Appendix of

"The Billion Pound Drop: The Blitz and Agglomeration Economies in London:"*

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Abstract — We exploit locally exogenous variation from the Blitz bombings to quantify the effect of redevelopment frictions and identify agglomeration economies at a micro-geographic scale. Employing rich location and office rental transaction data, we estimate reduced-form analyses and a spatial general equilibrium model. Our analyses demonstrate that more heavily bombed areas exhibit taller buildings today, and that agglomeration elasticities in London are large, approaching 0.2. Counterfactual simulations show that if the Blitz had not occurred, the concomitant reduction in agglomeration economies arising from the loss of higher-density redevelopment would cause London's present-day GDP to drop by some 10% (or £50 billion).

Keywords — redevelopment, regulation, office rents, agglomeration economies.

JEL codes — R14, R33, R38.

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Appendix

A.1 Redevelopment frictions in London

In addition to height restrictions, almost half of Inner London and a third of Greater London remain off-limits to higher density development as a result of historic designations including; Conservation Areas; the Thames Policy Area; Protected long-distance views of St. Pauls Cathedral, the Monument, the Tower of London, 43 'strategic views' of other locations; a protected 'Green belt', and over $37,000$ buildings and structures in Greater London which cannot be altered.

This extensive system of development control is consistently implicated as the principal reason for London registering the most expensive office rents in the world and more than twice as expensive as any other major European city (CBRE 2015, Cushman-Wakefield 2015). Consonant with this interpretation, research by Cheshire & Hilber (2008) show that the regulatory burden on office development in London was higher than for any major office location in Western Europe or the US, and provide direct evidence that the British planning system is indeed the cause.

While redevelopment frictions in London could also arise due to the option value of land incentivizing development delay (Dixit & Pindyck 1994), in the English housing market at least, such options are 'not of much value' (Cheshire 2018, p. 2) and do not seem to be exercised (Cheshire et al. 2018). Although these claims pertain to a somewhat different context than our own, they are nevertheless indicative that land option value frictions in London may be of secondary importance.

Theoretically it is also reasonable to assume that planning regulation is the dominant redevelopment friction in London due to the fact that other possible frictions are likely to be self-limiting. Specifically, when the supply of developable land is constrained due to; redevelopment costs, transaction costs, strategic behavior, or idiosyncratic owner-values; prices could eventually rise to a level where these barriers are overcome. By contrast, regulatory frictions may not respond to the price system or may even be strengthened as prices rise by special interest groups like land owners (Hilber & Robert-Nicoud 2013).

The more pronounced the redevelopment frictions, the more likely it is that regulations are the dominant cause. This assertion is lent empirical support by Hornbeck & Keniston (2017) who found that a large positive effect on land values which appeared as a result of the Great Boston Fire of 1872 (before development had been constrained by regulation) had entirely dissipated by 1894. But by contrast, in even-then tightly regulated San Francisco, the positive local density effects of the 1906 Earthquake and Fire have persisted to this day (Siodla 2015). Similarly, Akee (2009) recorded pronounced housing density and price differentials in adjacent but differently regulated Indian-trust and non-trust plots in Palm Springs, but once regulations were homogenized in the 1970s their densities and prices rapidly converged. If redevelopment frictions other than regulation were economically meaningful in these contexts, such outcomes should not be observed.

Note that the causal chain linking Blitz bombings to greater densities described in Section **??** has also demonstrably played out in London for destructive episodes other than the Blitz. The 1992 bombing of the 1903 Baltic Exchange building is now responsible for the erection of one of the tallest office buildings in London: Norman Foster's 'Gherkin'. At the time, the Baltic Exchange was a historically protected 'listed' building, which by law could not have been altered without special government permission. However, the irreparable damage caused by this attack led planners to approve the redevelopment of this 6-floor heirloom into a 40-floor icon. Although this case is exceptional, the Blitz bombings have similarly facilitated local regulatory relaxations across the entirety of Greater London.

A.2 The Blitz

During the Blitz Luftwaffe bombers operated almost exclusively at night and at close to their maximum altitudes and speeds.[1] Even under pristine daytime conditions and in the absence of enemy action, when flying at high altitudes the Luftwaffe was only able to achieve a circular error probable between 260-380m from their point of aim (Downes 2008, p. 286).[2] Therefore, even if German aircrews could successfully navigate to their target, the inherent inaccuracy of unguided gravity bombs released at altitude would necessarily lead to indiscriminate attacks. Maneuvering to specific targets at night, in imperfect weather, under black-out conditions below,

[1] When fully loaded German bombers could operate between 15,000-20,000 ft (4,600-6,100m) at 200mph (320km/h). German bombers flew at these heights and speeds in order to evade searchlights, and the intercepting aircraft and targeted anti-aircraft fire that such discovery would bring.

[2] Circular error probable is a standard measure of a weapon system's accuracy, and refers to the average radius from the point of aim within which 50% of ordnance (bombs) can be expected to fall. Note that unlike in England, the Luftwaffe had air superiority over Holland and so could operate at low altitudes and therefore with ruinous accuracy there.

while lacking modern day navigation systems, and avoiding searchlights, flak batteries, and decoy 'starfish' targets, presented a significant challenge to WWII airmen. For instance, during this period only one in five British air crews operating under similar night-time conditions flew to within 8km of their intended German targets, and the 'best' British circular error probable averaged a paltry 4.8km radius from point of aim (Hastings 2010).[3]

In anticipation of these difficulties, prior to the war the Germans had developed radio systems that could direct bombers in total darkness to within 1.6km of their targets (Hyde et al. 1987*b*, p. 126). But by the time the Blitz had started, these navigational aids were being continuously jammed and falsified by the British leaving them of limited effectiveness (Price 2009). On clear moonlit nights however, German airmen would have been able to visually navigate to a degree via the land-water boundary of the River Thames and its distinctive contours (Ingersoll 1941). Nevertheless, both locating specific targets and then accurately striking them at night remained extremely problematic. For instance, in the first two months of bombing, Battersea Power Station – perhaps the largest single target in London, had only received one minor hit ('a nick'), no bridge over the River Thames had been struck, and the docks despite great damage were still functioning (Ingersoll 1941). Realising the futility of hitting specific targets, from the night of October 8th-9th the German command switched from assigning bomber crews specific points of aim to targeting areas often comprised of several square miles, which they referred to as '*zielraum*' (Hyde et al. 1987*b*, p. 24). In addition, London, offering a larger target area, was deliberately attacked chiefly during moonless nights so that raids on smaller cities where greater accuracy was required could be conducted with the aid of moonlight (Hyde et al. 1987*b*, p. 42). Due to these factors, the Luftwaffe's night-time bombing at altitude during the London Blitz was by default a widespread 'area' phenomenon and local patterns of bombings are likely random. We investigate this issue statistically in Appendix A.5.

A.3 Other descriptive statistics

A.3.1 Agglomeration and bombings

In Figure A1 we plot agglomeration over space and indicate the locations of rental transactions. It is shown that most of our rental transactions are concentrated in Inner London, most notably,

[3]Low altitude attacks such as the famous Royal Air Force dam busting 'Operation Chastise', could however achieve impressive accuracy.

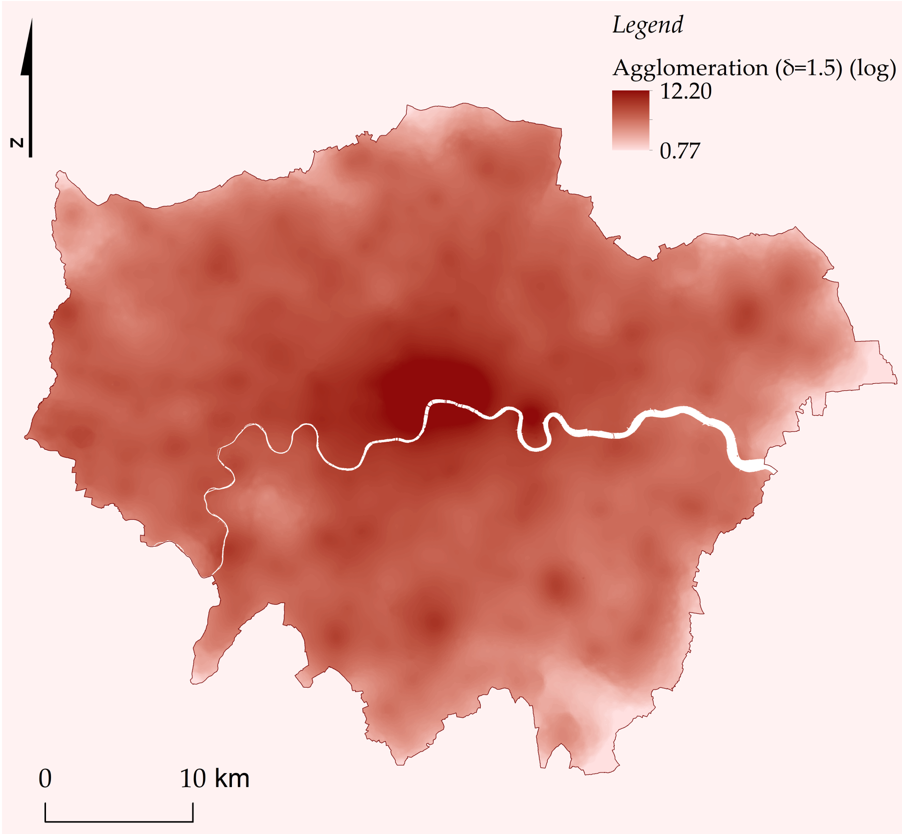


FIGURE A1 – AGGLOMERATION

Notes: We calculate agglomeration as per equation (??).

in West End and the City of London. Employment is particularly concentrated in and near the City of London. Areas close to the Bank of England have the highest employment densities. Because there is such a strong employment concentration in London's most important submarket, we will make sure in the sensitivity analysis that our results are not primarily driven by the City of London.

In Figure A2 we plot bombed sites for the City of London and the Docklands. It can be seen that the location of bombs seems to be as good as random, taking into account that bombings usually occur in sequence, because air planes flew in formation at specific speeds, in a certain direction, and dropped multiple bombs in succession.

In Figure A3a we present a map of the bomb density for Greater London based on the exact locations bombs fell during the Blitz. It is immediately observed that bombings are concentrated in Inner London. In particular the City of London and the boroughs of Westminster and Southwark were the most heavily bombed. Pimlico, a district of Westminster, has the highest bomb density. In Appendix A.3 we map bombs at a local level for the City of London and

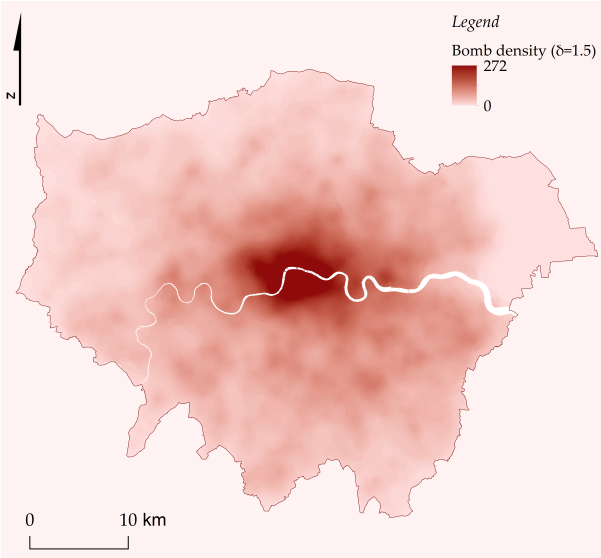
Figure A2 – Bombings in the City of London and the Docklands

Docklands. The variation at this more local level (*e.g.* within a borough) appears to be as good as random, but we will carefully test this presumption in the next subsection.

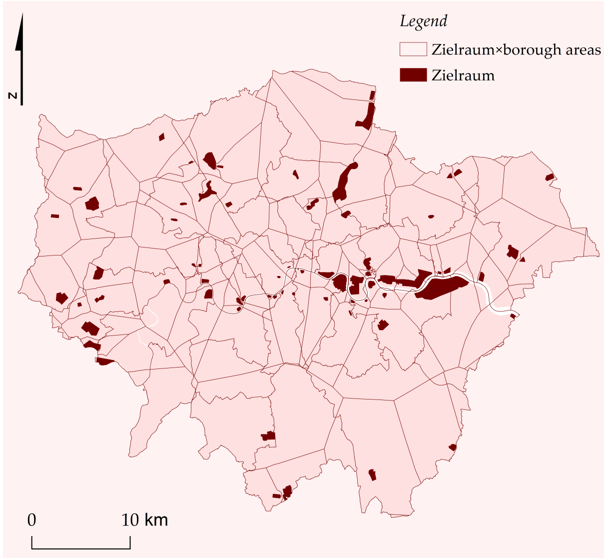
In Figure A3b we show the *zielraum* and *zielraum*×borough areas. Although *zielraum* are everywhere in Greater London, there is a concentration of relatively small target areas in Inner London along the Thames, which was used for navigation. Recall that for the econometric analyses we partition Greater London into small areas based on the distance to the nearest *zielraum* and borough and control for distance to the River Thames.

Figure A4 shows the population density in 1931. There is a strong positive correlation with agglomeration ($\rho = 0.748$), but population seems to be more spread than current employment and more heavily concentrated on the south bank of the River Thames.

In Figure A5 we report the relationship between bomb density and agglomeration. There is a strong positive relationship between bombings and the log of agglomeration: that is, heavily



(A) Bomb density



(B) Zielraum

Figure A3 – The Blitz in London

Notes: We calculate bomb density as per (??). We set δ to 1.5.

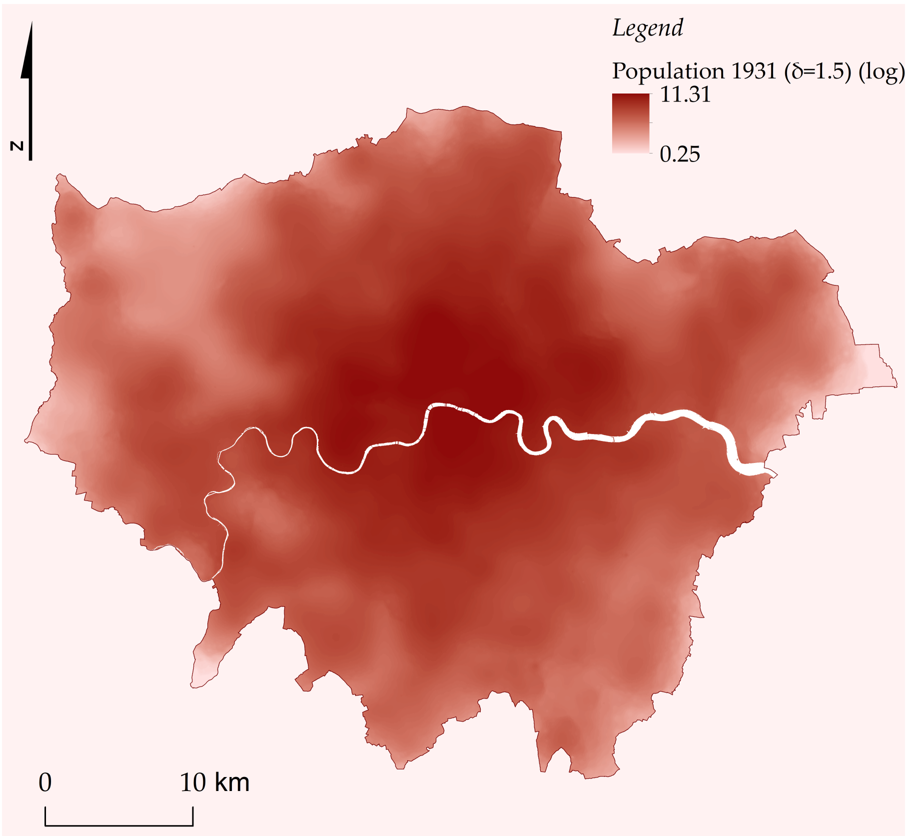


Figure A4 – Population density in 1931

Notes: We calculate population density in a similar way as in equation (??). We set δ to 1.5.

bombed areas have higher employment densities today. One might argue that this result arises from the fact that historically denser areas were bombed more heavily. The dashed line therefore

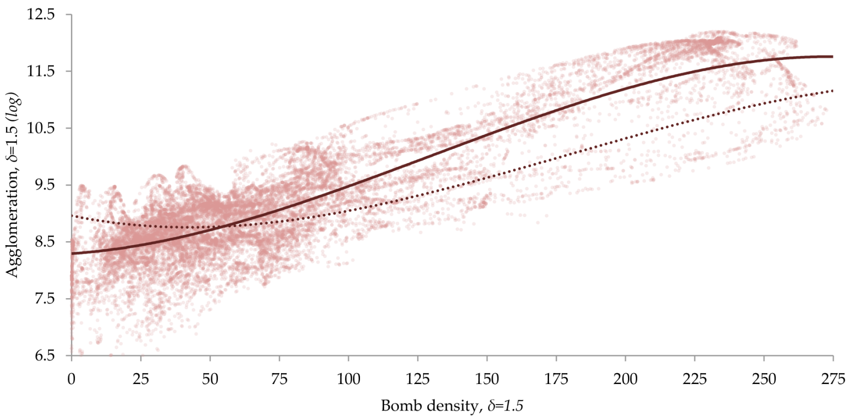


Figure A5 – Bomb density and agglomeration

Notes: We calculate the bomb density as per equation (**??**) and agglomeration as per equation (**??**). See the sensitivity analysis for more details regarding δ. The solid line represents a regression of log agglomeration on a third-order polynomial of bomb density, while the dotted line represents the same relationship, but controlling for a third-order polynomial of log population density in 1931.

represents a regression where we flexibly control for the log population density in 1931. Here we still observe a strong positive relationship between log of agglomeration and bomb density.

A.3.2 Descriptives for data on bombs

We report the descriptive statistics for the dataset on bombs in Table A1. The average distance to the River Thames is 5.3km. If bombs would have fallen randomly, the average distance to the Thames would be 8km: areas close to the Thames seem to have been bombed more heavily. Also the share of bombs that fell in conservation areas seem to be higher (22% versus 13%), but this is likely due to the fact that a greater proportion of Inner London has been preserved. Furthermore, areas close to infrastructure seem to have received more bombs. This may also reflect the fact that it was easier to construct new stations or highways on bombed sites.

A.3.3 Descriptives for building data

We report key descriptive statistics for the building sample in Table A2. The average building height is about 10m (about 3 floors) and the average footprint is 93m^2. For an office building the footprint is almost 300m^2. 0.3% of the office building sites were directly hit by a bomb in the Blitz. Note that for Inner London the percentage is higher (0.5%). This may seem low, but note that fires resulting from bombs spread across lots and caused most destruction.

A.3.4 Additional descriptives for rental data

In Table A3 we report descriptive statistics for all variables included in the rental dataset. Properties are often close to a highway (30% are within 500m of a highway), which is similar to

Table A1 – Descriptive statistics for the bomb census

	(1) mean	(2) sd	(3) min	(4) max
Distance to river Thames *(in km)*	5.299	4.592	0	21.99
In park,	0.0538	0.226	0	1
Park, 1-125m	0.107	0.309	0	1
Park, 125-250m	0.0813	0.273	0	1
Park, 250-500m	0.103	0.303	0	1
In large park	0.0405	0.197	0	1
Large park, 1-125m	0.0276	0.164	0	1
Large park, 125-250m	0.0311	0.174	0	1
Large park, 250-500m	0.0758	0.265	0	1
In water	0.0133	0.114	0	1
Water, 1-125m	0.193	0.394	0	1
Water, 125-250m	0.201	0.401	0	1
Water, 250-500m	0.333	0.471	0	1
Highway, $<$ 125m	0.0980	0.297	0	1
Highway, 125-250m	0.0787	0.269	0	1
Highway, 250-500m	0.133	0.339	0	1
Tube station, $<$ 125m	0.0252	0.157	0	1
Tube station, 125-250m	0.0601	0.238	0	1
Tube station, 250-500m	0.157	0.363	0	1
Railway station, $<$ 125m	0.0175	0.131	0	1
Railway station, 125-250	0.0476	0.213	0	1
Railway station, 250-500m	0.161	0.367	0	1
In conservation area	0.221	0.415	0	1
Conservation area, 1-125m	0.186	0.389	0	1
Conservation area, 125-250m	0.105	0.307	0	1
Conservation area, 250-500m	0.145	0.352	0	1
Listed buildings, $<$ 125m	1.542	4.601	0	85
Listed buildings, 125-250m	6.165	15.27	0	199
Listed buildings, 250-500m	24.69	52.88	0	484
Average household size	2.338	0.441	1.130	4.860
Share young people ($<$ 18)	0.211	0.0814	0	0.550
Share elderly people ($\geq$ 65)	0.129	0.0744	0	0.793
Share (re)married people	0.412	0.141	0.00493	0.821
Share foreigner (born elsewhere)	0.261	0.136	0.00906	0.806
Share unemployed	0.0434	0.0270	0	0.247
Share people in skilled occupation	0.0752	0.0427	0	0.288
Share high education *(level 4/5)*	0.320	0.166	0	0.805
Share owner-occupied housing	0.554	0.269	0	1
Share council housing	0.261	0.256	0	0.977

Note: The number of observations is 28,324

the share of observations within 500m to a tube station or railway station (respectively 24% and 23%). Most of the properties are in a conservation area (67% within 500m). This is not too surprising as 37% of the total land area in Inner London is within a conservation area.

A.3.5 Additional descriptives for housing data

To obtain data on missing floor spaces in MSOAs and for the analyses reported in Appendix A.7.6 we use data on house prices obtained from the Nationwide Building Society. The data provides information on 128,931 housing transactions, so the housing sample is substantially

Table A2 – Key descriptive statistics of the building sample

	(1) mean	(2) sd	(3) min	(4) max
Building height *(in m)*	9.959	3.680	5	304.2
Bomb density, B_i, $\delta = 1.5$	59.44	46.01	0.00119	272.7
Building site hit by bomb, b_i	0.00252	0.0501	0	1
Office building	0.0301	0.171	0	1
Footprint *(in m^2)*	92.71	360.1	25.00	187,106
Listed building	0.00660	0.0810	0	1
Distance to river Thames *(in km)*	6.717	4.473	0.000616	22.12
In conservation area	0.139	0.346	0	1

Note: The number of observations is 2,164,940

larger than the data on office rents and covers a much wider area of Greater London. In a recent working paper, Redding & Sturm (2016) provide preliminary evidence that house prices within 200m of areas heavily damaged (and therefore bombed) by the Blitz may be lower, due to negative social interactions (*e.g.* in heavily damaged areas more public council housing may have been constructed). Because we do not have information on the exact location of each property (only postcode areas), we cannot replicate this level of detail. We therefore include a control variable measuring the number of bombs within 200m of the postcode, which should have a negative effect on house prices.

In Table A4 we present the key descriptives for the housing sample. The average house price per m^2 is £$2,343$. The average size of a residential property is much smaller than an office at 91m^2. It can also be seen that the distance to the River Thames is much higher than in the office rents sample, demonstrating that residential properties are much less spatially concentrated and centrally located than commercial properties. Because we have much more observations outside Inner London than in the office building sample, the share of properties that are in a conservation area is also much lower (only 13.9%).

A.4 The decay parameter

In the paper, we calculate the spatially weighted density of bombs. One important parameter is the decay parameter δ, indicating how quickly agglomeration economies degrade with distance. Figure A6 shows the weight of one bomb at different distances from a location for different decay parameters. For $\delta = 1.5$, the weight of a bomb that fell 1km away is only 0.2231. For $\delta = 3$ the weight falls to 0.0498, and increases to 0.3716 for $\delta = 1$.

Table A3 – Full descriptive statistics for rental dataset

	(1) mean	(2) sd	(3) min	(4) max
Rent *(in £ per m^2)*	384.8	179.4	10.76	1,507
Bomb density, B_i, $\delta = 1.5$	215.0	43.52	0.124	269.2
Building site hit by bomb	0.0709	0.257	0	1
Agglomeration, A_i, $\delta = 1.5$	130,400	47,559	695.9	198,939
Distance to river Thames *(in km)*	1.320	1.291	0.00497	17.42
Highway, < 125m	0.149	0.356	0	1
Highway, 125-250m	0.0945	0.293	0	1
Highway, 250-500m	0.169	0.375	0	1
Tube station, < 125m	0.131	0.338	0	1
Tube station, 125-250m	0.301	0.459	0	1
Tube station, 250-500m	0.483	0.500	0	1
Railway station, < 125m	0.0393	0.194	0	1
Railway station, 125-250m	0.118	0.322	0	1
Railway station, 250-500m	0.255	0.436	0	1
Park, < 125m	0.457	0.498	0	1
Park, 125-250m	0.389	0.487	0	1
Park, 250-500m	0.131	0.338	0	1
Large park, < 125m	0.0455	0.208	0	1
Large park, 125-250m	0.0717	0.258	0	1
Large park, 250-500m	0.126	0.332	0	1
Water, < 125m	0.145	0.353	0	1
Water, 125-250m	0.262	0.440	0	1
Water, 250-500m	0.429	0.495	0	1
In conservation area	0.676	0.468	0	1
Conservation area, 1-125m	0.265	0.441	0	1
Conservation area, 125-250m	0.0310	0.173	0	1
Conservation area, 250-500m	0.0183	0.134	0	1
Listed buildings, < 125m	13.66	11.34	0	67
Listed buildings, 125-250m	54.51	36.31	0	190
Listed buildings, 250-500m	208.1	119.2	0	480
Size of the property *(in m^2)*	847.7	2,445	17.19	65,032
Building size *(in m^2)*	6,256	11,813	40.41	112,305
Number of floors in building	7.970	5.155	1	52
Floor of property	3.352	2.768	0	50
Building – newly constructed	0.0898	0.286	0	1
Building – refurbished	0.0916	0.288	0	1
Building – second hand	0.824	0.381	0	1
Construction/refurbishment year < 1950	0.237	0.425	0	1
Construction/refurbishment year 1950-1959	0.0327	0.178	0	1
Construction/refurbishment year 1960-1969	0.0421	0.201	0	1
Construction/refurbishment year 1970-1979	0.0418	0.200	0	1
Construction/refurbishment year 1980-1989	0.137	0.343	0	1
Construction/refurbishment year 1990-1999	0.215	0.411	0	1
Construction/refurbishment year > 2000	0.294	0.456	0	1
Average household size	1.752	0.335	1.150	4.610
Share young people (< 18)	0.0918	0.0741	0	0.496
Share elderly people ($\geq$ 65)	0.103	0.0641	0	0.552
Share (re)married people	0.289	0.0910	0.0484	0.646
Share foreigner (born elsewhere)	0.393	0.100	0.0459	0.713
Share unemployed	0.0413	0.0280	0	0.247
Share people in skilled occupation	0.0302	0.0295	0	0.159
Share high education *(level 4/5)*	0.515	0.128	0.0836	0.831
Share owner-occupied housing	0.299	0.134	0	0.939
Share council housing	0.213	0.214	0	0.915

Note: The number of observations is 9,202

Table A4 – Key descriptives for housing sample

	(1) mean	(2) sd	(3) min	(4) max
House price *(in £ per m^2)*	2,343	1,185	259.1	10,000
Bomb density, B_i, $\delta = 1.5$	58.35	43.14	5.93e-05	272.7
Bombs, < 200m	1.248	3.010	0	36
Agglomeration, A_i, $\delta = 1.5$	8,768	12,175	95.08	190,502
Distance to Thames *(in km)*	7.531	4.507	0	20.46
In conservation area	0.139	0.346	0	1
House size *(in m^2)*	91.22	35.61	24	278
Flat	0.420	0.494	0	1
Construction year < 1940	0.680	0.467	0	1
Construction year ≥ 2000	0.0333	0.180	0	1

Notes: The number of observations is 128,931.

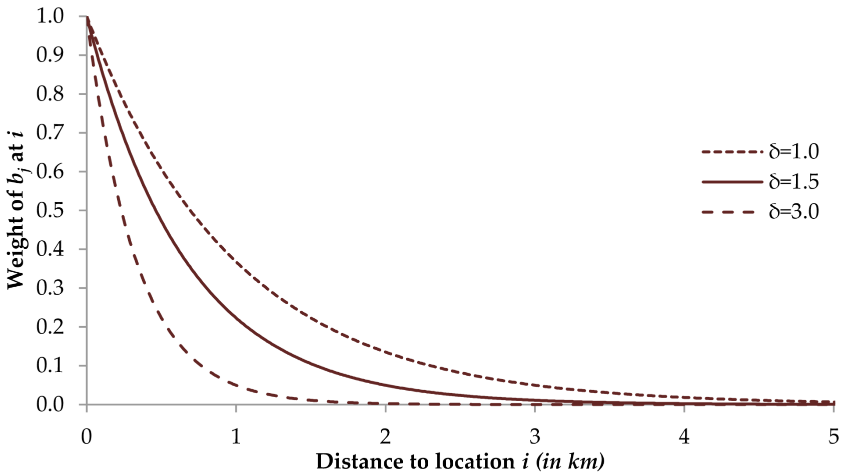


Figure A6 – Spatial weights for different δ

A.5 Are bombings spatially random?

A.5.1 Methodology

If bombings are (locally) randomly distributed over space, it is unlikely that there will be a correlation between unobservable locational endowments and bomb density. Hence, we aim to test more formally whether bombings are indeed not statistically significantly concentrated in space. One obvious approach to test this would be to gather data on the dependent variable of interest before WWII and regress that on bomb density (see Redding & Sturm 2016). Unsurprisingly however, locally granular pre-war data on office rents and/or land values do not exist.

Hence, we employ a point-pattern methodology to test whether bombings are statistically significantly concentrated in space. Our method exploits the feature that our data is continuous over space.[4] More specifically, we employ the method proposed by Duranton & Overman (2005, 2008). This concentration index controls for overall agglomeration, is invariant to scale and aggregation and, importantly, provides an indication of statistical significance. Below, we briefly discuss the procedure. For more details, we refer to Duranton & Overman (2005, 2008).

Let $K(d)$ denote the estimated kernel density at a given distance d, d_{ik} denotes the distance between location i and k, where $i = 1, ..., n$. Then:

$$\hat{K}(d) = \frac{1}{n(n-1)h} \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} \Omega\left(\frac{d - d_{ik}}{h}\right), \tag{A.1}$$

where n is the total number of bombs that fell, h is the bandwidth and:

$$\Omega(\cdot) = \frac{1}{\sqrt{2\pi}} \mathrm{e}^{-\frac{1}{2}\left(\frac{d-d_{ik}}{h}\right)^2}. \tag{A.2}$$

The above equation implies that we use a normal density function. Following Duranton & Overman (2005, 2008) and Klier & McMillen (2008), we use a bandwidth h equal to Silverman's plug-in bandwidth (see Silverman 1986). More specifically, $h = 1.06\sigma_{d_{ik}} n^{-1/5}$, where $\sigma_{d_{ik}}$ is the standard deviation of the estimated bilateral distances between bombs. Distances d cannot be negative, so we use the reflection method, proposed by Silverman (1986), to deal with this issue.

We aim to test whether the estimated concentration is statistically different from a random geographical pattern, so we have to define counterfactual location patterns. The most obvious way would be to assign bombs randomly to locations within Greater London. However, this approach would not take into account that bombings usually occur in sequence. On bombing runs, airplanes fly in formation, at specific speeds, in a certain direction, and drop multiple bombs in succession. Indeed, if we look more closely at the data, neighboring bomb locations often follow line patterns. Our counterfactual should therefore incorporate this feature; otherwise we might erroneously conclude that bomb sequences represent significant spatial concentration, when in fact the overall pattern of bomb sequences with respect to analysis areas are random.

To construct the counterfactual we use information on the technical characteristics of the

[4] It has been argued that many measures of concentration use arbitrary spatial units (such as provinces, local authorities or postcodes), which may be problematic as they may lead to biases in the measure of concentration (Briant et al. 2010).

Luftwaffe bombings. The principal bombers used by the Luftwaffe during the Blitz were the Junkers Ju88, Heinkel He111, and Dornier Do17, but by end of 1940 the obsolete Do17 had been largely phased out (Hyde et al. 1987*a*). Both the Ju88 and He 111 maximum bomb loads were typically $2,000$kg in total, with the Ju 88 usually carrying between 2-14 individual bombs and the He111 carrying 6-10 (Hyde et al. 1987*a*). The average cruising speed of the Ju88 and He111 when fully loaded with bombs was roughly 300kph. Since a greater number of bombs with lighter individual weights was the most common payload, we assume that on average 10 bombs were dropped within a time interval of five seconds, which implies that the bombs struck in a relatively straight line, each about 40m from the last. For each bootstrap run we pick $n/10$ randomly drawn locations and generate 10 bombing locations along a line, based on a randomly drawn angle and the average cruising speed. This counterfactual is of course not perfect. It might be that the locations of bombings are spatially autocorrelated in different ways. For example, when air planes observe fires caused by previous bombing runs, they may target these areas as well. Also, planes often flew in squadrons perhaps leading to broader patterns of concentration. In all these cases, we might be inclined to find spurious patterns of concentration, even if the overall pattern of these bombing clusters was random in practice.

A second feature that a valid counterfactual should incorporate is that the bombings may not be spatially random at the level of Greater London because the Luftwaffe may have used the River Thames to navigate on certain nights and, ceteris paribus, it may have been easier for bomber crews to target areas of London closer to it.[5] In addition, there may be geographical features, such as large parks or water bodies in which bomb strikes were not well recorded. Finally, as the goal of the bombings was to demoralize the population, it is logical to assume that denser areas were disproportionately targeted. We therefore employ a weighted bootstrap method, in which weights are dependent on the conditional probability that a local area was bombed. We use a conditional logit model in which the probability to be bombed is given by:

$$\Pr[b(x)] = \frac{\mathrm{e}^{\psi g(x)+\lambda(x)}}{\sum_{z=1}^{Z} \mathrm{e}^{\psi g(z)+\lambda(z)}}, \tag{A.3}$$

[5]The location of Barrage Balloons employed during the war could not have materially compromised the conditional randomness of Blitz bombings by preventing attacks. The primary purpose of Barrage Balloons was to force bombers to higher altitudes so that their attacks would be less precise. While the maximum altitude of Barrage Balloons was only $1,524$m, German bombers maintained altitudes three and four times this during the Blitz. Moreover, Barrage Balloons were often tethered near open spaces and gardens, for which we control in the empirical analysis.

where $z = 1, ..., Z$ are other locations, $g(x)$ are geographical features and $\lambda(x)$ are fixed effects. Location fixed effects should be small enough to effectively control for pre-war differences in population density, while not being so small as to absorb the effect of interest. We therefore choose to include either borough fixed effects or *zielraum*×borough fixed effects.[6] For the latter we calculate for each location x in a borough the distance to the nearest *zielraum* and add an identifier for the nearest *zielraum*.

To investigate whether there is a statistically significant concentration of bombings we calculate the difference between $\hat{K}(d)$ and the upper confidence band of the randomly generated bomb patterns, denoted by $\overline{K}(d)$. Hence, we define an index of concentration $\mathcal{C}$:

$$\mathcal{C} = \int_0^{\bar{d}} \max \hat{K}(d) - \overline{K}(d)(d)d. \tag{A.4}$$

When $\hat{K}(d) > \bar{K}(d)$ for at least one $d \in [0, \bar{(d)}]$, we conclude that bombs are statistically significantly concentrated; *i.e.* when $\mathcal{C} = 0$, bombings are (conditionally) random. Because we are mainly interested in local effects, we restrict $\bar{d} = 5$. Furthermore, we define the 95% confidence interval so that $\underline{K}(d) = 0.025$ and $\overline{K}(d) = 0.975$

To define $\underline{K}(d)$ and $\overline{K}(d)$, we treat each of the estimated density functions for each simulation as a single observation. Following Duranton & Overman (2005), we choose identical local confidence levels in such a way that the global confidence level is 2.5%. Note that, because we have so many bombs, the confidence intervals are very tight and therefore the data is predisposed to find a statistically significant concentration of bombings.

A.5.2 Conditional logit models and the concentration of bombings

Before we turn to the results of the concentration index $\mathcal{C}$, we estimate ψ and $\lambda(x)$ to obtain $\hat{\Pr}(b(x))$. We also run specifications where we include additional location and neighborhood attributes to determine $\hat{\Pr}(b(x))$. In Table A5 we report the main results for the conditional logit models (CLMs) that we use to predict the probability that a location is bombed.

In column (1) we show that indeed the bomb density tends to be higher close to the Thames; when moving further away the probability to be bombed becomes lower. However, the number

[6] The median area of the 33 boroughs in Greater London is 38.68km^2. The median size of a *zielraum*×borough area is only 2.84km^2.

Table A5 – Conditional logit models of the probability to be bombed
(Dependent variable: location hit by bomb)

	(1) CLM	(2) CLM	(3) CLM	(4) CLM	(5) CLM
Distance to Thames *(in km)*	-0.3135***	-0.2060***	-0.1033***	-0.0985***	-0.0926***
	(0.0048)	(0.0071)	(0.0098)	(0.0099)	(0.0102)
In the Thames	-0.4303***	-0.7738***	-0.9535***	-0.9436***	-0.9490***
	(0.1175)	(0.1179)	(0.1202)	(0.1203)	(0.1204)
In park	1.0862***	0.5449***	0.3371***	0.3347***	0.3355***
	(0.0534)	(0.0557)	(0.0593)	(0.0596)	(0.0596)
Park 1-125m	1.0061***	0.3587***	0.1394***	0.1224***	0.1205***
	(0.0242)	(0.0292)	(0.0349)	(0.0353)	(0.0353)
Park 125-250m	0.8621***	0.3097***	0.1343***	0.1155***	0.1087***
	(0.0278)	(0.0307)	(0.0350)	(0.0352)	(0.0352)
Park 250-500m	0.5764***	0.1982***	0.1334***	0.1394***	0.1350***
	(0.0273)	(0.0286)	(0.0304)	(0.0305)	(0.0306)
In large park	-0.7691***	-0.3986***	-0.3612***	-0.3374***	-0.3365***
	(0.0601)	(0.0623)	(0.0652)	(0.0654)	(0.0656)
Large park 1-125m	-0.5558***	-0.2212***	-0.1566***	-0.1494***	-0.1410***
	(0.0419)	(0.0437)	(0.0470)	(0.0472)	(0.0473)
Large park 125-250m	-0.4595***	-0.2080***	-0.1711***	-0.1672***	-0.1563***
	(0.0412)	(0.0420)	(0.0445)	(0.0446)	(0.0447)
Large park 250-500m	-0.2211***	-0.1156***	-0.1430***	-0.1484***	-0.1406***
	(0.0303)	(0.0311)	(0.0329)	(0.0328)	(0.0330)
In water	-1.4592***	-1.1073***	-0.9279***	-0.9048***	-0.9030***
	(0.0638)	(0.0643)	(0.0645)	(0.0645)	(0.0644)
Water 1-125m	-0.5093***	-0.2281***	-0.1987***	-0.1911***	-0.1904***
	(0.0188)	(0.0196)	(0.0201)	(0.0201)	(0.0202)
Water 125-205m	-0.6823***	-0.3832***	-0.2552***	-0.2523***	-0.2509***
	(0.0178)	(0.0190)	(0.0193)	(0.0193)	(0.0193)
Water 250-500m	-0.1259***	-0.0232	-0.0473***	-0.0478***	-0.0474***
	(0.0157)	(0.0160)	(0.0164)	(0.0164)	(0.0164)
Borough fixed effects (33)	No	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	No	No	Yes	Yes	Yes
Location attributes (13)	No	No	No	Yes	Yes
Demographic attributes (10)	No	No	No	No	Yes
Number of observations	7,081,000	7,081,000	7,081,000	7,081,000	7,081,000
Log-likelihood	-150,134	-145,448	-143,558	-143,483	-143,456

Notes: The number of observations is the number of bombs times the number of sampled alternatives ($28,324 \times 250$). Column numbers refer to the different estimates of the concentration index in Table A6. Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

of bombs that fell in the Thames is unexpectedly low, probably due to recording errors. The probability that a location close to a park or garden is bombed tends to be higher, possibly because of the presence of Barrage Balloons which were often tethered near open spaces. On the other hand, parks that are larger than 10 ha (*e.g.* Richmond Park, Greenwich Park) attracted fewer bombs, likely again because of recording issues. Similarly, locations in and close to water bodies have received fewer bombs.

The results are very similar once we control for borough and *zielraum*×borough fixed effects in, respectively, columns (2) and (3). In column (4) we add 13 location attributes, for which the estimated coefficients are available upon request. It appears that the probability to have been bombed is a bit higher close to highways and tube stations. It might be that infrastructure developments were easier and cheaper to construct in areas that were bombed. We find no evidence of a direct relationship between bombings and the presence of historic amenities (not reported in Table A5), as it seems that no fewer bombs have fallen in locations that are now conservation areas. Because the *zielraum*×borough areas are small and are often almost fully part of a conservation area, it may be hard to identify those effects.

In the final column of Table A5 we add 10 neighborhood attributes, leading to almost the same results. Areas that have been bombed now seem to host smaller and younger households, often immigrants, in line with preliminary evidence of Redding & Sturm (2016) which show that a higher share of war-time destruction is associated with a higher share of non-whites.

A.5.3 Are bombings spatially concentrated?

We report the results when we estimate the local and global concentration indices as per equation (A.4) for Greater London in Table A6. We run 250 bootstrap simulations, but we have experimented with a higher number of replications, leading to very similar results. In column (1) we randomly assign bombs to locations, where we do not take into account that bombs were dropped in consecutive series. We find then that bombs are statistically significantly concentrated, as $\hat{\mathcal{C}} = 0.0379$. When we generate a counterfactual pattern only based on line patterns of bombings, we still find that there is statistically significant concentration (column (2)). The concentration index is reduced to 0.0240 if we take into account that bombings may depend on distance to the River Thames and other geographical features that may imply that bombs have not been recorded (column (3)).

In column (4) we show results based on the inclusion of borough fixed effects. This is a strong predictor of the locations of bombs, as the concentration index is now reduced by another 90%. However, given that bombings are still not entirely random, we need more detailed fixed effects. When we include more detailed *zielraum*×borough fixed effects in column (5), we find that bombings are conditionally random as $\hat{\mathcal{C}} = 0$.[7] We have illustrated this graphically in Figure A7

[7] In additional specifications (available upon request) we make sure that the choice of fixed effects does not influence our results.

Table A6 – Concentration of bombings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Concentration index, $\mathcal{C}$	0.0379	0.0323	0.0240	0.0034	0.0000	0.0000	0.0000
Average of $\hat{K}$	0.0163	0.0163	0.0163	0.0163	0.0163	0.0163	0.0163
Average of $\underline{K}$	0.0085	0.0110	0.0112	0.0142	0.0142	0.0150	0.0149
Average of $\overline{K}$	0.0095	0.0158	0.0134	0.0164	0.0174	0.0169	0.0169
Probability weights dependent on:							
Geographical attributes (14)	No	No	Yes	Yes	Yes	Yes	Yes
Borough fixed effects (49)	No	No	No	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	No	No	No	No	Yes	Yes	Yes
Location attributes (16)	No	No	No	No	No	Yes	Yes
Neighbourhood attributes (10)	No	No	No	No	No	No	Yes
Number of observations	28,324	28,324	28,324	28,324	28,324	28,324	28,324

Notes: For the construction of the counterfactual we assume that airplanes fly at 300 km/h and drop 10 bombs within 5 seconds. We furthermore use probability weights in the bootstrap procedure dependent on a conditional logit model.

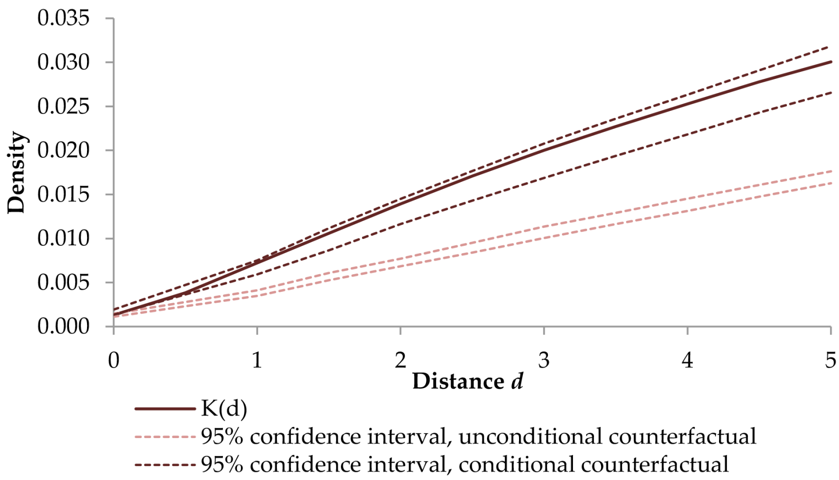


Figure A7 – K-density for bombings

Notes: The light dotted lines denote the 95% confidence bands for the unconditional counterfactual, while the dark dotted lined denote the 95% confidence bands with *zielraum*×borough fixed effects and geographic controls. The dark line represents the estimated K-density.

where we displayed the 95% confidence intervals for the unconditional counterfactual and the conditional counterfactual. In the latter case, the estimated K-density falls entirely within the 95% confidence bands. The randomness of bombings is confirmed when we include additional location attributes (*e.g.* distance to a highway, whether a property is in a conservation area) and neighborhood attributes (*e.g.* the average household size, the share of immigrants) in respectively columns (6) and (7) of Table A6. In the empirical analysis we therefore will control for *(i)* distance to the River Thames and other geographical features, and *(ii) zielraum*×borough fixed effects. Similarly, *zielraum*×borough fixed effects implicitly capture the extent to which the concentration of bombs was related to the presence of potential targets.

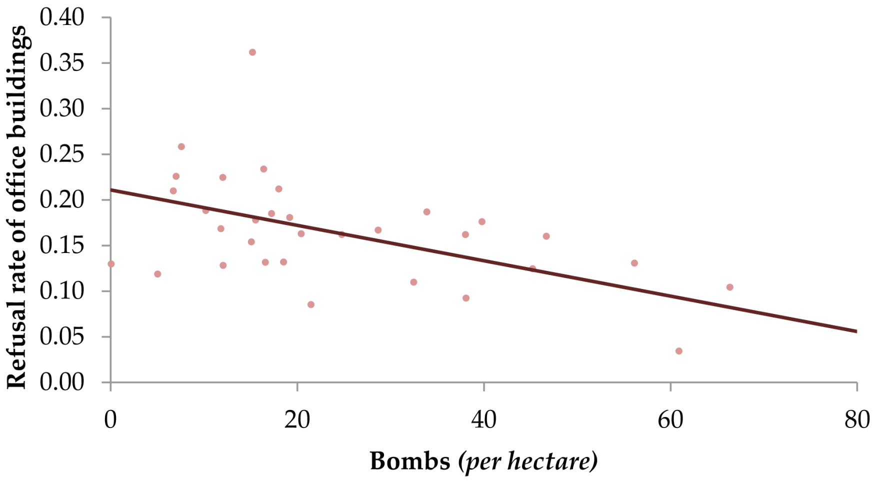


FIGURE A8 – REFUSAL RATE OF OFFICE DEVELOPMENTS IN LOCAL AUTHORITIES

A.6 Bombs and refusal rates

We use the refusal rate of office developments in Greater London as another measure for redevelopment restrictions; obtained from the Planning Statistics group at the Department for Communities and Local Government. The refusal rate as a measure of regulatory restrictiveness has been used earlier by Bertrand & Kramarz (2002), Hilber & Vermeulen (2016) and Cheshire et al. (2018), among others. We sum the total number of applications for office developments in each borough between 1997 and 2008 and then calculate the share of refused projects. As an alternative proxy for redevelopment restrictions, we use the share of office developments that only received a decision after 13 weeks or more, which we refer to as the delay rate.

Figure A8 reports the bivariate correlation between the bombs per km^2 and the refusal rate of office developments. As expected, there is a strong negative correlation ($\rho = -0.599$): regulatory constraints seem to be less restrictive where the bomb density is higher. One may argue that this is an underestimate if peripheral boroughs near the no-development greenbelt, where fewer bombs fell, may have been even more restrictive than more central locations. However, the correlation is almost identical if we only include local authorities within Inner London ($\rho = -0.615$).

As an alternative proxy for regulatory restrictiveness we use the delay rate. Figure A9 confirms the negative association between regulatory restrictiveness and bombs. The correlation between bomb density and the delay rate is lower ($\rho = -0.281$) but still is significant. For Inner London the correlation is $\rho = -0.205$.

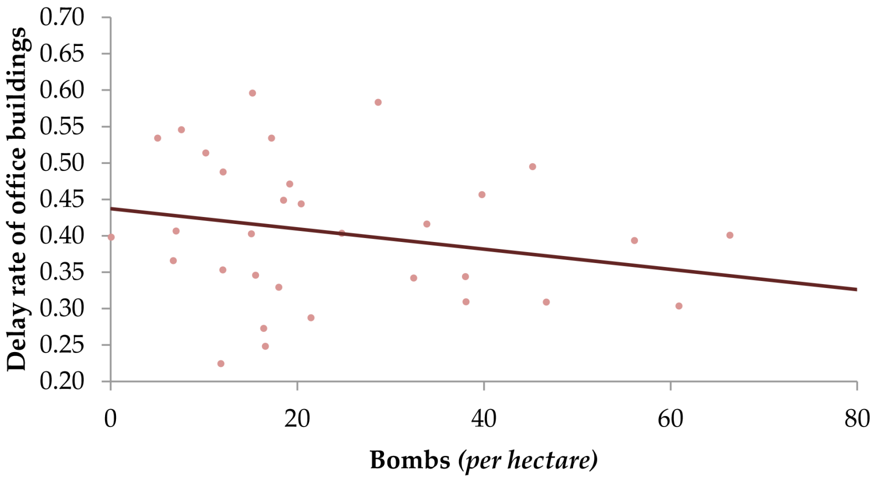


Figure A9 – Delay rate of office developments in local authorities

Table A7 – Regulatory constraints and Blitz bombings

	(Dep.var.: the refusal rate)			*(Dep.var.: the delay rate)*		
	(1) OLS	(2) OLS	(3) GMM	(4) OLS	(5) OLS	(6) GMM
Bomb density, *(std)*	-0.0391***	-0.0267	-0.0466***	-0.0280***	-0.0113	-0.0369
	(0.0098)	(0.0173)	0.0168	(0.0135)	(0.0496)	(0.0284)
Controls (3)	No	Yes	Yes	No	Yes	Yes
ϖ	—	—	1	—	—	1
$\bar{R}^2$	—	—	1	—	—	1
Number of observations	33	33	33	33	33	33
R^2	0.3585	0.4349		0.0791	0.1145	

Notes: Bomb density is standardised *(std)* to have mean zero and unit standard deviation. The controls include Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

To explore this further we estimate regressions of the refusal or delay rate on bomb density in each local authority. We report results in Table A7. Column (1) confirms the result shown in Figure A8: a standard deviation increase in bomb density is associated with a 3.9 percent decrease in the refusal rate. Given the average refusal rate of 16%, this means that the refusal rate decreases by almost 25% for a standard deviation increase in bomb density.

Ideally, one should control for the distance to the Thames and the population density in 1931, among other things. However, with only 33 observations we cannot include flexible trends of those variables. Hence, we include population in 1931 and distance to the Thames linearly. Moreover, it may be the case that local authorities that are known to be restrictive will receive fewer applications, leading to a lower refusal rate (Cheshire et al. 2018). We therefore also control for the log of applications. Column (2) shows that the point estimate is slightly lower and also more imprecise; the estimate is therefore not statistically significant at conventional levels.

Because of the few number of observations we cannot include more controls. However, we can use Oster's (2019) methodology to investigate whether omitted variable bias is an issue. Specifically, she proposes a GMM estimator to derive bias-corrected estimates of the impact of bomb density on regulatory constraints. There are two key input parameters that have to be determined. First, there is the maximum R^2, denoted by $\bar{R}^2$, from a hypothetical regression of the refusal rate on bomb density and all potential controls. Second, a parameter must be chosen that determines the relative degree of selection on observed and unobserved variables, which we denote by ϖ. Oster (2019) argues that $R^2 = \varpi = 1$ are reasonable upper bounds for those values. Oster (2019) shows that the estimator may lead to multiple solutions. Given the assumption that the bias from the unobservables is not so large that it reverses the direction of the covariance between the controls and bomb density, she shows that there is a unique solution for $\varpi = 1$. However, given the limited set of controls, we think this assumption may be invalid. Indeed, making this assumption leads to unrealistically large estimates. We therefore take the other proposed approach and choose the solution that is closest to the OLS estimates. Column (3) shows that there is now a strong and negative impact of bomb density on the refusal rate, with a similar order of magnitude as the coefficient reported in column (1). Hence, omitted variable bias seems unlikely to be very important, and even makes the effect somewhat stronger.

In columns (4)-(6) of Table A7 we take the delay rate as dependent variable. In the univariate regression in column (4), we show that the delay rate decreases by 2.8 percentage points (or about 7%) when bomb density increases by 1 standard deviation. The effect becomes imprecise once we include controls in column (5). However, when we show the bias-corrected estimate in column (6) we find a somewhat stronger point estimate, albeit still statistically insignificant at conventional levels.

We interpret the results reported here as suggestive and supporting the micro-economic evidence in Section ?? that Blitz bombings, as a proxy for more permissive regulation, is associated with taller buildings.

Table A8 – Bombings and building height; all buildings

(Dependent variable: the log of building height in m)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Bomb density, B_i, $\delta = 1.5$ *(std)*	0.0885***	0.0652***	0.0493***	0.0387***	0.0339***	0.0306***
	(0.0002)	(0.0003)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Building site hit by bomb, b_i	0.0136***	0.0172***	0.0248***	0.0260***	0.0270***	0.0296***
	(0.0050)	(0.0049)	(0.0047)	(0.0046)	(0.0046)	(0.0046)
Building – footprint *(log)*	0.1491***	0.1447***	0.1348***	0.1323***	0.1300***	0.1258***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Building – listed	0.1761***	0.1501***	0.0989***	0.0935***	0.0852***	0.0873***
	(0.0027)	(0.0027)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Geographical attributes (10)	No	Yes	Yes	Yes	Yes	Yes
Borough fixed effects (33)	No	No	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	No	No	No	Yes	Yes	Yes
Location attributes (10)	No	No	No	No	Yes	Yes
Neighborhood attributes (10)	No	No	No	No	No	Yes
Number of observations	2,099,815	2,099,815	2,099,815	2,099,815	2,099,815	2,099,8151
R^2	0.2531	0.2705	0.3592	0.3721	0.3755	0.3853

Notes: Bomb density is standardised *(std)* to have mean zero and unit standard deviation. Geographic attributes include the log of distance to the River Thames, whether the property is within 125m, 250m or 500m of a park, within 125m, 250m or 500m of a large park (>10ha) and within 125m, 250m or 500m of a water body. Location attributes include dummy variables whether the property is within 125m, 250m or 500m of a highway, within 125, 250m or 500m of a tube station, within 125m, 250m or 500m of a railway station, whether the property is in a conservation area or within 125m, 250m, or 500m of a conservation area. Neighborhood attributes are the mean household size, the share of young (<18 years) people, elderly (≥65 years), married, foreigners, unemployed, skilled occupations, highly educated, owner-occupied properties as well as the share of council housing. Standard errors are clustered at the building level and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

A.7 Sensitivity analysis for reduced-form analysis

A.7.1 Building height and bombings

We repeat the same set of specifications as in Section **??** for all buildings that have not been classified as offices. In Table A8 we find that again there are meaningful external and own-lot effects of bombings. However, the coefficients are somewhat smaller. This is not too surprising as it is mainly office buildings in London which are tall, implying that redevelopment frictions are most pronounced for them. The coefficient in column (6) implies that other buildings are 3.1% taller when bomb density increases by one standard deviation. Furthermore, buildings that have been hit directly by bombs are 3.0% taller. Hence, as expected, the effects are more pronounced for office buildings.

A.7.2 Bombings and rents

Here we show the 'reduced-form' effects of redevelopment frictions on rents. Table A9 reports the baseline results, where we regress office rents on bomb density and a dummy indicating whether a building site was hit a by a bomb. We cluster standard errors at the building level,

Table A9 – Reduced-form results: redevelopment frictions and rents

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

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Bomb density, B_i, $\delta = 1.5$ *(std)*	0.1055***	0.0987***	0.1326***	0.1341***	0.0963***	0.0835***
	(0.0078)	(0.0097)	(0.0148)	(0.0180)	(0.0179)	(0.0171)
Building site hit by bomb, b_i	-0.0690*	-0.0539*	-0.0562**	-0.0464*	-0.0453*	-0.0369
	(0.0392)	(0.0297)	(0.0269)	(0.0246)	(0.0239)	(0.0227)
Size of the property *(log)*	0.0322***	0.0422***	0.0488***	0.0503***	0.0515***	0.0522***
	(0.0096)	(0.0086)	(0.0066)	(0.0064)	(0.0062)	(0.0061)
Floor of property	0.0184***	0.0167***	0.0148***	0.0152***	0.0160***	0.0155***
	(0.0024)	(0.0022)	(0.0019)	(0.0019)	(0.0018)	(0.0018)
Building size *(log)*	0.0105	0.0114	0.0230***	0.0256***	0.0328***	0.0309***
	(0.0129)	(0.0105)	(0.0076)	(0.0072)	(0.0070)	(0.0068)
Number of floors in building	0.0042*	0.0055**	0.0049**	0.0047*	0.0053**	0.0055***
	(0.0022)	(0.0023)	(0.0025)	(0.0025)	(0.0022)	(0.0020)
Building – newly constructed	0.2707***	0.2769***	0.2716***	0.2613***	0.2580***	0.2552***
	(0.0270)	(0.0242)	(0.0202)	(0.0202)	(0.0197)	(0.0192)
Building – refurbished	0.1371***	0.1316***	0.1233***	0.1284***	0.1285***	0.1306***
	(0.0232)	(0.0205)	(0.0168)	(0.0165)	(0.0163)	(0.0159)
Listed building	0.0879***	0.0720***	0.0040	0.0058	0.0003	-0.0019
	(0.0250)	(0.0243)	(0.0221)	(0.0213)	(0.0192)	(0.0184)
Latest refurbishment decade dummies (7)	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects (15)	Yes	Yes	Yes	Yes	Yes	Yes
Geographical attributes (10)	No	Yes	Yes	Yes	Yes	Yes
Borough fixed effects (33)	No	No	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	No	No	No	Yes	Yes	Yes
Location attributes (13)	No	No	No	No	Yes	Yes
Neighborhood attributes (10)	No	No	No	No	No	Yes
Number of observations	9,202	9,202	9,202	9,202	9,202	9,202
R^2	0.2644	0.3958	0.5502	0.5742	0.5878	0.5966

Notes: Bomb density is standardised *(std)* to have mean zero and unit standard deviation. Geographic attributes include the log of distance to the River Thames, whether the property is within 125m, 250m or 500m of a park, within 125m, 250m or 500m of a large park (>10ha) and within 125m, 250m or 500m of a water body. Location attributes include dummy variables whether the property is within 125m, 250m or 500m of a highway, within 125, 250m or 500m of a tube station, within 125m, 250m or 500m of a railway station, whether the property is in a conservation area or within 125m, 250m, or 500m of a conservation area. Neighborhood attributes are the mean household size, the share of young (<18 years) people, elderly (≥65 years), married, foreigners, unemployed, skilled occupations, highly educated, owner-occupied properties as well as the share of council housing. Standard errors are clustered at the building level and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

because location attributes are available at the building level. To facilitate interpretation we standardize bomb density so that it has mean zero and unit standard deviation.

Column (1) is a parsimonious specification of office rents on bomb density, year fixed effects, and building attributes. The coefficient suggests that when the density of bombs increases by one standard deviation, rents increase by 10.6%. It is shown that, conditional on control variables, properties that are on sites that were bombed are $e^{-0.0690} - 1 = 6.7\%$ cheaper. When we would exclude building attributes, this effect is statistically insignificant and close to zero. Hence, for office tenants we do not find evidence that buildings can be more efficiently used if newer.[8]

[8]Note however that buildings on bombed sites are taller (see Section ??), so for landowners bombed sites can

Building quality has a statistically significant positive impact on rents. Properties that are on higher floors are also more expensive; 1.8% per floor, which is in line with Liu et al. (2018). Not surprisingly, new and recently refurbished buildings are much more expensive than second-hand buildings (respectively 31.1% and 14.7%).

In Appendix A.5 we discussed and showed that the bombings are not spatially random when geographic variables are omitted, such as distance to the Thames and whether a location is near a park or water body. Inclusion of such variables in column (2) does not change the results considerably: a standard deviation increase in bomb density implies a rent increase of 9.9%. In column (3) we add borough fixed effects, leading to a somewhat higher coefficient.

However, when including borough effects in Appendix A.5 we still find weak evidence that bombings may be spatially concentrated. We therefore include more detailed *zielraum*×borough fixed effects in column (4). This should control for most of the differences in pre-war population density that may have influenced bomb density. The rents in more heavily bombed areas are still higher: a standard deviation increase in bomb density increases rents by 13.4%, which is essentially the same as in the previous specification.[9]

When we control for a host of location attributes in column (5), the effect related to bomb density is somewhat lower. It should be noted that historic amenities seem to be important: properties either in or close to conservation areas are at least 25% more expensive.[10] In the final column (6), we include 10 additional demographic attributes. Although there is sometimes a statistically significant association between rents and demographics, the effect of bomb density remains essentially unaffected. All specifications suggest a meaningful positive effect of bomb density on office rents.

be used more efficiently because buildings there are allowed to be taller.

[9]It may seem surprising that including detailed fixed effects does not lead to different results for the coefficient of interest. We think the reason is that building attributes pick up a lot of spatial variation in rents and there we do observe substantial changes in coefficients once we include detailed fixed effects. For example, listed buildings that are disproportionally located in the city center are associated with higher rents if we do not include *zielraum*×borough fixed effects; however, if we include those, the listed building dummy is statistically insignificant.

[10]The coefficients of the control variables are available upon request. We find that office locations close to highways (within 125m) are less expensive (about 6%), possibly due to noise and air pollution. Somewhat surprisingly, this also holds for locations near railway stations. Apparently, the benefits of having increased accessibility are not offset by the negative effects of being located close to transport nodes. We also find that residential properties within 250m of a tube station are less expensive (about 4-10%), and those within 500m tend to be more expensive which broadly confirms the results of that commuters want to be close to train stations but not too close (Bowes & Ihlanfeldt 2001, Gibbons & Machin 2005).

Table A10 – Sensitivity analysis: clustering

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

	Output area	Ward	Constituency
	(1)	(2)	(3)
	2SLS	2SLS	2SLS
Agglomeration, A_i, $\delta = 1.5$, *(log)*	**0.2873*****	**0.2873*****	**0.2873****
	(**0.0678**)	(**0.0917**)	(**0.1376**)
Building attributes (14)	Yes	Yes	Yes
Year fixed effects (15)	Yes	Yes	Yes
Geographical attributes (10)	Yes	Yes	Yes
Borough fixed effects (33)	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	Yes	Yes	Yes
Location attributes (13)	Yes	Yes	Yes
Demographic attributes (10)	Yes	Yes	Yes
Number of observations	9,202	9,202	9,202
R^2			
Kleibergen-Paap F-statistic	125.6	50.93	46.91

Notes: **Bold** indicates instrumented. Bomb density is standardised *(std)* to have mean zero and unit standard deviation. Geographic attributes include the log of distance to the River Thames, whether the property is within 125m, 250m or 500m of a park, within 125m, 250m or 500m of a large park (>10ha) and within 125m, 250m or 500m of a water body. Location attributes include dummy variables whether the property is within 125m, 250m or 500m of a highway, within 125, 250m or 500m of a tube station, within 125m, 250m or 500m of a railway station, whether the property is in a conservation area or within 125m, 250m, or 500m of a conservation area. Neighborhood attributes are the mean household size, the share of young (<18 years) people, elderly (≥65 years), married, foreigners, unemployed, skilled occupations, highly educated, owner-occupied properties as well as the share of council housing. Standard errors are clustered at the building level and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

A.7.3 Clustering

One may be worried that the standard errors, which we cluster at the building level, are clustered at the wrong level. Clustering at the building level may be somewhat arbitrary, but there is no obvious preferred choice. Hence, showing that conclusions do not change when clustering at different levels is important. The first three columns in Table A10 repeat the preferred specification (column (6), Table **??**) for agglomeration economies. We show that when we cluster at higher levels, such as output areas, wards, or constituencies, the standard errors are a bit higher. However, in all specifications all coefficients remain statistically significant at the 1% level.

A.7.4 First-stage estimates

In Panel B of Table **??** we instrument agglomeration economies with bomb density. Here, we make sure that the instrument has the expected positive effect. In Table A11 we report first-stage estimates. The coefficient in column (1) implies that 1% increase in bomb density seems to

Table A11 – First-stage results: bombing and agglomeration
(Dependent variable: the log of agglomeration, A_i, $\delta = 1.5$)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Bomb density, B_i, $\delta = 1.5$ *(std)*	0.5495***	0.5327***	0.4023***	0.3749***	0.3100***	0.2908***
	(0.0096)	(0.0105)	(0.0175)	(0.0182)	(0.0193)	(0.0187)
Building site hit by bomb, b_i	-0.0740**	-0.0269	-0.0314	-0.0069	-0.0048	0.0010
	(0.0371)	(0.0284)	(0.0302)	(0.0203)	(0.0177)	(0.0167)
Number of observations	9,202	9,202	9,202	9,202	9,202	9,202
R^2	0.7468	0.8072	0.8850	0.9306	0.9503	0.9550

Note: Bomb density is standardised *(std)* to have mean zero and unit standard deviation. Geographic attributes include the log of distance to the River Thames, whether the property is within 125m, 250m or 500m of a park, within 125m, 250m or 500m of a large park (>10ha) and within 125m, 250m or 500m of a water body. Location attributes include dummy variables whether the property is within 125m, 250m or 500m of a highway, within 125, 250m or 500m of a tube station, within 125m, 250m or 500m of a railway station, whether the property is in a conservation area or within 125m, 250m, or 500m of a conservation area. Neighborhood attributes are the mean household size, the share of young (<18 years) people, elderly (≥65 years), married, foreigners, unemployed, skilled occupations, highly educated, owner-occupied properties as well as the share of council housing. Standard errors are clustered at the building level and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

translate into a 0.55% increase in agglomeration. However, because bombings are not random, this coefficient may be biased. Indeed, the elasticity reduces to 0.37 when adding geographic controls and *zielraum*×borough fixed effects in column (4). When including more location variables (column (5)) and demographic variables (column (6)), the elasticity is reduced to about 0.3.

A.7.5 Sensitivity analysis for agglomeration economies

We now test the robustness of the impact of agglomeration on office rents. The results of the various sensitivity analyses are reported in Table A12.[11]

Although we define agglomeration as employment density, in column (1) we investigate whether the use of a different proxy matters for our result. Using information on building-use type from the Points of Interest data, and building heights and footprints from the Ordnance Survey, we estimate each building's volume and then calculate weighted building volume in the spirit of equation (**??**). The estimated elasticity is remarkably close to the baseline estimate, suggesting that both employment density as well as office building volume are valid proxies for agglomeration economies.

Column (2) addresses the issue of firm sorting and inter-firm wage differences by including 1,102 firm fixed effects. The elasticity is then virtually identical to the baseline estimate.

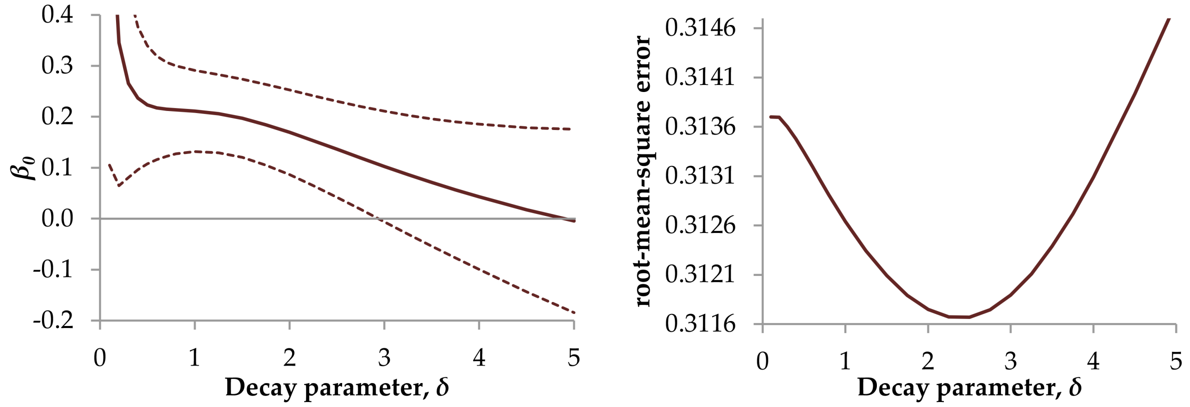
[11] We focus on 2SLS estimates. The OLS estimates are very similar and available upon request.

Table A12 – Sensitivity analysis: agglomeration economies

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

	Building volume	Firm sorting	Exact bombs	1931 population	Control for Thames	Only Inner London	No City of London	> 1km of Zielraums	Neighbourhood constr. year	Constituency fixed effects	1931 Parish fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Agglomeration, A_i, $\delta = 1.5$, *(log)*		**0.3390*****	**0.2873*****	**0.2852*****	**0.4563*****	**0.2739*****	**0.2555*****	**0.1908****	**0.3263*****	**0.1988*****	**0.3646*****
		(**0.1063**)	(**0.0579**)	(**0.0555**)	(**0.1070**)	(**0.0602**)	(**0.0615**)	(**0.0856**)	(**0.0594**)	(**0.0392**)	(**0.0564**)
Office building agglomeration,	**0.3249*****										
A_i, $\delta = 1.5$, *(log)*	(**0.0655**)										
Population 1931, $\delta = 1.5$, *(log)*				-0.0297							
				(0.0856)							
River Thames < 500m					-0.0773						
					(0.0734)						
River Thames 500-1000m					-0.1238*						
					(0.0724)						
River Thames 1000-1500m					-0.0935						
					(0.0715)						
River Thames 1500-2000m					-0.0307						
					(0.0648)						
River Thames 2000-2500m					0.0156						
					(0.0537)						
Mean construction year									-0.0147***		
year ÷10, $\delta = 1.5$									(0.0035)		
Building attributes (14)	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects (15)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical attributes (10)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location attributes (10)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic attributes (10)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borough fixed effects (33)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Firm fixed effects (1,102)	No	Yes	No	No	No	No	No	No	No	No	No
Constituency fixed effects (73)	No	No	No	No	No	No	No	No	No	Yes	No
Parish 1931 fixed effects (188)	No	No	No	No	No	No	No	No	No	No	Yes
Number of Observations	9,196	9,196	9,196	9,196	9,196	8,941	7,397	4,765	9,196	9,196	9,196
Kleibergen-Paap F-statistic	184.3	60.29	241.8	325.3	150.9	233.3	233	143.3	273.6	408	277.7

Notes: **Bold** indicates instrumented. Bomb density is standardised *(std)* to have mean zero and unit standard deviation. Geographic attributes include the log of distance to the River Thames, whether the property is within 125m, 250m or 500m of a park, within 125m, 250m or 500m of a large park (>10ha) and within 125m, 250m or 500m of a water body. Location attributes include dummy variables whether the property is within 125m, 250m or 500m of a highway, within 125, 250m or 500m of a tube station, within 125m, 250m or 500m of a railway station, whether the property is in a conservation area or within 125m, 250m, or 500m of a conservation area. Neighborhood attributes are the mean household size, the share of young (<18 years) people, elderly (≥65 years), married, foreigners, unemployed, skilled occupations, highly educated, owner-occupied properties as well as the share of council housing. Standard errors are clustered at the building level and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.



(A) Estimated parameters (B) Root-mean-squared error

Figure A10 – The choice of the decay parameter δ for agglomeration economies

When we only take into account bombs for which we know the exact location and exclude parachute mines in column (3), the coefficient is very similar again to the baseline estimate. Column (4) shows that also controlling for population density in 1931 does not change the result. In column (5) in Table A12 we flexibly control for the distance to the Thames. This leads to a somewhat stronger estimate for agglomeration (the elasticity is 0.4563). When we only include observations in Inner London, exclude the City of London, or exclude observations inside or within 1km of *zielraums* in columns (6), (7) and (8), respectively, the estimated effects are comparable to the baseline estimate. In column (9) we control for the average construction/refurbishment year in the neighborhood. Column (10) and (11) investigate whether the inclusion of alternative fixed effects (*i.e.* constituency and Parishes from 1931) change the results. If anything, the coefficients tend to be somewhat stronger.

The final sensitivity analysis focuses on the choice of the decay parameter δ, which indicates how quickly effects of agglomeration economies dissipate. We plot the estimated coefficient related to redevelopment frictions (β_0) with respect to δ. It is shown in Figure A10a that for $\delta < 3$, bomb density is significant at the 5% level. For very low levels of δ, we cannot sufficiently identify the effect, leading to unrealistically large estimates. In Figure A10b, the root-mean-squared error is minimized for $\delta \approx 2.25$, which is very close to the choice of $\delta = 1.5$.

A.7.6 Housing market analysis

Office rents and house prices should be (strongly) positively correlated (Lucas & Rossi-Hansberg 2002, Koster & Rouwendal 2013, Ahlfeldt et al. 2015). More specifically, Lucas & Rossi-Hansberg (2002) and Ahlfeldt et al. (2015) show that in an area with both employment and residential

Table A13 – Reduced-form results: redevelopment frictions and house prices
(Dependent variable: the log of house price per m^2)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
Bomb density, B_i, $\delta = 1.5$ *(std)*	0.0304***	-0.0610***	0.0340***	0.0297***	0.0206***	0.0354***	0.0616***
	(0.0019)	(0.0019)	(0.0025)	(0.0030)	(0.0029)	(0.0026)	(0.0057)
Bombs, < 200m	0.0136***	0.0121***	-0.0054***	-0.0038***	-0.0038***	-0.0029***	-0.0039***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0008)
House size *(log)*	-0.3613***	-0.3782***	-0.4157***	-0.4467***	-0.4567***	-0.5104***	-0.4870***
	(0.0054)	(0.0049)	(0.0041)	(0.0038)	(0.0037)	(0.0035)	(0.0074)
Number of bathrooms	0.0712***	0.0550***	0.0414***	0.0380***	0.0364***	0.0308***	0.0420***
	(0.0023)	(0.0021)	(0.0017)	(0.0016)	(0.0015)	(0.0014)	(0.0030)
Number of bedrooms	0.0547***	0.0580***	0.0610***	0.0656***	0.0682***	0.0727***	0.0719***
	(0.0020)	(0.0018)	(0.0015)	(0.0014)	(0.0014)	(0.0013)	(0.0028)
Private parking space	-0.0148***	0.0020	0.0457***	0.0493***	0.0473***	0.0397***	0.0446***
	(0.0025)	(0.0023)	(0.0019)	(0.0018)	(0.0017)	(0.0016)	(0.0032)
Garage	0.0549***	0.0628***	0.0538***	0.0500***	0.0504***	0.0305***	0.0213***
	(0.0026)	(0.0024)	(0.0020)	(0.0019)	(0.0018)	(0.0017)	(0.0036)
House type – detached	0.2468***	0.2674***	0.2507***	0.2317***	0.2255***	0.1798***	0.1672***
	(0.0048)	(0.0046)	(0.0041)	(0.0039)	(0.0038)	(0.0035)	(0.0081)
House type – semi-detached	0.0818***	0.0862***	0.0742***	0.0648***	0.0636***	0.0439***	0.0403***
	(0.0027)	(0.0025)	(0.0020)	(0.0019)	(0.0019)	(0.0016)	(0.0036)
House type – flat	0.0837***	0.0573***	-0.0353***	-0.0607***	-0.0703***	-0.0968***	-0.0831***
	(0.0033)	(0.0030)	(0.0024)	(0.0022)	(0.0022)	(0.0020)	(0.0041)
House type – maisonette	0.0698***	0.0439***	-0.0455***	-0.0689***	-0.0765***	-0.1015***	-0.0851***
	(0.0058)	(0.0053)	(0.0045)	(0.0043)	(0.0042)	(0.0038)	(0.0083)
Constuction year dummies (7)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects (15)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical attributes (10)	No	Yes	Yes	Yes	Yes	Yes	Yes
Borough fixed effects (33)	No	No	Yes	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	No	No	No	Yes	Yes	Yes	Yes
Location attributes (13)	No	No	No	No	Yes	Yes	Yes
Neighborhood attributes (10)	No	No	No	No	No	Yes	Yes
Number of observations	128,931	128,931	128,931	128,931	128,931	128,931	30,307
R^2	0.7022	0.7497	0.8309	0.8536	0.8592	0.8851	0.8893

Notes: Bomb density is standardised *(std)* to have mean zero and unit standard deviation. Geographic attributes include the log of distance to the River Thames, whether the property is within 125m, 250m or 500m of a park, within 125m, 250m or 500m of a large park (>10ha) and within 125m, 250m or 500m of a water body. Location attributes include dummy variables whether the property is within 125m, 250m or 500m of a highway, within 125, 250m or 500m of a tube station, within 125m, 250m or 500m of a railway station, whether the property is in a conservation area or within 125m, 250m, or 500m of a conservation area. Neighborhood attributes are the mean household size, the share of young (<18 years) people, elderly (≥65 years), married, foreigners, unemployed, skilled occupations, highly educated, owner-occupied properties as well as the share of council housing. Standard errors are clustered at the building level and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

land use, households' bid rents should be identical to bid rents of firms. This section investigates the extent to which the substitution of commercial rents for house prices is empirically valid. As most of London has mixed land use, we might expect results using house prices to be similar to those using office rents.[12]

We first focus on the results related to redevelopment frictions by estimating reduced-form regressions of house prices on bomb density. Table A13 reports these results. Column (1) shows

[12] As an illustration, in about 50% of the output areas, the ratio of jobs to households is larger than 0.25 and smaller than 2.5.

that a standard deviation increase in bombings seems to imply a house price increase of 3%, which drastically changes once we control for geographic variables. However, these results are not reliable as bombings are not random when one does not include location fixed effects. In column (3) we include borough fixed effects. Then, we find that a standard deviation increase in bomb density raises rents by 3.4%. Furthermore in line with Redding & Sturm (2016), we find negative local effects of the number of bombs within 200m. Per bomb, the price decrease is 0.5%. In heavily bombed areas this implies a strong price effect of up to 20% Hence, given that we are able to replicate the result of Redding & Sturm (2016), it seems that results using actual bomb damage data or bomb strikes are similar, which supports the validity of using bomb strikes in our estimations.

The effect of bomb density is similar once we include *zielraum*×borough fixed effects in column (4). The effect of nearby bombs is now 30% lower, but is still highly statistically significant. The results are very similar once we include location and demographic attributes in, respectively, columns (5) and (6). One may argue that housing prices and office rents are hardly correlated in fully residential areas, so that the estimated coefficient of bomb density may not capture redevelopment frictions in residential areas. In the final column we therefore only keep properties in mixed areas, *i.e.* we keep properties in output areas where the ratio of employment to households is larger than one. It is shown that the estimated effect is now below but close to the baseline estimate for the office market: a standard deviation increase in bomb density increases house prices by 6.2%.

Second, we focus on the effect of agglomeration economies on house prices of which the second-stage results are reported in Table A14. The results in the first two columns are again unreliable, but once we include borough fixed effects we find an elasticity of 0.0732, which is also somewhat lower than the estimate for the office market. This is confirmed once we include *zielraum*×borough fixed effects in column (4) and add location attributes and demographic controls in columns (6) and (7), respectively. Again, the correlation between house prices and rents is expected to be higher in mixed areas. Hence, in column (7), we only keep observations in output areas that have an employment to household ratio of larger than one. The estimated coefficient implies that doubling agglomeration leads to a house price increase of 12.3%, which is about two-thirds the estimated elasticity for the office market.

Table A14 – Results: agglomeration economies and house prices

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

	(1) 2SLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS	(6) 2SLS	(7) 2SLS
Agglomeration, A_i, $\delta = 1.5$, *(log)*	**0.0807*****	**-0.2439*****	**0.0732*****	**0.0788*****	**0.0566*****	**0.1024*****	**0.1778*****
	(**0.0046**)	(**0.0098**)	(**0.0053**)	(**0.0080**)	(**0.0081**)	(**0.0076**)	(**0.0170**)
Bombs, < 200m	0.0118***	0.0162***	-0.0041***	-0.0029***	-0.0032***	-0.0021***	-0.0031***
	(0.0007)	(0.0009)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0008)
Constuction year dummies (7)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects (15)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical attributes (10)	No	Yes	Yes	Yes	Yes	Yes	Yes
Borough fixed effects (33)	No	No	Yes	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	No	No	No	Yes	Yes	Yes	Yes
Location attributes (13)	No	No	No	No	Yes	Yes	Yes
Demographic attributes (10)	No	No	No	No	No	Yes	Yes
Number of observations	128,931	128,931	128,931	128,931	128,931	128,931	30,307
Kleibergen-Paap F-statistic	8,575	4,124	9,544	6,702	6,140	5,943	1,676

Notes: **Bold** indicates instrumented. Bomb density is standardised *(std)* to have mean zero and unit standard deviation. Geographic attributes include the log of distance to the River Thames, whether the property is within 125m, 250m or 500m of a park, within 125m, 250m or 500m of a large park (>10ha) and within 125m, 250m or 500m of a water body. Location attributes include dummy variables whether the property is within 125m, 250m or 500m of a highway, within 125, 250m or 500m of a tube station, within 125m, 250m or 500m of a railway station, whether the property is in a conservation area or within 125m, 250m, or 500m of a conservation area. Neighborhood attributes are the mean household size, the share of young (<18 years) people, elderly (≥65 years), married, foreigners, unemployed, skilled occupations, highly educated, owner-occupied properties as well as the share of council housing. Standard errors are clustered at the building level and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

A.8 Structural estimation

A.8.1 Commuting gravity equations

In Table A15 we consider various ways to estimate the commuting time elasticity. In the first two columns we use log-linear OLS specifications. Obviously, there are many zero flows (63%), because MSOAs are relatively small areas. Hence, these flows are excluded in the OLS specifications as one cannot take the log of zero. The commuting elasticity is then -0.053. In column (2) we address potential endogeneity of travel times – because area pairs with high flows may receive better infrastructure, leading to shorter travel times. This reverse causality may lead to a coefficient that is smaller in absolute terms. To address reverse causality, we use distance as an instrument for travel time. To be consistent with later specifications, we use a control function approach implying that in the first stage we regress travel time on distance and fixed effects, and then include the first stage error in the second stage. We observe that the first stage error is statistically significant, so that endogeneity is an issue. However, the travel time elasticity is hardly affected.

We think it is not very convincing to just exclude 63% of the data. We therefore use a two-way

TABLE A15 – COMMUTING TIME

(Dependent variable: the number of workers commuting between home and work locations)

	All positive flows	*Address endogeneity*	*All flows*	*Address endogeneity*	*All flows*	*Address endogeneity*
	(1) OLS	(2) CF	(3) Poisson	(4) Poisson-CF	(5) NegBinReg	(6) NegBinReg-CF
Commuting time *(in minutes)*, $-\hat{\varkappa} = -\hat{\kappa}\varepsilon$	-0.0527***	-0.0538***	-0.1005***	-0.1189***	-0.0950***	-0.1083***
	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0002)
First-stage residual		0.0052***		0.0575***		0.0414***
		(0.0003)		(0.0008)		(0.0002)
Residential location fixed effects (983)	Yes	Yes	Yes	Yes	Yes	Yes
Work location fixed effects (983)	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	352,300	352,300	966,289	966,289	966,289	966,289
R^2	0.6564	0.6797				

Notes: In columns (1) and (2) we take the log of commuting flow. 'CF' stands for Control Function. In columns (2), (4) and (6) we instrument travel time with distance. Bootstrapped standard errors are in parentheses (250 replications); *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

fixed effects Poisson model. The semi-elasticity in column (3) is now -0.101. We consider this as the preferred specification. Column (4) again addresses endogeneity of travel time by means of a control function approach. Again, we observe that the first-stage error is statistically significant, suggesting that travel time is endogenous. However, the elasticity is now -0.119, which is very similar to the preferred specification.

One may be concerned that the assumption of equidispersion (the sample mean being equal to the variance) does not hold. Because overdispersion is a feature of the data, a negative binomial regression with an additional free parameter may provide a better fit. In column (5) we show that the use of a negative binomial regression hardly affects the commuting time elasticity (-0.950). When we instrument for travel time, the travel time elasticity is essentially the same as in the preferred specification (-0.108). Hence, based on these results, endogeneity of travel times is not a main issue and the travel time elasticity is very robust.

A.8.2 Sensitivity of structural parameters

Here we inspect the robustness of the structural parameters. We report the main results in Table A16. In column (1) we consider the effect of residential externalities. Like Ahlfeldt et al. (2015) we use the same instrument to both estimate productivity and residential spillover parameters. Because the estimation of productivity externalities are independent of the estimation of residential externalities, this is feasible. It also means that the parameters $\{\hat{\kappa}, \hat{\varepsilon}, \hat{\varphi}, \hat{\gamma}_M, \hat{\delta}_M\}$ are unchanged compared to the baseline estimates. We find limited evidence of residential

Table A16 – Structural parameters – sensitivity

	Residential externalities	*Population in 1931*	*Borough fixed effects*	*Geography controls*	*No own agglomeration*	*No instruments*	*Housing prices*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Commuting time elasticity, $\hat{\kappa\varepsilon}$	0.1005***	0.1005***	0.1005***	0.1005***	0.1005***	0.1005***	0.1005***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Commuting heterogeneity, $\hat{\varepsilon}$	3.7979***	3.4308***	3.4850***	3.7135***	3.7135***	3.4138***	3.7135***
	(0.2864)	(0.2841)	(0.2495)	(0.2920)	(0.2924)	(0.2882)	(0.2923)
Redevelopment frictions, $\hat{\varphi}$	-0.0872**	-0.0684*	-0.1556***	-0.0948**	-0.0761*	-0.0898**	-0.0761*
	(0.0402)	(0.0404)	(0.0409)	(0.0421)	(0.0406)	(-0.0416)	(0.0406)
Productivity elasticity, $\hat{\gamma}^M$	0.1960***	0.2160***	0.0692**	0.0681***	0.2081***	0.0442**	0.2089***
	(0.0391)	(0.0345)	(0.0316)	(0.0238)	(0.0378)	(0.0181)	(0.0378)
Productivity decay, $\hat{\delta}^M$	0.6626*	0.6558**	0.9533	0.9191	0.6623*	0.6043***	0.6607*
	(0.3997)	(0.2754)	(1.5558)	(1.3479)	(0.3427)	(0.1297)	(0.3420)
Residential elasticity, $\hat{\gamma}^R$	-0.0293*						
	(0.0166)						
Residential decay, $\hat{\delta}^R$	0.3963						
	(1.3255)						
Geographical attributes (10)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location attributes (13)	Yes	Yes	No	No	Yes	Yes	Yes
Borough fixed effets	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zielraum×borough fixed effects (232)	Yes	Yes	No	Yes	Yes	Yes	Yes
Number of areas	983	983	983	983	983	983	983
Number of area pairs	966,289	966,289	966,289	966,289	966,289	966,289	966,289

Notes: We estimate the parameters using data at the Mid-layer Super Output Area (MSOA). In all columns except column (6) we instrument agglomeration $\tilde{A}_i$ with bomb density. Standard errors are bootstrapped (250 replications) and in parentheses; *** $p < 0.01$, ** $p < 0.5$, * $p < 0.10$.

externalities (γ_R). The coefficient is an order of magnitude smaller than the spillovers between firms. Moreover, it is negative and hardly statistically significant. We do not find a statistically significant decay for residential externalities (δ_R). This suggests that the exclusion of residential externalities in the baseline specifications will hardly lead to different predictions in our counterfactual scenarios.

Column (2) controls for population density in 1931 in each MSOA in the productivity and density regressions. We observe that this hardly impacts the results. The impact of redevelopment frictions is slightly lower, but both the productivity elasticity as well as the decay are hardly affected. This makes it more likely that Blitz bombings are indeed orthogonal to initial distribution of economic activity.

In columns (3) and (4) we include fewer controls. In column (3) we only include borough fixed effects and geographic controls. We show that only $\hat{\gamma}_M$ is now somewhat lower (0.0692). This also holds if we replace borough by *zielraum*×borough fixed effects. Hence, if we do not control for infrastructure and whether a property is close to or in a conservation area, productivity estimates are somewhat lower.

One may be concerned that agglomeration is mainly based on the number of workers in the own area. This holds particularly for the larger MSOAs. We therefore recalculate $\breve{A}_i$ to exclude employment in the own MSOA. In column (5) we observe that the results are essentially the same as in the baseline specification.

In the baseline specification we combine commercial floor space prices from *Estates Gazette* with residential floor space prices from *Nationwide*. When commercial floor space prices are missing (which holds for 80% of the locations), we use (adjusted) residential floor space prices. This may lead to some measurement error. In column (6) we therefore only use housing prices. The results clearly indicate that this does not matter: the estimated coefficients are very similar to the baseline specification.

A.8.3 Counterfactual experiments – solution algorithm

To solve for the new equilibrium in each of the counterfactual scenarios we follow a similar procedure as described in Ahlfeldt et al. (2015) and Brinkman & Lin (2019). We first choose starting values for transformed wages, floor space prices, amenities, and initial population equal to the ones obtained in the baseline scenario:

$$\{\omega_{i\mathcal{S}} = \omega_{i0}, \omega_{j\mathcal{S}} = \omega_{j0}, p_{i\mathcal{S}} = p_{i0}, \Psi_{i\mathcal{S}} = \Psi_{i0}, H_{\mathcal{S}} = H_0\}, \tag{A.5}$$

where 0 refers to the baseline scenario. Note that without residential externalities $\Psi_{i\mathcal{S}} = \Psi_{i0}$ for all scenarios.[13] We also determine for each counterfactual scenario $\mathcal{S}$ the counterfactual 'structural' density:

$$\Phi_{i\mathcal{S}} = \breve{\Phi}_i \mathrm{e}^{-\hat{\varphi}\left(\frac{b_{i\mathcal{S}}}{L_i}\right)}, \tag{A.6}$$

where the 'exogenous' density $\breve{\Phi}_i$ is kept fixed for different scenarios. Hence, we change $b_{i\mathcal{S}}$ and determine the impact on density, given $\hat{\varphi}$.

We then take the following steps:

[13] In case we allow for residential externalities, we update those after step 8.

1. We determine the commuting probability:

$$\pi_{ij\mathcal{S}} = \frac{\left(\frac{\Psi_{i\mathcal{S}} \mathrm{e}^{-\hat{\kappa}\tau_{ij}} w_{j\mathcal{S}}}{p_{i\mathcal{S}}}\right)^{\hat{\varepsilon}}}{\sum_{r=1}^{S} \sum_{s=1}^{S} \left(\frac{\Psi_{r\mathcal{S}} \mathrm{e}^{-\hat{\kappa}\tau_{rs}} w_{s\mathcal{S}}}{p_{r\mathcal{S}}}\right)^{\hat{\varepsilon}}}, \tag{A.7}$$

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

$$\pi_{ij|i\mathcal{S}} = \frac{\mathrm{e}^{-\hat{\kappa}\hat{\varepsilon}\tau_{ij}} \omega_{j\mathcal{S}}}{\sum_{s=1}^{S} \mathrm{e}^{-\hat{\kappa}\hat{\varepsilon}\tau_{is}} \omega_{s\mathcal{S}}}. \tag{A.8}$$

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

$$\begin{aligned} H_{Ri\mathcal{S}} &= \sum_{j=1}^{S} \pi_{ij\mathcal{S}} H_{\mathcal{S}}, \\ H_{Mi\mathcal{S}} &= \sum_{s=1}^{S} \pi_{si\mathcal{S}} H_{\mathcal{S}}. \end{aligned} \tag{A.9}$$

3. This provides us with the necessary information to determine agglomeration:

$$\Omega_{i\mathcal{S}} = \breve{\Omega}_i \left(\hat{\delta} \sum_{j=1}^{S} \mathrm{e}^{-\hat{\delta}\tau_{ij}} H_{Mj\mathcal{S}} \right)^{\hat{\gamma}}, \tag{A.10}$$

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

4. We obtain land use in each MSOA:

$$\begin{aligned} F_{Hi\mathcal{S}} &= \frac{(1-\beta) \sum_{j=1}^{S} \pi_{ij|i\mathcal{S}} \mathrm{e}^{-\hat{\kappa}\tau_{ij}} w_{j\mathcal{S}}}{p_{i\mathcal{S}}} H_{Ri\mathcal{S}}, \\ F_{Mj\mathcal{S}} &= \left(\frac{w_{j\mathcal{S}}}{\alpha A_j}\right)^{\frac{1}{1-\alpha}} H_{Mi\mathcal{S}}. \end{aligned} \tag{A.11}$$

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

$$\theta_{i\mathcal{S}} = \frac{F_{Mj\mathcal{S}}}{F_{Mj\mathcal{S}} + F_{Hi\mathcal{S}}}. \tag{A.12}$$

5. We have all the ingredients to determine the output (up to a constant) in each location:

$$Y_{i\mathcal{S}} = \Omega_{i\mathcal{S}} H_{Mi\mathcal{S}}^{\alpha} (\theta_{i\mathcal{S}} \Phi_{i\mathcal{S}} L_i^{1-\mu})^{1-\alpha} \tag{A.13}$$

6. The updated rents are given by:

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

7. The updated transformed wages are given by:

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

8. In the final step we obtain the counterfactual population. In the baseline scenario, we have:

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

Then, London's counterfactual population is given by:

$$H_{\mathcal{S}} = \breve{H}_{\mathcal{S}} \sum_{i=1}^{S} \sum_{j=1}^{S} \left(\frac{\Psi_{i\mathcal{S}} \mathrm{e}^{-\hat{\kappa}\tau_{ij}} \omega_{j\mathcal{S}}^{1/\hat{\varepsilon}}}{p_{i\mathcal{S}}^{1-\beta}} \right)^{\hat{\varepsilon}}. \tag{A.17}$$

We repeat these 8 steps until the values for transformed wages and rents between the current and previous iteration converges. In practice, it appears that we need about 25 iterations to obtain the new equilibrium values.

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