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Abstract

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JEL Classification: G10, R30

Keywords: Housing, supply constraints, greenbelts, urban growth boundary, open space, Gravity

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The Welfare Effects of Greenbelt Policy: Evidence from England*

Hans R.A. Koster†

August 31, 2020

Abstract — I measure the economic effects of *greenbelts* that prohibit new construction beyond a predefined urban fringe and therefore act as urban growth boundaries. I focus on England, where 13% of the land is designated as greenbelt land. I estimate a quantitative general equilibrium model that includes amenities, housing construction, a traffic congestion externality, agglomeration forces, productivity and household location choices. To identify causal effects of greenbelt land, I construct counterfactual greenbelts, use greenbelt land in 1973, or focus on areas within a km of greenbelt boundaries. Greenbelt policy appears to generate positive amenity effects, but also strongly reduces housing supply. I find the greenbelts seem to increase welfare, as the equivalent income increase of workers is 0.3% and land rents increase by about 6.5%. Whether greenbelts benefit workers critically depends on the presence of spillovers and greenbelt amenities.

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1 Introduction

In most countries urban growth leads to an increasing pressure on developable land in and around cities. Many cities regulate urban development by imposing several constraints on *e.g.* building height or type of land use. Local governments also frequently restrict the expansion of urban areas in order to prevent urban sprawl. These *urban growth boundaries* or *greenbelts* reduce land available for development at the urban fringe. Many U.S. cities, such as Portland (OR), Miami, Minneapolis Saint-Paul, and San Jose (CA), have urban growth boundaries (UGBs), and similar restrictions can be found in many other countries (*e.g.* Austria, Canada, China, France, Germany, Iran, the Netherlands, New Zealand, Norway). I focus on England, where greenbelts are important as they cover about 13% of the total area and surround most larger cities.

Land use regulation does not necessarily lead to welfare losses, because constraints may reduce negative land use externalities and frictions associated with development. However, when regulatory constraints are too strict, regulation may imply substantial economic losses. Greenbelt policy indeed intends to protect agricultural land and secure amenity benefits from open space (Brueckner 2001). At the same time, economists have argued that greenbelt policy should be relaxed to mitigate the 'housing affordability crisis' because restrictions on housing supply lead to possibly strong price increases (Cheshire 2014, Economist 2017). Despite the importance of greenbelts restricting the growth of cities and the potentially pronounced impacts on housing markets, to the best of my knowledge no study has yet attempted to evaluate the welfare effects of greenbelt policy.

This study seeks to measure the effects of greenbelt policy on the spatial distribution of economic activity. I use data on more than 10 million housing transactions in England between 1995 and 2017. Given information on the exact location, I can identify for each property the share of greenbelt land in its vicinity. I further exploit data at the Middle-layer Super Output Area (MSOA) level (which has on average a working population of about $3,800$) on commuting flows and the locations of individuals and their workplaces.

I first aim to identify the reduced-form *supply* and *amenity* effects of greenbelt land. The supply effect captures the reduction in the supply of housing in greenbelts. The amenity effect refers to the increased attractiveness of a location due to better access to green space. Estimates of these effects are possibly biased, as greenbelts are usually on the outskirts of cities, where land is usually cheaper. On the other hand, houses close to greenbelts tend to be larger and may have gardens. To address omitted variable bias, I pursue three identification strategies. First, to select feasible control observations, I construct counterfactual greenbelts. More specifically, I use information on the population in parishes (approximately the size of neighbourhoods) before implementation of greenbelt policy in 1955 and construct counterfactual greenbelts using information on population density and city size in 1951. I then compare prices and densities in areas inside actual greenbelts with areas which would have been expected to be inside a greenbelt based on the historic population distribution. Second, I exploit that greenbelt boundaries in England have hardly changed since their imposition in the 1970s. I gather data on approved and proposed greenbelt land in 1973 and compare price and density changes in those areas. Third, as one might be worried that the selection process of greenbelts is correlated to unobserved locational endowments other than the presence of greenbelt land, I only select areas close to greenbelt boundaries and apply spatial differencing, in the spirit of Turner et al. (2014).

The local *supply* and *amenity* effects of greenbelts are only one part of the story. The substantial reduction in the supply of developable land close to cities will also influence the spatial equilibrium, resulting in a different spatial distribution of production, implying *agglomeration* and *congestion* effects. These effects are relevant, because a large literature shows that workers are more productive when they are at their workplace in the vicinity of other workers (Ciccone & Hall 1996, Ciccone 2002, Arzaghi & Henderson 2008, Combes et al. 2008, Melo et al. 2009, De la Roca & Puga 2017) and because traffic congestion arises when people cluster together (Proost & Thisse 2019, Combes et al. 2019).[1]

To model the complex interactions of *amenity*, *supply*, *agglomeration* and *congestion* effects, I set up a quantitative spatial general equilibrium model, following Ahlfeldt et al. (2015). In this model, households and firms compete for floor space, while employees benefit from each other's presence due to agglomeration economies. Workers commute to work, so more concentration of firms typically implies higher commuting costs. I extend the model of Ahlfeldt et al. in four directions:

[1] I focus here on agglomeration and congestion effects in the labour market, but also allow for agglomeration effects in the housing market.

1. I embed land use restrictions in the model, as greenbelt land reduces the available land available for development at certain locations.

2. I estimate, rather than calibrate, the share of land in construction costs, which is critical in determining the effect of greenbelts on construction and floor space prices.

3. I allow for greenbelts to generate a higher amenity level; hence, I explicitly specify the amenity residual in Ahlfeldt et al. (2015).

4. I allow for endogenous travel times, *i.e.* for traffic congestion close to the workplace. There are several papers that show that UGBs affect the congestion level in a city and therefore have welfare implications through a potential reduction in congestion externalities (see Kanemoto 1977, Arnott 1979, Pines & Sadka 1985, Anas & Rhee 2007, Brueckner 2007).

Using the recursive structure of the model, together with the identification strategies to identify the amenity, supply effects outlined above, I *estimate* (rather than calibrate) the causal structural parameters of the model, enabling me to perform counterfactual experiments. To identify the share of construction cost spend on land inputs, I follow Combes et al. (2016) in using the first-order condition for profit maximisation with respect to building capital and relying on variation in systematic determinants of demand for real estate across space.

To identify the parameters related to agglomeration and congestion forces, I first propose a standard identification strategy using historic instruments. Alternatively, I use an insight by Bayer & Timmins (2007), who argue that characteristics of other, not too close, locations do not directly affect utility or productivity of a location, but only indirectly impact a certain location through the spatial equilibrium. Exogenous characteristics of far away locations therefore serve as a valid instrument for the number of workers or households choosing a certain location. Consequently, I use the share of greenbelt land far away – between 10 and 25km – because I will show that amenity effects are much more local and do not affect the utility or productivity of locations further than 10km away. Because one may question the identification strategy of using historic instruments to identify spillover effects, I also provide analyses where the instruments are only 'plausibly exogenous' (Conley et al. 2012).

I show that greenbelt policy has a small *positive* welfare effect on welfare. The income change that is necessary to compensate for greenbelts is -0.3%, which amounts to about £2 billion a year.

Moreover, greenbelt policy benefits absentee land owners as total land revenues of developed land are about 6.5% higher due to greenbelts, which amount to approximately £1 billion per year. Hence, it appears that greenbelts unequivocally benefit land owners and workers.[2] I note that benefits of greenbelts for workers dissipate once *(i)* no greenbelt amenities would exist, or *(ii)* spillovers would be set to zero. This shows that evaluating greenbelt policy in a general equilibrium framework with amenity and spillover effects is paramount.

My welfare measure arguably does not include all possible general equilibrium effects. Most notably, one may argue that city-wide amenity effects of greenbelts are not included, while these may be potentially important. The foremost city-wide amenity effects are likely *(i)* recreational visits – people that may live further away but go for recreation to greenbelts; and *(ii)* reductions in pollution due to greenbelts in the inner city. Using ancillary data I show that these city-wide effects are unlikely to be quantitatively important.[3]

Related literature. Most previous studies on the effects of land use regulation so far concentrate on housing supply restrictions and indicate that supply constraints are associated with increasing housing costs, a strong reduction in new construction and rapid price growth (Mayer & Somerville 2000, Glaeser et al. 2005, Green et al. 2005, Ihlanfeldt 2007). This effects is particularly pronounced for cities in England, in which land use regulation is very restrictive (Hilber & Vermeulen 2016). Recent evidence for England by Cheshire et al. (2018) shows that land use restrictions may also lead to higher vacancy rates and longer commutes. Glaeser & Ward (2009) find that local constraints in Massachusetts (so within a small area) do not increase the price of land because of close substitutes. At the same time, they find that density levels are too low from a welfare point of view. Koster et al. (2012) find that costs of regulation for home owners or developers (so-called 'own-lot effects') may be substantial (up to 10% of the housing value). Turner et al. (2014) evaluate the own-lot and amenity effects of land use regulation in the U.S.

[2] Note that the benefits of land for home-owners are small, as only 5% of the land is owned by home-owners (see Shrubsole 2019).

[3] More specifically, I use data on geocoded pictures, arguably capturing locational attractiveness. I find that greenbelts do attract fewer, so not more, visitors than nearby areas. Using data on pollution I show that pollution levels are lower in greenbelts, but the effects are confined to greenbelts. Hence, the greenbelts do not seem to contribute directly to the well-being of *non*-local residents. Furthermore, one may argue that greenbelts may be associated with a so-called 'warm-glow value' and/or 'existence value' (Davidson 2013), which are both very hard to measure. When an existence value exists, reductions in greenbelt land will not decrease utility per se as long as some greenbelt land is still there. Also, potential effects of increased biodiversity are not considered in this paper. These are in any case highly contested, at least partly because about one third of greenbelt land is used for (intensive) agriculture.

Own-lot effects appear to be substantial, but they do not find evidence for amenity effects, which makes it plausible that land use regulation has negative welfare consequences in that context.[4]

This paper also relates to a literature measuring local benefits of open space. Some studies have specifically focused on reduced-form house price impacts of greenbelt land. An early study by Correll et al. (1978) reports that properties near greenbelt land are generally more expensive, but the reported effects are unlikely to be causal. Jun (2006) shows no evidence of a significant difference between housing prices inside and outside the UGB, confirming that these areas are part of a single housing market. By contrast, Grimes & Liang (2009) find that land just inside the UGB in Auckland, New Zealand, is valued at approximately 10 times compared to land just outside the boundary, because of better redevelopment opportunities within the urban limit. While these reduced-form estimates show that UGBs are relevant, they do not provide clear implications as to whether greenbelts increase or decrease welfare. Other studies focus explicitly on the measurement of the benefits of open space. Bolitzer & Netusil (2000), for example, find that living close to green space increases property values by maximally 5%, while Irwin (2002) finds that an hectare of farmland in the vicinity increases property values by 0.75%. Anderson & West (2006), however, find that the value of proximity to open space is higher in dense neighbourhoods. Geoghegan (2002) shows that open space dedicated as 'permanent' increases near/by residential land values over three times as much as an equivalent amount of 'developable' open space. This may explain why I find somewhat stronger effects of greenbelt land on house prices, as greenbelt land is non-developable. I note that none of the papers provide general equilibrium effects, such as the effects through commuting and housing supply.

Finally, this paper contributes to a mostly theoretical literature on the effects of urban growth boundaries on commuting – more specifically, whether UGBs can be a second-best policy to reduce congestion externalities. Early papers by Kanemoto (1977), Arnott (1979) and Pines & Sadka (1985) show that a not-too-stringent UGB is a second-best policy to congestion tolls when traffic congestion is unpriced. However, these papers assume that all jobs are exogenously located at one urban centre. Anas & Rhee (2007) show that with cross-commuting, boundaries of any stringency can be inefficient even when tolls shrink cities, as boundaries do little to reduce

[4] Turner et al. (2014) do not present a general equilibrium analysis of supply restrictions, because they focus on the effects of areas close to municipal borders. By contrast, I focus on a situation where land use regulation is ubiquitous, and where general equilibrium effects are expected to be sizeable.

inefficient commuting from the suburb to the city centre. Brueckner (2007) corroborate this conclusion, and find that greenbelts may not be a useful instrument for addressing the distortions caused by unpriced traffic congestion.

The plan for the remainder of the paper is as follows. In Section 2 I explain how greenbelts were designated, introduce the datasets, and provide descriptives. In Section 3 I show reduced-form evidence for the effects of greenbelt land on house prices, dwelling density, and workplace earnings. I also briefly discuss exercises where I investigate recreational visits to greenbelts, proxied by geocoded pictures of residents, and pollution effects. Section 4 outlines the quantitative model. In Section 5 I report the estimated structural parameters and discuss the different counterfactual analyses. Section 6 concludes.

2 Context, data and descriptives

2.1 Greenbelts in England

There is a long-standing tradition in England to restrict urban growth. In the 1920s, proposals were put forward by the London Society and the Campaign to Protect Rural England (CPRE) to prevent development in a continuous belt within 2km of London. In the 1947 Town and Country Planning Act, local authorities (LAs) were for the first time allowed to take planning decisions and to incorporate greenbelt proposals in their development plans.

In 1955, Duncan Sandy, who was then the Minister of Housing, encouraged local authorities around the country to consider protecting land around cities by the formal designation of well-defined greenbelts. In a statement in the House of Commons he wrote:

> "*I am convinced that for the well-being of our people and for the preservation of the countryside, we have a clear duty to do all we can to prevent the further unrestricted sprawl of the great cities. The Development Plans submitted by the local planning authorities for the Home Counties provide for a Green Belt, some 7 to 10 miles deep, all around the built-up area of Greater London. [...]. No further urban expansion is to be allowed within this belt.*"

and:

> "*In other parts of the country, certain planning authorities are endeavouring, by adminis-*

trative action, to restrict further building development around the large urban areas. But I regret that nowhere has any formal Green Belt as yet been proposed. I am accordingly asking all planning authorities [...] to submit to me proposals for the creation of clearly defined Green Belts, wherever this is appropriate."

Greenbelts were eventually introduced in the two decades after 1955 around almost all the big cities (London, Birmingham, Liverpool and Manchester), but also around smaller cities (*e.g.* Bournemouth, York, Oxford and Cambridge). Almost all cities that put forward proposals for greenbelt land had at least a population of 100,000 inhabitants at that time and so qualified as "*large urban areas*". Most proposals were put forward in the late 60s and early 70s, while the final approval and exact demarcation of the greenbelt borders took place in the early 80s.[5] Since the official approval of greenbelts in the early 1980s no new greenbelts have been introduced and the total amount of greenbelt land essentially has not changed in the last 35 years.[6] Currently, greenbelts cover about 13% of *all* land in England (for comparison, built-up land covers about 10%) and should, according to the National Planning Policy Framework in 2012, offer appreciable amenities to the urban population by improving access to the open countryside, by providing opportunities for outdoor sport and recreation, and by retaining attractive landscapes close to urban areas. However, greenbelt land is often used for intensive agriculture, rather than used for recreational and nature purposes, and is therefore unlikely to provide the intended amenity value (Cheshire 2014, Bontemps et al. 2008). My calculations indicate that about one third of greenbelt land is used for agriculture, while only about 7% of the land is classified as accessible open spaces, parks or gardens.[7]

In Figure 1 I show the 14 greenbelts in England. In particular the Metropolitan Greenbelt around London is large, but also greenbelts around Birmingham (West-Midlands) and Manch-

[5] Greater London was the first urban area to discuss implementation of a greenbelt, already before World War II. However, only in the late 1950s greenbelt land around London was officially approved. The greenbelt area increased fivefold in 1965, while in 1971, the government decided to extend the Metropolitan Green Belt to include almost all of Hertfordshire. The Bristol and Bath Green Belt was adopted locally in 1957 and approved in 1966. The North West greenbelt around Manchester, Liverpool and Leeds was considered since the early 1960s, but it took about twenty years for official approval. The same holds for the greenbelt around York: formally created in 1980 after decades of being a local policy since the 1950s, the local development plan defines the greenbelt as being 'about 6 miles from York', in line with the suggestion by Duncan Sandy.

[6] For example, the total hectares of greenbelt land in 1997 was $1,652,310$, while it was $1,638,610$ in 2013, a change of less than 1%, which may as well be due to measurement error.

[7] In the empirical analysis I will therefore include specifications where I make a distinction between accessible vs. non-accessible and agricultural vs. non-agricultural greenbelt land.

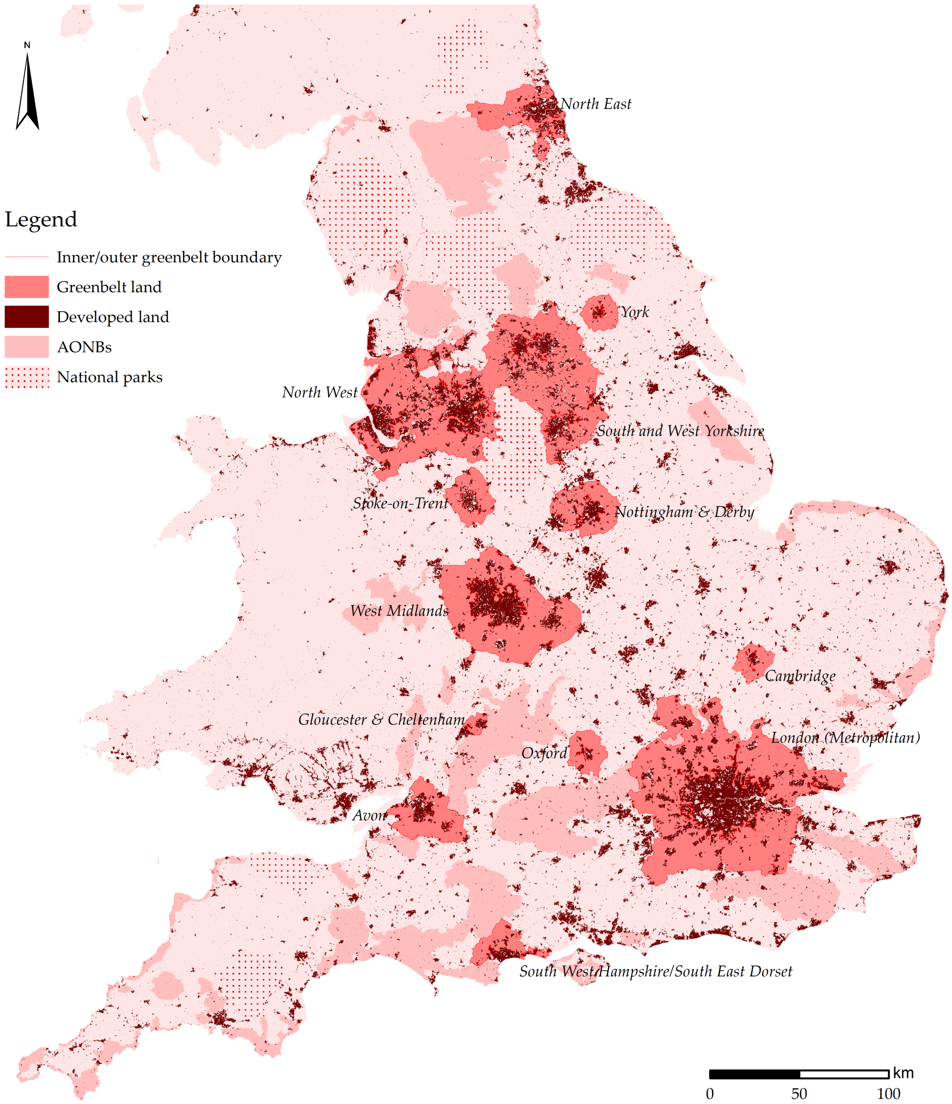
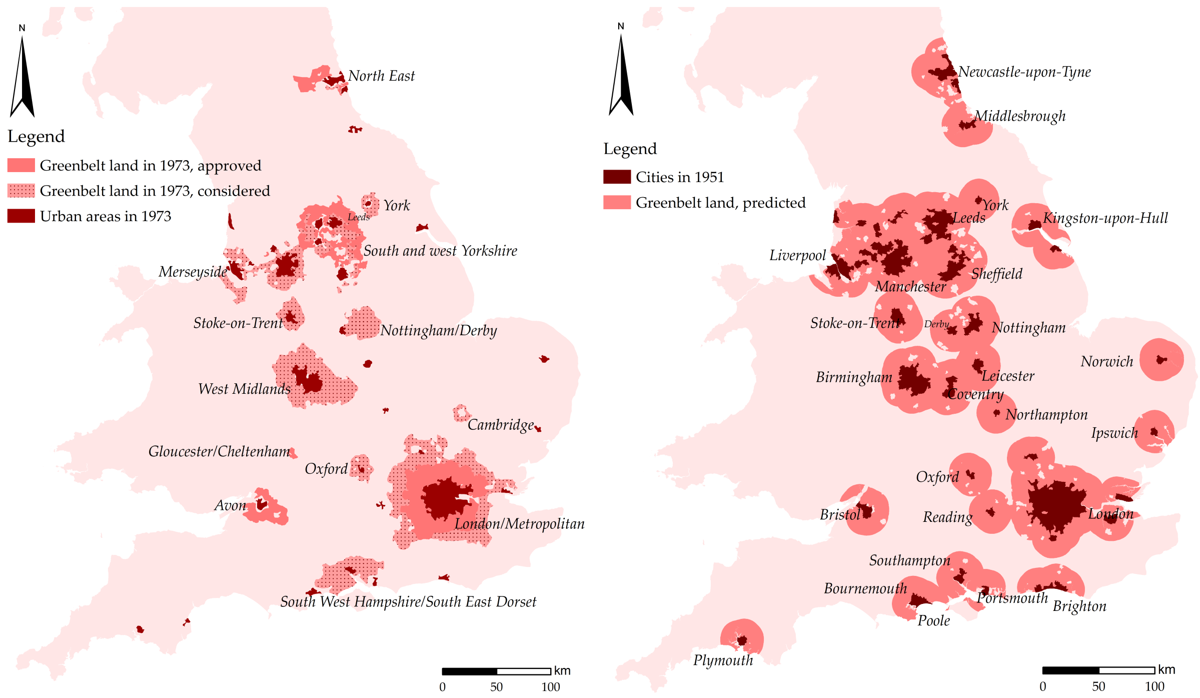


Figure 1 – Greenbelts in England

ester/Liverpool (North-West) are substantial. Note that development still occurred in greenbelts, as some places were already inhabited before the introduction of the greenbelt. Hence, people can live on designated greenbelt land. Figure 1 also displays national parks and Areas of Outstanding Natural Beauty (AONBs) (both of which do not overlap with greenbelts). It is likely that in those areas new development is also restricted. However, because those areas are usually in rural low-density areas, the welfare effects are expected to be an order of magnitude smaller.

Greenbelt land in 1973. In the empirical analysis I will use greenbelt land in earlier times, *i.e.* 1973, to identify amenity and supply effects. In Figure 2a I show approved and proposed greenbelt land in 1973. The approved greenbelts are around London, Bristol, Leeds, Bradford



(A) Greenbelts in 1973 (B) Counterfactual greenbelts

Figure 2 – Considered, approved and counterfactual greenbelts

and Newcastle. Most of the approved and proposed greenbelts are very similar to the current ones as can be seen in Figure 1. Although not officially approved until the early 1980s, the stringent building regulations typically already applied to the proposed greenbelt land. The correlation between the current share of greenbelt land and the share of approved and proposed greenbelt land in 1973 at the MSOA level is indeed reasonably high ($\rho = 0.622$). The most notable exception of considered greenbelt land that has not been granted eventually is a large area around Southampton. Part of that area is now the New Forest National Park.

Counterfactual greenbelts. I aim to construct counterfactual greenbelts so that I can compare amenities and productivity between actual and counterfactual greenbelts. Areas with counterfactual greenbelt land should then be similar in observables and unobservables to areas with greenbelt land. To construct counterfactual greenbelts I gather data on the population in parishes in 1951, which was just after the 1947 Town and Country Planning Act was implemented, but before greenbelt policies were introduced.[8] To identify urban areas I first select parishes with a population density of at least 10 people per ha in 1951, which applies to about 5% of

[8]Parishes are quite small. The median size is 847 hectares.

the areas. The next step is to amalgamate areas that are adjacent to each other and keep 37 amalgamated areas that have a population of more than 100 thousand. Recall that greenbelts were predominantly implemented around larger cities of at least 100 thousand inhabitants. Then I draw circles of 15km around each of these urban areas but exclude parishes in counterfactual greenbelts with a density of at least 10 persons per ha as these are areas that were already built up.[9]

In Figure 2b I display a map showing the counterfactual greenbelts. At the MSOA level, the correlation between the share of greenbelt land and the share of counterfactual greenbelt land is reasonably high and about 0.458. In general, I am able to predict the location of most greenbelts quite well, such as the greenbelts around London, Birmingham, Manchester and Liverpool. For example, in MSOAs with a share of greenbelt land above 90% the share of counterfactual greenbelt land is about 0.9. Only the Cheltenham/Gloucester greenbelt, as well as the greenbelt around Cambridge are not included in the counterfactual greenbelt sample because those cities had a population lower than $100,000$ in 1951. On the other hand, reasonably large cities such as Leicester, Norwich, Middlesbrough and Plymouth do not have greenbelts, although one would expect a greenbelt around those cities based on the 1951 population distribution.

2.2 Data

2.2.1 Micro-data

I make use of three datasets. The first dataset contains the universe of housing transactions from England from the *Land Registry* between 1995 and 2017. These data provide information on the transaction price as well as the housing type, the date of the transaction and the ownership structure (leasehold or freehold). A disadvantage of the Land Registry data is the limited amount of information on housing characteristics, most importantly the size of the property and house type.

I therefore merge the *Land Registry* data to additional characteristics using data on *Energy Performance Certificates* (EPCs). Since 2007 an EPC has been required whenever a home is constructed or sold. The dataset contains all EPCs issued since October 1, 2008. The data provide information of the energy performance of buildings and their characteristics that are

[9] For a more detailed description of the procedure I refer to Appendix A.1.

obtained by a physical inspection of the interior and exterior of the home by an independent assessor. This provides us with the floor area of the property, number of rooms, as well as the energy performance.

My merging strategy is to sequentially match individual sales to the EPC data using the full address or a subset of the address and the date of the sale and certificate.[10] About one third of the sales in the *Land Registry* remains unmatched, so I drop them from the analysis. I also drop transactions that are matched to multiple EPCs (about 15%).[11]

Information on greenbelts in 2012 is obtained from the *Department of Communities and Local Governments* (DCLG). Each local authority digitised land use information and DCLG merged these separate datasets. I aim to identify internal, external and supply effects using the boundaries of greenbelts, as these capture the actual urban containment boundaries. Hence, I determine the inner and outer boundaries and calculate the distance of each property to the nearest inner or outer boundary of a greenbelt.

I further gather data from *Ordnance Survey* (OS) on parks and green spaces. From the *Land Cover* dataset I obtain information on agricultural land and developed land in each postcode.

I drop observations of prices that are above £1.5 million or below £15,000 (less than 0.5% of the data). Because greenbelt boundaries have hardly changed between 1995 and 2017, matching greenbelt data from 2012 to transactions in the past will imply little measurement error. Moreover, although EPC data is available from 2008 onwards, I still match transactions from the Land Registry from before 2008 to EPC, thereby assuming that housing characteristics do not change. Hence, I use the full temporal extent of the data (1995-2017).[12] This leaves us with $10,210,717$ sales.

[10]Specifically, I first match a sale to an EPC using the primary address object name, secondary address object name, street name, and postcode. I then keep the certificate that is closest in days to the sale. I repeat this exercise for unmatched properties but allowing one of the address identifiers to be different. The final round of matching matches on the full postcode.

[11]The matching is harder for flats that often share an address, implying that the proportion of flats is reduced from 23% in the *Land Registry* sample to 3% in the final sample. My analysis therefore mainly focuses on single-family homes. One may be concerned that this implies sample selection. However, if I calculate floor space prices at the MSOA prices using the full Land Registry dataset and using the matched dataset, the correlation is 0.988.

[12]To make sure that measurement error in greenbelt land does not thwart my results, I also estimate regressions where I only include observations from 2012, which does not change the results (see Appendix B.1 for more details).

2.2.2 MSOA data

For the structural model I use data at the Middle-Layer Super Output Area. To obtain floor space prices I use the above sales data from the *Land Registry* and *EPCs* and regress log prices per square metre on housing characteristics and MSOA fixed effects. I obtain floor space prices by taking the exponent of the estimated fixed effects.[13] In the structural estimation I normalise floor space prices to have a geometric mean of 1.

Furthermore, for each MSOA I calculate the share of greenbelt land in the postcode, as well as the share in counterfactual greenbelts. For each centroid of a MSOA I calculate the distance to the nearest inner or outer greenbelt boundary.

From the 2011 census I obtain commuting flows between each of the $6,791$ MSOAs, which means that I have $46,117,681$ cells containing information on the number of workers commuting from home to work. Using this information I also calculate the total number or workers and (employed) residents in each area. From *Ordnance Survey* I obtain information on the road network in 2012. That is, I keep motorways, A-roads and B-roads for which I assume free-flow travel speeds of 110, 80 and 50km/h.[14] Using this network data I calculate free-flow travel times between each MSOA pair. To obtain actual travel times I obtain data on average speeds on major roads from the *Department of Transport* at the county level in 2015. Because counties are much smaller in urban areas, this will provide a reasonable proxy for actual speeds. I then match each road to the county in which it is and calculate actual travel times between each MSOA pair.[15]

2.2.3 Other data

To construct instruments for agglomeration, to be discussed later on, I gather data on historic population at the parish level for 1931. There were 11,450 Parishes in 1931 (these are usually

[13] The results of this regression are available upon request. Housing characteristics included in the regression are the log of house size, house type (*i.e.* terraced, semi-detached or detached), a dummy indicating whether the house is newly built, the number of rooms, the number of habitable rooms, the floor level (if it is an apartment), the height of the average floors, number of floors of the building, whether the property has a fireplace, and the quality of the windows, the roof, walls and overall energy efficiency. I also include a dummy indicating whether the property is freehold. All the coefficients have the expected signs and magnitudes.

[14] The average speed on motorways is obtained from `statista.com`.

[15] One may argue that I do not take into account different travel modes. While this may be realistic, it will further add to the complexity of the model. Not taking into account other travel models essentially implies a measurement error in travel times because some workers face different travel times given their mode choice. In the commuting gravity model, I will therefore instrument travel time by Euclidian distance, which is likely uncorrelated to the travel model. I show that the travel time elasticity is essentially unaffected.

considerably smaller than MSOAs and parliamentary constituencies). For each MSOA and constituency I calculate the share in each parish. I then assume that population is uniformly distributed within each parish by multiplying the share of each MSOA/constituency in each parish by the parish population.

For the structural estimation I further rely on information on historic travel times, in order to calculate historic travel times between MSOA pairs. I obtain data on railway networks from Garcia-López et al. (2015) on England's railway network in 1870. Assuming a speed of 50km/h I calculate travel time in minutes between each MSOA. I also gather data on developed land and soil characteristics. I refer to Appendix A.2 for more details.

For additional tests of the effects of greenbelt land and agglomeration economies on workplace earnings, I rely on data from the *Annual Hours of Survey and Earnings* on workplace statistics from the 2011 census. The lowest level the workplace earnings are available is at the parliamentary constituency level of which there are 533 in England.[16]

2.3 Descriptive statistics

Panel A in Table 1 reports descriptive statistics for the housing transactions data. On average 3.6% of the transactions are in a greenbelt. I show that the average price per m^2 of floor space is £1753 and the average floor size is $87m^2$. In greenbelts this is respectively £2057 and $91m^2$. Hence, houses in greenbelts are, on average, similar in size to other homes but a bit more expensive. The highest share of the properties are terraced properties (41%), as opposed to flats, semi-detached or detached properties. The average distance to the nearest greenbelt boundary is 16km. About one-third to one-fifth of the transactions take place within respectively 2.5 and 1km of a greenbelt border. So, a substantial share of homes are within walking distance from a greenbelt.

I also report descriptive statistics at the postcode level in Panel B in Table 1. On average, 6% of the land is greenbelt land. I observe on average 17 (the median is 13) dwellings in a postcode. The median size of a postcode is only 0.93 hectares.[17] In my sample 72% of land in postcodes is developed, which is much higher than the overall share of developed land (8.7% in England), because postcodes in urban areas are much smaller and therefore overrepresented. The share of

[16] For 4 observations I have missing data, so I exclude them from the analysis.

[17] Postcode are on average 10 hectares due to a few very large postcode.

Table 1 – Key descriptive statistics for micro-data

Panel A: Descriptives for house prices	(1) mean	(2) sd	(3) min	(4) max
Price per m^2	1,753.6450	1,268.0780	100.0000	10,000.0000
Size of the property in m^2	87.4042	31.6240	25.0000	250.0000
Share land in greenbelt	0.0361	0.1635	0.0000	1.0000
Share greenbelt land <500m	0.0853	0.1903	0.0000	1.0000
Distance to nearest greenbelt boundary *(km)*	16.4308	29.2519	0.0000	296.8268
Housing type – flat	0.0318	0.1756	0.0000	1.0000
Housing type – terraced	0.4127	0.4923	0.0000	1.0000
Share of developed land	0.8327	0.3044	0.0000	1.0000
Distance to the nearest city centre *(km)*	35.7984	33.4864	0.0802	313.6746
Panel B: Descriptives for postcode data	**(1) mean**	**(2) sd**	**(3) min**	**(4) max**
Number of dwellings	16.5550	14.9631	0.0000	646.0000
Area size of postcode *(ha)*	10.1194	50.6929	0.0010	7,826.5098
Share land in greenbelt	0.0624	0.2256	0.0000	1.0000
Distance to nearest greenbelt boundary *(km)*	18.6108	32.3029	0.0000	298.6461
Share of developed land	0.7218	0.3969	0.0000	1.0000
Distance to the nearest city centre *(km)*	37.4973	36.2033	0.0000	316.2100

Notes: The number of observations for house prices is $10,070,791$. For the postcode data, the number of observations is $1,446,902$.

developed land in greenbelts is only 5.6%, but definitely not zero.

I also report descriptive statistics for MSOAs in Table 1. England's total working population is $25,087,843$. The average population density is 15.6 persons per hectare. There is a very high correlation to dwelling density ($\rho = 0.980$). The floor space price is, on average, £$2,154$, but there is considerable variation. [18] Floor space price is also strongly positively correlated with density; the correlations with population density and worker density are respectively 0.331 and 0.489.

The share of greenbelt land in an MSOA is, on average, 0.152. This is higher than for postcodes, because postcodes are much smaller in cities. The correlation of historic population density with current densities is quite high: it is 0.691 for current population density and 0.378 for current working density.

3 Reduced-form results

In this section my aim is to show that greenbelt land have two major direct effects. First, it reduces the amount of land available for development and therefore lead to locally lower densities.

[18] The highest floor space can be found in London in the borough of Kensington-Chelsea.

Table 2 – Key descriptive statistics for MSOAs

	(1) mean	(2) sd	(3) min	(4) max
Population density *(per ha)*	15.5898	16.9580	0.0226	157.6159
Worker density *(per ha)*	14.9930	44.8514	0.0151	1,384.1327
Dwelling density *(per ha)*	13.4443	14.3000	0.0253	133.5981
Floor space price *(£per m^2)*	2,154.4578	1,197.6688	606.0063	12,336.7354
Share greenbelt land	0.1520	0.2715	0.0000	1.0000
Share counterfactual greenbelt land	0.2655	0.4022	0.0000	1.0000
Share land in proposed greenbelt	0.0802	0.2237	0.0000	1.0000
Distance to greenbelt boundary *(km)*	15.9403	29.1292	0.0003	295.3026
Distance to the nearest city centre *(km)*	34.0292	33.4134	0.0716	312.0949
Population in 1931 *(per ha)*	20.3612	39.5060	0.0000	354.7298

Notes: The number of MSOAs is $6,701$.

Second, it creates an amenity effect, leading locally to higher house prices. I will also consider three city-wide effects. Most importantly, I consider agglomeration effects of greenbelts, and two effects not considered in the general equilibrium model: recreational visits and air pollution.

3.1 Supply effects and housing density

3.1.1 Methodology

First, I am interested to what extent greenbelts limit development – in other words, to what extent the greenbelt policy is binding. Let us define d_i as the number of dwellings in postcode i and g_i is the share of greenbelt land in the postcode. As the size of (postcode) areas differ I control for the size of the area L_i, so the effect of g_i can be interpreted as the effect on *housing density*. Note that d_i is a positive count variable, but can be zero. I therefore use Poisson-Pseudo Maximum Likelihood to estimate:

$$d_i = \mathrm{e}^{\eta_1 g_i + \eta_2 \log L_i + \eta_3 m_i + \varsigma_{i\in\mathcal{A}} + \epsilon_i}, \tag{1}$$

where m_i are control variables, such as the distance to the city centre. η_1 is the coefficient of interest, η_2 and η_3 are other coefficients to be estimated, and $\varsigma_{i\in\mathcal{A}}$ denote local authority fixed effects

A concern with the above specification is that greenbelts are not randomly distributed over space, as greenbelt land can be found at the outskirts of cities and this may not be captured well by distance to the city centre. I then consider three identification strategies to identify the causal density effect. For the first identification strategy, I estimate weighted regressions with weights based on the share of land in the postcode in a counterfactual greenbelt. Hence, I compare postcodes inside actual greenbelts to postcodes inside areas where you would expect greenbelts based on the 1951 distribution of the population. A concern is that the latter areas are still different in unobservables.

For the second identification strategy I use data on approved and proposed greenbelt land in 1973. These areas are likely similar in unobservables. In the regression analysis I therefore estimate weighted regressions with weights based on the share in approved and proposed greenbelts in 1973.

As a third identification strategy I rely on spatial differencing. That is, I only include postcodes very close to a greenbelt border (*e.g.* within 1km), while controlling flexibly for *distance to the city centre*. The latter controls for the issue that greenbelt borders are near the urban fringe (where commutes are longer and density is generally lower).

3.1.2 Results

The results are reported in Table 3. In column (1) I include all postcodes and only control for postcode area size. It is shown that when the share of greenbelt land in a postcode is higher the number of dwellings is substantially lower. The coefficient implies that when the whole postcode area is in a greenbelt, the number of dwellings change by $e^{-0.466} - 1 = -37\%$. When I add distance to the city centre controls and local authority fixed effects, the reduction in dwellings is 48% (column (2)).

Column (3) further improves on identification by only including postcodes in counterfactual greenbelts. The reduction in dwellings is then 53%. The effect is considerably stronger once I focus on postcodes in approved and proposed greenbelts in 1973, as shown in Figure 2a, in column (4). More specifically, I only include observations in proposed or approved greenbelts in 1973. Columns (5) and (6) rely on spatial differencing. I find that postcodes in dwellings have about 60% fewer dwellings.

These reduced-form results confirm that the density of development is strongly affected by greenbelt policy with estimates that vary between 37% and 70%. However, it is still important to realise that the reduction is far from 100%; hence there are still (residential) buildings in a

Table 3 – Supply effects of greenbelts: effects on dwellings
(Dependent variable: the number of dwellings in a postcode)

	(1) Poisson	(2) Poisson	(3) Poisson	(4) Poisson	(5) Poisson	(6) Poisson
		+ Controls and fixed effects	Counterfactual greenbelts	Greenbelts in 1973	Greenbelt border <2.5km	Greenbelt border <1km
Share greenbelt land	-0.4661***	-0.6535***	-0.7560***	-1.1719***	-0.9440***	-0.9327***
	(0.0159)	(0.0142)	(0.0198)	(0.0255)	(0.0188)	(0.0189)
Area size of postcode *(log)*	0.0486***	0.1105***	0.1242***	0.2726***	0.2213***	0.2267***
	(0.0034)	(0.0026)	(0.0043)	(0.0070)	(0.0047)	(0.0051)
Location attributes	No	Yes	Yes	Yes	Yes	Yes
Local authority fixed effects	No	Yes	Yes	Yes	Yes	Yes
Number of observations	1,310,750	1,310,750	331,172	250,673	445,580	255,861
Log pseudo-likelihood	-11,099,109	-10,378,591	-2,445,062	-1,720,837	-3,296,865	-1,853,354

Notes: Location attributes refer to a linear, squared and cubic term of distance to the nearest city centre. In column (3) I only include observations that are in counterfactual greenbelts as defined in Section 2.1. Column (4) includes observations in areas that are in greenbelts that were approved or considered in 1973. In columns (5) and (6) I include transactions that are within 2.5km or 1km of a greenbelt boundary respectively. Standard errors are clustered at the MSOA level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

greenbelt, albeit in a much lower density.[19]

3.2 Amenity effects and house prices

3.2.1 Methodology

I estimate the local amenity effects of greenbelt policy using information on house prices. Let p_{it} be the house price in postcode i in year t and $\tilde{g}_i$ be the share of greenbelt land within 500m. One may argue that the amount of greenbelt land in the vicinity is correlated to housing attributes; houses with particular characteristics may be predominantly located in greenbelts. For example, because of historic city limits, properties in greenbelts may be disproportionally detached, while houses outside greenbelts may come more often in the form of apartments or terraced housing. To mitigate this problem I include (time-invariant) housing characteristics, denoted by c_i.

To control for unobservable locational attributes and for aggregate housing supply effects, I include local authority $\mathcal{A}$ fixed effects $\rho_{i\in\mathcal{A}}$. These fixed effects aim to capture time-invariant unobserved characteristics that could be correlated to the share of greenbelt land, such as overall accessibility of the area and provision of public goods. Moreover, they absorb price-increasing effects due to a limited supply of land in housing markets with lots of greenbelt land. I further

[19] The more convincing identification strategies (columns (4)-(6)) show larger supply effects. The reason is that if I compare greenbelts to other low-density areas in England (say in columns (1) and (2)), the supply effect of greenbelts is limited. However, if I use a control group of areas that are similar and geographically close, the effect is stronger because I compare areas that are just part of cities to areas that are restricted by greenbelts. This identifies arguably the 'true' supply effect of greenbelts.

control flexibly for distance to the nearest city centre of a city with at least 100,000 inhabitants. Let m_i then be a polynomial of distance to the city centre. Hence:

$$\log p_{it} = \zeta_1 \tilde{g}_i + \zeta_2 c_i + \zeta_3 m_i + \rho_{i\in\mathcal{A}} + \rho_t + \tilde{\epsilon}_{it}, \tag{2}$$

where ρ_t are year fixed effects and $\tilde{\epsilon}_{it}$ is an error term. To further address omitted variable bias I employ the same identification strategies as applied to measure the supply effect.

3.2.2 Results

In Table 4, I report the reduced-form amenity effects of greenbelts by looking at house prices. In column (1) I estimate a naive specification of having greenbelt land in the vicinity on house prices. I find that there is a strong effect of greenbelt land on house prices: a 10 percentage point increase in the share of greenbelt land increases prices by 2.4%. This is in line with papers finding an amenity effect of open space; greenbelts ensure that houses are closer to open space, which may generate positive benefits (see *e.g.* Irwin 2002, Anderson & West 2006, Brander & Koetse 2011). However, because I do not control for local authority fixed effects, the higher price might as well be due to a limited supply of land available for housing. In column (2) I include a wide range of housing attributes, I control flexibly for the distance to the nearest city centre, and, importantly, I include local authority fixed effects. The latter implies that I identify the amenity effect *within* housing markets. This has limited repercussions for the effect I find, as the coefficient is very similar to the previous specification.

In column (3) I improve on identification by only including observations in counterfactual greenbelts to counter the argument that greenbelts may be located mostly on the urban fringe. Those locations may have different characteristics in terms of demographic composition or type of housing provided. Although the number of observations now is reduced by more than 75%, the coefficient again is very similar.

Column (4) uses information on proposed and approved greenbelts. The impact of greenbelt land is still essentially the same: a 10 percentage point increase in the share of greenbelt land in the vicinity increases prices by 1.6%.

In the final two columns of Table 4 I focus on observations close to inner or outer greenbelt borders. In column (5) I include observations within 2.5km of a greenbelt border. This implies

Table 4 – Amenity effects of greenbelts: effects on house prices
(Dependent variable: the log of house price per m^2)

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) OLS	(6) OLS
		+ Controls and fixed effects	Counterfactual greenbelts	Greenbelts in 1973	Greenbelt border <2.5km	Greenbelt border <1km
Share greenbelt land 0-500m	0.2351***	0.2175***	0.1895***	0.1619***	0.1884***	0.1631***
	(0.0194)	(0.0097)	(0.0119)	(0.0123)	(0.0112)	(0.0118)
Housing and location attributes	No	Yes	Yes	Yes	Yes	Yes
Local authority fixed effects	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	10,070,791	10,070,791	2,394,057	1,952,693	3,763,739	2,172,516
R^2	0.3778	0.7763	0.7899	0.7911	0.7671	0.7680

Notes: Housing attributes include the log of house size, housing type dummies (flat, terraced, semi-detached, detached), the number of rooms and the number of habitable rooms, an indicator for newly built properties, the floor level of the property, the height of the property, the number of stories of the building, whether the property has a fire place, whether the property is freehold and variables capturing the energy efficiency of windows, roof, walls. Location attributes a linear, squared and cubic term of distance to the nearest city centre. In column (3) I only include observations that are in counterfactual greenbelts as defined in Section 2.1. Column (4) includes observations in areas that are in greenbelts that were approved or considered in 1973. In columns (5) and (6) I include transactions that are within 2.5km or 1km of a greenbelt boundary respectively. Standard errors are clustered at the MSOA level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

that I still include about one-third of the total number of observations. The coefficient again is very similar. Reducing the threshold distance to merely 1km does not materially change the results either.[20]

Hence, these reduced-form regressions show a strong positive amenity effect of greenbelt land. I have explored this further in a couple of sensitivity analyses reported in Appendix B.1. More specifically, one may argue that the benefits of greenbelt land may extend beyond 500m. I test this by including the share of greenbelt land within 500-1000m, 1000-1500m, 1500-2000m and 2000-2500m. I do not find statistically significant evidence that there are any effects beyond 500m. This specifically holds for the more convincing identification strategies based on spatial differencing.

One may be concerned that the effects of greenbelts partly capture a sorting effect, which would mean that households with price-increasing characteristics end up in the greenbelt (see Bayer et al. 2007). To test for sorting effects and other omitted variables I include output area (OA) fixed effects, which are very small areas and the lowest geographical level at which census

[20]The more convincing identification strategies (columns (4)-(6)) show smaller price effects. The reason is that if I compare greenbelts to other low-density areas in England (say in columns (1) and (2)), these areas may have otherwise lower house prices. However, if I use a control group consisting of areas that are similar and geographically close, the effect is stronger because I *e.g.* compare areas that are just part of cities to areas that are restricted by greenbelts. This identifies the local amenity effect of greenbelts.

estimates are provided (the median size of an OA is only 6.6ha). I find that the amenity effect of greenbelts is about the same, which strongly suggests that what I capture here is a direct amenity effect, rather than a sorting effect due to greenbelts.

I further make a distinction between 'accessible' and 'inaccessible' greenbelt land (*i.e.* parks and public spaces are an example of accessible greenbelt land, while agricultural land is typically inaccessible). I do not find consistent evidence that accessible greenbelt land offers a higher amenity value. I also make a distinction between agricultural and non-agricultural greenbelt land. The effect for agricultural greenbelt land is substantially stronger. This may seem surprising as households are unlikely to value intensive livestock farming that generates negative externalities (Bontemps et al. 2008). However, it may be that agricultural land is usually 'open' land, which may be valued higher by households than *e.g.* forested land (Irwin 2002, Montgomery 2015, pp. 114-115).

Finally, as the structural estimation results will mostly rely on census data from 2011 and the greenbelt data from 2012, I also re-estimate the preferred specifications for 2012 only, leading to essentially the same results.

3.3 City-wide reduced-form effects: agglomeration economies, recreation and pollution

One may argue that city-wide effects of greenbelts are potentially important. I consider arguably the most important ones: *(i)* agglomeration economies, *(ii)* recreational visits and *(iii)* reductions in air pollution.

If agglomeration economies are important, because densities are lower due to greenbelt policies, this may reduce productivity.[21] I test this in Appendix B.2 by investigating the effects of greenbelt land and employment density on wages. To mitigate the issue that employment density captures unobserved locational endowments rather than agglomeration economies, I first employ the standard strategy to instrument for agglomeration externalities. That is, I use population in 1931 (see *e.g.* Ciccone & Hall 1996, Combes et al. 2008). The identifying assumption when using historic data is that the unobserved reasons why people cluster in the past are uncorrelated to the current ones. This assumption may not exactly hold, *e.g.* because locations that offer

[21] On the other hand, this effect may be reversed because workers may be more productive when they are in areas with a lot of green space, *e.g.* because of lower congestion and pollution levels and positive health effects (see *e.g.* Graff Zivin & Neidell 2012, Montgomery 2015, pp. 103-125).

amenities in the past also do this today. I therefore show results using a methodology introduced by Conley et al. (2012) to allow for a 'plausibly exogenous' instrument, implying that correlation of the instrument with the error term is allowed. I show that the estimated effect is robust even with a substantial relaxation of the exclusion restriction (*e.g.* by assuming that 50% of the effect of historic density has a direct effect on earnings). I also consider an alternative identification strategy following an insight by Bayer & Timmins (2007). They argue that the "*fixed attributes of other locations [...] make ideal instruments for the share of individuals that choose a location*". More specifically, conditional on the share of greenbelt land in the own MSOA and given that direct amenity effects of greenbelts are (very) local I use the share of greenbelt land between 10 and 25km. The identifying assumption is then that the share of greenbelt land between 10-25km does not generate direct productivity effects other than via the effects on the spatial equilibrium of workers choosing each location. This leads to very similar results.

I find that agglomeration economies matter; the elasticity is about 0.02, which is in line with the previous literature (see Combes et al. 2008, Melo et al. 2009). The results are largely robust across different identification strategies and using different instruments. I do not find robust evidence for productive amenity effects, which would imply that conditional on employment density wages would be higher.

One may argue that the benefits of greenbelts may extend beyond 1km, for example because people may visit greenbelts to recreate, which would be in line with one of the intended goals of greenbelt policy ("*improving access to the open countryside, by providing opportunities for outdoor sport and recreation*"). If this is the case, also households further away from a greenbelt may appreciate greenbelt land and the estimate of the external effect may be an underestimate. However, these less localised effects are arguably difficult to capture by looking at (local) house price differentials. I propose another approach to test whether these effects are important. I exploit data on about 10 million geocoded pictures from *FlickR*, an online image hosting service, between 2000 and 2017. I expect locations that offer aesthetic amenities will have more visits by locals and tourists and therefore a higher picture density.[22] I address some issues with the data (see Appendix B.3 for more details). Since I have information on users' identifiers, I can

[22]Indeed, Ahlfeldt (2016) show that there is a strong positive correlation between picture density and historic and geographic amenities, such as access to open water or open space.

distinguish between residents' and tourists' pictures by keeping users who take pictures for at least 6 consecutive months between 2004 and 2017 in England. It seems unlikely that tourists stay for 6 consecutive months in England.[23] The results reported in Appendix B.3 show that, when controlling for dwelling density, the picture density is *lower* in greenbelts. The result indicate that there are 25-50% fewer pictures made by residents inside greenbelts. These results indicate that greenbelts are unlikely to be main recreation destinations and, hence, support the finding that external effects of greenbelts are local.

Another critique could be that greenbelts 'absorb' pollution from cities and therefore lead to lower pollution levels in cities with a greenbelt. I test this by exploiting data on concentrations of particulate matter (PM_{10}) and nitrogen oxides (NO_{x}). I show in Appendix B.4 that areas with more greenbelt land do seem to have lower pollution levels. However, I find that the effect is confined to the own MSOA. This implies that pollution reductions of greenbelts are quite local and do not seem to imply lower pollution levels throughout the city.

4 Structural model

In this section I introduce a structural model to analyse the general equilibrium effects of greenbelt policy. I adapt the model of Ahlfeldt et al. (2015) and embed land use restrictions as implied by greenbelts into the model. I take into account changes in commuting costs, positive amenity effects of greenbelts, as well as changes in residential externalities and agglomeration economies due to greenbelts. I improve on their model in four ways. First, I embed land use restrictions in the model, as greenbelt land reduces the density for development at certain locations (see Section 3.1). Second, I allow for greenbelts to generate a higher amenity level; hence, I explicitly specify the amenity residual in Ahlfeldt et al. (2015) (see Section 3.2). Third, I estimate, rather than calibrate, the share of land in construction costs, which is critical in determining the effect of greenbelts on construction and floor space prices. Fourth, I allow for endogenous travel times, *i.e.* for traffic congestion at the workplace.

4.1 Workers and amenities

There are $i = 1, ..., \mathcal{L}$ locations in the city, each with land area L_i. Land may be used for residential purposes and/or production. A worker z that lives in i and commutes to j has

[23] The correlation between tourists' and natives' pictures is 0.748.

preferences over a consumption good c_{ijz} and residential floor space ℓ_{ijz}. The worker also has an idiosyncratic preference for pair ij, denoted by ξ_{ijz}.[24] The idiosyncratic component of utility is revealed before making the decision to locate somewhere in England. I assume that utility is Cobb-Douglas:

$$U_{ijz} = \Psi_i \Big(\frac{c_{ijz}}{\beta}\Big)^{\beta} \Big(\frac{\ell_{ijz}}{1-\beta}\Big)^{1-\beta} \xi_{ijz}, \tag{3}$$

where Ψ_i is the given amenity level of a location and preferences for the consumption good $0 < \beta < 1$. The idiosyncratic component is drawn from a Fréchet distribution, so that $F(\xi_{ijz}) = \mathrm{e}^{-\bar{\nu}_i \bar{\upsilon}_j \xi_{ijz}^{-\varepsilon}}$, where $\bar{\nu}_i$ and $\bar{\upsilon}_j$ denote the average utility of living in i and working in j respectively, and $\varepsilon > 1$ governs the amount of commuting heterogeneity. Note that a higher value of ε implies a smaller dispersion of wages.

Workers earn a wage w_j at their workplace j. They have to commute to work, which implies a loss in the net wage. More specifically, the workers budget constraint is given by $\mathrm{e}^{-\kappa\tau_{ij}} w_j = p_i \ell_{ijz} + c_{ijz}$, where $\mathrm{e}^{-\kappa\tau_{ij}}$ represents iceberg commuting costs, τ_{ij} is the travel time between location i and j, and p_i is the price per unit of floor space.

The indirect utility is then given by $u_{ijz} = \Psi_i \mathrm{e}^{-\kappa\tau_{ij}} w_j p_i^{\beta-1} \xi_{ijz}$. Given the Fréchet distribution of ξ_{ijz} I can determine the probability that a worker chooses to reside in i and work in j:

$$\pi_{ij} = \frac{\bar{\nu}_i \bar{\upsilon}_j \left(\frac{\Psi_i \mathrm{e}^{-\kappa\tau_{ij}} w_j}{p_i^{1-\beta}} \right)^{\varepsilon}}{\sum_{r=1}^{\mathcal{L}} \sum_{s=1}^{\mathcal{L}} \bar{\nu}_r \bar{\upsilon}_s \left(\frac{\Psi_r \mathrm{e}^{-\kappa\tau_{rs}} w_s}{p_r^{1-\beta}} \right)^{\varepsilon}}. \tag{4}$$

I define 'transformed' wages as $\omega_j = \bar{\upsilon}_j w_j^{\varepsilon}$. The probability that a worker is employed in j, *conditional* on living in i, is given by:

$$\pi_{ij|i} = \frac{\mathrm{e}^{-\kappa\varepsilon\tau_{ij}} \omega_j}{\sum_{s=1}^{\mathcal{L}} \mathrm{e}^{-\kappa\varepsilon\tau_{is}} \omega_s}. \tag{5}$$

Note that I observe the number of workers in the data, H_{Mj}, as well as the number of households living at i, H_{Ri}. Given the above probability I can define the *commuting market clearing*

[24] Other than heterogeneity through idiosyncratic preferences I abstract from heterogeneity in *e.g.* income, as in Gaigné et al. (2018) or Tsivanidis (2020). In principle, allowing for heterogeneity is possible but would render the analysis considerably more complicated.

condition:

$$H_{Mj} = \sum_{i=1}^{\mathcal{L}} \pi_{ij|i} H_{Ri}, \tag{6}$$

which implies that the number of workers in j is the sum over the residential population multiplied by the probability that they commute to j.

The total residential floor consumption F_{Ri} at i is obtained by summing the floor space demand over all workers in a location:

$$F_{Ri} = \frac{(1-\beta)\sum_{j=1}^{\mathcal{L}} \pi_{ij|i} \mathrm{e}^{-\kappa\tau_{ij}} w_j}{p_i} H_{Ri}. \tag{7}$$

I assume that workers obtain expected utility equal to a reservation utility $\bar{u}$ which is the same for everyone. Moving is costless and population mobility implies that:

$$\bar{u} = \mathbb{E}[u] = \Gamma\Big(\frac{\varepsilon-1}{\varepsilon}\Big)\left(\sum_{i=1}^{\mathcal{L}}\sum_{j=1}^{\mathcal{L}} \bar{\nu}_i \bar{\upsilon}_j \Big(\frac{\Psi_i \mathrm{e}^{-\kappa\tau_{ij}} w_j}{p_i^{1-\beta}}\Big)^{\varepsilon}\right)^{\frac{1}{\varepsilon}}, \tag{8}$$

where $\Gamma(\cdot)$ is the Gamma function.

Using (8), Ahlfeldt et al. (2015) show that one can determine the level of residential amenities (up to a normalization). I can write:

$$\frac{\tilde{\Psi}_i \Gamma\big(\frac{\varepsilon-1}{\varepsilon}\big)}{\bar{u}} = \Big(\frac{H_{Ri}}{\bar{H}}\Big)^{1/\varepsilon} \frac{p_i^{1-\beta}}{W_i^{1/\varepsilon}}, \tag{9}$$

where $\tilde{\Psi}_i = \Psi_i/(\prod_j^{\mathcal{L}} \Psi_j)^{1/\mathcal{L}}$. Hence, the $\sim$ indicates that I normalise variables by dividing them by their respective geometric mean. W_i is defined as:

$$W_i = \sum_{j=1}^{\mathcal{L}} \mathrm{e}^{-\kappa\varepsilon\tau_{ij}} \omega_j. \tag{10}$$

Rewriting (9) yields:

$$\tilde{\Psi}_i = \tilde{H}_{Ri}^{1/\varepsilon} \tilde{p}_i^{1-\beta} \tilde{W}_i^{-1/\varepsilon}, \tag{11}$$

Based on the reduced-form results, I expect $\tilde{\Psi}_i$ to be higher in areas that are close to or inside greenbelts. Moreover, I allow for residential externalities. That is, the amenity level in a neighbourhood may positively or negatively depend on density of households in the vicinity. Hence:

$$\tilde{\Psi}_i = \breve{\Psi}_i e^{\zeta_R g_i} \left(\delta_R \sum_{j=1}^{\mathcal{L}} e^{-\delta_R \tau_{ij}} H_{Rj} \right)^{\gamma_R} \equiv \breve{\Psi}_i e^{\zeta_R g_i} A_{Ri}^{\gamma_R}, \tag{12}$$

where $\breve{\Psi}_i$ is an amenity constant, $g_i = G_i/L_i$ is the share of greenbelt land in i, ζ_R indicates the direct impact of greenbelt land on amenities, γ_R is the elasticity of residential density externalities A_{Ri} and δ_R captures the decay of those externalities.

4.2 Production and agglomeration economies

I now turn to production. A single final good is produced in a perfectly competitive market with constant returns to scale and sold to the wider economy without costs. Cobb-Douglas production in location j is given by:

$$Y_j = \Omega_j H_{Mj}^{\alpha} F_{Mj}^{1-\alpha}, \tag{13}$$

where Ω_j denotes the final goods productivity at j, and F_{Mj} is the amount of floor space consumed by firms. Profit maximization implies that commercial floor space consumption equals:

$$F_{Mj} = \left(\frac{w_j}{\alpha \Omega_j} \right)^{\frac{1}{1-\alpha}} H_{Mi}. \tag{14}$$

Final goods productivity of a location can be written as:

$$\Omega_j = (1-\alpha)^{\alpha-1} \alpha^{-\alpha} p_j^{1-\alpha} w_j^{\alpha}. \tag{15}$$

I assume that productivity is dependent on greenbelt land in the vicinity, as well as employment density (because of agglomeration economies). There is a large literature showing that firms are more productive in the vicinity of others (see *e.g.* Combes et al. 2008, Melo et al. 2009). I then define:

$$\Omega_j = \breve{\Omega}_j e^{\zeta_M g_j} \left(\delta_M \sum_{i=1}^{\mathcal{L}} e^{-\delta_M \tau_{ij}} H_{Mi} \right)^{\gamma_M} \equiv \breve{\Omega}_j e^{\zeta_M g_j} A_{Mj}^{\gamma_M}, \tag{16}$$

where $\breve{\Omega}_j$ denotes the constant exogenous productivity of a location j, ζ_M is the direct impact of greenbelt land on productivity, γ_M is the agglomeration elasticity, A_{Mj} is a measure of employment density, and δ_M captures the spatial decay of agglomeration economies.

4.3 Land, construction and greenbelts

Greenbelts limit the available supply of land for development. Let Λ_i be the amount of developed land in i and L_i the total land area in location i. In line with the reduced form estimations in Section 3.1, I assume that the relationship between the share of built-up land and greenbelts is given by:

$$\frac{\Lambda_i}{L_i} = \Phi_i \mathrm{e}^{\varphi g_i}, \tag{17}$$

where Φ_i is a location-specific constant.

I assume that floor space F_i is supplied in a competitive construction market that uses land available for development Λ_i and capital K_i as inputs, with land prices P_i and the rental costs of capital denoted by r. I use a standard Cobb-Douglas production function. Land market clearing then implies that:

$$F_i = F_{Mi} + F_{Ri} = \Upsilon_i K_i^{\mu} \Lambda_i^{1-\mu}, \tag{18}$$

The first-order condition for optimal use of capital is then:

$$K_i^* = \left(\frac{\mu \Upsilon_i p_i}{r}\right)^{\frac{1}{1-\mu}} \Lambda_i, \tag{19}$$

which I plug in (18) to obtain:

$$\frac{F_i}{\Lambda_i} = \Upsilon_i^{\frac{1}{1-\mu}} \left(\frac{\mu p_i}{r}\right)^{\frac{\mu}{1-\mu}}. \tag{20}$$

By plugging in the first-order condition (19) into (18), I can solve for innate supply conditions Υ_i:

$$\Upsilon_i = \left(\frac{r}{\mu p_i}\right)^{\mu} \left(\frac{F_i}{\Lambda_i}\right)^{1-\mu}. \tag{21}$$

4.4 Traffic congestion

In the model of Ahlfeldt et al. (2015), travel times between two locations are exogenous. However, from a large literature on transportation it is clear that travel times are endogenous because of congestion. Traffic congestion mostly occurs in peak hours when commuting to work (Vickrey 1969, Peer et al. 2015, Proost & Thisse 2019). Workplaces tend to be more spatially concentrated than residences, hence congestion tend to occur mostly at the workplace. I therefore focus on congestion costs at the *workplace*.[25]

Pigou (1932) assumed a relationship between traffic flow and travel speed, but what matters here is the relationship between (traffic) density and travel time (Small & Verhoef 2007). I assume a generalisation of the relationship between density and travel time proposed by Underwood (1961) and for which there is ample empirical support (see *e.g.* Daganzo et al. 2011, Geroliminis & Daganzo 2008, Adler et al. 2019, Russo et al. 2019):

$$\tau_{ij} = \tau_{ij}^{f} T_i \breve{T}_j \mathrm{e}^{\lambda \mathcal{D}_{Mj}}, \tag{22}$$

where τ_{ij}^{f} is the free-flow travel time between i and j, T_i and $\breve{T}_j$ are location-specific constants, and $\lambda > 0$ is the congestion elasticity. Importantly, the density of traffic is given by:

$$\mathcal{D}_{Mj} = \frac{\sum_{s=1}^{\mathcal{L}} \mathrm{e}^{-\kappa \tau_{sj}} H_{Ms}}{\sum_{j=1}^{\mathcal{L}} \mathrm{e}^{-\kappa \tau_{sj}} \mathcal{R}_s}, \tag{23}$$

where $\mathcal{R}_s$ is the amount of roads at s. Hence, I divide the spatially weighted employment in a commuting area by the total available roads, to obtain traffic density of workers. Equation (22) is, for example, in line with traffic congestion models, where congestion is modelled as a bathtub that is filled up by traffic (Arnott & Rowse 2013, Fosgerau 2015).

4.5 Welfare

To evaluate whether greenbelt policy is welfare improving I will analyse the change in expected utility once greenbelt land will be removed. The change in expected utility can be interpreted as the the change in income that is necessary to obtain the same utility as in the baseline situation. The equivalent income increase that is necessary to make households in the original scenario have the same utility as in the new scenario can be defined as (using (8)):

$$\begin{gathered}\left(\sum_{i=1}^{\mathcal{L}} \sum_{j=1}^{\mathcal{L}} \bar{\nu}_{i1} \bar{\upsilon}_{j1} \left(\frac{\Psi_{i1} \mathrm{e}^{-\kappa \tau_{ij1}} w_{j1}}{p_{i1}^{1-\beta}} \right)^{\varepsilon} \right)^{\frac{1}{\varepsilon}} = \left(\sum_{i=1}^{\mathcal{L}} \sum_{j=1}^{\mathcal{L}} \bar{\nu}_{i0} \bar{\upsilon}_{j0} \left(\frac{\Psi_{i0} \mathrm{e}^{-\kappa \tau_{ij0}} w_{j0} \Delta \bar{w}}{p_{i0}^{1-\beta}} \right)^{\varepsilon} \right)^{\frac{1}{\varepsilon}}, \\ \Delta \bar{w} = \frac{\bar{u}_1}{\bar{u}_0}, \end{gathered} \tag{24}$$

[25] I will show in Appendix C.2 that congestion at the home location indeed matters less.

where $\Delta\bar{w}$ is the income increase that compensates for the utility differential. I refer to $\Delta\bar{w}$ as the change in *equivalent income*.

However, as the workers in my model are renters, I should also take into account the change in the land rents for absentee landlords. Given that construction firms make zero profits, I have:

$$P_i = \frac{F_i p_i}{\Lambda_i} - r^{\frac{\mu}{\mu-1}}(\mu p_i \Upsilon_i)^{\frac{1}{1-\mu}}. \tag{25}$$

Then, the change in aggregate land prices is given by $(P_{i1}\Lambda_{i1})/(P_{i0}\Lambda_{i0}) - 1$.

4.6 Model estimation

4.6.1 The gravity equation and wages

I use the recursive structure of the model to solve for the parameters of interest $\{\kappa, \varepsilon, \lambda, \varphi, \zeta_R, \gamma_R, \delta_R, \zeta_M, \gamma_M, \delta_M\}$. I assume the expenditure on labour costs $\alpha = 0.75$, in line with the long-run average in the UK (Batini et al. 2000). The share of household's expenditure on floor space is assumed to be $1 - \beta = 0.13$ (ONS 2017). I estimate the model at the MSOA level, and obtain information on bilateral commuting pairs. I only keep commuting pairs for which the free-flow travel time is less than 120 minutes (one-way), as there are few people (about 1%) commuting more than this.

Note that in what follows I use nearly the same identification strategies to identify the parameters of interest as outlined in the reduced-form regressions (see Section 3), but note that the dependent variables are now different and based on the model-implied location fundamentals.

Let us define $\varkappa \equiv \kappa\varepsilon$. In the first step I estimate a gravity equation, by defining the following moment condition:

$$\mathbb{E}\Big[\pi_{ij}\bar{H} - \mathrm{e}^{-\varkappa\tau_{ij} + \tilde{\nu}_i + \tilde{\upsilon}_j}\Big] = 0, \tag{26}$$

where $\bar{H}$ is England's total population, $\varkappa$ is the commuting travel time elasticity, $\tilde{\nu}_i$ is a residential location fixed effect absorbing $\{\Psi_i, p_i, \bar{\nu}_i\}$; and $\tilde{\upsilon}$ is a workplace fixed effects absorbing $\{\bar{\upsilon}_j, w_j\}$ (see equation (4)). Because the dependent variable $\pi_{ij}\bar{H}$ has many zeroes, I estimate equation (26) by a Poisson model with two-way fixed effects. In Appendix C.1 I consider different specifications to obtain $\varkappa$. Most importantly, I consider the issue that travel times might be endogenous: between locations where there is a higher commuting flow, it is more likely that new transport infrastructure is provided, leading in turn to lower travel times. Travel times are also endogenous because a higher flow may imply that congestion may be more severe, which in turn increases travel times. Moreover, travel times may be measured with error. I show in Appendix C.1 that when instrumenting travel times with euclidean distance, endogeneity hardly matters for the estimate of $\varkappa$.

Using data on the (working) population H_{Ri}, $\forall i$, and the number of workers H_{Mj}, $\forall j$, and the estimated parameter $\hat{\varkappa}$, I can recover transformed wages ω_j at each location j in the second step by solving:

$$\mathbb{E}\left[H_{Mj} - \sum_{i=1}^{\mathcal{L}} \pi_{ij|i} H_{Ri}\right] = 0. \tag{27}$$

Again, I focus on location pairs that are within 120 minutes free flow travel time from each other.

4.6.2 Commuting heterogeneity

In the third step I recover ε by using information on the distribution of estimated household incomes in England.[26] Following Ahlfeldt et al. (2015), I choose ε in such a way that it minimises the squared differences between the variances within local authority areas of log transformed wages in the model and log wages in the data:

$$\mathbb{E}\left[\sigma^2_{\log w_{i\in z}} - \left(\frac{1}{\varepsilon}\right)^2 \sigma^2_{\log \hat{\omega}_{i\in z}}\right] = 0. \tag{28}$$

Using $\hat{\varepsilon}$, I obtain $\hat{\kappa} = \hat{\varkappa}/\hat{\varepsilon}$.

4.6.3 Effects of greenbelt policy on land and construction

By log-linearising equation (17) I estimate the impact of greenbelts on the land available for development:

$$\mathbb{E}\left[\log \frac{\Lambda_i}{L_i} - \varphi g_i - \nu_{i\in\mathcal{G}}\right] = 0, \tag{29}$$

where φ captures the parameter of interest. Note that greenbelt policy is expected to lead to less land available for development (as shown in the reduced-form results, Section 3.1), hence φ is expected to be negative. I also use alternative identification strategies to identify φ. More specifically, I use *(i)* only areas for which the share in counterfactual greenbelts is above 90%,

[26] I obtain data on estimated household incomes by MSOA by the Office of National Statistics from 2011.

(ii) only areas for which the share in proposed or approved greenbelt land in 1973 exceeds 90%, and *(iii)* I focus on MSOAs that are within 1km of a inner or outer greenbelt boundary. In this way, I mitigate endogeneity issues.

The next step is to recover the share of construction costs used for capital, denoted by μ. Using the estimated parameters $\{\hat{\kappa}, \hat{\varepsilon}\}$, implied transformed wages; data on floor space prices; number of residents and workers; productivities; and amenities; I can calculate floor space consumption using (7) and (14). By log-linearising (20), I have:

$$\mathbb{E}\left[\log \frac{F_i}{\Lambda_i} - \frac{\mu}{1-\mu} p_i - \psi S_i - \nu_{i \in \mathcal{G}} - \nu_{i \in C}\right] = 0. \tag{30}$$

Hence, I recover μ obtain from a standard linear regression. However, I face severe endogeneity issues because the amount of floor space may also impact the floor space price. As I will show in Appendix C.3, this may even imply that μ has the wrong sign if I estimate the above equation by OLS.

Following Combes et al. (2016) I therefore propose to instrument for p_i using the distance to the city centre as instrument for floor space prices. According to the monocentric city model (Alonso 1964, Mills 1967, Muth 1969), demand for housing closer to the city centre is higher due to shorter commutes, while this is not due to differences in supply conditions. Still, one may be concerned that unobserved supply conditions are correlated to distance to the centre. It has been argued that constructions costs are related to soil conditions and therefore the locations of city centres may related to, say, the depth to bedrock (Rosenthal & Strange 2008, Barr et al. 2011, Holl 2019). I therefore proceed in the following way: *(i)* I include greenbelt and county fixed effects, as well as detailed variables capturing supply conditions, S_i, including soil conditions, elevation and share of workforce in construction (which may affect the wages for construction workers); *(ii)* I consider Conley et al.'s (2012) methodology to relax the assumption of strictly exogenous instruments. This enables me to construct bounds on the estimated μ if the instruments are only 'plausibly exogenous'; *(iii)* I consider alternative instruments based on temperature, as a proxy for amenities and therefore demand for housing (see Glaeser et al. 2001). I refer to Appendix C.3 for more details.

4.6.4 Amenities and residential externalities

Armed with estimates for transformed wages $\hat{\omega}$, $\hat{\kappa}$ and $\hat{\varepsilon}$ and data on H_{Ri}, H_{Mi} and floor space prices p_i, I can recover amenities Ψ_i up to a normalization using equation (11).

I first identify the impact of greenbelts and residential externalities Ψ_i on amenities using the following moment condition:

$$\mathbb{E}\left[\log \Psi_i - \zeta_R g_i - \gamma_R \log A_{Ri}(\delta_R) - \nu_{i\in\mathcal{G}}\right] = 0. \tag{31}$$

The above equation is non-linear in parameters γ_R and δ_R. Recall that A_{Ri} is a function of H_{Rj}, $\forall j$. I therefore sum H_{Rj} by 1 minute travel time 'doughnuts' and estimate the above equation by non-linear least squares.[27] I again use the above discussed identification strategies to identify ζ_R.

A concern with the above equation is that H_{Rj} is endogenous. For example, part of residential externalities may be due to unobserved locational endowments and not due to an externality. I therefore use the standard strategy to instrument for spatial externalities. That is, I use population in 1931 (see *e.g.* Ciccone & Hall 1996) to estimate in a 'first stage':

$$\mathbb{E}\left[\log A_{Ri}(\delta_R) - \tilde{\zeta}_R g_i - \tilde{\gamma}_R \log\left(\sum_{j=1}^{\mathcal{L}} \mathrm{e}^{-\delta_R \tilde{\tau}_{1870ij}} H_{1931j}\right) - \tilde{\vartheta}_{Ri\in\mathcal{G}}\right] = 0, \tag{32}$$

where H_{1931j} is the population in the same MSOA in 1931 and $\tilde{\tau}_{1870ij}$ is the travel time over the railway network of 1870 (which was the closest year I had infrastructure data from). I then obtain a predicted value for agglomeration, denoted by $\log \hat{A}_{Ri}$, and plug that in equation (31). To determine ζ_R, γ_R and δ_R simultaneously I minimise the mean squared error of equation (31).

Still, the identifying assumption that the unobserved reasons why people cluster are uncorrelated over 80 years may fail to be fully convincing. I therefore also consider the alternative identification strategy discussed earlier: I use the share of greenbelt land between 10 and 25km. The identifying assumption is then that the share of greenbelt land far away does not generate direct utility effects other than via the effects on the spatial equilibrium of households choosing each location.

[27] More specifically, for each location i, I calculate the travel time to all j. I then generate variables that sum residents for a given travel time ring, implying that I will include 120 variables; total number of residents between 0-1 minute travelling, 1-2 minutes travelling, etc.

Hence, I estimate:

$$\mathbb{E}\left[\log A_{Ri}(\delta_R) - \breve{\zeta}_R g_i - \breve{\gamma}_R \frac{\sum_{j=1}^{\mathcal{L}} g_j L_j I_{10<d_{ij}\leq 25}}{\sum_{j=1}^{\mathcal{L}} L_j I_{10<d_{ij}\leq 25}} - \breve{\vartheta}_{Ri\in\mathcal{G}}\right] = 0. \tag{33}$$

Again, I plug in a predicted value of agglomeration in equation (31) and minimise the mean squared error in (31) to obtain values for the parameters of interest.

4.6.5 Productivity and agglomeration economies

I also recover productivity Ω_i using equation (15) using a similar strategy:

$$\mathbb{E}\left[\log \Omega_i - \zeta_M g_i - \gamma_M \log\log A_{Mi}(\delta_M) - \nu_{i\in\mathcal{G}}\right] = 0. \tag{34}$$

I estimate the above equation by non-linear least squares. Further, to address endogeneity concerns, I again use population in 1931 in each MSOA to obtain the predicted employment density in each MSOA today:

$$\mathbb{E}\left[\log A_{Mi}(\delta_M) - \tilde{\zeta}_M g_i - \tilde{\gamma}_M \log\left(\sum_{j=1}^{\mathcal{L}} \mathrm{e}^{-\delta_M \tilde{\tau}_{1870ij}} H_{1931j}\right) - \tilde{\vartheta}_{Mi\in\mathcal{G}}\right] = 0. \tag{35}$$

I plug in $\log \hat{A}_{Mi}$ in (34) to estimate γ_M and δ_M. I also use the alternative strategy of using the share of greenbelt land between 10 and 25km as an instrument for A_{Mi}:

$$\mathbb{E}\left[\log A_{Mi}(\delta_M) - \breve{\zeta}_M g_i - \breve{\gamma}_M \frac{\sum_{j=1}^{\mathcal{L}} g_j L_j I_{10<d_{ij}\leq 25}}{\sum_{j=1}^{\mathcal{L}} L_j I_{10<d_{ij}\leq 25}} - \breve{\vartheta}_{Mi\in\mathcal{G}}\right] = 0. \tag{36}$$

4.6.6 Traffic congestion elasticity

To obtain the congestion elasticity λ I first log-linearise equation (22) to obtain the following moment condition:

$$\mathbb{E}\left[\log \frac{\tau_{ij}}{\tau_{ij}^f} - \log T_{Ri} - \log T_{Mj}\right] = 0. \tag{37}$$

Recall that τ_{ij}^f is the free-flow travel time between i and j. I estimate the above equation using a regression with two-way fixed effects. In the second step, I recover the workplace fixed effects, resulting in the following moment condition:

$$\mathbb{E}\left[\log \hat{T}_{Mi} - \lambda \mathcal{D}_{Mi} - \nu_{i\in G}\right] = 0, \tag{38}$$

where $\tilde{\mu}_{i\in G}$ are greenbelt fixed effects and I use the estimated parameter $\hat{\kappa}$ to calculate traffic density $\mathcal{D}_{Mi}$. I estimate this condition by OLS.[28]

One may be concerned that $\mathcal{D}_{Mi}$ is endogenous because of reverse causality – short travel times may attract households and workers that are interested in short commutes leading to a higher density. I follow a similar strategy as when measuring agglomeration economies: I instrument traffic densities either with the traffic density in 1930, which is defined as the population density within commuting by train. Alternatively, I use the commuting-time weighted share of greenbelt land between 10 and 25km as an instrument for traffic density at i.

4.6.7 Standard errors

I obtain standard errors by bootstrapping the whole procedure. More specifically, I first select randomly $\mathcal{L}$ MSOAs (with replacement) and, given this set of locations, estimate each of the consecutive steps. In this way I take into account that errors are correlated between different equations.

5 Model parameters and counterfactuals

5.1 Structural parameters

In Table 5 I report estimated parameters of interest when I do not instrument for residential and employment density. I report cluster-bootstrapped standard errors based on 250 replications. I find a commuting semi-elasticity $\varkappa = \kappa\varepsilon$ with respect to flows that is considerably lower than Ahlfeldt et al. (2015). The reason is that I use the actual travel time between i and j, rather than the free-flow travel time. I show in Appendix C.1 that this matters: the commuting time elasticity is about twice as strong when using free-flow travel times. In Appendix C.1 I further report a couple of different specifications allowing for potential endogeneity of travel times. In Appendix C.4 I show that about 50% of utility has 'melted' away with a commute of 45 minutes commute and only 15% remains with a two-hour commute. It indicates that workers strongly

[28] I show in Appendix C.2 that my results are robust to omitting home location fixed effects.

Table 5 – Structural parameters

	All areas	*Counterfactual greenbelts*	*Greenbelts in 1973*	*Greenbelt border <1km*
	(1)	(2)	(3)	(4)
Commuting time elasticity, $\hat{\varkappa}$	-0.0821***	-0.0821***	-0.0821***	-0.0821***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Commuting heterogeneity, $\hat{\varepsilon}$	5.3066***	5.3066***	5.3066***	5.3066***
	(0.0263)	(0.0263)	(0.0263)	(0.0263)
Congestion elasticity, $\hat{\lambda}$	0.1274***	0.1274***	0.1274***	0.1274***
	(0.0015)	(0.0000)	(0.0000)	(0.0000)
Greenbelt restrictions, $\hat{\varphi}$	-1.2510***	-1.0149***	-2.2221***	-1.8262***
	(0.0354)	(0.0631)	(0.0434)	(0.0483)
Share capital in construction costs, $\hat{\mu}$	0.7601***	0.6452	0.6959***	0.8216***
	(0.0324)	(0.4297)	(0.1190)	(0.0899)
Residential amenity effect, $\hat{\zeta}_R$	0.0599***	0.0115	0.0666***	0.0302*
	(0.0081)	(0.0130)	(0.0111)	(0.0167)
Residential elasticity, $\hat{\gamma}_R$	-0.2184***	-0.2344***	-0.2237***	-0.2497***
	(0.0066)	(0.0128)	(0.0086)	(0.0181)
Residential decay, $\hat{\delta}_R$	0.0620***	0.0571***	0.0566***	0.0632***
	(0.0031)	(0.0049)	(0.0085)	(0.0059)
Productive amenity effect, $\hat{\zeta}_M$	-0.0053	0.0658***	0.0883**	0.0425
	(0.0088)	(0.0138)	(0.0350)	(0.0262)
Productivity elasticity, $\hat{\gamma}_M$	0.0909***	0.1103***	0.0941***	0.1222**
	(0.0078)	(0.0151)	(0.0183)	(0.0570)
Productivity decay, $\hat{\delta}_M$	0.0220***	-0.0044	0.3473**	0.0063
	(0.0031)	(0.0058)	(0.1647)	(0.1469)
Greenbelt fixed effects	Yes	Yes	Yes	Yes
Number of areas	6,701	6,701	6,701	6,701
Number of area pairs	19,673,517	19,673,517	19,673,517	19,673,517

Notes: We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

dislike commuting.

The commuting heterogeneity parameter $\hat{\varepsilon}$ is very similar to the one reported by Ahlfeldt et al. (2015) and within the range provided by Eaton & Kortum (2002). I further note that $\hat{\varkappa}$, $\hat{\varepsilon}$ and $\hat{\kappa}$ are the same for different identification strategies because those parameters are identified in the gravity equation.

I further identify the congestion externality, $\hat{\lambda}$. The parameter indicates that travel times increases by $e^{0.1274} - 1 = 13.6\%$ if traffic density $\mathcal{D}_M$ increases by one standard deviation. In Appendix C.2 I show that this coefficient is highly robust to different specifications and to addressing endogeneity concerns with respect to traffic density.

When identifying the effect of greenbelt restrictions, I use different identification strategies. I have obtained $\hat{\varphi}$ by a regression of the log of the share of the built-up area on the share of greenbelt land. I show that, unsurprisingly, the reduction in land used for development due to greenbelts is very strong: a 10 percentage point increase in greenbelt land lead to decrease in the share of built-up land of $\mathrm{e}^{-1.251 \cdot 0.1} - 1 = 11.8\%$. This effect is very similar in terms of magnitude when compared to the reduced-form results on dwelling density (see Section 3.1). The effect is similar once I include MSOAs in counterfactual greenbelts (column (2)), but the effects are stronger in areas that are in proposed or approved greenbelts in 1973 (column (3)), or once I focus on areas within 1km of a inner or outer greenbelt boundary (column (4)). In the latter specification, the reduction in the share of built-up land is 16.7% for a 10 percentage point increase in greenbelt land.

Let us now consider the share of capital in construction costs, $\hat{\mu}$. I find in column (1) that $\hat{\mu} = 0.760$. This value is essentially the same as the one picked in Ahlfeldt et al. (2015). Moreover, it is very close to the value estimated in Combes et al. (2016). In column (2) where I focus on counterfactual greenbelts, $\hat{\mu}$ seems to be somewhat lower, but this is entirely because I lack statistical power. In other words, $\hat{\mu}$ is not statistically significantly different from the previous specification. When only including greenbelts in 1973 or when focusing on areas within 1km of a greenbelt boundary, I find $\hat{\mu} \approx 0.75$, but the estimates are less precise than when using all areas. Since a strategy using distance to the city centre as an instrument for floor space prices may raise concerns, I devote considerable space to evaluating identification in Appendix C.3. The most notable robustness analysis relaxes the assumption of strict exogeneity of the distance to the city centre instrument. I then can construct reasonably informative bounds on $\hat{\mu}$, at least when I use data on all MSOAs.

In line with the reduced-form results I find a statistically significant residential amenity effect, denoted by $\hat{\zeta}_R$, which is robust across specifications. The baseline estimate, reported in column (1), suggests that amenities Ψ_i increase by 0.60% when the share of greenbelt land increases by 10 percentage points. In contrast to Ahlfeldt et al. (2015), which focused on one city (*i.e.* Berlin) where historic amenities are positively correlated with residential densities, I find evidence of *negative* residential externalities. That is, in principle people do not prefer dense residential areas. The effect is quite strong: doubling population density leads to a decrease in amenities Ψ_i of 15.1% (see column (1)). At the same time, the estimate of the decay parameter $\hat{\delta}_R$ implies the effect is quite localised: I show in Appendix C.4 that only about 15% of this effect remains after 30 minutes travelling. I emphasise that both $\hat{\gamma}_R$ and $\hat{\delta}_R$ are very robust across different identification strategies.

The productivity estimates are also in line with expectations. Whether greenbelt land implies a productive amenity effect is not entirely clear, as different identification strategies lead to different conclusions. A 10 percentage point increase in the share of greenbelt land is associated with a 0% to 0.9% increase in productivity. An explanation for a positive productive amenity effect may be that workers are more satisfied and healthy, and therefore more productive, in greener environments (Montgomery 2015). However, note that the productive amenity effect is small and not statistically significant in two of our approaches. Hence, evidence for a productive amenity effect is mixed. I further find an agglomeration elasticity of 0.091. This is somewhat higher than the mean estimate (0.058) provided by Melo et al. (2009) but very similar to Ahlfeldt et al. (2015). The decay parameter $\hat{\delta}_M$ is 0.0220, which implies that about 50% of the productive effect of density has been gone after a 30 minutes drive (see Appendix C.4). After a one hour drive, 30% remains.[29] The decay is weak compared to Arzaghi & Henderson (2008) and Ahlfeldt et al. (2015). This makes sense as these studies identify productivity externalities *within* cities, while this study takes into account the whole of England. Hence, one would expect the decay to be less strong, because for example input-output linkages are usually less important on short distances. Unsurprisingly, because of the data selections I make, the decay parameter is hard to estimate in the other specifications

In Appendix C.5 I consider two extensions. First, I estimate the model where I assume away any spillover effects. I show that the other parameters are very similar. I will also will show counterfactual analyses where I set agglomeration effects to zero. Second, I instrument for density using population in 1931 or the share of greenbelt land between 10 and 25km. The congestion elasticity is very similar to the baseline results. The residential elasticity is consistently negative and around -0.25, while the productive elasticity is around 0.10. I find similar decay parameters for agglomeration economies.

[29] Note that in column (3), where I focus on areas in greenbelts in 1973, I find an unrealistically strong decay, albeit very imprecise. The reason is that I only identify the effects on low-density MSOAs in mostly rural areas, which makes it hard to identify the decay parameter properly.

Table 6 – Results of counterfactual analyses

	Scenario 1: 10% reduction	*Scenario 2: No greenbelts*	*Scenario 3: Full greenbelts*
	(1)	(2)	(3)
Panel A: Baseline			
Change in output *(in %)*	0.9985	0.9947	1.0015
Change in expected utility *(in %)*	0.9988	0.9967	1.0039
Change in overall land rents *(in %)*	0.9814	0.9364	1.0517
Concentration of residential population	1.0046	1.0245	1.0193
Concentration of workers	0.9958	0.9904	1.0063
Panel B: No greenbelt amenities $\{\zeta_R, \zeta_M\} = 0$			
Change in output *(in %)*	0.9984	0.9937	1.0030
Change in expected utility *(in %)*	1.0010	1.0053	0.9964
Change in overall land rents *(in %)*	0.9824	0.9395	1.0499
Concentration of residential population	0.9914	0.9694	1.0121
Concentration of workers	0.9958	0.9895	1.0074
Panel C: No spillovers $\{\lambda, \gamma_R, \delta_R, \gamma_M, \delta_M\} = 0$			
Change in output *(in %)*	0.9983	0.9969	1.0037
Change in expected utility *(in %)*	1.0004	1.0036	1.0016
Change in land rents *(in %)*	0.9675	0.8863	1.0946
Concentration of residential population	1.0040	1.0321	1.0236
Concentration of workers	0.9960	0.9930	1.0133

Notes: I proxy concentration by the Gini coefficient. I normalise all values with respect to the baseline scenario. I calibrate the costs of building capital r using data on land prices, the share of developed land, floor space prices, as well as the estimated demand for floor space.

5.2 *Counterfactual analyses and welfare*

5.2.1 Aggregate effects

Armed with the estimated structural parameters, I calculate counterfactual scenarios to investigate changes in the provision of greenbelt land for workers and absentee landlords. Given that the parameters are reasonably robust for different identification strategies, I use the estimated parameters reported in column (1) of Table 5. The procedure to obtain the counterfactual outcomes is described in Appendix C.6.

I consider 3 experiments: I first determine inner greenbelt boundaries and shift the boundary approximately 800m outwards so that the total amount of greenbelt land is reduced by 10%. In the second experiment I remove all greenbelt land. In the third experiment I increase the size of greenbelts by assuming that all counterfactual greenbelts now will be designated greenbelt land.

Let us first concentrate on a 10% reduction in greenbelt land. In Panel A, I show that the decrease in output is 0.15%. The effects on utility are of the same order of magnitude, as the equivalent income decrease is 0.12%. If one multiplies this with the median gross earnings and the working population, this amounts to approximately a gain of £790 million per year. The effects on land rents are considerably larger in percentage terms; the total reduction in land rents is 2%. Given a discount rate of 1.8% (see Bracke et al. 2018), a total amount of developed land of 2km^2, and a median land price of £461 per m^2, the loss in land prices is equal to £300 million per year.[30] Hence, the gains for workers and absentee landlords are in the same order of magnitude. Note that homeowners only benefit slightly from land price increases due to greenbelts: as only 5% of the land is owned by homeowners; most of the benefits of greenbelts accrue to other parties owning the land. Shrubsole (2019) shows that about 30% of England's land is owned by the aristocracy (which may even be an underestimate), 18% by corporations, 17% by oligarchs and bankers, 17% is unaccounted, while 8.5% is owned by the public sector.

In the second counterfactual, where I consider removing all greenbelt land, the effects are somewhat amplified, but the conclusions are the same. The equivalent income increase of greenbelt policy is 0.33%. The total costs for workers if greenbelts are removed are £2.1 billion per year. Land prices decrease by 6.8%, which is equivalent to a total loss in land prices of £1 billion per year. Further, notice that the concentration of the residential population increases. The reason may be that workers do not have to move beyond ('leapfrog') a greenbelt to find affordable housing any more, so that development becomes somewhat more concentrated (see *e.g.* Levkovich et al. 2019). On the other hand, concentration of workers slightly decreases.

The third counterfactual scenario describes what happens if one would increase greenbelt land as to match the counterfactual greenbelts (see Figure 2). I observe that the equivalent income change is about 0.4%. Hence, workers are better off. Total land revenues increase by approximately 5%, because land becomes more scarce and therefore more expensive.

What are the exact sources of the benefits of greenbelts? In Panel B I turn off the amenity effect by setting $\zeta_R = \zeta_M = 0$. I then show that greenbelts would imply a *loss* to workers of about 0.5%. Because land revenues would still decrease by about 6%, the overall welfare effect would be less clear-cut. Hence, greenbelt amenities are important to understand why greenbelts imply a positive welfare effect for workers.

[30] I obtain data on estimated land prices for 326 local authorities from the *Department for Communities and Local Government* from 2014. I deflate land prices to 2011 values using the consumer price index.

Panel C in Table 6 assumes away spillovers. Hence, traffic congestion, residential externalities and agglomeration economies are set to zero. Now I find that greenbelts would *decrease* utility of workers (see column (2)). Greenbelts lead to more concentration of workers, leading to more severe *negative* residential externalities (recall that $\hat{\zeta}_R < 0$), which in turn leads to lower utility of workers. Once these residential externalities are set to zero, greenbelts imply a small negative external effect. In absence of spillovers, effects on land rents would be stronger. Overall land rents when greenbelts would be taken away change by -11.4%.

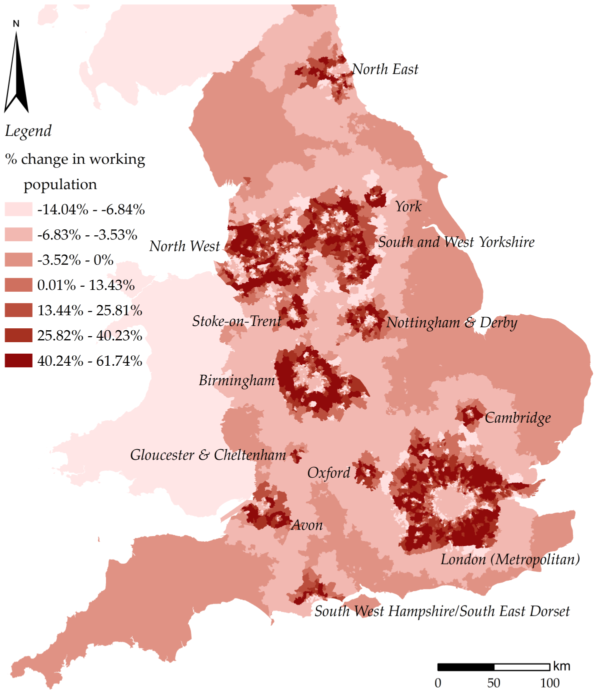
In sum, the results in Panel B and C show that it is paramount to allow for (the interplay between) supply effects, amenities and spillovers.

5.2.2 Local effects

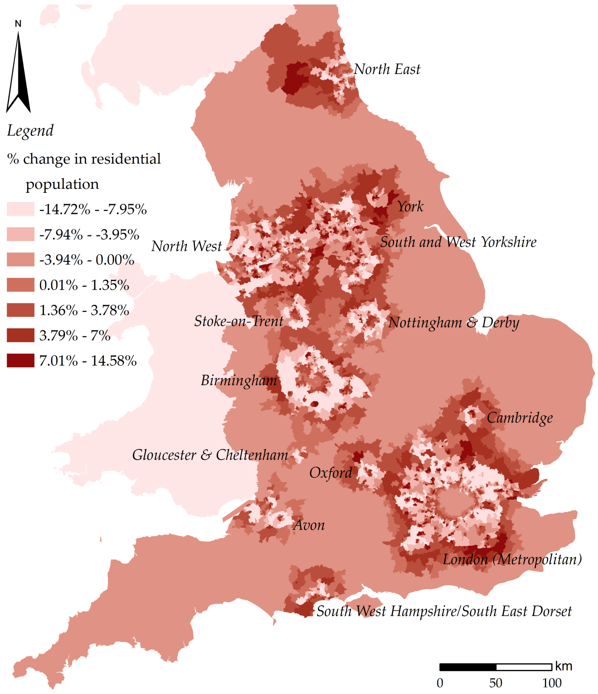
Although aggregate effects may seem modest, local effects are large. I plot the local effects of Scenario 2 (no greenbelts) in Figure 3.

I observe a relatively large influx of workers (Figure 3a) in areas that were formerly greenbelts. For households, the picture is more nuanced (see Figure 3b). Because greenbelt amenities are now zero (because no greenbelt land exists any more) some areas in former greenbelts are now less attractive and actually lose population. Although percentage effects may seem large (up to 15%), absolute numbers are low because few households lived in greenbelts in the first place.

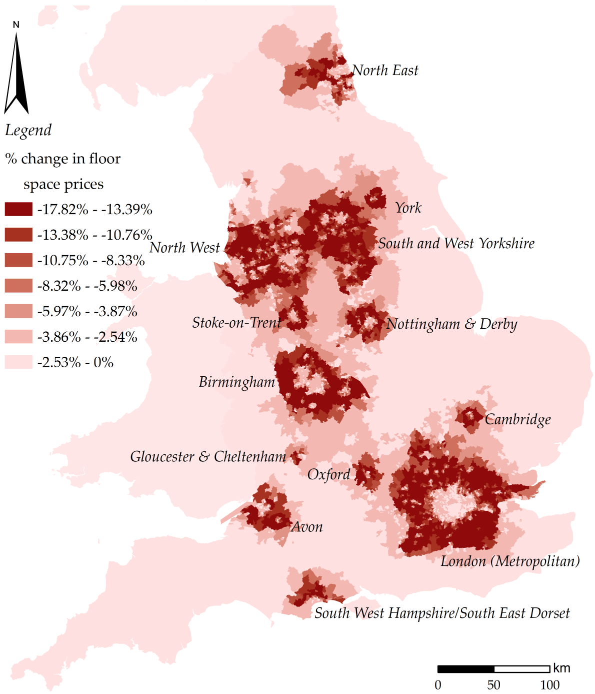
Floor space prices drop substantially (Figure 3c). In former greenbelt areas, this can be up to 18%, due to a loss in open space amenities. On the other hand, also outside greenbelts prices drop substantially. For example, in London, Manchester and Birmingham, prices drop by approximately 3-10%. Given that England's cities are known to be expensive (Hilber & Vermeulen 2016), removing greenbelt land seems to imply a substantial improvement in housing affordability. Wage effects are somewhat smaller on average, but throughout England, wages net of commuting increase. However, in greenbelts they tend to increase more substantially. Note that, despite lower floor space prices and higher wages, net utility of workers is still lower because of more intense negative residential externalities.



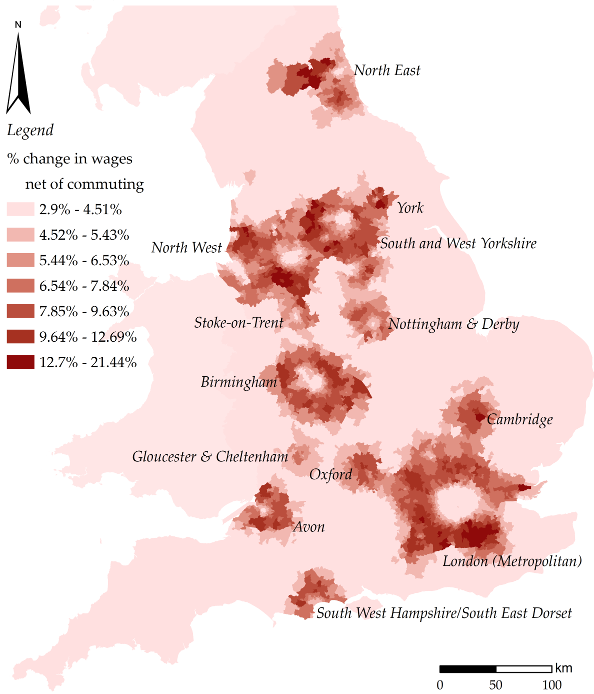
(A) Workers, H_M



(B) Residential population, H_R



(C) Floor space prices, p



(D) Wage net of commuting costs, $\mathbb{E}[w]$

Figure 3 – Counterfactual 2: no greenbelts

6 Conclusions

In this paper, I have investigated the economic effects of greenbelt policy that prohibit new construction beyond a predefined boundary. I focus on England, where 13% of the land area is designated greenbelt land. Greenbelts were constituted between the 1950s and 1970s – a time when cities were much smaller – and hardly have changed ever since.

Using reduced-form regressions I first establish that greenbelts imply positive amenity effects as measured by house prices. These effects are quite local and are mostly relevant within 500m. Unsurprisingly, greenbelt policies are binding: within greenbelts the density is more than 50% lower. I also find evidence for agglomeration effects, and weak evidence for a productive amenity effect. Ancillary analyses focusing on city-wide effects of greenbelts show that greenbelts are not a main recreational destination and that reductions in air pollution due to greenbelt land are very local.

I proceed by setting up a general equilibrium model taking into account the effects of greenbelts on amenity values, commuting, residential externalities, agglomeration economies and traffic congestion. I show that these are all very important.

A counterfactual analysis then shows that greenbelt policy *increase* the utility of workers: the equivalent income increase due to greenbelts is about 0.3%, which amounts to £2 billion a year. Moreover, further monetary gains accrue to absentee land owners as total land revenues are about 6.5% higher. Given assumptions, this amounts to roughly £1 billion per year. Hence, due to the presence of greenbelt amenities and spillovers, greenbelts unequivocally imply welfare gains.

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Appendix A. Data and descriptives

A.1 Counterfactual greenbelts

To construct counterfactual greenbelts I exploit data on the population in Parishes from the 1951 census. Parishes are the lowest unit for which the data are available, and are rather small. The median size is 847ha. In line with the suggestion by Duncan Sandy, the Minister of Housing at that time, greenbelts were mainly implemented around larger cities of at least 100 thousand inhabitants. To identify 'large urban areas' I first select parishes with a population density of at least 10 people per hectare, about 5% of the Parishes. I then amalgamate all those areas and keep 37 amalgamated urban areas that have a population of more than 100 thousand inhabitants. I then draw circles of 15km around each of these urban areas, in line with the suggestion of Duncan Sandy (*"The Development Plans submitted by the local planning authorities for the Home Counties provide fo a Green Belt, some* 7 *to* 10 *miles deep, [...]."*). The last step is to erase the areas in the counterfactual greenbelts with a density of at least 10 persons per hectare because that land has already been converted to built-up land, and is therefore not part of a greenbelt.

A.2 Developed land and soil type

To estimate the impact of greenbelts on land available land I use data from *Ordnance Survey* on exact polygons of all buildings in England. I plot these data in Figure A1. As one can see, most of England is not built-up. Only 2% of the land is occupied by buildings. In greenbelts this is considerably lower.

I also use information on the so-called parent soil material from the *British Geological Survey.* They provide spatially detailed (1:50,000) information on 147 parent soil materials. I group those in five broad categories: loamy, rocky, sandy soils, as well as clay and other materials. Figure A2 shows that these categories are indeed spatially related.

To make sure that our estimates do not hinge on a particular grouping of soils I also consider the classification used by the *British Geological Survey*, who make a distinction between 'light', 'medium' and 'heavy' soils. Furthermore, I tap into a completely different database from the *British Geological Survey* on the type of superficial deposits to select similar soil types.

A.3 Additional descriptives

I report descriptive statistics of parliamentary constituency data in Table A1. The average male full-time weekly earnings are £521. The constituency with the highest earnings is Poplar, which includes the Canary Wharf business district. The lowest earnings are found in St. Ives in Cornwall.

The share of greenbelt land in a constituency is 21%, which is somewhat higher than in the more

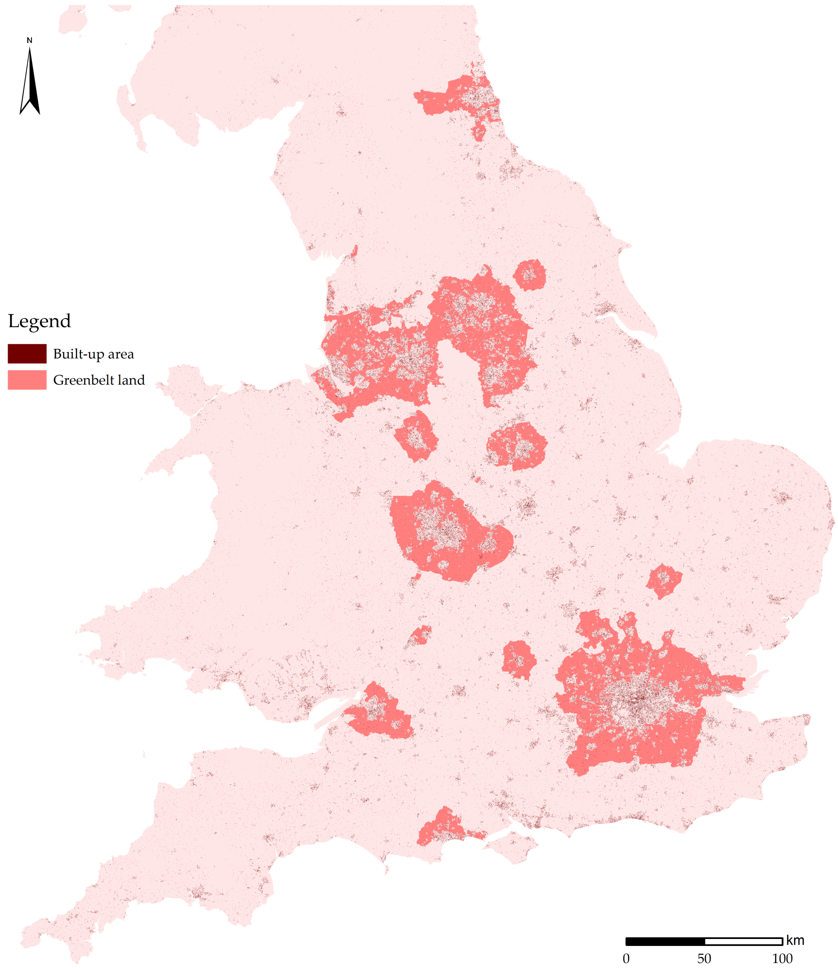

Figure A1 – Built-up land in Great Britain

fine-grained postcode or MSOA data. Unsurprisingly, most observations are in areas with a lower share of greenbelt land. Hence, when focusing on smaller areas, the share of greenbelt land should be lower. The share of greenbelt land in the own constituency and between 10-25km is positively correlated ($\rho = 0.314$).

I also calculate the *employment* density, which is on average 11.4 workers per ha. The *population* density in 1931 was 15.5 persons per hectare. The correlation is quite high ($\rho = 0.671$).

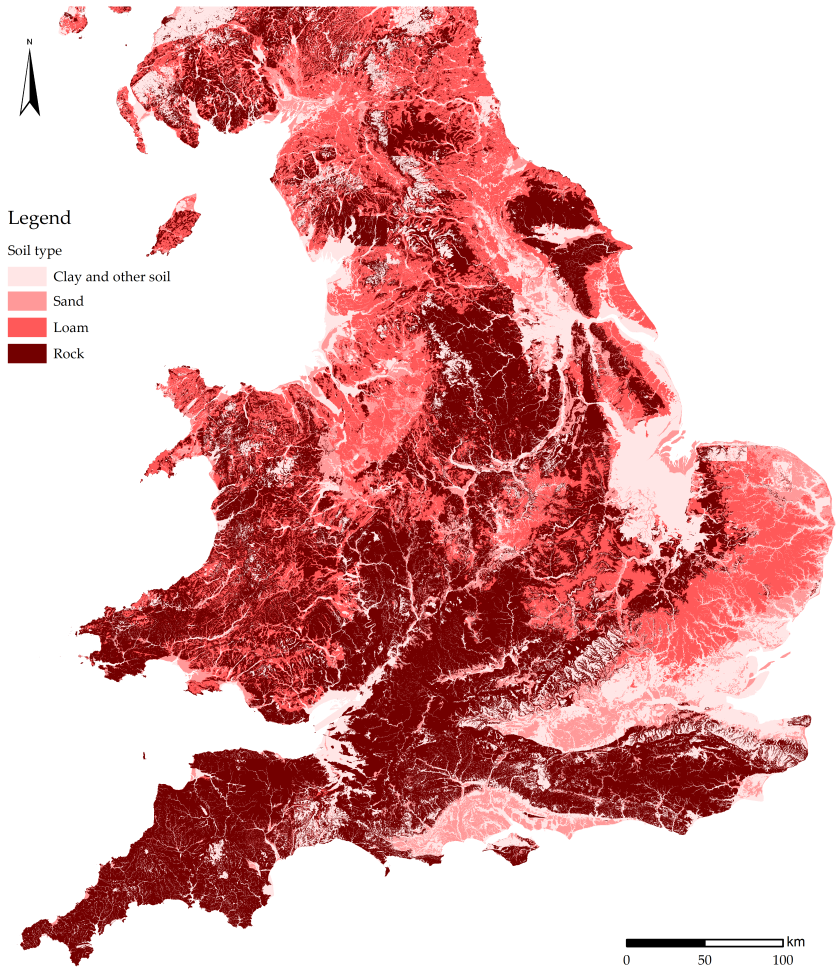

Figure A2 – Soil type in Great Britain

Table A1 – Descriptive statistics for parliamentary constituency data

	(1) mean	(2) sd	(3) min	(4) max
Median male weekly earnings *(£)*	521.5371	83.0595	350.0000	1,083.3000
Share greenbelt land	0.2141	0.2700	0.0000	0.9420
Share greenbelt land, 10-25km	0.2760	0.2056	0.0000	0.7359
Employment density *(per ha)*	11.3978	28.2813	0.1159	519.8376
Population density in 1931 *(ha)*	15.5043	32.3950	0.0000	242.6233
Share higher managerial occupations	0.1032	0.0383	0.0435	0.3178
Share lower managerial occupations	0.2227	0.0378	0.1412	0.3568
Share intermediate occupations	0.1389	0.0193	0.0935	0.2016
Share self-employed	0.1097	0.0304	0.0308	0.1997
Share technical occupations	0.0771	0.0142	0.0430	0.1301
Share semi-routine occupations	0.1589	0.0277	0.0596	0.2261
Share routine occupations	0.1257	0.0353	0.0326	0.2455
Share never worked and long-term unemployed	0.0638	0.0382	0.0071	0.2790
Share <25 years	0.3120	0.0371	0.1146	0.4567
Share people 25-44 years	0.2598	0.0530	0.1632	0.6171
Share people 45-64 years	0.2549	0.0231	0.1709	0.3062
Share people >64 years	0.1733	0.0480	0.0268	0.3166

Notes: The number of parliamentary constituencies is 529.

Appendix B. Reduced-form effects

B.1 Sensitivity analyses for reduced-form price effects

Here I report some additional sensitivity checks for the reduced-form analyses, where I focus on the effects of greenbelts on house prices. The results are reported in Table B1. I report coefficients for each of the four identification strategies: *(i)* include all observations, *(ii)* include only observations in counterfactual greenbelts, *(iii)* include only observations in greenbelts in 1973, and *(iv)* focus on locations close to greenbelt borders.

In Panel A I test for the geographical extent of the amenity effect. I show that for each of the identification strategies I find strong and positive amenity effects within 500m. However, beyond 500m the coefficients do not display a consistent pattern. Generally they are statistically insignificant. This holds in particular for what I consider as the most convincing identification strategy where I only include properties close to greenbelt borders. The finding that the amenity effect of greenbelts is local is in line with a literature showing that amenity effects of open space are very local (Bolitzer & Netusil 2000, Anderson & West 2006).[31]

Panel B investigates whether the detail of the fixed effects impacts the results. Instead of 326 local authority fixed effects I include $159,867$ output area fixed effects to capture sorting effects related to greenbelts and to further address omitted variable bias. Recall that output areas are the lowest geographical level at which census estimates are provided; the median size of an OA is only 6.6ha. Fortunately, this leads to very similar results: I find that increasing the share of greenbelt land by 10 percentage points increases prices by 1.5%, which is essentially the same as the baseline results reported in Table 4. Hence, this increases the belief that my identification strategies indeed identify a causal amenity effect of greenbelts, as unobserved locational endowments captured by the detailed fixed effects seem to be uncorrelated to the share of greenbelt land within 500m.

In Panels C and D of Table B1 I distinguish between different types of greenbelt land. I first make a distinction between so-called 'accessible' and 'inaccessible' greenbelt land in Panel C. Accessible greenbelt land is officially designated as parks or gardens and therefore open to the public. I classify 7.3% of greenbelt land as 'accessible'. The coefficients show that there are no large differences between the amenity effect of accessible and inaccessible greenbelt land, although the impact of accessible greenbelt land is slightly higher.

In Panel D I make a distinction between agricultural and non-agricultural greenbelt land. Using the

[31] The finding of a positive coefficient in column (3) for the share of greenbelt land 2000-2500m may be a Type II error as there is relatively limited variation in the share of greenbelt land 2000-2500m for the sample with observations in greenbelt land in 1973, as greenbelts have changed little since 1973.

Table B1 – Amenity effects of greenbelts: sensitivity

(Dependent variable: the log of house price per m^2)

	(1) OLS	(2) OLS	(3) 2SLS	(4) OLS
	All observations	Counterfactual greenbelts	Greenbelts in 1973	Greenbelt border <2.5km
Panel A: Geographical extent of amenity effect				
Share greenbelt land 0-500m	0.1343***	0.1568***	0.1217***	0.1248***
	(0.0101)	(0.0124)	(0.0118)	(0.0117)
Share greenbelt land 500-1000m	-0.0004	-0.0376*	-0.0035	0.0093
	(0.0160)	(0.0218)	(0.0204)	(0.0183)
Share greenbelt land 1000-1500m	0.0542**	0.0366	0.0501*	0.0356
	(0.0212)	(0.0309)	(0.0283)	(0.0241)
Share greenbelt land 1500-2000m	0.0571**	0.0823**	0.0027	0.0544
	(0.0286)	(0.0378)	(0.0374)	(0.0332)
Share greenbelt land 2000-2500m	0.0226	0.0158	0.1251***	0.0315
	(0.0263)	(0.0372)	(0.0360)	(0.0312)
Number of observations	10,070,791	2,394,057	1,952,693	3,763,739
R^2	0.7770	0.7906	0.7924	0.7679
Panel B: Output area fixed effects and sorting				
Share greenbelt land 0-500m	0.1544***	0.1671***	0.1427***	0.1487***
	(0.0084)	(0.0110)	(0.0106)	(0.0096)
Number of observations	10,069,771	2,393,629	1,952,358	3,763,258
R^2	0.8721	0.8730	0.8800	0.8736
Panel C: Accessible and inaccessible greenbelt land				
Share accessible greenbelt land 0-500m	0.2200***	0.2529***	0.2462***	0.2238***
	(0.0324)	(0.0438)	(0.0389)	(0.0366)
Share non-accessible greenbelt land 0-500m	0.2172***	0.1851***	0.1536***	0.1832***
	(0.0104)	(0.0124)	(0.0130)	(0.0122)
Number of observations	10,070,791	2,394,057	1,952,693	3,763,739
R^2	0.7763	0.7899	0.7912	0.7671
Panel D: Agricultural and non-agricultural greenbelt land				
Share agricultural greenbelt land 0-500m	0.3081***	0.2615***	0.2810***	0.2830***
	(0.0205)	(0.0260)	(0.0260)	(0.0249)
Share non-agricultural greenbelt land 0-500m	0.1582***	0.1452***	0.0848***	0.1259***
	(0.0147)	(0.0175)	(0.0163)	(0.0175)
Number of observations	10,070,791	2,394,057	1,952,693	3,763,739
R^2	0.7764	0.7900	0.7916	0.7673
Panel E: Only 2012				
Share greenbelt land 0-500m	0.2072***	0.1860***	0.1604***	0.1814***
	(0.0104)	(0.0133)	(0.0134)	(0.0117)
Number of observations	360,591	87,968	71,581	134,683
R^2	0.6535	0.6422	0.3545	0.6343

Notes: I control for housing and location attributes, as well as local authority and year fixed effects in all specifications. I include output area fixed effects in Panel B. Housing attributes include the log of house size, housing type dummies (flat, terraced, semi-detached, detached), the number of rooms and the number of habitable rooms, an indicator for newly built properties, the floor level of the property, the height of the property, the number of stories of the building, whether the property has a fire place, whether the property is freehold and variables capturing the energy efficiency of windows, roof, walls. Location attributes a linear, squared and cubic term of distance to the nearest city centre. In column (2) I only include observations that are in counterfactual greenbelts as defined in Section 2.1. Column (3) includes observations in areas that are in greenbelts that were approved or considered in 1973. . In columns (4) I include transactions that are within 2.5km of a greenbelt boundary. Standard errors are clustered at the MSOA level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Land Cover dataset I classify 36% of greenbelt land as agricultural. I find a somewhat higher effect of agricultural greenbelt land on prices, as compared to non-agricultural greenbelt land. This may seem surprising as households are unlikely to value intensive livestock farming that generates negative externalities (Bontemps et al. 2008). However, it may be that agricultural land is usually 'open' land, which may be valued higher by households than *e.g.* forested land (Irwin 2002, Montgomery 2015).

In Panel E I only include observations in 2011. As the structural estimation results will rely on Census data from 2011 I want to make sure that amenity effects are roughly the same over time. I find evidence for this: the results relying solely on housing transactions in 2011 are not materially different from the baseline reduced-form estimates.

B.2 Reduced-form effects: agglomeration economies and productive amenity effects

B.2.1 Methodology

Using data at the parliamentary constituency level I estimate the following regression:

$$\log w_i = \theta_1 g_i + \theta_2 \log\left(\frac{H_{Mi}}{L_i}\right) + \theta_3 v_i + \nu_{i\in\mathcal{G}} + \breve{\epsilon}_i, \tag{B.1}$$

where w_i are observed earnings, H_{Mi} number of workers, L_i is the size of the area and v_i are controls. θ_1, θ_2, θ_3 are parameters to be estimated, $\nu_{i\in\mathcal{G}}$ are greenbelt fixed effects, and $\breve{\epsilon}_i$ is an error term.

A concern with the above equation is that H_{Mi} is endogenous. For example, part of agglomeration economies may be due to sorting of workers and not due to an externality. Moreover, there may be correlation of employment to unobserved natural advantages of a location (Ellison & Glaeser 1997). The first step is to include occupation and age controls, which will mitigate the issue that more able workers sort themselves into urban areas.

To control for unobserved locational endowments I first employ the standard strategy to instrument for agglomeration externalities. That is, I use population in 1931 (see *e.g.* Ciccone & Hall 1996, Combes et al. 2008). The identifying assumption when using historic data is that the unobserved reasons why people cluster in the past are uncorrelated to the current ones. This assumption may be hard to defend, *e.g.* because locations that offer amenities in the past also do this today.

I therefore also consider an alternative identification strategy following an insight by Bayer & Timmins (2007). They argue that the "*fixed attributes of other locations [...] make ideal instruments for the share of individuals that choose a location*". That is, fixed attributes of other location influence the equilibrium and the share of workers choosing a certain location i, but have no direct effect on productivity at i other than via a change in the density.

Table B2 – Productive amenity effects and agglomeration economies

(Dependent variable: the log of earnings at the workplace in £ per week)

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS
	Baseline OLS			Population density 1931		Share greenbelts 10-25km	
Share greenbelt land	0.0175	0.0411**	0.0364**	0.0389*	0.0315*	0.0443**	0.0133
	(0.0223)	(0.0202)	(0.0177)	(0.0203)	(0.0180)	(0.0206)	(0.0221)
Employment density *(log)*	0.0397***	0.0314***	0.0124*	**0.0275*****	**0.0257*****	**0.0372*****	**0.0744****
	(0.0042)	(0.0038)	(0.0068)	**(0.0045)**	**(0.0097)**	**(0.0077)**	**(0.0303)**
Occupation controls	No	No	Yes	No	Yes	No	Yes
Age controls	No	No	Yes	No	Yes	No	Yes
Greenbelt fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	529	529	529	529	529	529	529
R^2	0.1476	0.3965	0.6374				
Kleibergen-Paap F-statistic				1440	491.7	168.5	31.13

Notes: **Bold** indicates instrumented. We estimate the regressions at the parliamentary constituency level. Earnings refer to the median of male weekly earnings. In columns (4) and (5) I use population density in 1931 as an instrument for employment density. In columns (6) and (7) I use the share of greenbelt land within 10-25km from the parliamentary constituency as an instrument for employment density. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

More specifically, conditional on the share of greenbelt land in the own MSOA and given that direct amenity effects of greenbelts are (very) local I use the share of greenbelt land between 10 and 25km. The identifying assumption is then that the share of greenbelt land between 10-25km does not generate direct productivity effects other than via the effects on the spatial equilibrium of workers choosing each location. One concern is that there are environmental effects, such as pollution, which is impacted by greenbelt land far away (see *e.g.* Yang & Jinxing 2007), and hence impacts the amenity level at a certain location. In Appendix B.4 I show that those effects are confined to the own MSOA.

Because the identification of spillover effects is less convincing compared to supply and amenity effects, I also will also provide some robustness checks where the instruments are only 'plausibly exogenous' (Conley et al. 2012, see).

B.2.2 Results

Regression results are reported in Table B2. In column (1) I run a naive regression of log earnings on the share of greenbelt land and employment density in a parliamentary constituency (recall that this is the lowest level at which the earnings data are available). I do not find robust evidence for a productive amenity effect, but I find evidence that agglomeration economies are important. The elasticity falls within the range (0.02-0.05) suggested by the literature (see *e.g.* Combes et al. 2008, Melo et al. 2009).

If I include greenbelt fixed effects I find evidence for a productive amenity effects: when the share of greenbelt land increases by 10 percentage points, earnings increase by 0.4%. The agglomeration elasticity (0.0314) is similar to the previous specification.

Given my aggregate cross-sectional data on earnings, I cannot track workers over time and include worker fixed effects to control for sorting of able workers in cities (Combes et al. 2008, De la Roca & Puga 2017). To investigate whether this is an issue I include 8 occupation controls in order to control for the share of workers in higher managerial positions, lower managerial positions, intermediate occupations, self-employed, technical occupations, semi-routine occupations, routine occupations, and long-term unemployed. Moreover, I include 4 age controls. The results show that the productive amenity effect is still observed, but the effect of agglomeration economies becomes somewhat smaller; the elasticity is now 0.0124.

One may argue that current employment density is correlated to unobserved locational endowments. The familiar way to deal with this is to use long-lagged instruments (see *e.g.* Ciccone & Hall 1996, Combes et al. 2008). Initially, I follow this approach and use population density in 1931 as an instrument for current employment density. In Appendix B.2 I display the first-stage results, and show that the instrument is strong. The elasticity of population density in 1931 with current employment density is 0.83 without controls and 0.52 with controls. Going back to Table B2, when instrumenting but without the inclusion of controls, in column (4) I find that the agglomeration elasticity is now slightly lower. The results are essentially unaffected when I include occupation and age controls, suggesting that the issue of sorting is unimportant (column (5)).

In columns (6) and (7) I take another approach, by using greenbelt land far away as an instrument, as it is unlikely that greenbelt land far away generates local amenity effects. However, it does impact the aggregate spatial distribution of employment and so the employment density in the own area. The first-stage results reported in Appendix B.2 show that a high share of greenbelt land between 10 and 25km implies that employment density in the own location is higher, which makes sense as greenbelt land displaces employment to other areas. Going back to Table B2, I find that the instrument is sufficiently strong; albeit less strong than population density in 1931. The agglomeration elasticity is, however, essentially the same as in the OLS specifications (see column (5)). When I include occupation and age controls, the agglomeration elasticity becomes somewhat larger, but at the same time is quite imprecisely estimated. Hence, it is not statistically significantly different from the baseline OLS equation at the 1% level. Hence, whatever identification strategy I choose, I find consistent evidence for agglomeration economies. The elasticity of wages with respect to density is around 0.03.

I consider also alternative identification strategies to identify the effect of greenbelt land on wages (using counterfactual or greenbelt land in 1973, or applying spatial differencing) in Appendix B.2. The reduced-form evidence on the productive amenity effect is somewhat mixed and often not statistically significant and close to zero when applying other identification strategies.

Table B3 – Total effects of greenbelts on wages
(Dependent variable: the log of earnings at the workplace in £ per week)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLSS
		All observations		Counterfactual greenbelts	Greenbelts in 1973	Greenbelt border <2.5km
Share greenbelt land	0.0117	0.0238	0.0411**	0.0325*	-0.0226	0.0368
	(0.0241)	(0.0214)	(0.0176)	(0.0169)	(0.0271)	(0.0581)
Occupation controls	No	No	Yes	Yes	Yes	Yes
Age controls	No	No	Yes	Yes	Yes	Yes
Greenbelt fixed effects	No	Yes	Yes	Yes	Yes	Yes
Number of observations	529	529	529	401	301	90
R^2	0.0004	0.3178	0.6350	0.5895	0.6636	0.7207

Notes: Earnings refer to the median of male weekly earnings. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

B.2.3 Total effect of greenbelts and first-stage results

Greenbelts may imply a productive amenity effect, but arguably the main effect of greenbelt is through lower densities. It may therefore be informative to consider the total effect of greenbelts, by excluding employment density from the regression. I report results in Table B3. The results are not particularly clear-cut and suggest, if anything, that the overall effect of greenbelts on earnings is slightly positive. This would suggest that the productive amenity effect exceeds any reduction in wages due to lower agglomeration economies. However, note that for most identification strategies, *conditional on employment density*, the productive amenity effect is economically small and statistically insignificant.

In Table B4 I report first-stage results. In columns (2) and (3) I use population density in 1931 as an instrument for current employment density. Unsurprisingly, I find a strong correlation between past population density and current employment density. The elasticity is 0.831 without controls and 0.518 with occupation and age controls.

In columns (3) and (4) I use the share of greenbelt land 10-25km from a constituency as an instrument for employment density. In column (3) I find a strong effect of the share greenbelt land further away: a 10 percentage point increase in the share greenbelt land 10-25km is associated with an increase in the own employment density of 43%. The effect is still 11% once I include occupation and age controls in column (4).

B.2.4 Plausibly exogenous historic instruments

Furthermore, I estimate regressions where I allow the instruments to be 'plausibly exogenous', implying that the instrument may have a direct effect on the outcome variable other than via employment density. This may be true when unobserved locational endowments of the past are correlated to unobserved

Table B4 – First-stage results

(Dependent variable: the log of employment density)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
	Population density 1931		Share greenbelts 10-25km	
Share greenbelt land	-0.0595	0.1715**	-1.0163***	0.1623
	(0.1189)	(0.0823)	(0.2031)	(0.1181)
Population density in 1931 *(log)*	0.8314***	0.5182***		
	(0.0219)	(0.0231)		
Share greenbelt land 10-25km			4.2997***	1.1389***
			(0.3299)	(0.2047)
Occupation controls	No	Yes	No	Yes
Age controls	No	Yes	No	Yes
Greenbelt fixed effects	Yes	Yes	Yes	Yes
Number of observations	529	529	529	529
R^2	0.7748	0.9149	0.3555	0.8407

Notes: We estimate the regressions at the parliamentary constituency level. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

endowments today. More specifically, let us consider:

$$\log w_i = \theta_1 g_i + \theta_2 \log\left(\frac{H_{Mi}}{L_i}\right) + \theta_3 v_i + \theta_4 \log\left(\frac{H_{Ri,1931}}{L_i}\right) + \nu_{i\in\mathcal{G}} + \breve{\epsilon}_i. \tag{B.2}$$

In a standard IV, θ_4 is assumed to be zero. However, let us consider the case that $\theta_4 > 0$. To determine the appropriate size of θ_4 I estimate a reduced-form regression of $\log w_i$ on the instrument and controls, but exclude the endogenous employment density variable. The estimated θ_4 then indicates the maximum direct impact of historic endowments on current wages. I multiply θ_4 by Π, indicating the share of the effect that is assumed to be direct, while $1 - \Pi$ indicates the impact of historic density on wages via increased employment density.

Table B5 reports the results. In column (1) I assume $\Pi = 0$, which renders the effect of employment density to be zero. This is anticipated, as all of the impact of historic population density is assumed to be direct, so that the effect of employment density on wages should be equal to zero. Hence, it is more informative to choose lower values for Π. When I assume that 50% of the impact of historic population on wages is via employment density, the estimated elasticity is 0.0138, which is somewhat lower than 2SLS estimate, but not statistically significantly different. The impact is slightly stronger if I assume that 75% of the effect of historic population density on wages is via employment density. More importantly, the confidence interval is now smaller.

I repeat the same exercise, but now include occupation and age controls. This leads to virtually the same results, with the point estimate being 0.0193 when I assume that 75% of the effect of historic population density on wages is via employment density (see column (6)). However, the 95% confidence bands are

Table B5 – Agglomeration economies: plausibly exogenous instruments

	No controls			*+ Age and occupation controls*		
	Π = 1.00	Π = 0.50	Π = 0.25	Π = 1.00	Π = 0.50	Π = 0.25
	(1)	(2)	(3)	(4)	(5)	(6)
Share greenbelt land	0.0373	0.0381	0.0385	0.0359	0.0337	0.0701
	[-0.0030 0.0777]	[-0.0016 0.0778]	[-0.0009 0.0780]	[0.0016 0.0701]	[-0.0006 0.0680]	[0.0128 -0.0056]
Employment density *(log)*	**0.0000**	**0.0138**	**0.0206**	**0.0000**	**0.0128**	**0.0193**
	[-0.0089 0.0362]	**[0.0050 0.0362]**	**[0.0119 0.0362]**	**[-0.0184 0.0442]**	**[-0.0056 0.0442]**	**[0.0008 0.0442]**
Occupation controls	No	No	No	Yes	Yes	Yes
Age controls	No	No	No	Yes	Yes	Yes
Greenbelt fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	529	529	529	529	529	529

Notes: **Bold** indicates instrumented. We estimate the regressions at the parliamentary constituency level. Earnings refer to the median of male weekly earnings. We use population density in 1931 as an instrument for employment density. 95% confidence intervals are in brackets

somewhat larger than without controls.

B.2.5 Other identification strategies

In Table B6 I report results for the reduced-form regressions when I choose alternative identification strategies to identify productive amenity effects. In Panel A I only include observations in counterfactual greenbelts. That is, I estimate weighted regressions where the weight is equal to the share of land in counterfactual greenbelts. What one can observe is that the productive amenity effect is small and statistically insignificant. The agglomeration elasticity is around 0.03 throughout the different specifications.

In Panel B I weight the observations by the share of land in proposed or approved greenbelts in 1973 (see Figure 2a). I still do not find evidence for a productive amenity effect. The agglomeration elasticity is slightly sensitive to the inclusion of controls, but roughly in line with earlier findings.

In Panel C in Table B6 I only include parliamentary constituencies with centroids that are within 1km of an inner or outer greenbelt border. This dramatically reduces the number of observations and, unsurprisingly, leads to somewhat imprecise results. Generally speaking, I find a positive agglomeration elasticity, which is in the same ballpark as the previous estimates.

B.3 Reduced-form effects: visits to greenbelts

In this subsection I investigate whether greenbelts are a main destination for natives and tourists. In order to proxy for the attractiveness of a postcode I use data on geocoded pictures from *FlickR*, an online hosting service for media. Using geocoded pictures involves care. First, to avoid the possibility of inaccurate geocoding, I keep only one geocoded picture per location defined by its geographical coordinates per user per hour of the day. This reduces the number of pictures by about 45%. Second, one may

Table B6 – Productive amenity effects and agglomeration economies: sensitivity

(Dependent variable: the log of earnings at the workplace in £ per week)

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS
	Baseline OLS			Population density 1931		Share greenbelts 10-25km	
Panel A: Counterfactual greenbelts							
Share greenbelt land	0.0207	0.0100	0.0254	0.0111	0.0219	0.0076	0.0135
	(0.0224)	(0.0200)	(0.0170)	(0.0201)	(0.0173)	(0.0204)	(0.0203)
Employment density *(log)*	0.0246***	0.0199***	0.0279***	**0.0100**	**0.0420*****	**0.0421****	**0.0750***
	(0.0073)	(0.0063)	(0.0096)	(**0.0084**)	(**0.0150**)	(**0.0185**)	(**0.0419**)
Occupation controls	No	No	Yes	No	Yes	No	Yes
Age controls	No	No	Yes	No	Yes	No	Yes
Greenbelt fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	402	402	402	402	402	402	402
R^2	0.0311	0.3457	0.5984				
Kleibergen-Paap F-statistic				507.9	267	52.40	22.46
Panel B: Greenbelts in 1973							
Share greenbelt land	0.0523	-0.0140	-0.0041	-0.0225	0.0116	-0.0254	0.0082
	(0.0372)	(0.0301)	(0.0271)	(0.0340)	(0.0286)	(0.0425)	(0.0298)
Employment density *(log)*	0.0211**	0.0181**	0.0394***	**0.0137**	**0.0727*****	**0.0122**	**0.0654****
	(0.0103)	(0.0076)	(0.0114)	(**0.0111**)	(**0.0202**)	(**0.0172**)	(**0.0275**)
Occupation controls	No	No	Yes	No	Yes	No	Yes
Age controls	No	No	Yes	No	Yes	No	Yes
Greenbelt fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	301	301	301	301	301	301	301
R^2	0.0148	0.5333	0.6776				
Kleibergen-Paap F-statistic				252	133.7	69.94	58.14
Panel C: Spatial differencing							
Share greenbelt land	0.1714**	0.0632	0.0751	0.0745	0.0890	0.1013	0.1267*
	(0.0858)	(0.0630)	(0.0572)	(0.0683)	(0.0599)	(0.0869)	(0.0723)
Employment density *(log)*	0.0345*	0.0089	0.0548***	**0.0149**	**0.0747****	**0.0291**	**0.1284****
	(0.0198)	(0.0139)	(0.0198)	(**0.0197**)	(**0.0307**)	(**0.0343**)	(**0.0560**)
Occupation controls	No	No	Yes	No	Yes	No	Yes
Age controls	No	No	Yes	No	Yes	No	Yes
Greenbelt fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	93	93	93	93	93	93	93
R^2	0.0516	0.6231	0.7479				
Kleibergen-Paap F-statistic				81.95	50.71	16.57	12.25

Notes: **Bold** indicates instrumented. We estimate the regressions at the parliamentary constituency level. Earnings refer to the median of male weekly earnings. In columns (4) and (5) I use population density in 1931 as an instrument for employment density. In columns (6) and (7) I use the share of greenbelt land within 10-25km from the parliamentary constituency as an instrument for employment density. In Panel B I use the share of proposed greenbelt land as an instrument for the share of greenbelt land. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

argue that the patterns of pictures taken by tourists and residents may be very different. Since I have information on users' identifiers, I can distinguish between residents' and tourists' pictures by keeping users who take pictures for at least 6 consecutive months between 2000 and 2018 in England. It seems unlikely that tourists stay for 6 consecutive months in the area. Note that the correlation between natives' and tourists' pictures is equal to 0.748. Third, many recorded pictures may not be related to recreational visits but to ordinary events in daily life occurring inside the house. Hence, in the regressions I control

Table B7 – Visits to greenbelts: effects on pictures

(Dependent variable: the number of pictures by residents in an MSOA)

	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
		+ Controls and fixed effects	Counterfactual greenbelts	Greenbelts in 1973	Greenbelt border <2.5km	Greenbelt border <1km
Share greenbelt land	-0.7221***	-0.4605***	-0.1919***	-0.5682***	-0.3350***	-0.8090***
	(0.0016)	(0.0023)	(0.0000)	(0.0000)	(0.0039)	(0.0062)
Area size of MSOA *(log)*	0.2101***	0.4994***	0.6191***	0.6827***	0.6750***	0.8677***
	(0.0002)	(0.0004)	(0.0000)	(0.0000)	(0.0012)	(0.0019)
Number of dwellings *(log)*		1.3364***	0.5942***	0.6618***	1.3707***	1.2023***
		(0.0021)	(0.0000)	(0.0001)	(0.0044)	(0.0062)
Location attributes	No	Yes	Yes	Yes	Yes	Yes
Local authority fixed effects	No	Yes	Yes	Yes	Yes	Yes
Observations	6,791	6,789	1,803	1,473	2,436	1,374
Log pseudo-likelihood	-6,363,647	-3,540,378	-402,663	-390,950	-747,506	-385.865

Notes: Location attributes are a linear, squared and cubic term of distance to the nearest city centre. In column (3) I only include observations that are in counterfactual greenbelts as defined in Section 2.1. Column (4) includes observations in areas that are in proposed or approved greenbelts in 1973. In columns (5) and (6) I include transactions that are within 2.5km or 1km of a greenbelt boundary respectively. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

flexibly for the number of dwellings in a postcode, by including a 3$^{\text{rd}}$-order polynomial of dwellings. I then estimate:

$$q_i = e^{\iota_1 g_i + \iota_2 \log L_i + \iota_3 \log d_i + \iota_4 m_i + \varpi_{i \in \mathcal{A}} + \check{\xi}_i}. \tag{B.3}$$

where q_i is the number of pictures of residents in a postcode between 2000 and 2018, g_i is the share of the postcode in the MSOA, L_i is the land area of an MSOA, d_i is the number of dwellings in an MSOA, m_i is a flexible function of distance to the nearest city centre, and $\varpi_{i \in \mathcal{A}}$ are local authority fixed effects. Table B7 reports the results.

In the specification in column (1) I do not control for location attributes or detailed fixed effects. I find that pictures are 51% lower in greenbelts. At least part of this effect can be explained that in denser areas there are more people to make pictures. In column (2) I therefore control for the number of dwellings in an MSOA. This does indeed lead to a lower effect: the reduction in pictures is 37% when an MSOA is fully in a greenbelt.[32] Hence, the lack of pictures in greenbelts cannot be explained by differences in density. The most likely explanation therefore seems that greenbelts are just not very popular places to go.

In column (3) I estimate a weighted Poisson regression, where the weight is the share of an MSOA in a counterfactual greenbelt. I show that the effect of greenbelt land on pictures is now considerably smaller (-17%). In column (4) I weight the observations by their share in approved or considered greenbelt land

[32] I have experimented with including flexible functions of area size and number of dwellings, but this hardly changes the results. Those results are available upon request.

in 1973. The impact is now stronger, but comparable to the specification in column (2).

In the final two columns I focus on areas close to greenbelt areas. I again find negative coefficients. In column (5), where I include areas within 2.5km of a greenbelt border, the coefficient implies that pictures will reduce by 28% when an MSOA is (fully) in a greenbelt. In the final column I include only areas within 1km of a border. The effect then is even stronger: the reduction in pictures is 55%.

I consider sensitivity of the results by replacing the dependent variable by the number of pictures *by tourists*, or by focusing on smaller areas (the number of pictures in postcodes). The conclusion remains unchanged: greenbelts do not seem be main destinations for visits of tourists. If greenbelts are not destinations for visits, does this question the positive price effect I found earlier? I do not think so: given that the positive amenity effect of greenbelts is very local, it most likely captures the local view effect on green space.

B.4 Reduced-form effects: pollution

It has been argued that greenbelts also may reduce air pollution in cities (Yang & Jinxing 2007). If this indeed the case, it may be that amenity levels may be influenced also further away from a greenbelt. I test this more explicitly by using data on two sources of pollution: particulate matter (PM_{10}) and nitrogen oxide (NO_x). I gather data from the *UK National Atmospheric Emissions Inventory* for 2016, which modelled air pollution in a very detailed way at a 1km grid.

As dependent variable I take the log of one of the sources of pollution and estimate regressions of the following form:

$$\log a_i = \chi_1 g_i + \sum_{\mathcal{R}} \chi^g_{\mathcal{R}} g_{i\mathcal{R}} + \chi_2 \log\left(\frac{d_i}{L_i}\right) + \sum_{\mathcal{R}} \chi^d_{\mathcal{R}} \left(\frac{d_{i\mathcal{R}}}{L_{i\mathcal{R}}}\right) + \chi_3 m_i + \varpi_{i\in\mathcal{A}} + \bar{\xi}_i. \tag{B.4}$$

where a_i denotes pollution and χ_1, $\chi^g_{\mathcal{R}}$ $\forall\mathcal{R}$, χ_2, $\chi^d_{\mathcal{R}}$ $\forall\mathcal{R}$, χ_3, and $\varpi_{i\in\mathcal{A}}$ are parameters to be estimated. I include 2.5km distance bands of the share of greenbelt land in each band, as pollution in a certain location may be influenced by other locations. I control for the density of dwellings in each band. I report results in Table B8 for particulate matter and in Table B9 for nitrogen oxide.

I show in column (1) in Table B8 that the share of greenbelt land in the own MSOA is negatively associated with the concentration of particulate matter. Further away, I find a negative coefficient for greenbelt land between 0 and 2.5km and a positive coefficient for greenbelt land between 2.5 and 5km, which is somewhat hard to interpret. I therefore include dwelling density, a flexible function of distance to the nearest city centre and local authority fixed effects in the next specification. Column (2) does still find an effect of greenbelt land on the concentration of particulate matter inside the MSOA. The

Table B8 – Greenbelts and pollution: particulate matter

(Dependent variable: the log of PM_{10})

	(1) OLS	(2) OLS	(3) WLS	(4) WLS	(5) OLS	(6) OLS
		+ Controls and fixed effects	Counterfactual greenbelts	Greenbelts in 1973	Greenbelt border <2.5km	Greenbelt border <1km
Share greenbelt land	-1.3581***	-0.2277***	-0.2369***	-0.3312***	-0.3336***	-0.4214***
	(0.0525)	(0.0367)	(0.0501)	(0.0570)	(0.0511)	(0.0681)
Share greenbelt land 0-2500m	-1.0188***	-0.0072	0.1048	0.0915	0.0055	0.1357
	(0.1192)	(0.0844)	(0.1274)	(0.1386)	(0.1157)	(0.1671)
Share greenbelt land 2500-5000m	1.6690***	-0.0877	-0.1042	-0.2286**	-0.0975	-0.1273
	(0.0662)	(0.0594)	(0.0952)	(0.1029)	(0.0885)	(0.1259)
Dwellings per ha *(log)*		0.5713***	0.5430***	0.5263***	0.5277***	0.4942***
		(0.0063)	(0.0103)	(0.0156)	(0.0150)	(0.0225)
Dwellings per ha 0-2500m *(log)*		0.1498***	0.1447***	0.1988***	0.1779***	0.1944***
		(0.0157)	(0.0238)	(0.0334)	(0.0322)	(0.0460)
Dwellings per ha 2500-5000m *(log)*		-0.0211	-0.0281	-0.0464	-0.0547*	-0.0801
		(0.0167)	(0.0232)	(0.0311)	(0.0326)	(0.0503)
Location attributes	No	Yes	Yes	Yes	Yes	Yes
Local authority fixed effects	No	Yes	Yes	Yes	Yes	Yes
Number of observations	6,791	6,789	3,169	2,252	2,436	1,374
R^2	0.1271	0.8644	0.7915	0.7922	0.7881	0.7411

Notes: Location attributes a linear, squared and cubic term of distance to the nearest city centre. In column (3) I only include observations that are in counterfactual greenbelts as defined in Section 2.1. Column (4) includes observations in areas that are in proposed or approved greenbelts in 1973. In columns (5) and (6) I include transactions that are within 2.5km or 1km of a greenbelt boundary respectively. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

coefficient implies that particulate matter is reduced by 2.3% for a 10 percentage point increase in the share of greenbelt land. Outside the own MSOA I do not find statistically significant effects. Note that dwelling density, unsurprisingly, leads to an increase in PM_{10} (the elasticity is about 0.5). Also dwelling density outside the MSOA impacts pollution in the own MSOA. These results are confirmed in column (3) where I weight areas based on their share in counterfactual greenbelts. In column (4), where I focus on areas in greenbelts in 1973, the results are similar, except that I find also effects beyond 2500m. This is likely a Type II error, as there are few areas which are inside greenbelts in 1973, but now far away from greenbelts. This finding is in line with column (3) of Panel A in Table B1, where I find a positive price effect between 2000 and 2500m of a greenbelt.[33]

When I only exploit local variation in pollution in columns (5) and (6), I confirm that *inside* greenbelts the concentration of PM_{10} is lower, but there is no effect of greenbelt land beyond the own MSOA.

In Table B9 I report the results for nitrogen oxide. In areas with a high concentration of motor vehicle traffic, such as in and around large cities, nitrogen oxides emitted can be an important source of air pollution, as NO_x is mostly produced from the reaction between nitrogen and oxygen during combustion

[33] This may be related to observations around Southampton, which was a proposed greenbelt in 1973, but ended up being designated as a national park in 2005.

Table B9 – Greenbelts and pollution: nitrogen oxide

(Dependent variable: the log of NO_x)

	(1) OLS	(2) OLS	(3) WLS	(4) WLS	(5) OLS	(6) OLS
		+ Controls and fixed effects	Counterfactual greenbelts	Greenbelts in 1973	Greenbelt border <2.5km	Greenbelt border <1km
Share greenbelt land	-0.7323***	-0.0457	-0.1946**	-0.4374***	-0.4277***	-0.5167***
	(0.0639)	(0.0571)	(0.0765)	(0.0891)	(0.0793)	(0.1078)
Share greenbelt land 0-2500m	-1.3465***	0.0696	0.3302*	0.6341***	0.1969	0.1857
	(0.1398)	(0.1315)	(0.1945)	(0.2167)	(0.1796)	(0.2644)
Share greenbelt land 2500-5000m	1.6845***	-0.1669*	-0.0819	-0.2757*	0.0172	0.0673
	(0.0757)	(0.0926)	(0.1454)	(0.1609)	(0.1374)	(0.1992)
Dwellings per ha *(log)*		0.3751***	0.2957***	0.2156***	0.1840***	0.1217***
		(0.0098)	(0.0158)	(0.0243)	(0.0233)	(0.0357)
Dwellings per ha 0-2500m *(log)*		0.2902***	0.3259***	0.4010***	0.3545***	0.3460***
		(0.0244)	(0.0364)	(0.0522)	(0.0500)	(0.0729)
Dwellings per ha 2500-5000m *(log)*		-0.0319	-0.0051	-0.0311	-0.1293**	-0.1147
		(0.0261)	(0.0354)	(0.0486)	(0.0506)	(0.0796)
Location attributes	No	Yes	Yes	Yes	Yes	Yes
Local authority fixed effects	No	Yes	Yes	Yes	Yes	Yes
Number of observations	6,791	6,789	3,169	2,252	2,436	1,374
R^2	0.0705	0.6957	0.5395	0.5033	0.5005	0.4464

Notes: Location attributes a linear, squared and cubic term of distance to the nearest city centre. In column (3) I only include observations that are in counterfactual greenbelts as defined in Section 2.1. Column (4) includes observations in areas that are in proposed or approved greenbelts in 1973. In columns (5) and (6) I include transactions that are within 2.5km or 1km of a greenbelt boundary respectively. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

of fuels. Column (1) shows that the concentration of nitrogen oxides inside greenbelts is lower, but again I find both positive and negative coefficients beyond the own MSOA. Including local authority fixed effects solves the issue (column (2)) Again, in line with the results found for PM_{10}, I find that coefficients are insignificant beyond the own MSOA, confirming the conclusion that, if anything, the impact of greenbelts on pollution is local and therefore is absorbed in revealed amenity levels Ψ_i.

Appendix C. Structural model

C.1 Gravity models

In Table C1 I report results of several commuting gravity models identifying the commuting time elasticity, $\varkappa$.

I start with the baseline commuting gravity with residence and workplace location fixed effects. I estimate the model by Pseudo-Maximum Likelihood Poisson regressions. I find a (semi-)elasticity of -0.08, indicating that when commuting time increases by 1 minute the number of commuters decreases by $e^{-0.0821} - 1 = 7.9\%$.

Note that I use the actual travel time between i and j, rather than the free-flow travel time, as in Ahlfeldt et al. (2015). I show in column (2) that this matters: the elasticity when using free-flow travel times is almost twice as strong.

One may argue that travel times are endogenous. On the one hand, commuting times are longer on links where there are many commuters leading to longer travel times. On the other hand, there may be reverse causality as busy links with lots of commuters may attract infrastructure investments, leading to lower travel times. As an instrument for commuting times I therefore use the euclidean distance. Because a Poisson model is a non-linear model I cannot employ 2SLS. Alternatively, I use a control function approach where the first-stage error is inserted as a control variable in the second stage. This leads to a very similar effect. The first-stage error appears to be statistically significant, suggesting that endogeneity is relevant. However, the travel time elasticity is hardly affected and essentially the same as compared to

Table C1 – Commuting gravity models

(Dependent variable: the number of commuters between i and j)

	(1) Poisson	(2) Poisson	(3) Poisson-CF	(4) Poisson-CF	(5) Poisson-CF
	Baseline	*Free-flow*	*Endogeneity*	*<60 minutes*	*>0 commuters*
Commuting time *(minutes)*	-0.0821***		**-0.0853*****	**-0.1123*****	**-0.0724*****
	(0.0002)		(**0.0002**)	(**0.0003**)	(**0.0003**)
Commuting time, free-flow *(minutes)*		-0.1533***			
		(0.0005)			
First-stage error			0.0173***	0.0513***	0.0125***
			(0.0007)	(0.0008)	(0.0007)
Residence location fixed effects	Yes	Yes	Yes	Yes	Yes
Work location fixed effects	Yes	Yes	Yes	Yes	Yes
Number of areas	6,701	6,701	6,701	6,701	6,701
Number of area pairs	19,673,517	19,673,517	19,673,517	7,069,155	2,077,634

Notes: **Bold** indicates instrumented. We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). We instrument travel times by euclidian distance in columns (2), (3) and (4). Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

Table C2 – Commuting congestion models

(Dependent variable: the log of the ratio of travel time and free-flow travel time between i and j)

	Baseline specification	*Population 1931*	*Greenbelts 10-25km*	*Total Population*	*Commuting <30 minutes*	*No residential fixed effects*
	(1)	(2)	(3)	(4)	(5)	(6)
Traffic density, $\mathcal{D}_M$	-0.1274***	**-0.152**3***	**-0.1422***		-0.1461***	-0.1248***
	(0.0016)	(**0.0026**)	(**0.0028**)		(0.0049)	(0.0016)
Total traffic density, $\mathcal{D}_M + \mathcal{D}_R$				-0.1419***		
				(0.0019)		
Residence location fixed effects	Yes	Yes	Yes	Yes	Yes	No
Number of areas	6,701	6,701	6,701	6,701	6,701	6,701
Number of area pairs	19,673,517	19,673,517	19,673,517	19,673,517	19,673,517	19,673,517

Notes: **Bold** indicates instrumented. I measure traffic density in standard deviations. I estimate the parameters using data at the Mid-layer Super Output Area (MSOA). Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

the baseline specification.

In column (3) I reduce the maximum commute in the data from 120 to 60 minutes. This reduces the number of location pairs by almost 65%. The coefficient again is very similar: when commuting time increases by 1 minute the number of commuters decreases by 11%. In column (4) I make sure that the results are not influenced by the large number of pairs without any commuters as I keep only pairs with at least one commuter. Now, the elasticity is slightly lower, but quantitatively very close to the baseline specification.

C.2 Travel time and congestion costs

Here I report alternative specifications to estimate the traffic congestion elasticity. I measure traffic density in standard deviations. In column (1) I report the baseline specification. The coefficient indicates that a standard deviation increase in (workplace) traffic density leads to a travel time that is 12.7% lower. Hence, traffic density has a substantial impact on travel times.

One may argue that traffic density is endogenous, *e.g.* because infrastructure is constructed in places where traffic density is higher, leading to shorter travel times. Furthermore, actual travel times are used to determine the 'relevant' traffic density. In column (2) I instrument workplace traffic density by the population density in 1931. I observe that this hardly matters for the estimated coefficient. If anything, I find a slightly stronger effect of traffic density on travel times. When I instrument traffic density with the share of greenbelt land between 10 and 25km I find a very similar coefficient, which is reassuring.

To calculate traffic density I only take into account workplace density. One might be worried that ignoring residential density might lead to incorrect estimates. Column (4), in which I add both residential and

Table C3 – Share of capital in construction costs

(Dependent variable: the log of the ratio of built-up land over all land in i)

	OLS	*Instrument for prices*	*+ controls, county f.e.*	*Counterf. greenbelts*	*Greenbelts in 1973*	*Greenbelt border <1km*	*Temperature instruments*	*Add controls*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of construction costs in capital, μ	-1.4242***	**0.5769*****	**0.7601*****	**0.6452**	**0.6959*****	**0.8216*****	**0.7788*****	**0.7189*****
	(0.2331)	(**0.0193**)	(**0.0324**)	(**0.4297**)	(**0.1190**)	(**0.0899**)	(**0.0140**)	(**0.0182**)
Supply condition variables	No	No	Yes	Yes	Yes	Yes	No	Yes
County fixed effects	No	No	Yes	Yes	Yes	Yes	No	No
Greenbelt fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of areas	6,791	6,791	6,791	1,295	1,020	1,385	6,791	6,791
R^2	0.112							
Kleibergen-Paap F-statistic		796.95	73.87	5.10	9.89	4.58	134.63	159.96

Notes: **Bold** indicates instrumented. Soil condition variables include the share of sandy, rock, loam and clay soils; as well as elevation, the average slopes, the thickness of the sediment layer, the share of accessible bedrock, and the share of workers in the construction sector. We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

workplace density, shows that this hardly matters. Column (5) investigates whether the results change if I only consider commuting pairs that are within 30 minutes travelling. I show that this does not materially influences the results. Furthermore, when I leave out residential fixed effects in the estimation in column (6), I also find a very similar congestion elasticity.

C.3 Capital cost share in construction

The capital cost share in construction, μ, is obtained through a regression of total floor space consumption on floor space prices as stipulated in (30). Table C3 reports the results.

Column (1) shows a naive regression of the log of the ratio of built-up land over all on floor space prices. Reverse causality thwarts a causal interpretation of this coefficient. I find a *negative* μ, implying that lower floor space prices are associated with a higher share of built-up area (meaning more supply of floor space).

Column (2) then instruments for floor space by the distance to the city centre. The idea is that closer to the city centre, commutes are shorter and agglomeration economies are more pronounced so that prices are higher, which makes it more attractive to construct taller buildings (Alonso 1964, Mills & Lubuele 1997, Muth 1969). The first-stage results in Table C4 confirm this hypothesis: when distance to the nearest city centre doubles, the price decreases by 8.6%. When I control for supply conditions and county fixed effects, the price decrease for doubling the distance to the city centre is 3.1-6.7% (*e.g.* soil type, elevation).

Going back to column (2) in Table C3, I find that $\mu = 0.577$. This implies that floor space prices have a positive effect on the ratio of floor space supply to total developed land. The reason is that when floor

Table C4 – Share of capital in construction, first-stage results

(Dependent variable: the log of floor space price in i)

		+ controls and county f.e.	*Counterfactual greenbelts*	*Greenbelts in 1973*	*Greenbelt border <1km*	*Temperature instruments*	*Add controls*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance to the nearest	-0.1243***	-0.0714***	-0.0514**	-0.0961***	-0.0454**		
city centre *(log)*	(0.0045)	(0.0083)	(0.0233)	(0.0295)	(0.0206)		
January temperature *(in °C)*						-0.0198**	0.0263***
						(0.0096)	(0.0099)
July temperature *(in °C)*						0.1454***	0.1649***
						(0.0093)	(0.0097)
Supply condition variables	No	Yes	Yes	Yes	Yes	No	Yes
County fixed effects	No	Yes	Yes	Yes	Yes	No	No
Greenbelt fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of areas	6,791	1,295	1,020	1,385	1,385	6,791	6,791
R^2	0.639	0.819	0.785	0.837	0.789	0.599	0.665

Notes: Soil condition variables include the share of sandy, rock, loam and clay soils; as well as elevation, the average slopes, the thickness of the sediment layer, the share of accessible bedrock, and the share of workers in the construction sector. We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

space prices increase, according to the first-order condition (19), the amount of capital should increase, which in turn increases the ratio of floor space to developed land.[34]

However, when I control for potential supply conditions and county fixed effects $\hat{\mu}$ is somewhat higher (0.76). This value is particularly close to the value assumed in Ahlfeldt et al. (2015) and not statistically significantly different from the value of 0.80 estimated in Combes et al. (2016) for single-family houses. When I consider selections of samples, *e.g.* by selecting areas in counterfactual greenbelts, greenbelts in 1973, or when areas are within 1km of a greenbelt border, the instrument is much less strong. Particularly in column (4) this leads to wildly imprecise results. Still, the point estimates are close to 0.76 and reasonably precise in column (5) and (6).

To the extent one is worried that distance to the city centre is still correlated to supply conditions, *conditional on the inclusion of* 150 *county fixed effects and 10 variables capturing differences in supply conditions*, I also consider alternative instruments. More specifically, I calculate the average temperature in January and July as a potential demand shifter, following Glaeser et al. (2001). I expect that higher temperatures are considered as an amenity and are therefore associated with higher floor space prices. This is confirmed by a first-stage regression in columns (6) and (7) of Table C4, in which particularly July temperatures are correlated with higher prices. More specifically, a one degree increase in July temperatures (*i.e.* 0.87 of a standard deviation) is associated with a price increase of about 15%. Going back to column (7) in Table C3, I find $\hat{\mu} = 0.78$, which is virtually the same as the baseline estimate

[34] The coefficient of floor space prices is 1.36. Hence, a one percent increase in floor space prices leads to an increase in the ratio of floor space to developed land in i of 1.36%.

reported in column (3). When adding supply condition variables in column (8), I obtain a very similar results.[35]

An alternative approach is to consider the distance to the city centre to be an imperfect, only 'plausibly exogenous', instrument. I consider Conley et al.'s (2012) methodology to relax the assumption of strictly exogenous instruments and construct bounds on the estimated μ if the instrument is only 'plausibly exogenous'. Consider the following regression

$$\log \frac{F_i}{\Lambda_i} = \frac{\mu}{1-\mu} p_i + \tilde{\psi} cc_i + \psi S_i + \nu_{i \in \mathcal{G}} + \nu_{i \in C} \tag{C.1}$$

where cc_i is the distance to the city centre and $\tilde{\psi}$ captures the direct impact of distance to the city centre, conditional on the effect of prices, supply conditions and county and greenbelt fixed effects. In a standard IV-framework with exogenous instruments $\tilde{\psi} = 0$. However, if distance to the city centre still captures favourable supply conditions, $\tilde{\psi} > 0$; hence, construction costs and therefore prices are *lower* closer to the city centre.

Of course, the actual value of $\tilde{\psi}$ is unknown, but one may guess reasonable upper bound values. If one, for example, takes into account the first-stage values, the effect is negative and between -0.05 and -0.1. Let's then assume that $\tilde{\psi} = \{0.1, 0.05\}$, implying that construction costs would decrease by 5-10% per kilometre, which seems sizeable.

Table C5 reports the results. In Panel A I consider $\tilde{\psi} = 0.1$. I find statistically significant point estimates of around 0.8 in all specifications. However, the bounds are only informative when I use all areas; in column (3)-(5) the bounds are too imprecise too be meaningful. In the preferred specification in column (2) I find that $\hat{\mu}$ is between 0.70 and 0.85. The point estimate $\hat{\mu} = 0.82$ is very similar to the baseline estimate (*i.e.* $\hat{\mu} = 0.76$). Hence, the downward bias of μ due to potential endogeneity of the instrument is limited.

Note that the lower bounds do not change when I consider $\tilde{\psi} = 0.05$ in Panel B. This is because when the instrument is only plausibly exogenous and captures supply conditions I find an underestimate of μ when using standard IV. The preferred specification in column (2) suggests that the bounds are only slightly narrower, suggesting that the estimate is between 0.70 and 0.83. All in all, these results suggest that even if the instrument is only plausibly exogenous I would still yield reasonably precise estimates for the preferred specification.

[35] However, once I include more detailed county fixed effects, or make selections, I have a weak first-stage and the second-stage does not imply meaningful results. The reason is that within counties or 'greenbelt areas' there are no meaningful temperature differences to identify the effect of prices on floor space supply.

Table C5 – Share of capital in construction, plausibly exogenous instrument

(Dependent variable: the log of the ratio of built-up land over all land in i)

		Greenbelt fixed effects	*+ controls and county f.e.*	*Counterfactual greenbelts*	*Greenbelts in 1973*	*Greenbelt border <1km*
		(1)	(2)	(3)	(4)	(5)
Panel A: $\tilde{\psi} = 0.10$						
Share of construction	μ	0.6843***	0.8204***	0.7902***	0.7690***	0.8719***
costs in capital		(0.0127)	(0.0227)	(0.1328)	(0.0823)	(0.0609)
	$\underline{\mu}$	0.5424***	0.6954***	4.2771	0.1839	-0.1221
		(0.0210)	(0.0365)	(53.3370)	(1.0885)	(3.5998)
	$\overline{\mu}$	0.7043***	0.8501***	0.8910***	0.8530***	0.9290***
		(0.0121)	(0.0210)	(0.0796)	(0.0621)	(0.0802)
Supply condition variables		No	Yes	Yes	Yes	Yes
County fixed effects		No	Yes	Yes	Yes	Yes
Greenbelt fixed effects		Yes	Yes	Yes	Yes	Yes
Number of areas		6,791	6,791	1,295	1,020	1,385
Panel B: $\tilde{\psi} = 0.05$						
Share of construction	μ	0.6384***	0.7946***	0.7363***	0.7374***	0.8509***
costs in capital		(0.0153)	(0.0267)	(0.1961)	(0.0971)	(0.0724)
	$\underline{\mu}$	0.5424***	0.6954***	4.2771	0.1839	-0.1221
		(0.0210)	(0.0365)	(53.3368)	(1.0890)	(3.6009)
	$\overline{\mu}$	0.6623***	0.8294***	0.8674***	0.8354***	0.9180***
		(0.0144)	(0.0243)	(0.1010)	(0.0704)	(0.0960)
Supply condition variables		No	Yes	Yes	Yes	Yes
County fixed effects		No	Yes	Yes	Yes	Yes
Greenbelt fixed effects		Yes	Yes	Yes	Yes	Yes
Number of areas		6,791	6,791	1,295	1,020	1,385

Notes: We report the point estimate (μ), the 5% lower bound ($\underline{\mu}$), as well as the 95% upper bound ($\overline{\mu}$). Soil condition variables include the share of sandy, rock, loam and clay soils; as well as elevation, the average slopes, the thickness of the sediment layer, the share of accessible bedrock, and the share of workers in the construction sector. We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

C.4 Decay

I report the decay of commuting and residential and production externalities in Table C6. It is shown that most of utility is gone after one hour commute, which confirms previous papers. The decay is essentially the same as in Ahlfeldt et al. (2015). The latter paper finds that after 30 minutes travelling, 64% of utility is left, while in my case it is 63%.

By contrast, I find less steep decay for residential and production externalities. For the former, most of the externalities take place within 5 minutes travelling, while this is 25 minutes for production externalities. The reason for the less steep decay may be that I include data from all of England, instead of one city. Hence, interactions also take place over longer distances.

Table C6 – Decay of externalities and commuting costs

	Utility after commuting $(1 \times e^{-\hat{\kappa}\tau})$	*Residential externalities* $(1 \times e^{-\hat{\delta}_R \tau})$	*Production externalities* $(1 \times e^{-\hat{\delta}_M \tau})$
	(1)	(2)	(3)
0 minutes	1.0000	1.0000	1.0000
1 minute	0.9847	0.9399	0.9782
2 minutes	0.9695	0.8835	0.9570
3 minutes	0.9547	0.8304	0.9361
4 minutes	0.9400	0.7805	0.9158
5 minutes	0.9256	0.7336	0.8959
7 minutes	0.8974	0.6481	0.8573
10 minutes	0.8567	0.5382	0.8026
15 minutes	0.7930	0.3948	0.7190
20 minutes	0.7340	0.2897	0.6441
25 minutes	0.6793	0.2125	0.5770
30 minutes	0.6288	0.1559	0.5169
45 minutes	0.4986	0.0615	0.3716
60 minutes	0.3954	0.0243	0.2672
120 minutes	0.1563	0.0006	0.0714

Notes: We report proportional reductons in utility of commuting, residential externalities and agglomeration economies with travel time. Results are based on the coefficients reported in column (1). Table 5.

C.5 Spillover effects

I also estimate models where I assume away endogenous spillovers (hence $\lambda = \gamma_R = \delta_R = \gamma_M = \delta_M = 0$). Table C7 shows that, because the estimation of $\{\hat{\varkappa}, \hat{\epsilon}, \hat{\varphi}, \hat{\mu}\}$ is independent of spillovers, I obtain identical parameter estimates. For the residential amenity effect, I find very similar estimates, except for the estimates based on counterfactual greenbelts. Also for the productive amenity effect, I find similar estimates, with the preferred specification in column (1) being small and statistically insignificant.

One may be concerned that the estimates of the parameters related to spillovers $\{\lambda, \gamma_R, \delta_R, \gamma_M, \delta_M\}$ are biased because I did not yet address endogeneity of residential and commercial density. In Table C8 I therefore use the fitted values of $\log A_{Ri}$ and $\log A_{Mi}$, obtained in a first stage based on variation in population in 1931 or the share of greenbelt land between 10 and 25km. I show in Table C8 that the coefficients are not materially influenced when solely using variation in historic densities (Panel A) or the share of greenbelt land that is far away (Panel B). The congestion elasticity is very similar to the baseline results. The residential elasticity is consistently negative and around -0.18, while the productive elasticity ranges from 0.067-0.151. I find a statistically significant decay parameters of agglomeration economies; the point estimates of $\hat{\delta}_M$ are similar to the baseline estimate.

Table C7 – Structural parameters without spillover effects

	All areas	*Counterfactual greenbelts*	*Greenbelts in 1973*	*Greenbelt border <1km*
	(1)	(2)	(3)	(4)
Commuting time elasticity, $\hat{\varkappa}$	-0.0821***	-0.0821***	-0.0821***	-0.0821***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Commuting heterogeneity, $\hat{\varepsilon}$	5.3066***	5.3066***	5.3066***	5.3066***
	(0.0263)	(0.0263)	(0.0263)	(0.0263)
Greenbelt restrictions, $\hat{\varphi}$	-1.2510***	-1.0149***	-2.2221***	-1.8262***
	(0.0354)	(0.0631)	(0.0434)	(0.0483)
Share capital in construction costs, $\hat{\mu}$	0.7601***	0.6452	0.6959***	0.8216***
	(0.0324)	(0.4297)	(0.1190)	(0.0899)
Residential amenity effect, $\hat{\zeta}_R$	0.0671***	0.0110	0.0769***	0.0579***
	(0.0079)	(0.0141)	(0.0146)	(0.0174)
Productive amenity effect, $\hat{\zeta}_M$	-0.0015	0.0698***	0.0887***	0.0408**
	(0.0088)	(0.0148)	(0.0188)	(0.0187)
Greenbelt fixed effects	Yes	Yes	Yes	Yes
Number of areas	6,701	6,701	6,701	6,701
Number of area pairs	19,673,517	19,673,517	19,673,517	19,673,517

Notes: We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

C.6 Counterfactual experiments – solution algorithm

To solve for the new equilibrium in each of the counterfactual scenarios I follow a similar procedure as described in Ahlfeldt et al. (2015) (see the Supplement). I first choose starting values for transformed wages, floor space prices, travel times, and initial population equal to the ones obtained in the baseline scenario:

$$\{\omega_{i\mathcal{S}} = \omega_{i0}, \omega_{j\mathcal{S}} = \omega_{j0}, p_{i\mathcal{S}} = p_{i0}, \tau_{ij\mathcal{S}} = \tau_{ij0}, H_{\mathcal{S}} = H_0\}, \tag{C.2}$$

where 0 refers to the baseline scenario. I also determine for each counterfactual scenario $\mathcal{S}$ the counterfactual amount of developed land using:

$$\frac{\Lambda_{i\mathcal{S}}}{L_i} = \Phi_i \mathrm{e}^{\varphi g_{i\mathcal{S}}}, \tag{C.3}$$

where $g_{i\mathcal{S}} = G_{i\mathcal{S}}/L_i$ is the counterfactual share of greenbelt land in each MSOA. Note Φ_i does not change for different scenarios. Furthermore, using ancillary data on land prices, I calibrate building capital costs as:

$$r^* = \hat{\mu} p_{i0} \left(\frac{F_{i0}}{\Lambda_{i0}}\right)^{\frac{\hat{\mu}-1}{\hat{\mu}}}, \tag{C.4}$$

I then take the following steps:

Table C8 – Structural parameters: instrumenting for density

	All areas	*Counterfactual greenbelts*	*Greenbelts in 1973*	*Greenbelt border <1km*
	(1)	(2)	(3)	(4)
Panel A: Instrument for density is population in 1931				
Congestion elasticity, $\hat{\lambda}$	0.1523***	0.1523***	0.1523***	0.1523***
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Residential amenity effect, $\hat{\zeta}_R$	0.0671***	0.0131	0.0294*	0.0263
	(0.0081)	(0.0139)	(0.0161)	(0.0168)
Residential elasticity, $\hat{\gamma}_R$	-0.2436***	-0.2397***	-0.2889***	-0.2826***
	(0.0059)	(0.0186)	(0.0461)	(0.0250)
Residential decay, $\hat{\delta}_R$	0.0621***	0.0569***	0.0537***	0.0606***
	(0.0029)	(0.0049)	(0.0083)	(0.0055)
Productivity amenity effect, $\hat{\zeta}_M$	-0.0022	0.0624***	0.1037**	0.0420
	(0.0087)	(0.0158)	(0.0511)	(0.0323)
Productivity elasticity, $\hat{\gamma}_M$	0.0828***	0.1221***	0.1480**	0.0913
	(0.0072)	(0.0342)	(0.0669)	(0.0634)
Productivity decay, $\hat{\delta}_M$	0.0217***	-0.0023	0.0260	0.0057
	(0.0034)	(0.0230)	(0.1678)	(0.1478)
Greenbelt fixed effects	Yes	Yes	Yes	Yes
Number of areas	6,701	6,701	6,701	6,701
Number of area pairs	19,673,517	19,673,517	19,673,517	19,673,517
Panel B: Instrument for density is the share greenbelt land 61-120 minutes travelling				
Congestion elasticity, $\hat{\lambda}$	0.1422***	0.1422***	0.1422***	0.1422***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Residential amenity effect, $\hat{\zeta}_R$	0.0671***	0.0176	0.0298*	0.0299*
	(0.0075)	(0.0139)	(0.0156)	(0.0179)
Residential elasticity, $\hat{\gamma}_R$	-0.2332***	-0.2520***	-0.3079***	-0.2505***
	(0.0053)	(0.0190)	(0.0596)	(0.0276)
Residential decay, $\hat{\delta}_R$	0.0588***	0.0544***	0.0496***	0.0634***
	(0.0019)	(0.0050)	(0.0093)	(0.0072)
Productive amenity effect, $\hat{\zeta}_M$	0.0008	0.0609***	0.0968***	0.0316
	(0.0086)	(0.0150)	(0.0343)	(0.0201)
Productivity elasticity, $\hat{\gamma}_M$	0.0715***	0.1188***	0.0986*	0.1051
	(0.0063)	(0.0206)	(0.0560)	(0.1152)
Productivity decay, $\hat{\delta}_M$	0.0126***	0.0021	0.0058	-0.3033*
	(0.0039)	(0.0098)	(0.2001)	(0.1823)
Greenbelt fixed effects	Yes	Yes	Yes	Yes
Number of areas	6,701	6,701	6,701	6,701
Number of area pairs	19,673,517	19,673,517	19,673,517	19,673,517

Notes: We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). We not report parameter estimates for $\hat{\varkappa}$, $\hat{\varepsilon}$ and $\hat{\varphi}$, which are identical to the ones reported in Table 5. Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

1. I determine the commuting probability:

$$\pi_{ij\mathcal{S}} = \frac{\left(\frac{\Psi_{i\mathcal{S}} \mathrm{e}^{-\hat{\kappa}\tau_{ij\mathcal{S}}} w_{j\mathcal{S}}}{p_{i\mathcal{S}}}\right)^{\hat{\varepsilon}}}{\sum_{r=1}^{\mathcal{L}} \sum_{s=1}^{\mathcal{L}} \left(\frac{\Psi_{r\mathcal{S}} \mathrm{e}^{-\hat{\kappa}\tau_{rs\mathcal{S}}} w_{s\mathcal{S}}}{p_{r\mathcal{S}}}\right)^{\hat{\varepsilon}}}, \tag{C.5}$$

as well as the probability that a worker is employed in j, which is *conditional* on living in i:

$$\pi_{ij|i\mathcal{S}} = \frac{\mathrm{e}^{-\hat{\kappa}\hat{\varepsilon}\tau_{ij}}\omega_{j\mathcal{S}}}{\sum_{s=1}^{\mathcal{L}} \mathrm{e}^{-\hat{\kappa}\hat{\varepsilon}\tau_{is}}\omega_{s\mathcal{S}}}. \tag{C.6}$$

2. Based on the commuting probabilities I determine the residential population and workers in each area:

$$\begin{aligned} H_{Ri\mathcal{S}} &= \sum_{j=1}^{\mathcal{L}} \pi_{ij\mathcal{S}}\bar{H}, \\ H_{Mi\mathcal{S}} &= \sum_{s=1}^{\mathcal{L}} \pi_{si\mathcal{S}}\bar{H}. \end{aligned} \tag{C.7}$$

Recall that $\bar{H}$ is the total population in England, which does not change for the different scenarios.

3. This provides us with the necessary information to determine amenities in a location:

$$\Psi_{i\mathcal{S}} = \breve{\Psi}_i \mathrm{e}^{-\hat{\zeta}_R g_{i\mathcal{S}}} \left(\hat{\delta}_R \sum_{j=1}^{\mathcal{L}} \mathrm{e}^{-\hat{\delta}_R \tau_{ij\mathcal{S}}} H_{Mj\mathcal{S}}\right)^{\hat{\gamma}_R}, \tag{C.8}$$

4. and productivity:

$$\Omega_{i\mathcal{S}} = \breve{\Omega}_i \mathrm{e}^{-\hat{\zeta}_M g_{i\mathcal{S}}} \left(\hat{\delta}_M \sum_{j=1}^{\mathcal{L}} \mathrm{e}^{-\hat{\delta}_M \tau_{ij\mathcal{S}}} H_{Mj\mathcal{S}}\right)^{\hat{\gamma}_M}, \tag{C.9}$$

where the exogenous location fundamentals $\breve{\Psi}_i$ and $\breve{\Omega}_i$ are kept fixed in each scenario.

5. I obtain land use in each MSOA:

$$\begin{aligned} F_{Hi\mathcal{S}} &= \frac{(1-\beta)\sum_{j=1}^{\mathcal{L}} \pi_{ij|i\mathcal{S}} \mathrm{e}^{-\hat{\kappa}\tau_{ij\mathcal{S}}} w_{j\mathcal{S}}}{p_{i\mathcal{S}}} H_{Ri\mathcal{S}}, \\ F_{Mj\mathcal{S}} &= \left(\frac{w_{j\mathcal{S}}}{\alpha A_j}\right)^{\frac{1}{1-\alpha}} H_{Mi\mathcal{S}}. \end{aligned} \tag{C.10}$$

I then define the share of commercial floor space use as:

$$\theta_{i\mathcal{S}} = \frac{F_{Mj\mathcal{S}}}{F_{Mj\mathcal{S}} + F_{Hi\mathcal{S}}}. \tag{C.11}$$

6. I update the use of building capital using the first-order condition for optimal use:

$$K_{i\mathcal{S}} = \left(\frac{\hat{\mu}\Upsilon_i p_{i\mathcal{S}}}{r}\right)^{\frac{1}{1-\hat{\mu}}} \Lambda_{i\mathcal{S}}, \tag{C.12}$$

7. I then determine the output (up to a constant) in each location:

$$Y_{i\mathcal{S}} = \Omega_{i\mathcal{S}} H_{Mi\mathcal{S}}^{\alpha} (\theta_{i\mathcal{S}} \Upsilon_i K_{i\mathcal{S}}^{\hat{\mu}} \Lambda_{i\mathcal{S}}^{1-\hat{\mu}})^{1-\alpha} \tag{C.13}$$

8. The updated rents are given by:

$$\begin{aligned} p_{i\mathcal{S}} &= \frac{(1-\alpha)\tilde{Y}_{i\mathcal{S}}}{\theta_{i\mathcal{S}} \Upsilon_i K_{i\mathcal{S}}^{\hat{\mu}} \Lambda_{i\mathcal{S}}^{1-\hat{\mu}}} && \text{if} \quad \{H_{Mi\mathcal{S}} > 0\} \mid \{H_{Mi\mathcal{S}} > 0 \;\&\; H_{Ri\mathcal{S}} > 0\} \\ p_{i\mathcal{S}} &= \frac{(1-\beta)\sum_{j=1}^{\mathcal{L}} \pi_{ij|i\mathcal{S}} \omega_{i\mathcal{S}}^{1/\hat{\varepsilon}} \mathrm{e}^{-\hat{\kappa}\tau_{ij}}}{(1-\theta_{i\mathcal{S}}) \Upsilon_i K_{i\mathcal{S}}^{\hat{\mu}} \Lambda_{i\mathcal{S}}^{1-\hat{\mu}}} && \text{if} \quad \{H_{Ri\mathcal{S}} > 0\} \mid \{H_{Mi\mathcal{S}} > 0 \;\&\; H_{Ri\mathcal{S}} > 0\} \end{aligned} \tag{C.14}$$

9. The updated transformed wages are given by:

$$\omega_{i\mathcal{S}} = \frac{\alpha Y_{i\mathcal{S}}}{H_{Mi\mathcal{S}}}. \tag{C.15}$$

10. Now I obtain the counterfactual population. In the baseline scenario, I have:

$$H_0 = \frac{\bar{u}^{\hat{\varepsilon}}}{\Gamma\left(\frac{\hat{\varepsilon}-1}{\hat{\varepsilon}}\right)^{\hat{\varepsilon}}} = \breve{H}_{\mathcal{S}} \sum_{i=1}^{\mathcal{L}} \sum_{j=1}^{\mathcal{L}} \left(\frac{\Psi_{i0} \mathrm{e}^{-\hat{\kappa}\tau_{ij\mathcal{S}}} \omega_{j0}^{1/\hat{\varepsilon}}}{p_{i0}^{1-\beta}} \right)^{\hat{\varepsilon}}. \tag{C.16}$$

from which I derive the counterfactual utility level.

11. In the final step I update travel times:

$$\tau_{ij\mathcal{S}} = \tau_{ij}^{f} T_i \breve{T}_j \mathrm{e}^{\lambda \mathcal{D}_{Mi\mathcal{S}}}, \tag{C.17}$$

where traffic densities depend $\mathcal{D}_{Mi\mathcal{S}}$ depend on counterfactual values of $H_{Mj\mathcal{S}}$, $\forall j$. I treat T_i and $\breve{T}_j$ as constants across different scenarios.

I repeat these 11 steps until the values for transformed wages and rents between the current and previous iteration converges. In practice, it appears that I need about 25 iterations to obtain the new equilibrium values.