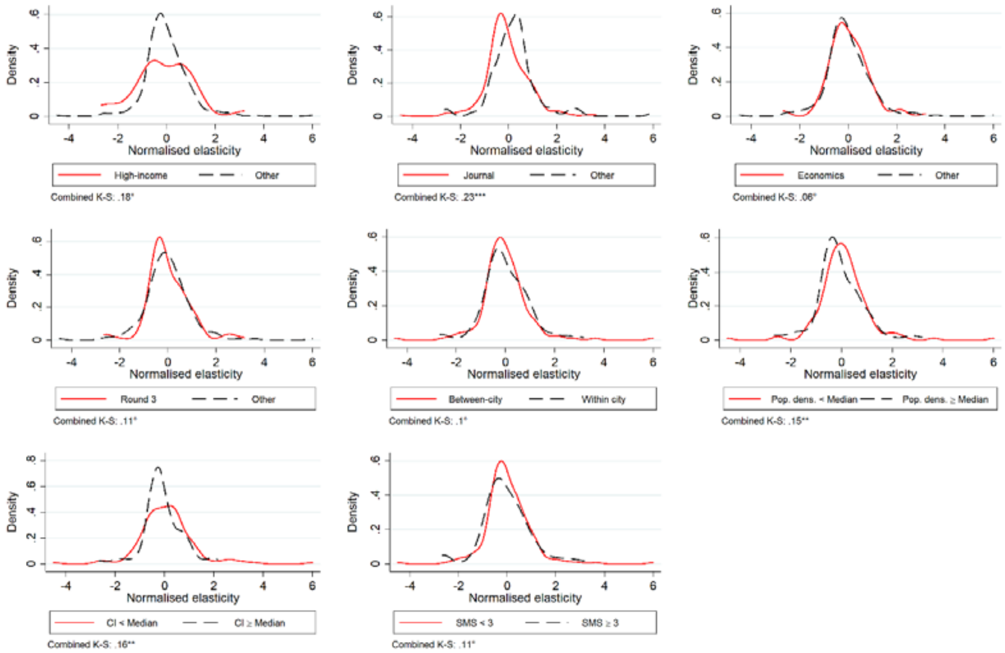
In Figure 3, we illustrate how the distribution of normalised elasticity estimates varies in selected attributes. At the bottom of each panel we report (two-sided) Kolmogorov-Smirnov test statistics and significance levels. We find a statistically significant difference in the distributions with respect to publication venue (less positive elasticities in journals) and citation index (less positive elasticities for higher index values), which may reflect publication bias or quality of peer review. Estimated elasticities form higher-density contexts are larger, on average.

Fig. 2. Normalised elasticity estimates vs. publication year and quality of evidence



Notes: Elasticity estimates (e) are normalised within outcome elasticity groups (listed in Table 3) 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).

Fig. 3. Distribution of normalised elasticity estimates by attributes



Notes: Elasticity estimates normalised within outcome elasticity groups (listed in Table 3) 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 4 presents the results of a multivariate analysis simultaneously controlling for all attributes considered in Figure 3. We first run a pooled regression using the normalised estimated density elasticity as an outcome. Being published in an academic journal decreases the estimated elasticity by a 0.4 standard deviation. In addition, a one standard-deviation increase in the citation index results in a 0.09 standard deviation reduction in the estimated elasticity. The conditional effect of a high SMS score is insignificant, but the point estimate is negative. So, in line with Figures 2 and 3, the overall impression is that higher quality is associated with less positive density elasticity estimates.

In the remaining columns of Table 4, we perform meta-analyses (Stanley & Jarrell 1989; Melo et al. 2009) of the raw elasticity estimates in some of the more populated outcome categories. The first interesting finding is that once we control for study fixed effects, we find that the estimated density elasticity of wages in non-high-income countries is about twice as large as for high-income countries (column 3). It is worth noting that this effect is identified from one multi-country study covering Brazil, China, and India, in addition to the US (Chauvin et al. 2016), which is why we do not add further controls to save degrees of freedom. However, the unconditional citation-weighted mean in the evidence base is 0.08 for non-high-income countries (from 9 analyses), confirming the 100% premium over high-income countries (see Table A11b in the appendix for a tabulation of mean elasticity estimates by high-income and non-high-income countries).

The important second insight is that if the population density in the studied area increases by 1000 inhabitants per square kilometre, the estimated density elasticity of rent increases by 0.063, on average. This effect is qualitatively and quantitatively consistent with recent evidence from French cities. Combes et al. (2018) show that the estimated elasticity can vary from 0.205 for a small urban area to 0.378 for an urban area of the size of Paris. Applying the 0.063-estimate from Table 4, column (4), this corresponds to an increase in density by 2,750 inhabitants per square kilometre, which in turn corresponds to going from cities like Grenoble or Lens (1000/km^2) to a city like Paris (3,700/km^2) (Demographia 2018). In line with Glaeser & Gottlieb (2008), we do not find a similar effect of density on the estimated density elasticity of wages. So it appears that increasing cost of density rather than decreasing productivity gains curb agglomeration benefits, leading to a bell-shaped net-agglomeration benefits curve (Henderson 1974).

The third relevant finding is that the density elasticity estimates of sustainable mode choice are significantly lower for non-high-income countries. A potential explanation that is consistent with the large estimated density elasticity of wages in developing countries is an indirect income effect that works in the opposite direction of the direct density effect. While a compact urban form ceteris paribus may favour alternative modes, higher incomes in more urbanised areas increase the affordability of car trips. Fourth, the mean estimated density elasticity of energy consumption reduction is much larger when identified from studies exploring *within-city variation.* In this context, it is worth noting that the citation-weighted unconditional mean density elasticity of energy consumption reduction, at 0.16, is much larger for non-high-income countries than for high-income countries. Given the small numbers (two estimates from non-high-income countries), it is difficult to separate the *within-city* and *non-high-income country* effects. It may be that within cities, population density is generally more strongly correlated with the share of multi-family houses, which tend to be more energy efficient. This relationship might be particularly strong in developing countries where often high densities imply formal housing as opposed to informal housing (Henderson et al. 2016).

Tab. 4. Meta-analysis of density elasticity estimates

	(1) Normalised density elasticity estimate	(2) Estimated density elasticity of wages	(3) Estimated density elasticity of wages	(4) Estimated density elasticity of rent	(5) Estimated density elasticity of commuting reduction	(6) Estimated density elasticity of energy use reduction	(7) Estimated density elasticity of sustainable mode choice
Category ID	All	1	1	3	4	11	13
Non-high-income	-0.111	0.025	0.050***	-	-0.247	-0.195	-0.162***
country	(0.25)	(0.02)	(0.00)		(0.21)	(0.26)	(0.04)
Not published in	0.401**	0.004		-0.021	0.150	0.364***	0.164
academic journal	(0.19)	(0.02)		(0.07)	(0.13)	(0.10)	(0.16)
Non-economics	0.043	0.007		-0.081	0.041	0.003	-
discipline	(0.18)	(0.02)		(0.07)	(0.07)	(0.06)	
Round 3 [a]	0.077	0.022*		-0.109^{+}	0.003	0.101*	-0.178**
	(0.18)	(0.01)		(0.06)	(0.06)	(0.05)	(0.07)
Within-city variation	-0.136	-0.020^{+}		-0.146	-0.071	0.187**	-0.085
	(0.18)	(0.01)		(0.10)	(0.07)	(0.07)	(0.11)
Citation index	-0.091*	-0.005^{+}		0.307^{+}	0.058	-0.010	0.030
normalised by s.d.	(0.05)	(0.00)		(0.18)	(0.05)	(0.01)	(0.04)
SMS >=3	-0.203	-0.014		-0.040	-0.025	0.070	-0.007
	(0.16)	(0.01)		(0.08)	(0.05)	(0.07)	(0.09)
Pop. density in study	-0.008	-0.005		0.063**	0.011	0.017	-0.001
area (1000/km²)	(0.01)	(0.00)		(0.03)	(0.07)	(0.04)	(0.00)
Constant	0.000	0.048***	0.048***	0.131***	0.051**	0.115***	0.183***
	(0.05)	(0.01)	(0.00)	(0.02)	(0.02)	(0.02)	(0.04)
Study effects	-	-	Yes	-	-	-	-
N	337	47	47	13	36	21	76
r2	0.043	0.126	0.846	0.805	0.306	0.763	0.131

Note: Normalised elasticity estimates in (1) are normalised within outcome groups (those listed in Table 3) to have a zero mean and a unity standard deviation. Citation index normalised by the global standard deviation. All explanatory variables are normalised to have a zero mean within outcome groups. 10 observations drop out in (1) 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. Population density in study area is from Demographia World Urban Areas (2018). [a] Round 3 consists of previously known evidence and recommendations by colleagues. Standard errors (in parentheses) are clustered on studies (one study can contain multiple analyses, the unit of observation). + $p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Original 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 urban area and regional statistics database and the following regression model:

$$\ln(Y_{i,c}) = \beta \ln\left(\frac{P_i}{A_i}\right) + \tau \ln\left(\frac{G_i}{P_i}\right) + \mu_c + \epsilon_{i,c}, \tag{2}$$

where $Y_{i,c}$ is an outcome in city i in country c, 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 estimated density elasticity of an outcome 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 5 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 3, we find that pollution concentrations are higher in denser cities. At the local level, the effect of concentrating sources of pollution in space dominates the effect of reduced aggregate emissions (due to shorter car trips and more energy-efficient housing). Our estimate has been confirmed by two recent studies (Carozzi & Roth 2018; Borck & Schrauth 2018). Furthermore, our results consistently suggest that income inequality increases in density. Our results are qualitatively and quantitatively (see the results for US cities reported in section 3.3 in the appendix) consistent with Baum-Snow et al. (2017). 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, 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. We note that the statistically insignificant effect of density on crime (conditional on country fixed effects), masks heterogeneity across US and non-US cities. In line with Glaeser and Sacerdote (1999), we find that crime rates increase in density for US cities, whereas the opposite is true for other OECD countries (see appendix 3,4).

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 estimate 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 estimate 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 estimated across US cities (>1.4), whereas the within-country elasticity estimate for the rest of the world is in line with the baseline elasticity estimate from the cross-sectional model excluding fixed effects. Therefore, in this case we prefer the conservative non-fixed effects model. The estimated 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 estimated 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. 5. Original 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 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 self-reported 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.

6 Recommended elasticity estimates

In Table 6 we condense the quantitative evidence, including our original estimates, into recommended density elasticity estimates which we provide for each outcome category. Specific to each category, we either recommend a citation-weighted mean across the elasticity estimates in our evidence base as reported in Table 3, an estimate from a high-quality original research paper or one of our original estimates. The selected dedicated analyses use comprehensive data and make sensible choices in the research design, i.e. they avoid excessive "overcontrolling" for endogenous variables and exploit plausibly exogenous variation. In general, we prefer the citation-weighted mean in the evidence base as well as estimates from dedicated high-quality original research papers over our original 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, in particular if the recommended elasticity estimate is in line with our original analysis of OECD data.

Our aim is to provide a compact and accessible comparison of density effects across categories. The baseline results are best understood as referring to high-income countries. Where possible, we acknowledge cross-country differences in Table 6. Nevertheless, we wish to remind the reader that we likely miss 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 elasticity estimate against the quality and quantity of the evidence base, before applying any of the elasticity estimates reported in Table 6 in further research. In a nutshell, we see sufficient evidence that seriously engages with separating the effects of density from the effects of correlated unobserved fundamentals to allow for a causal interpretation in the following categories: 1: Wage and productivity; 3: Rent, 4: Vehicle miles travelled; 10: Pollution reduction; 12: Average speed. For the other categories, the estimated elasticities are better interpreted as associations in the data. We stress that significant uncertainty surrounds the effects of density on income inequality, urban green, health, and self-reported well-being. In general, the recommended elasticities are best understood as describing area-based effects that include composition effects.

There is an important additional elasticity estimate that is implicitly determined by the elasticity estimates reported in Table 6. 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 $T = 0.66$ (Albouy & Lue 2015) and the elasticity estimates reported in Table 6, the resulting quality-of-life elasticity estimate at 0.04 is close to the citation-weighted mean from the evidence base (0.03). However, we must note that there is considerable variation in the collected quality-of-life elasticity estimates including both negative (Chauvin et al. 2016) and positive effects (Albouy & Lue 2015).

Tab. 6. Recommended elasticity estimates by category

ID	Elasticity	Value	Comment
1	Wage	0.04	Citation-weighted mean in review, roughly in line with Melo et al. (2009). 0.08 for non-high-income countries. Net of selection effects, elasticity estimates about halve (Combes & Gobillon 2015).
2	Patent intensity	0.21	Citation-weighed mean in review, in line with original analysis of OECD data.
3	Rent	0.15	Citation-weighed mean in review. In line with evidence from the US (dedicated analysis based on Albouy & Lue, 2015 data). Estimated elasticity increases in density (original meta-analysis) and is 0.21 for France (Combes et al. 2018).
4	Vehicle miles travelled (VMT) reduction	0.06	Citation-weighted mean in review, roughly in line with Duranton & Turner (2018) and Ewing & Cervero (2010).
5	Variety value (price index reduction)	0.12	Dedicated analysis on request using data from Couture (2016), in line with Ahlfeldt et al. (2015).
6	Local public spending	0.17	Citation-weighted mean in review, roughly in line with dedicated high-quality paper (Carruthers & Ulfarsson 2003).
7	Inter-quintile wage gap reduction	-0.035	Original analysis of OECD data[a]. -0.057 for the US. US estimate in line with dedicated high-quality paper (Baum-Snow et al. 2017) (section 3 in appendix).
8	Crime rate reduction	0.085	Dedicated analysis on request (Tang 2015), in line with original analysis of OECD non-US city data. Dedicated high-quality paper (Glaeser & Sacardote) and original analysis suggest a negative value for the US.
9	Green density	0.28	Original analysis of OECD data (evidence base non-existent)
10	Pollution reduction	-0.13	Dedicated high-quality paper (Carozzi & Roth 2018). In line with Borck & Schrauth (2018) and original analysis of OECD data
11	Energy use reduction	0.07	Citation-weighted mean in review
12	Average speed	-0.12	Citation-weighted mean of two (no further evidence) high-quality papers (Duranton & Turner 2018; Couture et al. 2018)
13	Car use reduction	0.05	Citation-weighted mean in review
14	Mortality rate reduction	-0.09	Dedicated paper (Reijneveld et al. 1999)
15	Self-reported well-being	-0.0037	Only direct estimate in literature (Glaeser et al. 2016). In line with original analysis of OECD data

Notes: Density elasticity estimates are best understood as referring to large cities in high-income countries. In general, they represent correlations and not necessarily causal estimates. If our recommended elasticities differ between US and non-US cities, we report the former as the baseline and mention the latter in the comments, because, as shown in Table 1, the density distribution of US cities is not representative. [a] Original analysis uses the wage gap between 80th and the. 20th 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.

7 Monetary equivalents

For a quantitative comparison of density effects across categories, 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 PV dollar effects, assuming an infinite horizon and a conventional 5% discount rate (de Rus 2010). We summarise the results in Table 7. As 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), a 1% increase in density and the inverse of the 5% discount rate (e.g. 0.04 × $35,000 × 1 × 1%/5% for the wage effect). By changing any of the factors a context-specific monetary equivalent can be calculated.

The exercise summarised in Table 7 is ambitious and there are some limitations. First, the monetary equivalents are estimates that most closely refer to large metropolitan areas in high-income countries. 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 7 do not necessarily correspond to the short-run effect of a policy-induced change in density. As an example, an increase in population holding the developed area constant will increase population density, but not necessarily the green density. However, the green density will be higher than in a counterfactual were the population growth was achieved holding density constant. Third, 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, while for the not genuinely area-based outcomes we would ideally apply density effects that come net of selection effects, the literature only offers such estimates in the productivity category. So, for consistency across categories, we strictly apply the baseline elasticities capturing area-based effects from Table 6. 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 7.

Tab. 7. 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		PV of 1%
ID	Outcome	Elast.	Variable	Value	Unit	Value	dens. incr.
1	Wage	0.04	Income ($)	35,000	-	1	280
2	Patent intensity	0.21	Patents (#)	2.06E-04	Patent value ($/#)	793K	7
3	Rent	0.15	Income ($)	35,000	Expenditure share	0.33	347
4	VMT[b] reduction	0.06	VMT[b] (mile)	10,658	Priv. cost $/mile	0.83	107
5	Variety value[c]	0.12[b]	Income ($)	35,000	Expenditure share[d]	0.14	115
6	Local public spending	0.17	Total spending ($)	1,463	-	1	50
7	Wage gap[e] reduction	-0.035	Income ($)	35,000	Inequality premium	0.048	-12
8	Crime rate[f] reduction	0.085	Crimes (#)	0.29	Full cost ($/#)	3,224	16
9	Green density	0.28	Green area (p.c., m²)	540	Park value ($/m²)	0.3	100
10	Pollution reduction	-0.13	Rent ($)	11,550	Rent-poll. elasticity	0.3	-90
11	Energy use reduction	0.07	Energy (1M BTU)	121.85	Cost ($/1M BTU)	18.7	32
	(private and social effects)	0.07	CO2 emissions (t)	25	Social cost ($/t)	43	15
12	Average speed	-0.12	Driving time (h)	274	VOT ($/h)	10.75	-71
13	Car use reduction	0.05	VMT[b]	10,658	Social cost ($/mile)[g]	0.016	2
14	Health	-0.09	Mortality risk (#)	5.08E-04	Value of life ($/#)[h]	7M	-64
15	Self-reported well-being[j]	-0.004	Income ($)	35,000	Inc.-happ. elasticity	2	-52

Notes: Monetery equivalents represent area-based effects, including selection effects. [a] The per-capita present value for an infinite horizon and 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] Assuming a wage gap of high-skilled vs. low-skilled that corresponds to the 80th vs. 20th percentiles in the wage distribution. [f]All crimes against individual and households, [g]Emissions externality [h]Statistical value of life. [i]Pre-mature (> 70) mortality rate. [j] Self-reported well-being. See appendix section 5 for a discussion of the assumptions on quantities and unit values by category.

Despite these limitations, Table 7 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.[6] 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 density include cost savings in the provision of local public services, preserved green spaces, lower crime rates (outside the US), and reduced energy use, which creates a sizeable social benefit (reduced carbon emissions) in addition to private cost savings. Besides the aforementioned congestion effects, the cost of density comes in the form of increased pollution concentration, inequality, adverse health effects and reduced well-being.

[6] The results by Combes at al. (2018) suggest that this result may not apply to small cities as the rent elasticity increases in city size.

Given that we have gone a long way in computing category-specific estimates 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 8. 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). Since health effects are itemised in 14, we use an estimate of the health cost arising from density-related pollution from Carozzi & Roth (2018) to restrict the pollution effect to an amenity channel. 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. In the baseline scenario (*Sum* row), we assume that public services are nationally funded. In an alternative accounting (indicated in the bottom of the table), we assume that public services are locally funded, so that density-induced cost savings fully capitalise into rents (via lower taxes).

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 $627, p.c. can be interpreted as a welfare gain to which the external welfare effects of $60 in column (6) can be added. 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. With perfectly elastic demand, an increase in rent that exceeds an increase in disposable income necessarily reflects a positive quality-of-life effect.

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, because local demand is downward-sloping (Arnott & Stiglitz 1979). Increases in density – or the policies that enforce increased density – may then also increase rents because the cost of supplying space is higher. By implication, observed rent increases do not necessarily reflect demand-driven capitalization effects exclusively, but potentially to some extent spatial differences in the slope of the supply curve (Hilber & Vermeulen 2016; Hilber 2017). 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 demand was perfectly elastic, we would expect the aggregate amenity effect to equal the quality-of-life effect.

The amenity effect reported in column (3) with an PV of $100 per capita, is substantial, but smaller than the after-tax compensating differential ($156) in column (2), suggesting a role for the supply side (as long as demand is locally downward-sloping). The role of self-reported 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). Indeed, the amenity effect and the quality-of-life effect are closer if we exclude the well-being effect as a (dis)amenity category. Similarly, the gap shrinks if we treat local public services as fully locally financed, which implies that the savings are passed on to individuals and are capitalised into rents.

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. 2018) and compute a range for the monetary equivalent of the effect of a 1% density increase on construction cost as 0.04–0.07 (estimated 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) / 5% (discount rate) = $70–120. Thus, density-induced increases in the cost of housing supply are a plausible explanation for the gap between the estimated amenity and quality-of-life effects if demand is locally downward sloping. 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 section 2.2.

In columns (4) and (5) we change the perspective and ask how a policy-induced marginal increase in the density of a city would affect residents. 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 $291 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 $56 if we include well-being effects and assume that there are no tax effects due to savings in public services. 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, but is close to zero. Of course, the flipside is that there is a positive external benefit to land owners and given the non-linearity in the density effect on rent documented in Section 4.2 the effect on renters may be positive in supply-elastic markets.

Overall, the evidence suggests that density is a net amenity. This does not imply, however, that everybody necessarily benefits from densification policies. 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, has yet to be conducted.

Tab. 8. 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	-190[b]	0	190[c]	190[c]	0
2	Innovation	0	0	0	0	0	6
3	Value of space	347	347	0	0	-347	0
4	Job accessibility	0	0	87[d]	87[d]	87[d]	0
5	Services access	0	0	99[e]	99[e]	99[e]	0
6	Eff. of pub. services delivery	0	0	0	0	0	50
7	Social equity	0	0	0	0	0	-12
8	Safety	0	0	16	16	16	0
9	Urban green	0	0	100	100	100	0
10	Pollution reduction	0	0	-47[f]	-47[f]	-47[f]	0
11	Energy efficiency	0	0	32	32	32	15
12	Traffic flow	0	0	-71	-71	-71	0
13	Car use reduction	0	0	0	0	0	0[g]
14	Health	0	0	-64	-64	-64	0
15	Self-reported well-being	0	0	-52	-52	-52	0
	Sum	627	152	100	291	-56	60
	Excl. subj. well-being	-	-	152	342	-4	60
	Locally financed pubic services	-	106		340	-6	
	Factor incomes and externality	686	-	-	-	-	-
	Locally financed pubic services	637	-	-	-	-	-

Notes: [a] The present value per capita for an infinite horizon and a 5% discount rate. All values in \$. [b] Amenity equivalent of after-tax wage increase assuming a marginal tax rate of 32% as in Albouy and Lue (2015). [c] After-tax wage increase as discussed in [b]. [d] Excludes \$19.18 of driving energy cost (\$0.15/mile gasoline cost) discounted at 5%, which are itemised in 11 [e] Assumes a 10.2% elasticity to avoid double-counting of road trips already included in 4. [f] Amenity effect, excludes health effect itemised in 14. [g] 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.

8 Conclusion

We provide the first quantitative evidence review of the effects of density on a broad range of outcomes. Synthesising the reviewed evidence and a range of original estimates, we report recommended density elasticity estimates for 15 distinct outcome categories along with monetised values of density effects for application in research and policy analysis. While there are sizeable benefits and costs associated with increases in density, the former exceed the latter for a typical large city in the developed world.

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 most developed 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, 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.

We provide suggestive evidence that the costs and benefits of agglomeration may be larger in developing-country cities. However, because the evidence from non-high-income countries is scarce, it is not possible to property evaluate whether our key result that density is a net-amenity generalises to non-high-income countries. 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.

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Gabriel M. Ahlfeldt,[♣] Elisabetta Pietrostefani[♠]

Appendix to The economic effects of density: A synthesis

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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).

[♣] London School of Economics and Political Sciences (LSE) and Centre for Economic Policy Research (CEPR), Houghton Street, London WC2A 2AE, g.ahlfeldt@lse.ac.uk, www.ahlfeldt.com

[♠] London School of Economics and Political Sciences (LSE).

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. An important number of papers were added to the *productivity*, *innovation*, *job accessibility* and *mode choice* categories through the citation tree analysis (Tab A2). For papers that were not accessible through online resources, we reached out to citing and cited authors. In a hand full of cases, we did not receive a response, the studies therefore remain excluded. Upon inspection (excluding empirically irrelevant work, duplications of working papers, and journal articles, etc.) this systematic literature search resulted in 195 studies and 313 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. Further studies were suggested to us during presentations of this paper and following our submission of this paper for publication. This step increases the evidence base to 268 studies and 473 analyses (160 additional observations). 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.

Panel 1 of 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. Pane 2 of Table A2 summarises the distribution of analyses collected by outcome categories and compact city characteristics. The large majority of 353 out of 473 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 density elasticity estimates, this number is reduced to 347. Table A3 compares the subsample of analyses for which we were able to compute outcome elasticity estimates 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	9	3	3	0	25	17	57
2	Innovation	3	1	2	1	5	1	13
3	Value of space	6	1	6	1	2	10	26
4	Job accessibility	3	1	3	0	19	5	31
5	Services access	2	0	1	0	0	8	11
6	Efficiency of public services delivery	2	0	1	0	0	4	7
7	Social equity	3	1	0	0	4	3	11
8	Safety	2	3	0	0	3	3	11
9	Open space preservation and biodiversity	4	1	0	0	0	0	5
10	Pollution reduction	2	1	1	0	2	4	10
11	Energy efficiency	5	2	2	0	7	6	22
12	Traffic flow	2	0	0	0	1	1	4
13	Sustainable mode choice	7	3	1	0	27	5	43
14	Health	2	1	0	0	5	1	9
15	Well-being	2	0	1	0	0	5	8
	Total	54	18	21	2	100	73	268

Panel 2

	Compact city effects	Compact city characteristics			
#	Outcome category	Economic	Morph.	Mixed	Total
1	Productivity	67	-	-	67
2	Innovation	14	1	-	15
3	Value of space	18	8	2	28
4	Job accessibility	32	15	11	58
5	Services access	16	2	**0**	18
6	Efficiency of public services delivery	21	2	-	23
7	Social equity	13	**0**	-	13
8	Safety	19	4	-	23
9	Open space preservation and biodiversity	2	5	-	7
10	Pollution reduction	18	3	**0**	21
11	Energy efficiency	26	8	1	35
12	Traffic flow	4	2	1	7
13	Sustainable mode choice	76	33	17	126
14	Health	13	3	-	16
15	Well-being	14	2	**0**	16
	Total	353	88	32	473

Notes: Panel 1: Google Scholar, Web of Science, EconLit, CesIfo searches all part of evidence collection step one. Step 2 contains results from 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, and studies from citation trees. 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 estimates sample

	All analyses		Elasticity estimates sample	
	Mean	S.D.	Mean	S.D.
Non-high-income country [a]	0.11	0.31	0.084	0.28
Academic journal	0.79	0.41	0.77	0.42
Economics	0.26	0.44	0.29	0.45
Within-city	0.47	0.5	0.47	0.5
Round 3 [d]	0.34	0.47	0.4	0.49
Year of publication	2007	8.4	2008	6.9
Citation index	1.7	1.7	1.7	1.4
SMS (methods score)	2.2	1	2.4	0.86
Positive & significant [b]	0.67	0.47	0.69	0.46
Insignificant [b]	0.14	0.34	0.15	0.36
Negative & significant [b]	0.19	0.4	0.16	0.37
Qualitative result score [c]	0.48	0.8	0.53	0.76
N	473		347	

Notes: Elasticity estimates sample is the sample of analyses from which a density elasticity estimate 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. [d] Round 3 consists of previously known evidence and recommendations by colleagues.

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:

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

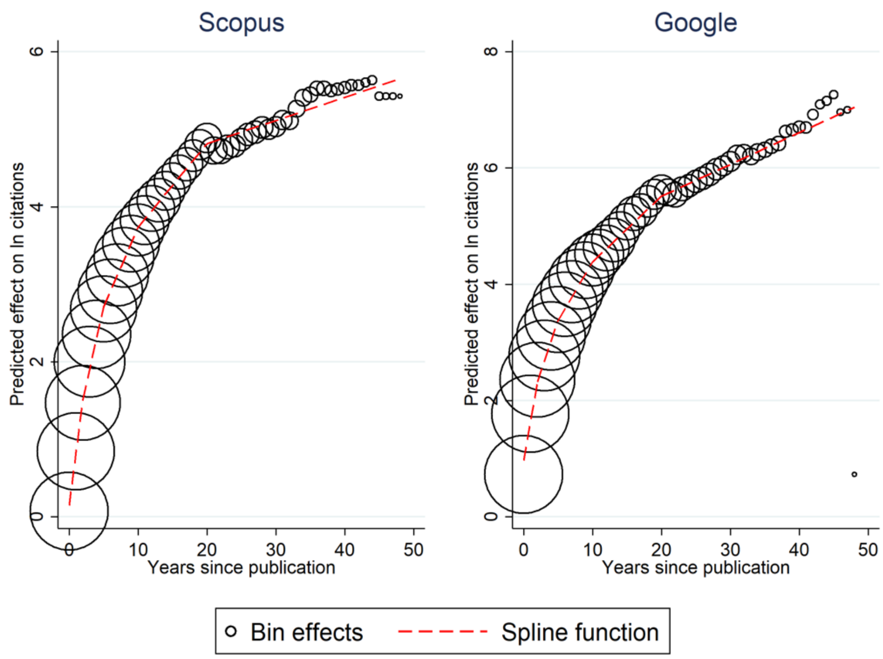
, where $(YSP_{pt} - n > 0)$ is a dummy variable that takes the value of one if the condition is true and zero otherwise. In the figure below, we compare the fit provided by a linear spline function allowing for changes in the marginal effect after 2, 5, 10, and 20 years since publications (dashed lines) 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:

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

, 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.

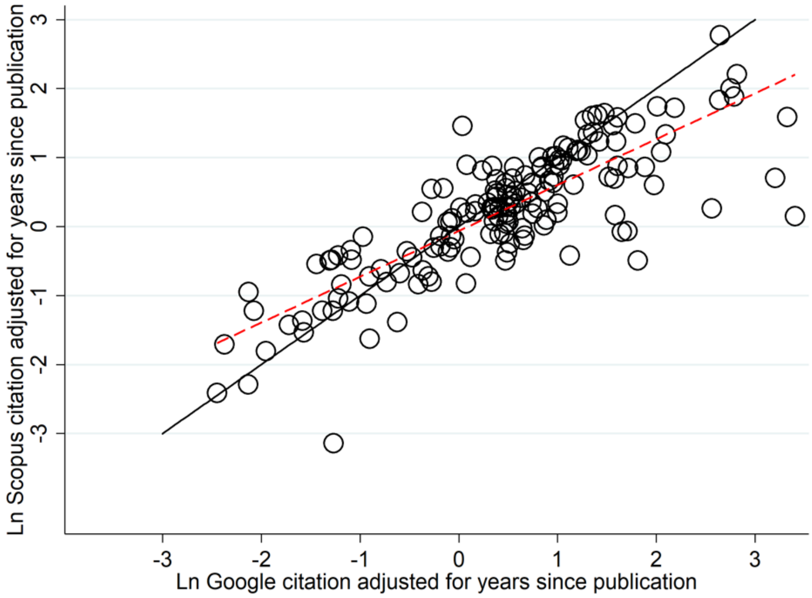
Fig. A1. Cumulated citation counts vs. years since publication (within-paper effects)



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 A1, 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).

Fig. 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 Table A4, 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)	(2)	(3)	(4)	(5)	(6)
	Ln Scopus citation adjusted for years since publication	Ln Scopus citation adjusted for years since publication	Ln Scopus citation adjusted for years since publication	Ln Scopus citation adjusted for years since publication	Ln Scopus citation adjusted for years since publication	Ln Scopus citation adjusted for years since publication
Ln SNIP score	0.798***		0.834***	1.001***		
	(0.17)		(0.14)	(0.14)		
Year – 2000		0.051***	0.052***	0.054***		0.055***
		(0.01)	(0.01)	(0.01)		(0.01)
Ln SJR score					0.360***	0.523***
					(0.08)	(0.10)
Constant	-0.332***	-0.186**	-0.654***	-0.759***	-0.063	-0.462***
	(0.12)	(0.09)	(0.12)	(0.07)	(0.08)	(0.05)
Discipline effects	-	-	-	Yes	-	Yes
r2	0.112	0.203	0.325	0.398	0.072	0.371
N	225	225	225	225	225	225

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

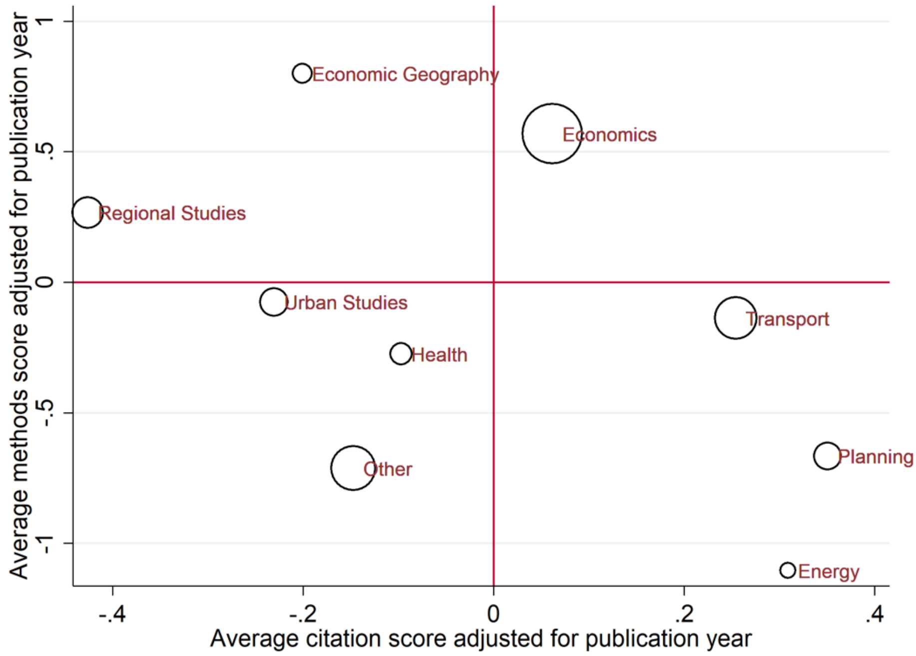
	(1) Ln Scopus citation adjusted for years since publication	(2) Ln Scopus citation adjusted for years since publication	(3) Ln Scopus citation adjusted for years since publication	(4) Ln SNIP score	(5) Ln SNIP score	(6) Ln SNIP score
Scientific methods scale score	0.160**	0.234	0.074	0.074***	0.020	0.024
	(0.06)	(0.14)	(0.12)	(0.03)	(0.04)	(0.04)
Year – 2000			0.048***			-0.001
			(0.01)			(0.01)
Constant	-0.292*	-0.456	-0.394	0.386***	0.507***	0.506***
	(0.17)	(0.31)	(0.24)	(0.06)	(0.09)	(0.09)
Discipline effects	-	Yes	Yes	-	Yes	Yes
r2	0.027	0.081	0.234	0.031	0.181	0.182
N	258	258	258	228	228	228

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 A3, 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. A3. Quality measures: Methods-based vs. citation-based by discipline



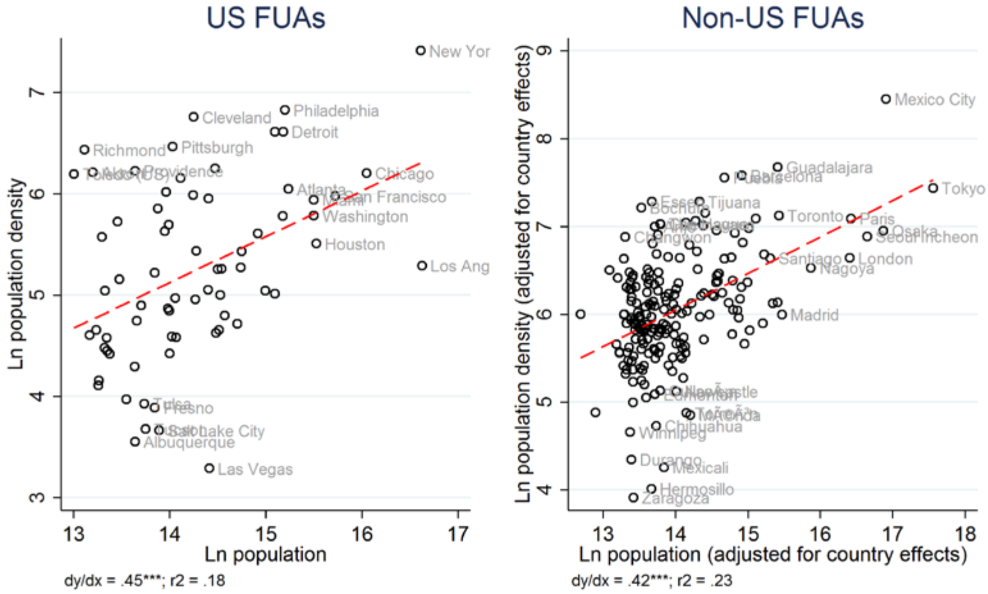
Notes: The values plotted on the x-axis are the discipline fixed effects recovered from regressions of the Google citation count adjusted for years since designation effects against discipline effects and a publication year trend (the model from TableA5, column 3). The values on the y-axis are the discipline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

2 Density elasticity estimates in the literature

2.1 Estimating the elasticity of density with respect to city size

In Figure A4, 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. A4. 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 estimate. In the extreme case, where land area does not change at all over time, the elasticity estimate 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 estimate. 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 estimate 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 estimate 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 reported in the main paper, which uses 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 A5 and Table A7.

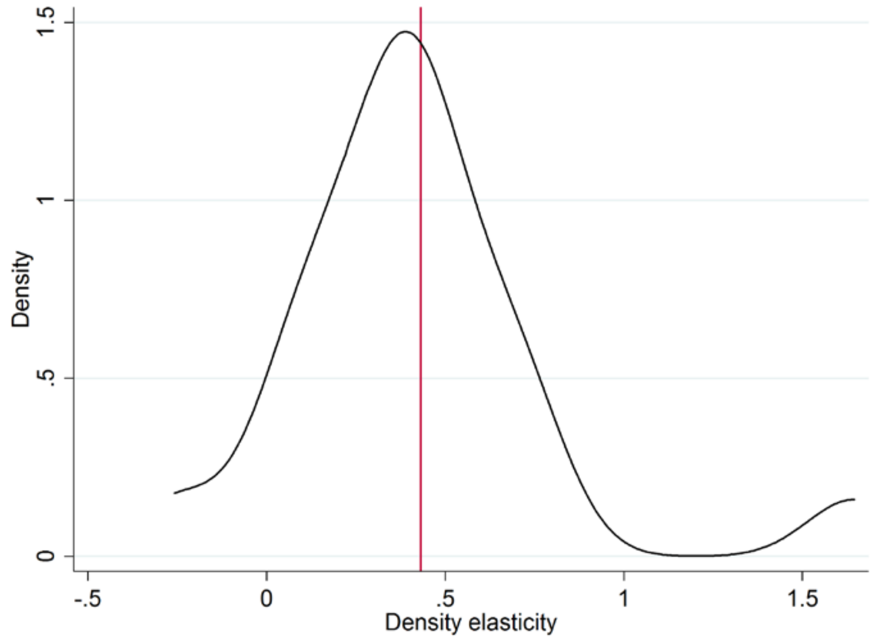
We note that our preferred estimate of the elasticity of density with respect to city size is within close range of Combes et al. (2018), who report an estimate of the elasticity of land area with respect to population of approximately 0.7 for French cities, implying an estimate of the elasticity of 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. Estimates of the 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. A5. Elasticity of density with respect to population: Distribution of estimates 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. Estimates of the 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 Estimating the elasticity of construction cost with respect to density

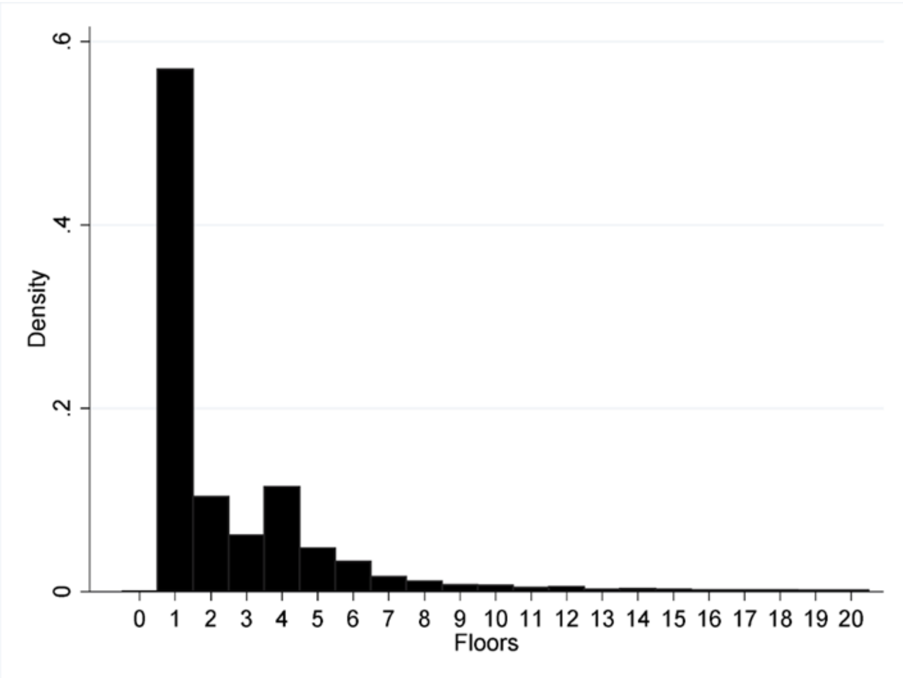
We assume that density impacts on construction costs through two principle channels. On the one hand, constructing a dwelling unit with exactly the same specification is likely more expensive in denser places because such places are usually more congested (higher cost of moving materials, less space 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 (2018). 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. A6. 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.

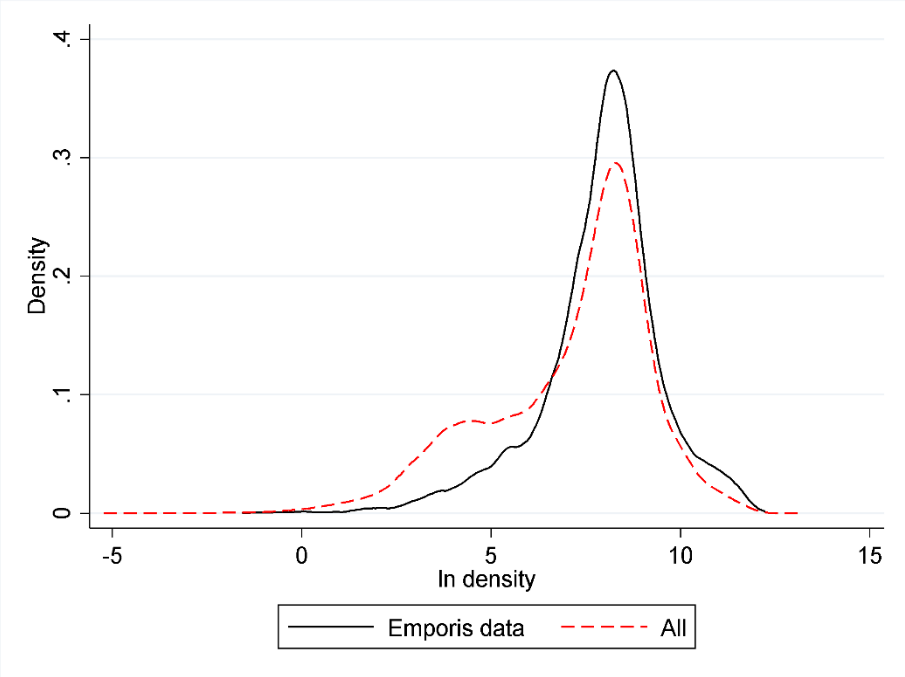
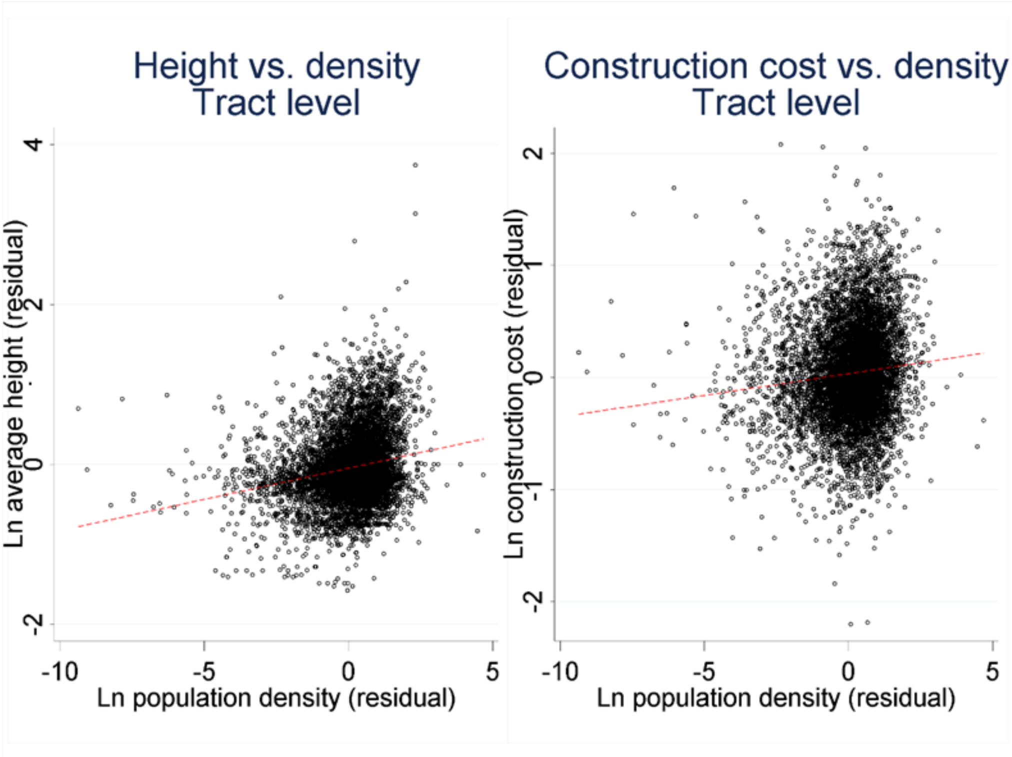


Fig. A7. Census tract population density distribution: Emporis sample vs. all tracts

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 2018) 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. A8. 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. Our estimate of the density elasticity of construction cost is 0.07. 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 estimate is reduced to 0.43 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 elasticity estimates 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 0.25 for the US, which is close to the respective elasticity estimated by Ahlfeldt & McMillen (2018) from a global sample of small structures (up to five floors). In keeping with intuition, this elasticity estimate decreases considerably to approximately 0.14 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 0.02 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 0.23 density elasticity estimates is slightly larger than the implied 0.02 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 0.01, 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. Estimates of the density elasticity of construction costs I

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ln floor space construction cost						
Ln census tract	0.070***	0.053***	0.043***			0.023***	0.009***
population density	(0.003)	(0.004)	(0.004)			(0.002)	(0.002)
Ln Building height				0.250***	0.137***	0.140***	0.094***
				(0.006)	(0.008)	(0.008)	(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. Estimates of the density elasticity of construction costs II

	(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

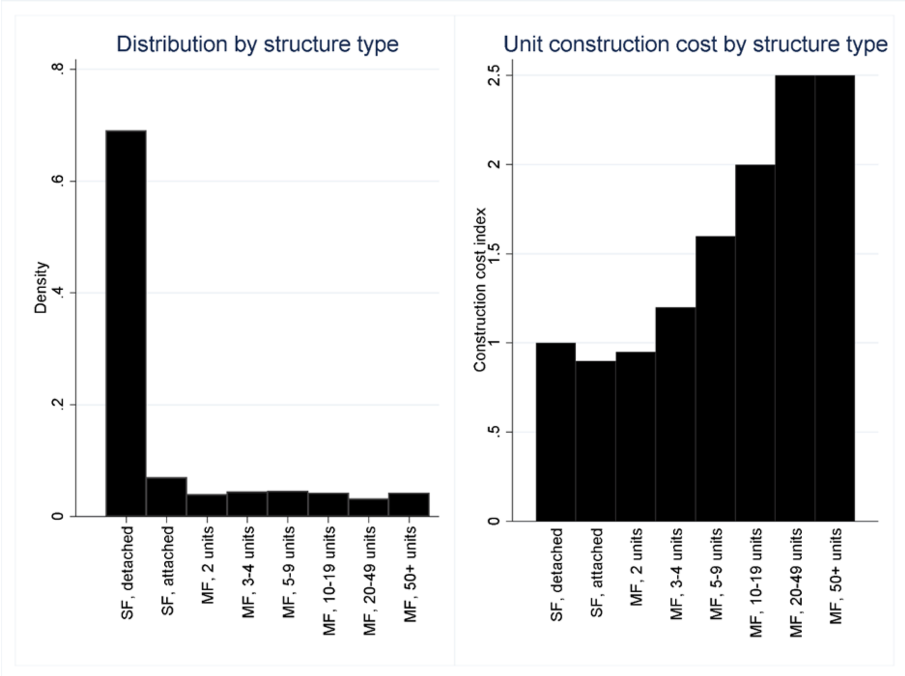
As noted, our primary concerns with the estimation of density effects using the Emporis data are the selectivity of the sample and an imperfect control for structural quality. These concerns motivate a complementary analysis in which we rely on engineering estimates of construction costs. This approach 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 A9 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 A9, 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. A9. Household accommodation by structure

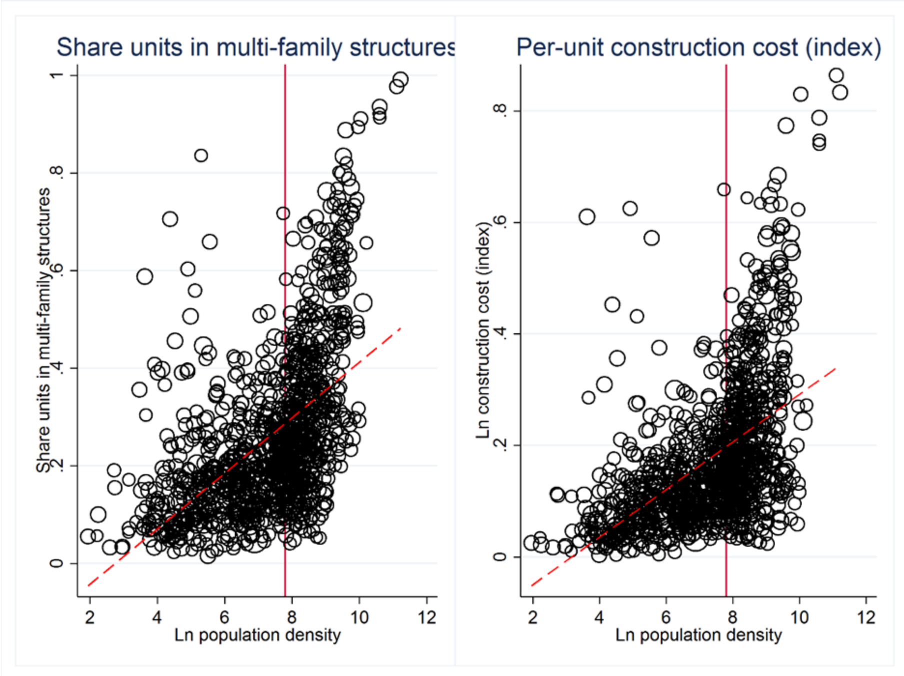


Notes: Left panel uses household-level data from American Community Survey (ACS), weighted by household weights. SF = single family house, MF = multi-family house (Ruggles et al. 2017). Right panel illustrates the construction cost index by Ellis (2004), mapping the closest of the eight categories in 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 A10, 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 A8. 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. A10. 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 A10, 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 0.043-0.056. As discussed above, these estimates capture the structure effect of density exclusively. Adding the 0.02 location effect estimated by Gyourko and Saiz (2006) (at the mean of the density distribution), we obtain a combined effect in the range of 0.06 to 0.75, 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 0.038-0.066 from the 5th to the 95th percentile in the density distribution across PUMAs.

Tab. A10. Estimates of the density elasticity of construction costs (index-based models) III

	(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 and estimate of the 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 estimate 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 0.04-0.07 is a conservative estimated 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 estimated marginal effects into elasticity estimates

Where possible, we convert reported marginal effects in levels or reported semi-elasticities into density elasticity estimates (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 required 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 an implied density elasticity estimate by regressing the natural logarithm of an outcome value against the natural logarithm of the midpoint of the density interval.

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 estimate 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 estimated 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, our estimated 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 density elasticity estimates. 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 elasticity estimates are not directly comparable to house price elasticity estimates 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 estimate of the density elasticity of land price with respect to density into an estimate of the density 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 et al. (2015).

2.6 Density elasticity estimates: High-income vs. non-high-income

In the table below, we compare citation-weighted median and mean elasticity estimates between high-income countries and non-high-income countries. The table complements Table 3 in the main paper. Evidently, the evidence base from non-high-income countries is limited. Notably we observe that mean elasticity estimates differ between high-income and non-high-income countries in outcome categories where we are able to observe this. For productivity, the unconditional citation-weighted mean in the evidence base is 0.08 for non-high-income countries, while 0.04 for high income countries. Within the quality of life category, we also observe that while density has an average positive effect on quality of life in high-income places, it has an average negative effect in non-high-income countries. Another relevant finding is that estimates of the density elasticity of non-car use are significantly lower for non-high-income countries.

Tab. A11. Average density elasticity estimates by high-income and non-high-income

		High-income [a]				Non-High-income [a]			
ID	Elasticity of outcome with respect to density	N	Median	Mean	S.D.	N	Median	Mean	S.D.
1	Labour productivity	38	0.04	0.04	0.03	9	0.08	0.06	0.07
1	Total factor productivity	13	0.05	0.05	0.03	2	0.10	0.06	0.06
2	Patents p.c.	7	0.20	0.21	0.11	0	-	-	-
3	Rent	13	0.16	0.15	0.13	0	-	-	-
4	Commuting reduction	35	0.06	0.07	0.11	1	-0.21	-0.21	-
4	Non-work trip reduction	7	-0.06	-0.20	0.44	0	-	-	-
5	Metro rail density	3	0.00	0.01	0.02	0	-	-	-
5	Quality of life	5	0.02	0.05	0.06	3	-0.05	-0.04	0.03
5	Variety (consumption amenities)	1	0.19	0.19	-	0	-	-	-
5	Variety price reduction	2	0.12	0.12	0.06	0	-	-	-
6	Public spending reduction	20	0.11	0.17	0.25	0	-	-	-
7	90th-10th pct. wage gap reduction	1	0.17	0.17	-	0	-	-	-
7	Black-white wage gap reduction	1	-0.00	0.00	-	0	-	-	-
7	Diss. index reduction	3	0.33	0.66	0.94	0	-	-	-
7	Gini coef. reduction	1	4.56	4.56	-	0	-	-	-
7	High-low skill wage gap reduction	3	-0.12	-0.13	0.07	0	-	-	-
8	Crime rate reduction	13	0.36	0.24	0.47	0	-	-	-
9	Foliage projection cover	1	-0.06	-0.06	-	0	-	-	-
10	Noise reduction	1	0.04	0.04	-	0	-	-	-
10	Pollution reduction	10	-0.12	0.02	0.43	8	0.33	0.07	0.54
11	Energy consumption reduction	19	0.07	0.07	0.10	2	0.04	0.08	0.13
11	Energy consumption reduction: Public transit	1	-0.37	-0.37	-	0	-	-	-
12	Speed	2	-0.13	-0.12	0.01	0	-	-	-
13	Car usage (incl. shared) reduction	22	0.04	0.05	0.07	0	-	-	-
13	Non-car use	72	0.14	0.17	0.24	4	0.02	0.04	0.06
14	Cancer & other serious disease reduction	5	-0.30	-0.33	0.20	0	-	-	-
14	KSI & casualty reduction	4	0.17	0.01	0.61	0	-	-	-
14	Mental-health	1	0.01	0.01	-	0	-	-	-
14	Mortality reduction	3	-0.29	-0.36	0.17	0	-	-	-
15	Reported health	3	-0.32	-0.27	0.11	0	-	-	-
15	Reported safety	1	0.07	0.07	-	0	-	-	-
15	Reported social interaction	6	-0.04	-0.13	0.19	0	-	-	-
15	Reported wellbeing	1	-0.00	0.00	-	0	-	-	-

Notes: [a] Weighted by the citation index introduced in section 3.2 and appendix section 1.2. Outcome categories correspond to ID as follows: 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 Original 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 estimates 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 estimates 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 estimates 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 estimates 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 estimates 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 estimates 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 estimates 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 estimates 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 estimates 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 estimates 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 estimates of ln CO2 emissions p.c. with respect to population density

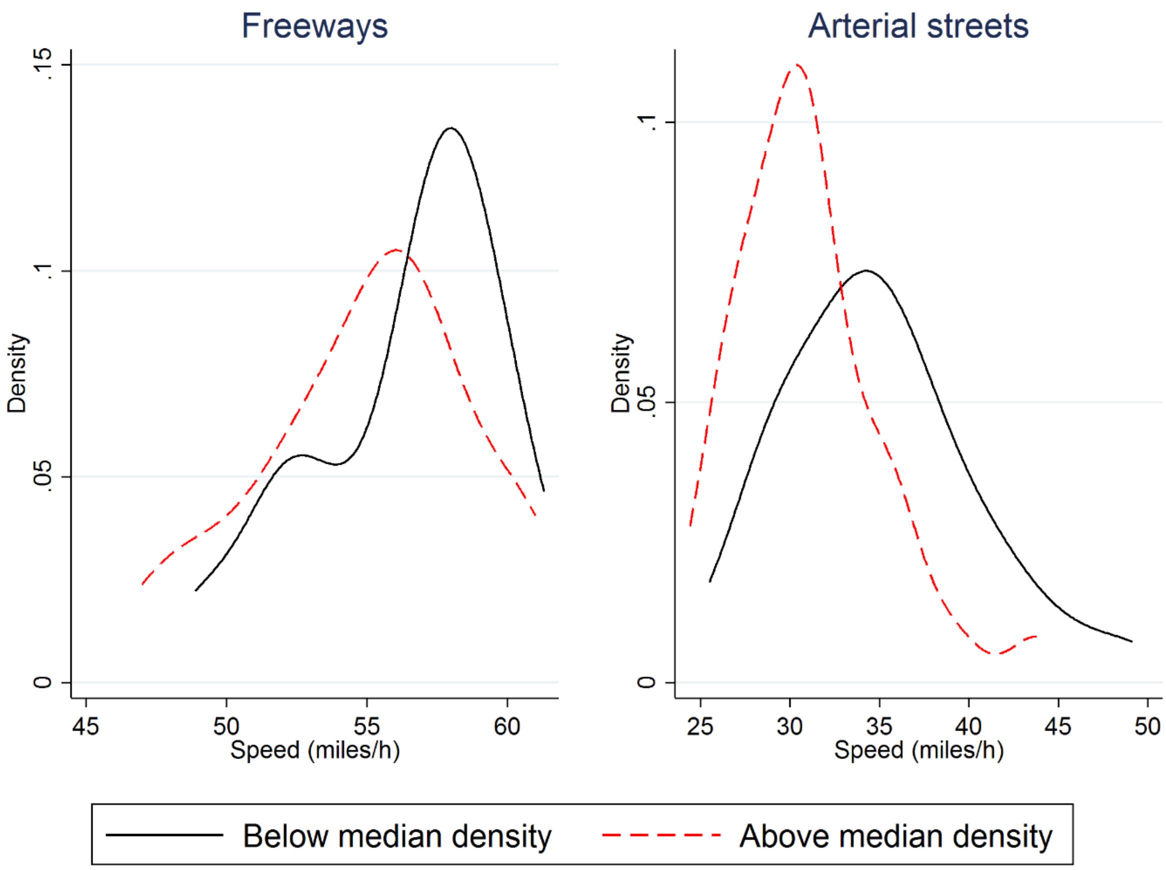
	(1) Ln CO2 emissions p.c.	(2) Ln CO2 emissions p.c.	(3) Ln CO2 emissions p.c.	(4) Ln CO2 emissions p.c.	(5) Ln CO2 emissions p.c.	(6) Ln CO2 emissions p.c.
Ln population density	-0.225***	-0.224***	-0.189***	-0.173***	-0.190***	-0.170***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)	(0.05)
Ln GDP per capita		0.503***	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. A11. 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 estimate 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 estimate a significant elasticity of peak time speed with respect to population density of -0.063. Interestingly, we estimate 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 estimate 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 estimate 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 estimate 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 estimate 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 estimate 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 elasticity estimates

This section provides a justification of the recommended elasticity estimates 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 elasticity estimates in further research.

Before we proceed to the discussion of the category-specific density elasticity estimates, we wish to remind the reader, that, as discussed in Section 2.1 in the main paper, there is fundamental problem in identifying density effects because density is endogenous and potentially determined by unobserved location fundamental factors (e.g. a favourable geography). Studies that estimate density effects from plausibly exogenous variation (e.g. by making use of natural experiments or instrumental variables) are the minority. For most estimates, the causal interpretation rests on the assumption that the variation in density within and between cities is largely historically determined by factors that have limited contemporaneous effects on outcomes. For individual-, firm-, and unit-based outcomes (e.g. wages, innovation, rent, wellbeing), the collected density elasticity estimates often capture composition effects. In this case, a density elasticity estimate does not give the effect of an exogenous change in density on an outcome such as the productivity of individuals, the innovative activity of firms, or the value of housing units. For individual- and firm- based outcomes, the density elasticity estimate, in addition, captures the composition effect that usually arises because more productive individuals and firms self-select into more productive areas. The density elasticity of rent captures the effect of a change in the quality of housing stock if developers make choices that depend on rents and incomes, which in turn depend on density.

4.1 Wage elasticity

The literature reports both wage and TFP elasticities with respect to density, the former being by far the most frequently reported parameter. While we find a significant difference between the wage and the TFP elasticity in our review, it is notable that high quality papers analysing both wage and TFP within a consistent framework do not report the existence of such a difference (Combes et al. 2010). We choose the citation-weighted average value of the wage elasticities in our sample of 0.04, which is close to the results from recent high-quality work (Combes et al. 2012) and meta-analysis (Melo et al. 2009). The citation-index-weighted mean elasticity is almost identical if we restrict the sample to 19 analyses that disentangle density effects from unobserved location fundamentals using instrumental variables or natural experiments. Therefore, a causal interpretation of our recommended elasticity seems justifiable. While there is some variation in the estimated density elasticities of wage and TFP, the estimates in the literature do not appear to be systematically related to the average density level in the considered study areas. However, it is noteworthy that, within the admittedly smaller sample of studies from non-high-income countries, the citation-weighted average of the density elasticity of wages, at 0.08, is about twice as large. We also note 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. An important qualification is that the recommended 0.04 elasticity is best interpreted as an area-based effect that partially captures a productivity effect on identical workers and particle captures a shift in composition towards more productive workers (a sorting effect). Studies that control for unobserved heterogeneity of workers by identifying from movers across agglomerations tend to find elasticities that are about 50% lower (Combes & Gobillon, 2015). We recommend the 0.04 elasticity as an area-based effect that is consistent with the area-based estimates recommended for the other categories, for which estimates controlling for unobserved micro-level heterogeneity are typically not available.

4.2 Patents

While there is a sizeable literature engaged with the effects of urban form on innovation, we only found seven studies that provided estimates that either directly corresponded to or could be converted into estimates of the density elasticity of patents. Some studies report marginal effects that cannot be converted into elasticity estimates due to missing descriptive statistics. We recommend the citation-weighted mean in the evidence base of 0.21, which is in line with Carlino et al. (2007) and Sedgley & Elmslie (2004) who use instruments for density. The recommended elasticity estimate is also in line with our original analysis of US FUAs. While this consistency is reassuring, we are somewhat hesitant to recommending a causal interpretation. In general, we find the evidence provided by Carlino et al. (2007) quite convincing. Actually, we consider it the most credible study on the effects of density on innovation in our evidence base. However, it can be argued that the instruments may not be excludable. As an example, favourable climate may attract high-skilled workers. Lagged density may be endogenous to the same fundamentals as current density, and consumption amenities are likely endogenous to density itself and, thus, the fundamentals that determine density. We acknowledge that the comprehensive set of control variables makes the instruments more likely excludable. Yet, compared to the other categories for which we recommend a causal interpretation, the identifying variation in our view is less plausibly exogenous.

More generally, the evidence base in this category is relatively thin and our original elasticity estimates for the world-wide sample, at 0.13, are somewhat smaller than the recommended elasticity. More work aiming at comparable elasticity estimates from different geographic contexts would be desirable.

4.3 Rents

We recommend the citation-weighted mean elasticity from the evidence base of 0.15. This estimate is almost identical to the density elasticity of rent in the data set used by Albouy & Lue, (2015), which was kindly provided by the authors. This estimate is also within the range of other good quality and relevant papers. In particular, the citation-index-weighted mean elasticity, at 0.13, is very close if we restrict the sample to six analyses that disentangle density effects from unobserved location fundamentals using instrumental variables or natural experiments (SMS = 4). Therefore, a causal interpretation of our recommended elasticity seems justifiable and we are thus reasonably confident in recommending the mean elasticity of 0.15 as an average even though the evidence base is not as well developed as it is, for example, for wages. It is important to note, however, that the density elasticity of rent appears to vary in density. Our meta-analysis of the reviewed elasticities suggests that elasticity increases by 0.063 if the population density in the considered study area increases by 1000 inhabitants per square kilometre. This effect is qualitatively and quantitatively consistent with the positive effect of city size on the density elasticity of rent documented by Combes et al (2018) for French cities. The non-log-linearity in the effect of density on rent also explains why Combes et al (2018) find a larger elasticity for French cities than Albouy and Lue (2015) find for US cities. The 0.06 difference in the density elasticity (0.21 for French cities vs. 0.15 for US cities) corresponds to a difference in density of about 1000 inhabitants per square kilometre, almost exactly the difference reported in the Demographia World Urban Areas (2018). So, as a rule of thumb we can recommend the following approximation of a context-specific density elasticity of rent:

$$\beta_c = 0.15 + 0.63 \times \left(\frac{D_c - 1200}{1000}\right),$$

where 0.15 is the average density elasticity applicable to the US average, 0.63 is the marginal effect of an increase in density by 1000 residents per square kilometre, 1200 is the average density of US cities measured in population per square kilometre reported in the Demographia World Urban Areas (2018), and D_c is the density measured in population per square kilometre in a specific context.

4.4 Vehicle miles travelled

We recommend the citation-weighted mean elasticity from the evidence base of 0.06. The evidence base, including 36 analyses, is relatively large. There is sizeable variation in the estimated density elasticity across analyses (standard deviation of 0.12). Our recommended elasticity, however, is relatively close to Duranton & Turner (2018), a dedicated high-quality paper, and to the mean elasticity recommended in the meta-analysis (0.04) by Ewing & Cervero (2010). Moreover, the citation-index-weighted mean elasticity is almost identical if we restrict the sample to four analyses from two papers that disentangle density effects from unobserved location fundamentals using instrumental variables or natural experiments (SMS = 4). Therefore, a causal interpretation of our recommended elasticity seems justifiable and we are reasonably confident in recommending this elasticity, even though there is significant heterogeneity that remains to be explored.

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 sizeable 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 elasticity estimates 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 two elasticity estimates (0.12), 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 and causal 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), which is identified from quasi-experimental variation. The recommended elasticity is based on a small sample of high-quality evidence. More research is required to substantiate the findings and to allow for a causal interpretation.

4.6 Local public spending

We recommend the citation-weighted mean elasticity estimate from the evidence base of 0.17. This elasticity is within reasonable close range of Carruthers & Ulfarsson (2003) who find an 0.144 elasticity of total spending. Overall, the evidence base is relatively thin as most estimates come from a hand full of studies providing multiple estimates of density elasticities for distinct spending categories. More research is required in this area. There is significant heterogeneity that remains to be explored. Disentangling the effects of density from correlated unobserved fundamental effects to establish causality remains a challenge in this category.

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 (Baum-Snow et al. 2017). 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). We believe, however, that our original estimates are closer to the thought experiment conducted here, which refers to an increase in overall urban density. Our original analysis of OECD data suggests a -0.035 elasticity estimate of the income quintile wage gap reduction with respect to density (Table 5 in the main paper). Reassuringly, our -0.057 elasticity estimate for the US is within close range of Baum-Snow et al (2017). However, a sizeable evidence base with comparable results has yet to be developed. Disentangling the effects of density from correlated unobserved fundamentals to establish causality remains a challenge in this category.

4.8 Crime rate reduction

The literature of the effects of urban form on crime rates is small, but mostly points to a normatively positive effect of density on crime rates (crimes, p.c. as opposed to crimes per area) of sizeable 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 estimate, 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, his estimates (level-level model) are almost identical for crimes against persons and property. Moreover, Tang's estimate is close to our original estimate of the density elasticity of crime rate reduction for non-US cities (setion 3.4 of this appendix). Importantly, however, we stress, that our original analysis reveals that the elasticity is negative for US cities, i.e. higher densities tend to be associated with higher crime levels in the US. This is in line with Glaeser & Sacerdote (1999). Therefore, we consider the recommended elasticity estimate to be suitable for non-US countries exclusively. More comparable evidence is required to substantiate our recommended elasticity for non-US countries and to allow for a more comprehensive analysis of heterogeneity. Disentangling the effects of density from correlated unobserved fundamentals to establish causality remains a challenge in this category.

4.9 Urban green

As discussed in the context of the presentation of our original 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 original elasticity estimate of green space density with respect to population density of 0.0283. Of course, we must stress that this estimate should be considered preliminary as a sizeable evidence base with comparable results has yet to be developed. Disentangling the effects of density from correlated unobserved fundamentals to establish causality remains a challenge in this category.

4.10 Pollution reduction

The literature on the effects of density on pollution concentrations is relatively small. Moreover, the quantitative results prevailing in the literature are highly inconsistent as reflected by a standard deviation of 0.47 relative to a weighted mean elasticity of pollution reduction with respect to a density of 0.04. Our original cross-sectional estimate of approximately -0.12 (using OECD data) is close to the elasticity reported by Albouy & Stuart (2014). Moreover, this elasticity has been substantiated by a recent working paper by Carozzi and Roth (2018) who provide an elasticity estimate of -0.13 and shortly after, by Borck & Schraut (2018), who provide very similar estimates. In our view, Carozzi & Roth (2018) and Borck & Schraut (2018) are the most credible estimates in the evidence base. Given the consistency of their independent estimates for the US (Carozzi & Roth) and Germany (Borck & Schraut) as well as the consistency with our original estimates from a sample of OECD cities, we are confident in recommending the -0.13 elasticity from Carozzi and Roth (2018). Given that both Carozzi & Roth (2018) and Borck & Schraut (2018) use instrumental variable strategies to disentangle density effects from correlated fundamental effects, a causal interpretation seems justifiable. A larger evidence base, however, would be desirable to substantiate findings.

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 estimate of energy use reduction with respect to density across the reviewed analyses of 0.07 as a recommended elasticity estimate. We note that the respective elasticity of public transport seems to be negative (meaning more energy is consumed) and large (-0.37), 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. Since few studies seek to disentangle the effects of density from correlated unobserved fundamentals, establishing causality remains a challenge in this category.

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. 2018; Duranton & Turner 2018). They yield very similar elasticities with a mean of -0.12. Because the evidence base is quantitatively thin we contribute an original 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 -0.63%, 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 -0.12 elasticity from the small literature. Since both studies (Couture et al. 2018; Duranton & Turner 2018) use plausible instrumental variables to disentangle density effects from correlated unobserved fundamental effects, a causal interpretation seems justifiable. 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 estimate of the density elasticity of car use reduction of 0.05 is the quality-weighted average from the evidence base. Ewing & Cervero (2010), in a dedicated meta-analysis, report estimates of the density elasticity of walking and public transit use of 0.07. We note that this elasticity of non-car usage with respect to density is consistent with the recommended elasticity of car usage reduction of 0.05 since car trips typically account for roughly 50% of overall trips. We note that the estimated elasticity of non-car use with respect to density of 0.16 in our evidence base is driven by outliers since the median value is 0.1. We further note that Ewing & Cervero (2010) discuss 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. Since few studies seek to disentangle the effects of density from correlated unobserved fundamentals, establishing causality, despite a large evidence base, remains a challenge in this category.

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 density elasticity estimates 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 original 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 original estimates – unless the evidence is highly inconsistent or inconclusive – we use an estimated of the elasticity of mortality rate reduction with respect to density, derived from Reijneveld et al.'s (1999) 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. Since few studies seek to disentangle the effects of density from correlated unobserved fundamentals, establishing causality remains a challenge in this category.

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 estimate of the 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 estimate of the elasticity of density with respect to city size presented in section 2.1. The resulting elasticity estimate of reported life satisfaction with respect to density is -0.0037, which is roughly within the range of our original analysis of OECD data (-0.007). While we proceed using the -0.0037 elasticity estimate implied by Glaeser et al.'s (2016) analysis, we caution against uncritical application of this elasticity unless further research substantiates our quantitative interpretation. Since few studies seek to disentangle the effects of density from correlated unobserved fundamentals, establishing causality remains a challenge in this category.

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 7 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. 2018) 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. 2018).

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 estimate of 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 6 in the main paper we use an adjusted elasticity estimate 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 estimates 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 estimates 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 estimate of 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). We note that with this approach we presumably capture dis-amenity effects and health effects, both of which should be associated with a negative willingness to pay. Carozzi & Roth (2018) compute the pure health effect using estimates of the pollution effect on death risk and the statistical value of live. Accordingly, a log-point increase in density leads to an annualised per capita effect of -\$370. It follows that a percentage point increase in density is associated with -\$.215 which, at a 5% discount rate over an infinite horizon, gives a per capita present value of -\$43. This is about half of the -\$90 per capita present value gross effect we compute. To avoid double counting with the health effect discussed in 5.14, we subtract the -\$43 health effect from the -\$90 gross effect in the accounting reported in Table 8 in the main paper.

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). We note that the per capita present monetised pollution effect on health we infer from Carozzi & Roth (2018) of -$43 (see 5.10) corresponds to about two-thirds of the health effect of -$64 we compute with our approach.

5.15 Wellbeing

We use an estimate of the elasticity of self-reported well-being with respect to income of 0.5, which is 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.

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Gabriel M. Ahlfeldt[♣], Elisabetta Pietrostefani[♠]

Studies reviewed in The economic effects of density

Version: February 2019

Summary of study attributes

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
P1	Abel et al.	2012	a	1	Labour productivity	PD	US	OLS IV	4	2.10	0.0300
P2	Aberg	1973	a	1	Productivity	PD	Sweden	OLS	2	0.10	0.0170
P3	Ahlfeldt & Feddersen	2015	a	1	Labour productivity	ED	Germany	DID IV	4	4.92	0.0380
P4	Ahlfeldt & Wendland	2013	a	1	Total factor productivity	SPP	Germany	Panel FE	3	1.01	0.0590
P5	Ahlfeldt, Redding, et al.	2015	a	1	Total factor productivity	ED	Germany	DID, GMM	4	2.01	0.0620
P6	Albouy & Lue	2015	a	1	Wages	PD	US	OLS CONTR	2	1.07	0.0680
P8	Andersson et al.	2014	a	1	Wages	ED	Sweden	Panel FE	3	1.18	0.0100
P9	Andersson et al.	2016	a	1	Wages	ED	Sweden	Panel	3	1.83	0.0300
P10	Au & Henderson	2006	a	1	Productivity	ED	China	OLS IV	4	2.40	0.0130
P11	Baldwin et al.	2010	a	1	Labour productivity	ED	Canada	FD, GMM, IV	3	1.32	0.0200
P12	Baldwin et al.	2007	a	1	Labour productivity	PD	Canada	CrossSec FE	2	0.23	0.0674
P13	Barde	2010	a	1	Wages	ED	France	CrossSec, IV	4	0.58	0.0350
P14	Barufi et al.	2016	a	1	Wages	ED	Brazil	Panel IV	3	0.61	0.0730
P16	Baum-Snow & Pavan	2012	a	1	Log hourly wage	PD	US	Panel, IV	4	2.94	0.0870
P17	Brülhart & Mathys	2008	a	1	Labour productivity	ED	Europe	Panel GMM	3	2.00	-0.0800
P18	Chauvin et al.	2016	a	1	Wages	PD	China	Panel IV	3	0.61	0.2000

♣ London School of Economics and Political Sciences (LSE) and Centre for Economic Policy Research (CEPR), Houghton Street, London WC2A 2AE, g.ahlfeldt@lse.ac.uk, www.ahlfeldt.com

♠ London School of Economics and Political Sciences (LSE).

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
P19	Chauvin et al.	2016	a	1	Wages	PD	India	Panel IV	3	0.61	0.0750
P20	Chauvin et al.	2016	a	1	Wages	PD	US	Panel IV	3	0.61	0.0500
P21	Chauvin et al.	2016	a	1	Wages	PD	Brazil	Panel IV	3	0.61	0.0260
P23	Ciccone	2002	a	1	Labour productivity	ED	Europe	FE, IV	4	3.79	0.0450
P24	Ciccone & Hall	1996	a	1	Total factor productivity	ED	US	OLS IV	3	5.58	0.0530
P25	Cingano & Schivardi	2004	a	1	Total factor productivity	PD	Italy	CrossSec	2	1.82	0.0540
P26	Combes et al.	2012	a	1	Total factor productivity	ED	France	Panel IV	4	4.88	0.0320
P27	Combes et al.	2008	a	1	Wages	ED	France	Panel IV	4	9.07	0.0300
P28	Combes et al.	2017	a	1	Total earning	ED	China	Panel OLS	3	1.72	0.0970
P29	Combes et al.	2015	a	1	Total earnings	ED	China	OLS IV	4	0.93	0.1100
P30	Combes et al.	2008	a	1	Total factor productivity	ED	France	Panel IV	4	2.29	0.0400
P31	Combes et al.	2008	a	1	Wages	ED	France	Panel IV	4	2.29	0.0500
P32	Combes & Li	2018	a	1	Earnings per hour	ED	China	OLS IV	4	1.06	0.1000
P33	Davis & Weinstein	2001	a	1	Productivity	ED	Japan	OLS	2	0.52	0.0628
P34	Dekle & Eaton	1999	a	1	Wages	ED	Japan	Panel FE	3	0.74	0.0100
P35	Dericks & Koster	2018	a	1	Total factor productivity	ED	UK	Panel, IV	4	1.06	0.0720
P37	Echeverri-Carroll & Ayala	2011	a	1	Wages	PD	US	OLS IV	4	0.43	0.0305
P38	Faberman & Freedman	2016	a	1	Wages	PD	US	Panel IV	3	0.61	0.0698
P39	Fingleton	2003	a	1	Wages	ED	UK	OLS	2	1.12	0.0170
P40	Fingleton	2006	a	1	Wages	ED	UK	OLS	2	1.67	0.0250
P41	Fu	2007	a	1	Wages	ED	US	CrossSec FE	2	2.07	0.0370
P44	Graham	2007	a	1	Labour productivity	ED	UK	GLS CONTR	2	2.44	0.0402
P45	Graham	2000	a	1	Labour productivity	ED	UK	OLS	2	0.18	0.0080
P46	Graham	2007	a	1	Labour productivity	ED	UK	Panel OLS	3	0.83	0.0200
P47	Graham	2005	a	1	Labour productivity	ED	UK	Panel OLS	3	0.29	0.1290
P48	Graham & Kim	2008	a	1	Labour productivity	ED	UK	Panel OLS	3	0.91	0.0790
P49	Graham et al.	2010	a	1	Labour productivity	ED	UK	Panel GMM	3	1.33	0.0905
P50	Henderson	2003	a	1	Labour productivity	ED	US	Panel IV	3	6.58	0.0240
P52	Henderson	1986	a	1	Total factor productivity	ED	Brazil	CrossSec, IV	4	1.31	0.1000
P53	Kanemoto et al.	1996	a	1	Total factor productivity	PD	Japan	CrossSec	2	0.24	0.0890
P54	Lall et al.	2004	a	1	Industry productivity	ED	India	OLS	2	1.22	0.0170

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
P55	Larsson	2014	a	1	Wages	ED	Sweden	Panel IV	3	1.41	0.0100
P56	Mion & Naticchioni	2005	a	1	Wages	ED	Italy	Panel OLS	3	0.83	0.0340
P57	Monkkonen et al.	2018	a	1	Labour productivity	ED	Mexico	Panel	3	1.06	-0.0800
P58	Moomaw	1985	a	1	Labour productivity	PD	US	OLS	2	0.39	0.0930
P59	Moomaw	1983	a	1	Total factor productivity	PD	US	CrossSec	2	0.16	0.0884
P60	Morikawa	2011	a	1	Total factor productivity	PD	Japan	Panel	2	0.92	0.1100
P61	Nakamura	1985	a	1	Labour productivity	PD	Japan	CrossSec	2	0.64	0.0781
P62	Rappaport	2008	a	1	Total factor productivity	PD	US	CGEM	1	0.78	0.1500
P63	Rice et al.	2006	a	1	Labour productivity	PD	UK	OLS IV	4	2.37	0.0350
P64	Rosenthal & Strange	2008	a	1	Wages	ED	US	OLS, GMM, IV	4	5.69	0.0450
P65	Sveikauskas	1975	a	1	Labour productivity	PD	US	CrossSec	2	1.07	0.1391
P66	Sveikauskas et al.	1988	a	1	Labour productivity	PD	US	CrossSec	2	0.41	0.0130
P67	Tabuchi	1986	a	1	Labour productivity	PD	Japan	CrossSec IV	4	0.21	0.0615
P68	Wheeler	2001	a	1	Total factor productivity	ED	US	CrossSec	2	1.21	0.0170
P69	Eckert et al.	2018	a	1	Wages	PD	Denmark	OLS FE	3	0.35	0.0539
I1	Andersson et al.	2005	a	2	Patents/capita	ED	Sweden	Poisson	2	0.82	0.0190
I3	Bettencourt et al.	2007	a	2	Patents/capita	PD	US	FGLS	2	2.99	0.2900
I4	Carlino et al.	2007	a	2	Patents/capita	ED	US	OLS IV	4	4.45	0.2000
I5	Echeverri-Carroll & Ayala	2011	a	2	Patents/capita	PD	US	OLS IV	1	0.43	0.0504
I8	Knudsen et al.	2008	a	2	Patents per 100,000 pop	PD	US	OLS	2	1.54	0.3000
I11	Ó hUallacháin	1999	a	2	Patents/capita	PD	US	OLS	2	0.71	0.3100
I13	Sedgley & Elmslie	2004	a	2	Average patents	PD	US	GMM IV	4	0.82	0.0020
VS2	Ahlfeldt, Redding, et al.	2015	a	3	House prices	PD	Germany	SPVAR IV	4	1.07	0.0465
VS3	Albouy & Lue	2015	a	3	House prices	PD	US	OLS CONTR	2	1.07	0.1560
VS9	Combes et al.	2018	a	3	House prices	PD	France	OLS IV	4	1.06	0.2080
VS10	Dericks & Koster	2018	a	3	Rent	ED	UK	Panel, IV	4	1.06	0.2873
VS13	Kholodilin & Ulbricht	2015	a	3	House prices	PD	Europe	OLS QR	2	0.62	0.2500
VS15	Koster et al.	2014	a	3	Rent	ED	Netherlands	Panel, IV	4	0.82	0.0820
VS16	Liu et al.	2016	a	3	Rent	ED	US	OLS FE	2	0.71	0.1000
VS17	Lynch & Rasmussen	2004	a	3	House prices	PD	US	OLS CONTR	2	0.48	-0.0179
VS21	Palm et al.	2014	a	3	Rent	PD	US	OLS FE	2	0.54	0.0450

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
VS23	Song & Knaap	2004	a	3	House prices	PD	US	OLS IV	4	1.07	-0.0170
VS26	Cheshire & Dericks	2018	a	3	Rent	ED	UK	QUASI-EXP	4	1.06	0.1840
VS21	Palm et al.	2014	a	3	Rent	PD	US	OLS FE	2	0.54	0.0450
JA1	Albouy & Lue	2015	a	4	Commuting cost red.	PD	US	LPROB	2	1.07	-0.0230
JA3	Bento et al.	2005	c	4	VMT per household	EPD	US	LOGIT	2	2.41	0.0600
JA5	Bhat et al.	2009	b	4	VMT per household	BS	US	LOGIT	2	4.85	0.0100
JA8	Brownstone & Thomas	2013	a	4	Red. total vehicle mileage/year	HD	US	OLS	2	1.16	0.1222
JA9	Cervero & Kockelman	1997	a	4	VMT per household	ED	US	LOGIT	2	3.43	0.2470
JA10	Cervero & Kockelman	1997	a	4	VMT per household	LU	US	LOGIT	2	3.43	0.0000
JA11	Cervero & Kockelman	1997	b	4	VMT per household	SC	US	LOGIT	2	3.43	0.0000
JA12	Cervero & Kockelman	1997	b	4	VMT per household	BS	US	LOGIT	2	3.43	0.1900
JA13	Champman et al.	2004	b	4	VMT per person	SC	US	LOGIT	2	0.13	0.0800
JA14	Chapman & Frank	2004	c	4	VMT per person	LU	US	LOGIT	2	0.13	0.0400
JA15	Chatman	2003	a	4	Commercial trip length red.	ED	US	LOGIT, TOBIT	2	0.45	0.2327
JA16	Chatman	2003	a	4	VMT commercial trips	PD	US	LOGIT, TOBIT	2	0.45	-0.5800
JA19	Duranton & Turner	2015	a	4	VKT per person	PD	US	Panel IV	4	1.30	0.0850
JA21	Fan	2007	b	4	Miles travelled per person	PCD	US	OLS	2	1.06	0.0700
JA22	Fan	2007	b	4	Miles travelled per person	SC	US	OLS	2	1.06	0.1100
JA23	Frank & Bradley	2009	b	4	VMT per household	SC	US	OLS	2	0.33	0.1100
JA24	Frank	2009	c	4	VMT per household	LU	US	OLS	2	0.33	0.0400
JA27	Holtzclaw et al.	2002	a	4	VMT per household	HD	US	OLS	2	1.94	0.1400
JA28	Cervero & Kockelman	1997	c	4	VKT per household	LU	US	OLS	2	0.87	0.1000
JA29	Cervero & Kockelman	1997	a	4	VMT per household	ED	US	OLS	2	0.87	0.0000
JA30	Cervero & Kockelman	1997	a	4	VMT per household	PD	US	OLS	2	0.87	0.0000
JA31	Kuzmyak et al	2006	c	4	VMT per household	LU	US	OLS	2	0.43	0.0900
JA34	Mashall	2008	a	4	Vehicle Km travelled	PD	US	COR	0	1.43	0.3000
JA36	Pouyanne	2004	a	4	Commuting length reduction	ED	France	OLS, LOGIT	2	0.34	0.1104
JA37	Pouyanne	2004	a	4	Commuting length reduction	PD	France	OLS, LOGIT	2	0.34	0.2065
JA38	Pickrell & Schimek	1996	a	4	VMT per household	PD	US	OLS	2	0.69	0.0700
JA40	Sun et al	1998	a	4	VMT per household	ED	US	OLS - ANOVA	2	0.45	0.0000
JA41	Sun et al	1998	c	4	VMT per household	LU	US	OLS - ANOVA	2	0.45	0.1000

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
JA43	Vance & Hedel	2007	a	4	VKT per person	ED	Germany	PROBIT IV	4	1.51	0.0100
JA44	Vance & Hedel	2007	b	4	VKT per person	SDI	Germany	PROBIT IV	4	1.51	0.0400
JA45	Vance & Hedel	2007	c	4	VKT per person	LU	Germany	PROBIT IV	4	1.51	0.0600
JA46	Veneri	2010	a	4	Av. Commuting time	PD	Italy	OLS, ML	2	1.02	-0.0212
JA47	Fan	2007	b	4	Daily transit travel time	PCD	US	OLS	2	1.06	0.0000
JA48	Frank et al.	2008	b	4	transit trips per household	SC	US	LOGIT	2	1.06	0.1200
JA49	Zhou & Kockelman	2008	a	4	VMT per household	ED	US	OLS -PROBIT	2	1.44	0.0200
JA50	Zhou & Kockelman	2008	a	4	VMT per household	PD	US	OLS -PROBIT	2	1.44	0.1200
JA51	Yang et al.	2012	a	4	Commuting time reduction	PD	China	OLS CONTR	2	2.25	-0.2085
JA52	Boarnet et al.	2004	a	4	Non-work VMT per person	ED	US	OLS	2	0.28	0.0300
JA53	Boarnet et al	2004	a	4	Non-work VMT per person	PD	US	OLS	2	0.28	-0.0400
JA54	Chatman	2008	a	4	Non Work VMT per person	ED	US	LOGIT	2	1.74	-0.1900
JA55	Chatman	2008	a	4	Non Work VMT per person	PD	US	LOGIT	2	1.74	-1.0500
JA56	Chatman	2008	b	4	Non Work VMT per person	SC	US	LOGIT	2	1.74	-0.0600
JA58	Cervero & Kockelman	1997	a	4	VMT	ED	US	LOGIT	2	3.43	0.0630
SA1	Ahlfeldt & Maennig	2015	a	5	Quality of life	ED	Germany	DID, GMM	4	2.01	0.1500
SA2	Ahlfeldt, Moeller, et al.	2015	a	5	Underground station density	PD	Germany	SPVAR IV	4	1.07	0.0350
SA3	Albouy	2008	a	5	Quality of life	PD	US	OLS FE	2	2.15	0.0200
SA4	Albouy & Lue	2015	a	5	Quality of life	PD	US	OLS CONTR	2	1.07	0.0150
SA8	Chauvin et al.	2016	a	5	Real wages	PD	China	Panel IV	3	0.61	-0.0520
SA9	Chauvin et al.	2016	a	5	Real wages	PD	India	Panel IV	3	0.61	-0.0690
SA10	Chauvin et al.	2016	a	5	Real wages	PD	US	Panel IV	3	0.61	-0.0200
SA11	Chauvin et al.	2016	a	5	Real wages	PD	Brazil	Panel IV	3	0.61	-0.0100
SA12	Couture	2016	a	5	Restaurant prices	PD	US	OLS LOGIT IV	4	3.61	0.0800
SA13	Couture	2016	a	5	Restaurant prices	PD	US	OLS LOGIT IV	4	3.61	0.1600
SA14	Levinson	2008	a	5	Rail station density	PD	UK	Panel	3	1.28	0.0023
SA15	Levinson	2008	a	5	Underground station density	PD	UK	Panel	3	1.28	0.0027
SA17	Schiff	2015	a	5	Cuisine variety	PD	US	OLS IV	4	0.92	0.1850
SA18	Baum-Snow & Pavan	2012	a	5	Real wages	PD	US	Panel, IV	4	2.94	0.0160
PS2	Carruthers & Ulfarsson	2003	a	6	Red. spending capital	PD	US	CrossSec FE	2	0.98	0.1440
PS3	Carruthers & Ulfarsson	2003	a	6	Red. spending education	PD	US	CrossSec FE	2	0.98	0.1920

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
PS4	Carruthers & Ulfarsson	2003	a	6	Red. spending police	PD	US	CrossSec FE	2	0.98	0.0960
PS5	Carruthers & Ulfarsson	2003	a	6	Red. spending roadways	PD	US	CrossSec FE	2	0.98	0.2880
PS6	Carruthers & Ulfarsson	2003	a	6	Red. spending sewerage	PD	US	CrossSec FE	2	0.98	-0.1440
PS7	Carruthers & Ulfarsson	2003	a	6	Red. total spending	PD	US	CrossSec FE	2	0.98	0.1440
PS8	Carruthers & Ulfarsson	2003	b	6	Red. total spending	GAR	US	CrossSec FE	2	0.98	0.0195
PS9	Carruthers & Ulfarsson	2003	a	6	Red. spending transport	PD	US	CrossSec FE	2	0.98	-0.4800
PS10	Carruthers & Ulfarsson	2003	a	6	Red. spending trash	PD	US	CrossSec FE	2	0.98	0.0960
PS11	Hortas-Rico & Sole-Olle	2010	a	6	Admin spending per capita	UL	Spain	OLS CONTR	2	1.39	0.1075
PS12	Hortas-Rico & Sole-Olle	2010	a	6	Red. community facilities	UL	Spain	OLS CONTR	2	1.39	0.1069
PS13	Hortas-Rico & Sole-Olle	2010	a	6	Red. culture and sports	UL	Spain	OLS CONTR	2	1.39	0.1509
PS14	Hortas-Rico & Sole-Olle	2010	a	6	Red. housing and community development per capita	UL	Spain	OLS CONTR	2	1.39	0.0753
PS15	Hortas-Rico & Sole-Olle	2010	a	6	Red. spending police	UL	Spain	OLS CONTR	2	1.39	0.0920
PS16	Hortas-Rico & Sole-Olle	2010	a	6	Red. total spending	UL	Spain	OLS CONTR	2	1.39	0.1058
PS17	Hortas-Rico & Sole-Olle	2010	a	6	Red. spending trash	UL	Spain	OLS CONTR	2	1.39	0.3058
PS19	Ladd	1994	a	6	Change per capita spending	PD	US	CrossSec FE	2	0.19	-0.0302
PS20	Prieto et al.	2015	a	6	Paving cost per capita	PD	Spain	LOGIT	2	1.23	0.8120
PS21	Prieto et al.	2015	a	6	Sewage cost per capita	PD	Spain	LOGIT	2	1.23	0.5070
PS22	Prieto et al.	2015	a	6	Water supply cost per capita	PD	Spain	LOGIT	2	1.23	0.3970
SE1	Ananat et al.	2013	a	7	Red. in black-white wage gap	ED	US	OLS FE	2	0.92	-0.0033
SE2	Baum-Snow et al.	2016	a	7	High-low skill wage gap red.	PD	US	Panel IV	4	2.69	-0.0674
SE5	Galster & Cutsinger	2007	a	7	Dissimilarity index	PD	US	OLS CONTR	2	0.51	2.5675
SE8	Rothwell	2011	a	7	Dissimilarity index	PD	US	CrossSec IV	4	1.25	0.3920
SE9	Rothwell & Massey	2009	a	7	Dissimilarity index	PD	US	CrossSec IV	4	1.88	0.3261
SE10	Rothwell & Massey	2010	a	7	Red. Gini coefficient	PD	US	CrossSec IV	4	1.33	4.5635
SE11	Wheeler	2004	a	7	Red. 90th vs. 10th decile	PD	US	GLS IV	4	0.35	0.1700
SE12	Baum-Snow & Pavan	2012	a	7	Skill wage gap	PD	US	Panel, IV	4	2.94	-0.2093
SE13	Baum-Snow & Pavan	2012	a	7	Skill wage gap	PD	US	Panel, IV	4	2.94	-0.1163
SF6	Glaeser & Sacerdote	1999	a	8	Crime per capita	PD	US	OLS IV	3	2.04	-0.5581
SF10	Raleigh & Galster	2015	a	8	Red. assault	PD	US	OLS CONTR	2	0.66	0.3562
SF11	Raleigh & Galster	2015	a	8	Red. burglary	PD	US	OLS CONTR	2	0.66	0.3417

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
SF13	Raleigh & Galster	2015	a	8	Red. narcotics	PD	US	OLS CONTR	2	0.66	0.8142
SF14	Raleigh & Galster	2015	a	8	Property theft	PD	US	OLS CONTR	2	0.66	0.4580
SF15	Raleigh & Galster	2015	a	8	Red. robbery	PD	US	OLS CONTR	2	0.66	0.8288
SF16	Raleigh & Galster	2015	a	8	Red. vandalism	PD	US	OLS CONTR	2	0.66	0.3562
SF17	Raleigh & Galster	2015	a	8	Vehicle theft	PD	US	OLS CONTR	2	0.66	0.2763
SF18	Raleigh & Galster	2015	a	8	Red. violence	PD	US	OLS CONTR	2	0.66	0.5234
SF20	Tang	2015	a	8	Red. assault	PD	UK	Panel	3	0.45	0.0845
SF21	Tang	2015	a	8	Property theft	PD	UK	Panel	3	0.45	0.0902
SF22	Twinam	2016	a	8	Red. assault	PD	US	Panel IV	4	0.78	0.5314
SF23	Twinam	2016	a	8	Red. robbery	PD	US	Panel IV	4	0.78	0.4679
OG4	Lin et al.	2015	b	9	Foliage Projection Cover	HD	Australia	OLS	1	0.87	-0.0600
PO1	Albouy & Stuart	2014	a	10	Red. Pollution	PD	US	NLLS CONTR	2	1.68	-0.1500
PO3	Hilber & Palmer	2014	a	10	Red. NOx μg/m3	PD	non-OECD	Panel FE	3	0.36	-0.7816
PO4	Hilber & Palmer	2014	a	10	Red. PM10 μg/m3	PD	non-OECD	Panel FE	3	0.36	0.3482
PO5	Hilber & Palmer	2014	a	10	Red. SOx μg/m3	PD	non-OECD	Panel FE	3	0.36	-1.8367
PO6	Hilber & Palmer	2014	a	10	Red. NOx μg/m3	PD	OECD	Panel FE	3	0.36	0.2382
PO7	Hilber & Palmer	2014	a	10	Red. PM10 μg/m3	PD	OECD	Panel FE	3	0.36	-0.4740
PO8	Hilber & Palmer	2014	a	10	Red. SOx μg/m3	PD	OECD	Panel FE	3	0.36	2.0080
PO9	Salomons & Berghauser	2012	a	10	Red. Noise	PD	Netherlands	CORR	1	2.31	0.0400
PO10	Sarzynski	2012	a	10	Red. CO m. metric tons	PD	World	CrossSec	2	1.37	0.2280
PO11	Sarzynski	2012	a	10	Red. Nox m. metric tons	PD	World	CrossSec	2	1.37	0.4380
PO12	Borck & Schrauth	2018	a	10	NO2	PD	Germany	Panel IV	4	1.06	-0.1610
PO13	Sarzynski	2012	a	10	Red. SO2 m. metric tons	PD	World	CrossSec	2	1.37	0.3760
PO14	Sarzynski	2012	a	10	Red. VOCs m. metric tons	PD	World	CrossSec	2	1.37	0.3300
PO15	Stone	2008	a	10	Red. NOx μg/m3	PD	US	Panel	2	2.33	0.1900
PO16	Tang & Wang	2007	b	10	Red. CO2 concentration	HD	China	CORR	1	2.18	-0.2300
PO17	Borck & Schrauth	2018	a	10	CO	PD	Germany	Panel IV	4	1.06	-0.1200
PO18	Borck & Schrauth	2018	a	10	PM10	PD	Germany	Panel IV	4	1.06	-0.1140
PO19	Borck & Schrauth	2018	a	10	O3	PD	Germany	Panel IV	4	1.06	-0.0600
PO20	Carozzi & Roth	2018	a	10	Average residential PM2.5	PD	US	Panel IV	4	1.06	-0.1300
EN3	Barter	2000	a	11	Red. Emission/capita	PD	Eastern Asia	DESC	0	0.46	0.2940

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EN5	Brownstone & Thomas	2013	a	11	Red. gasoline consumption	HD	US	OLS	2	1.16	0.1440
EN7	Cirilli & Veneri	2014	a	11	CO2 emissions commutes	PD	Italy	OLS IV	4	1.32	0.2346
EN8	Glaeser & Kahn	2010	a	11	CO2 private driving	PD	US	CORR	1	7.41	0.0821
EN9	Glaeser & Kahn	2010	a	11	CO2 electricity	PD	US	CORR	1	7.41	0.0682
EN10	Glaeser & Kahn	2010	a	11	CO2 heating	PD	US	CORR	1	7.41	-0.0339
EN11	Glaeser & Kahn	2010	a	11	CO2 Total	PD	US	CORR	1	7.41	0.0527
EN12	Glaeser & Kahn	2010	a	11	CO2 public transport	PD	US	CORR	1	7.41	-0.3685
EN13	Glaeser & Kahn	2010	a	11	Red. gasoline consumption	PD	US	CORR	1	7.41	0.0320
EN14	Glaeser & Kahn	2010	a	11	Red. gasoline consumption	PD	US	CORR	1	7.41	0.0974
EN15	Holden & Norland	2005	a	11	Red. domestic energy	HD	Norway	OLS	2	2.28	0.1100
EN16	Hong & Shen	2013	a	11	Red. CO2 transport	PD	US	OLS IV	4	1.79	0.3100
EN19	Larson et al.	2012	b	11	Red. residential energy	FACAP	US	OLS	2	1.16	0.0338
EN20	Larson et al.	2012	b	11	Red. residential energy	FACAP	US	OLS	2	1.16	0.0467
EN23	Muñiz & Galindo	2005	a	11	Red. ecological footprint	PD	Spain	OLS	2	2.38	0.3648
EN25	Norman et al.	2006	b	11	Red. CO2 emissions	HD	Canada	CORR	1	3.92	0.0890
EN26	Osman et al.	2016	a	11	Red. gasoline consumption	PD	Egypt	OLS	1	2.44	0.0354
EN30	Su	2011	a	11	Gasoline consumption	PD	US	OLS CONTR	2	1.41	0.0680
EN31	Su	2011	b	11	Gasoline consumption	FSDI	US	OLS CONTR	2	1.41	-0.0920
EN32	Travisi et al.	2010	b	11	Env. impact reduction	PD	Italy	Pooled WLS	3	2.63	0.0092
EN34	Borck & Tabuchi	2016	a	11	CO2 Reduction	PD	US	Panel	3	0.79	0.4651
EN35	Fragkias et al.	2013	a	11	Red. CO2	PD	US	Panel	2	4.96	0.0017
C2	Couture et al.	2018	a	12	Travel speed	PD	US	OLS IV	4	2.82	-0.1300
C3	Duranton & Turner	2018	a	12	Travel speed	PD	US	Panel IV	4	1.30	-0.1100
MC6	Boarnet et al	2008	a	13	Miles walked per person	ED	US	LOGIT	2	1.57	0.0000
MC7	Boarnet et al	2011	a	13	Walking trips per person	ED	US	LOGIT	2	2.72	0.1400
MC8	Boarnet et al	2011	a	13	Walking trips per person	PD	US	LOGIT	2	2.72	0.5000
MC9	Boarnet et al.	2008	a	13	Miles walked per person	PD	US	LOGIT	2	1.57	0.1300
MC10	Boarnet et al.	2011	b	13	Walking trips per person	SC	US	LOGIT	2	2.72	-0.0900
MC11	Boarnet et al	2011	b	13	Walking trips per person	BS	US	LOGIT	2	2.72	-0.3500
MC12	Boarnet et al	2008	b	13	Miles walked per person	SC	US	LOGIT	2	1.57	0.4500
MC15	Boer et al.	2007	a	13	Miles walked per person	PD	US	LOGIT	2	1.58	0.2100

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
MC16	Boer et al.	2007	b	13	Miles walked per person	PD	US	LOGIT	2	1.58	0.3900
MC20	Cervero	2002	c	13	Transit mode choice	LU	US	LOGIT	2	2.98	0.5300
MC21	Cervero	2002	c	13	Transit mode choice	PD	US	LOGIT	2	2.98	0.3900
MC24	Cervero & Kockelman	1997	a	13	Non-personal vehicle	ED	US	LOGIT	2	3.43	0.0980
MC25	Cervero & Kockelman	1997	a	13	Non-pers. vehicle	ED	US	LOGIT	2	3.43	0.0840
MC28	Cervero & Kockelman	1997	a	13	Alternative to car (ACU)	LU	US	LOGIT	2	3.43	0.0000
MC29	Cervero & Kockelman	1997	b	13	Alternative to car (ACU)	SC	US	LOGIT	2	3.43	0.0000
MC30	Cervero & Kockelman	1997	b	13	Alternative to car (ACU)	SC	US	LOGIT	2	3.43	0.0000
MC31	Cervero & Kockelman	1997	c	13	Non-person vehicle choice	LU	US	LOGIT	2	3.43	0.0000
MC34	Chao & Qing	2011	a	13	Walking choice	PD	US	OLS CONTR	2	2.14	0.1573
MC35	Chatman	2003	c	13	Driving choice	ED	US	LOGIT TOBIT	2	0.44	0.4373
MC36	Chatman	2009	a	13	Walk/bike trips per person	PD	US	BINOMIAL	2	3.13	0.1600
MC37	Chatman	2009	b	13	Walk/bike trips per person	SC	US	BINOMIAL	2	3.13	0.3000
MC41	de Sa & Ardern	2014	a	13	Walking/cycling choice	PD	Canada	LOGIT	2	0.36	0.1093
MC43	Fan	2007	b	13	Daily walking time per person	PCD	US	OLS	2	1.06	0.0800
MC44	Frank & Bradley	2009	b	13	Walk trips per household	FAR	US	OLS	2	0.33	0.2000
MC45	Frank	2009	c	13	Walk trips per household	LU	US	OLS	2	0.33	0.0800
MC46	Frank et al.	2008	a	13	Cycle choice	PD	US	LOGIT	2	3.03	-0.0800
MC47	Frank et al.	2008	a	13	Cycle choice	PD	US	LOGIT	2	3.03	0.8400
MC48	Frank et al.	2008	a	13	Transit mode choice	PD	US	LOGIT	2	3.03	0.2400
MC49	Frank et al.	2008	a	13	Transit mode choice	PD	US	LOGIT	2	3.03	0.2600
MC50	Frank et al.	2008	b	13	Walk choice	PD	US	LOGIT	2	3.03	0.2800
MC51	Frank et al.	2008	a	13	Walk choice	PD	US	LOGIT	2	3.03	0.4300
MC52	Frank et al.	2008	b	13	Transit mode choice	FAR	US	LOGIT	2	3.03	0.1700
MC53	Frank et al.	2008	b	13	Transit mode choice	SC	US	LOGIT	2	3.03	0.2400
MC54	Frank et al.	2008	c	13	Transit mode choice	LU	US	LOGIT	2	3.03	0.1900
MC56	Frank et al.	2008	b	13	Transit mode choice	FAR	US	LOGIT	2	3.03	0.2100
MC57	Frank et al.	2008	b	13	Transit mode choice	SC	US	LOGIT	2	3.03	0.2000
MC58	Frank et al.	2008	c	13	Transit mode choice	LU	US	LOGIT	2	3.03	0.0900
MC59	Frank et al.	2008	b	13	Walk mode choice	SC	US	LOGIT	2	3.03	0.2800
MC60	Frank et al.	2008	b	13	Walk trips per household	SC	US	LOGIT	2	3.03	0.5500

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
MC61	Frank et al.	2008	b	13	Walk mode choice	SC	US	LOGIT	2	3.03	0.2100
MC63	Greenwald & Boarnet	2001	a	13	Walk trips per person	PD	US	PROBIT	2	0.07	0.3400
MC64	Joh et al.	2009	a	13	Walk trips per person	ED	US	OLS	2	0.34	0.1900
MC65	Joh et al	2009	b	13	Walk trips per person	SC	US	OLS	2	0.34	-0.2700
MC66	Joh et al	2009	b	13	Walk trips per person	BS	US	OLS	2	0.34	0.0100
MC68	Cervero & Kockelman	1997	a	13	Walk/bike mode choice	ED	US	OLS	2	0.87	0.0000
MC69	Cervero & Kockelman	1997	a	13	Walk/bike mode choice	PD	US	OLS	2	0.87	0.0000
MC70	Cervero & Kockelman	1997	c	13	Walk/bike mode choice	LU	US	OLS	2	0.87	0.2300
MC73	Lund et al.	2004	b	13	Transit mode choice	SC	US	LOGIT	2	1.14	1.0800
MC79	Nielsen et al.	2013	a	13	Cycle distance	PD	Denmark	Heckman	2	1.86	0.0870
MC81	Pouyanne	2004	a	13	Car share rate	PD	France	OLS, LOGIT	2	0.34	-0.0210
MC82	Pouyanne	2004	a	13	Cycling choice	PD	France	OLS, LOGIT	2	0.34	2.0143
MC83	Pouyanne	2004	a	13	Public transport choice	PD	France	OLS, LOGIT	2	0.34	0.4203
MC84	Pouyanne	2004	a	13	Walking choice	PD	France	OLS, LOGIT	2	0.34	0.4390
MC85	Rajamani & Handy	2003	c	13	Transit mode choice	LU	US	LOGIT	2	1.04	-0.0400
MC86	Rajamani et al	2003	a	13	Walk mode choice	PD	US	LOGIT	2	1.04	0.0100
MC87	Rajamani et al	2003	c	13	Walk mode choice	LU	US	LOGIT	2	1.04	0.3600
MC88	Reilly & Landis	2002	a	13	Transit mode choice	PD	US	LOGIT	2	0.36	0.2000
MC89	Reilly	2002	a	13	Walk mode choice	PD	US	LOGIT	2	0.36	0.1600
MC90	Rodríguez & Joo	2004	a	13	Transit mode choice	PD	US	LOGIT	2	2.80	-0.2000
MC93	Targa et al.	2005	a	13	Walk trips per person	PD	US	Poisson	2	0.35	0.0300
MC94	Targa & Clifton	2005	b	13	Walk trips per person	BS	US	Poisson	2	0.35	0.3200
MC95	Targa & Clifton	2005	c	13	Walk trips per person	LU	US	Poisson	2	0.35	0.0800
MC98	Zegras	2007	b	13	Daily automobile use	BD	Chile	OLS -LOGIT	2	0.89	-0.0400
MC99	Zegras	2007	b	13	Automobile use per household	SC	Chile	OLS -LOGIT	2	0.89	-0.1500
MC100	Zegras	2007	c	13	Automobile use per household	LU	Chile	OLS -LOGIT	2	0.89	-0.0100
MC101	Zhang	2004	a	13	Driving choice red.	ED	Hong Kong	LOGIT	2	1.63	0.0700
MC102	Zhang	2004	a	13	Driving choice red.	PD	Hong Kong	LOGIT	2	1.63	0.1100
MC103	Zhang	2004	a	13	Driving choice	ED	Hong Kong	LOGIT	2	1.63	0.0770
MC104	Zhang	2004	a	13	Driving choice	PD	Hong Kong	LOGIT	2	1.63	0.0390
MC105	Zhang	2004	a	13	Taxi red.	ED	Hong Kong	LOGIT	2	1.63	0.0240

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
MC106	Zhang	2004	a	13	Taxi red.	PD	Hong Kong	LOGIT	2	1.63	0.1280
MC107	Zhang	2004	a	13	Taxi red.	ED	Hong Kong	LOGIT	2	1.63	0.1180
MC108	Zhang	2004	a	13	Taxi red.	PD	Hong Kong	LOGIT	2	1.63	0.0260
MC109	Zhang	2004	a	13	Public transport choice	ED	Hong Kong	LOGIT	2	1.63	0.0060
MC110	Zhang	2004	a	13	Public transport choice	PD	Hong Kong	LOGIT	2	1.63	0.0140
MC111	Zhang	2004	a	13	Transit choice	ED	Hong Kong	LOGIT	2	1.63	0.0110
MC112	Zhang	2004	a	13	Transit choice	PD	Hong Kong	LOGIT	2	1.63	0.0050
MC113	Zhang	2004	a	13	Driving choice red.	ED	US	LOGIT	2	1.63	0.0010
MC114	Zhang	2004	a	13	Driving choice red.	PD	US	LOGIT	2	1.63	0.0400
MC115	Zhang	2004	a	13	Car share red.	ED	US	LOGIT	2	1.63	0.0030
MC116	Zhang	2004	a	13	Car share red.	PD	US	LOGIT	2	1.63	0.0330
MC117	Zhang	2004	a	13	Car share red.	ED	US	LOGIT	2	1.63	0.0440
MC118	Zhang	2004	a	13	Car share	PD	US	LOGIT	2	1.63	0.0710
MC119	Zhang	2004	a	13	Driving choice	ED	US	LOGIT	2	1.63	0.0310
MC120	Zhang	2004	a	13	Driving choice	PD	US	LOGIT	2	1.63	0.0440
MC121	Zhang	2004	a	13	Public transport choice	ED	US	LOGIT	2	1.63	0.0040
MC122	Zhang	2004	a	13	Public transport choice	PD	US	LOGIT	2	1.63	0.1260
MC123	Zhang	2004	a	13	Transit choice	ED	US	LOGIT	2	1.63	0.0900
MC124	Zhang	2004	a	13	Transit choice	PD	US	LOGIT	2	1.63	0.1180
MC125	Zhang	2004	a	13	Walking/cycling choice	ED	US	LOGIT	2	1.63	0.0040
MC126	Zhang	2004	a	13	Walking/cycling choice	PD	US	LOGIT	2	1.63	0.0600
MC127	Zhang	2004	a	13	Walking/cycling	ED	US	LOGIT	2	1.63	0.0260
MC128	Zhang	2004	a	13	Walk choice	PD	US	LOGIT	2	1.63	0.1050
MC129	Zhao	2014	a	13	Cycling choice	ED	China	LOGIT	2	2.78	0.1265
MC130	Zhao	2014	a	13	Cycling choice	PD	China	LOGIT	2	2.78	0.0034
MC133	Zhao	2014	a	13	Walking choice	ED	China	LOGIT	2	2.78	0.0418
MC134	Zhao	2014	a	13	Walking choice	PD	China	LOGIT	2	2.78	0.0013
MC135	Cervero & Kockelman	1997	a	13	Non-pers. vehicle	ED	US	LOGIT	2	3.43	0.1130
H1	Chaix et al.	2006	a	14	IHD risk red.	PD	Sweden	Panel LOGIT	3	2.40	-0.2986
H2	Chaix et al.	2006	a	14	Lung cancer risk red.	PD	Sweden	Panel LOGIT	3	2.40	-0.1949
H3	Chaix et al.	2006	a	14	Pulmonary disease red.	PD	Sweden	Panel LOGIT	3	2.40	-0.5779

ID	Author	Year	Cause	Cat.	Outcome	Density	Country	Model	SMS	CI	Elasticity
H4	Fecht et al.	2016	a	14	Premature mortalities	PD	UK	CrossSec	2	2.40	-0.2900
H5	Fecht et al.	2016	b	14	Premature mortalities	SDI	UK	CrossSec	2	1.22	-0.5000
H6	Graham & Glaister	2003	a	14	KSI reduction	ED	UK	LOGLIN	2	0.88	-0.0510
H7	Graham & Glaister	2003	a	14	KSI reduction	PD	UK	LOGLIN	2	0.88	0.3990
H9	Graham & Glaister	2003	a	14	Pedestrian casualty red.	ED	UK	LOGLIN	2	0.88	-0.8260
H10	Graham & Glaister	2003	a	14	Pedestrian casualty red.	PD	UK	LOGLIN	2	0.88	0.5290
H12	Howe et al.	1993	a	14	Red. all cancer rate	PD	US	COR	1	0.51	-0.0550
H14	Mahoney et al.	1990	a	14	Mortality red. (all cancers)	PD	US	LOGIT	2	2.55	-0.0380
H15	Melis et al.	2015	a	14	Red. metal health prescript.	PD	Italy	OLS, panel	2	1.54	0.0127
H16	Reijneveld et al.	1999	a	14	Mortality red.	PD	Netherlands	LOGLIN	2	0.29	-0.0906
WB3	Brueckner & Largey	2006	a	15	# times attends club meeting	PD	US	PROBIT IV	4	1.10	-0.0796
WB4	Brueckner & Largey	2006	a	15	# people can confide in	PD	US	PROBIT IV	4	1.10	-0.0056
WB5	Brueckner & Largey	2006	a	15	# close friends	PD	US	PROBIT IV	4	1.10	-0.0081
WB6	Brueckner & Largey	2006	a	15	Social contacts	PD	US	PROBIT IV	4	1.10	-0.0159
WB7	Brueckner & Largey	2006	a	15	Visit neighbour/week	PD	US	PROBIT IV	4	1.10	-0.0446
WB8	Fassio et al.	2013	a	15	Self-rep. env. health	PD	Italy	COR	1	1.97	-0.3384
WB9	Fassio et al.	2013	a	15	Self-rep. social satisfaction	PD	Italy	COR	1	1.97	-0.4232
WB10	Fassio et al.	2013	a	15	Self-rep. physical health	PD	Italy	COR	1	1.97	-0.1380
WB11	Fassio et al.	2013	a	15	Self-rep. psychological status	PD	Italy	COR	1	1.97	-0.3189
WB12	Glaeser et al.	2016	a	15	Self-rep. well-being	PD	US	Panel	3	1.30	-0.0037
WB13	Harvey et al.	2015	b	15	Perceived safety	FAR	US	OLS, LOGIT	2	1.07	0.0690
WB10	Fassio et al.	2013	a	15	Self-rep. physical health	PD	Italy	COR	1	1.96	-0.1380

Legend

	Cause	CI
a	Residential and employment density	Citations Index
b	Morphological density	
c	Mixed Use	

	Category
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	Wellbeing

Density	
PD	Population density
ED	Employment or other economic density
SPP	Spillover potential
HD	Development density
FACAP	Floor area per capita
GAR	Geographic area reduction
FAR	Floor area ration and related measures
FSDI	Freeway density

	Maryland Scientific Method Scale (WWC)
0	Descriptive data
1	Correlations, cross-sectional no control variables
2	Cross-sectional, adequate control variables
3	Panel data methods
4	Instrumental variables, RDD
5	Randomised control trials

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