Neighborhood Effects: Evidence from Wartime Destruction in London

By

Stephen J. Redding, Princeton University, NBER and CEPR
Daniel M. Sturm, London School of Economics and CEPR

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Stephen J. Redding
Princeton University, NBER & CEPR†

Daniel M. Sturm
London School of Economics & CEPR‡

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Abstract

We use the German bombing of London during the Second World War as an exogenous source of variation to provide evidence on neighborhood effects. We construct a newly-digitized dataset at the level of individual buildings on wartime destruction, property values, and socioeconomic composition in London before and after the Second World War. We develop a quantitative spatial model, in which heterogeneous groups of individuals endogenously sort across locations in response to differences in natural advantages, wartime destruction and neighborhood effects. We find substantial and highly localized neighborhood effects, which magnify the direct impact of wartime destruction, and make a substantial contribution to observed patterns of spatial sorting across locations.

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KEYWORDS: Agglomeration, Neighborhood effects, Second World War, Spatial Sorting

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†Department of Economics and School of Public and International Affairs, JRR Building, Princeton, NJ 08544. Tel: + 1 609 258 4016. Email: reddings@princeton.edu.

‡Department of Economics, Houghton Street, London, WC2A 2AE. Tel: + 44 20 7955 7522. Email: d.m.sturm@lse.ac.uk.

1 Introduction

A key research question in economics is the explanation of the large observed differences in property prices and socioeconomic outcomes across neighborhoods. At one end of the spectrum, there are prosperous areas, such as parts of Hampstead in London. At the other extreme, there are poorer areas, such as parts of nearby Haringey in London. One class of explanations emphasizes differences in location fundamentals, such as green areas and scenic views. According to this perspective, Hampstead has attractive fundamentals, in the form of a hilltop location and park, which bids up house prices, such that only the rich can afford to live there. In contrast, another group of hypotheses stresses neighborhood effects, in which individual behavior is influenced by the socioeconomic composition of the population. These neighborhood effects can arise either because individuals directly have preferences over neighborhood composition, or because neighborhood composition indirectly affects local public goods, such as schools or crime.[1] In either case, there is spatial sorting, such that some locations have high property prices and shares of rich residents, while others have low property prices and shares of rich residents.

We use the German bombing of London during the Second World War as a natural experiment to determine the relative importance of these explanations. Our approach exploits two key features of this empirical setting. First, we show that wartime destruction provides an exogenous shock, in the sense that it is uncorrelated with the pre-war characteristics of locations within geographical grid cells in London. This finding is consistent with the primitive bomb-aiming technology at the time and the fact that much of the bombing occurred at night. Second, we show that wartime destruction has long-lasting effects on building structures, because reconstruction occurred at a time of rationing, shortages, financial constraints, and pressure to expand council (social) housing. Therefore, the new buildings were of lower quality than those destroyed.

We use these two features of wartime destruction to estimate the strength of neighborhood effects. The main idea behind our empirical approach is as follows. If high-income residents care more about the quality of buildings than low-income residents, the reduction in the quality of buildings in bombed locations has the direct effect of making them relatively less attractive to high-income residents. If there are neighborhood effects, such that high-income residents value living near other high-income residents, this change in socioeconomic composition has the additional indirect effect of making these bombed locations less attractive to high-income residents. To the extent that these neighborhood effects extend in space, this change in socioeconomic composition affects surrounding locations, making them less attractive to high-income residents. Therefore, the strength of these spillover effects from bombed locations to surrounding locations

[1] Recent research on these neighborhood effects includes Kling et al. (2007), Galiani et al. (2015), Bayer et al. (2016), Chetty et al. (2016), and Chetty et al. (2018), as reviewed in Chyn and Katz (2021).

can be used to estimate the strength of neighborhood effects.

To implement this idea, we construct a newly-digitized and highly-spatially-disaggregated dataset on war-time destruction, property values and socioeconomic composition in London before and after the Second World War. We digitize and geolocate the bomb damage maps compiled by the London County Council (LCC), and use these maps to measure the pre-war built-up area and levels of wartime destruction for individual buildings. We combine this information on wartime destruction with data on commercial and residential property values for these individual buildings before the Second World War. We determine the socioeconomic status of the inhabitants of each building before the Second World War using data on socioeconomic composition by street segment from the New Survey of London Life and Labour (NSOL).

To examine the long-run effects of wartime destruction, we combine these pre-war data with contemporary information on property values and socioeconomic composition. We measure post-war residential property values using transactions-level data for individual properties from 1995-2020. We measure post-war socioeconomic composition using data from the 2001 population census, which are reported for 9,041 Output Areas that cover the LCC area. We aggregate our building-level data on wartime destruction, pre-war socioeconomic outcomes and post-war property values to these Output Areas. We use the 2001 population census, because it is the first census after the Second World War to report representative data on socioeconomic composition at such a fine spatial scale, and it plausibly allows us to capture the long-run adjustment of patterns of spatial sorting to the shock of wartime destruction. We confirm that our results are capturing long-run effects using data from the 2011 population census.

We begin by validating our use of the German bombing of London as an exogenous source of variation. For London as a whole, we find that war destruction was heavier in poorer areas. This pattern of results is consistent with the German air force initially targeting the docks in the East of London, and with the Eastern parts of London historically being poorer. However, once we control for geographical location within London using a 1 kilometer hexagonal grid, we find that wartime destruction is uncorrelated with pre-war property values and socioeconomic composition within these hexagons. These findings are consistent with it being challenging to target individual buildings or streets using the available bomb-aiming technology, especially when much of the bombing occurred at night under conditions of a wartime blackout.

We next show that wartime destruction has long-lived effects on post-war property values and socioeconomic composition in bombed locations. Even after controlling for geographical location within London using our 1 kilometer hexagonal grid, we find a negative and highly statistically significant effect on post-war property values. We find these effects only for residential property damage and not for commercial property damage. This pattern of results is consistent with the mechanism in our model, in which rebuilt residential buildings are of lower quality than those destroyed, which reduces the amenities from living in those buildings, and leads to a change in socioeconomic composition. This pattern of results also suggests that our results are not capturing a direct negative amenity value from looking at post-war buildings, because otherwise we would expect to find similar results for commercial property damage.

We find that these causal impacts of wartime destruction on property values and socioeconomic composition are not only statistically significant but also economically relevant. Comparing undamaged and completely destroyed output areas, we find a decline in post-war property values from 11-18 percent, a decrease in the share of high-income residents of 4 percentage points, an increase in the share of low-income residents of 6 percentage points, and a decline in an index of overall socioeconomic composition of 5 percent.

We then establish that wartime destruction has spillover effects on neighboring locations. After again controlling for geographical location within London using our 1 kilometer hexagonal grid, we find negative, statistically significant and highly-localized effects of wartime destruction on post-war property values and socioeconomic composition in neighboring locations. As destruction in a neighboring location within 100 meters increases from zero to complete destruction, we find that property values decline by 7-10 percent, and our index of socioeconomic composition falls by 3 percentage points. These spillover effects extend beyond the immediately contiguous buffer of 0-100 meters, but decline rapidly with distance, such that there is little evidence of statistically significant spillover effects beyond 300 meters.

To interpret these empirical findings, we develop a quantitative model of the spatial sorting of workers from different socioeconomic groups across locations. We consider a city consisting of workers from three different occupations (low, middle and high-income). Workers in each occupation choose a residence and workplace within London, taking into account their wages, residential amenities, the cost of living and commuting costs. These three groups of workers are imperfect substitutes in production and hence receive different wages. They can also differ in the share of their income that they spend on housing and the responsiveness of their location decisions to spatial variation in real income. There is a single final good that is costlessly traded across locations. Productivity depends on natural advantages and agglomeration forces that depend on employment density. Residential amenities depend on the physical characteristics of each location (e.g. scenic views and the quality of buildings) and neighborhood effects (surrounding socioeconomic composition).

We interpret wartime destruction in the model as an exogenous shock that destroys buildings and reduces residential amenities, because the reconstructed buildings are of lower quality than those destroyed. Since high-income workers spend a smaller share of their income on housing and value higher amenities more than low-income workers, they are more willing to pay the higher housing prices for living in locations with higher amenities. Therefore, the reduction in residential amenities from wartime destruction affects patterns of spatial sorting, as high-income residents sort away from bombed locations, and low-income residents sort into these locations. In the presence of neighborhood effects, these changes in socioeconomic composition in bombed locations spill over to surrounding locations. As high-income residents sort away from bombed locations, this reduces the attractiveness of neighboring locations to high-income residents.

We contribute to several strands of existing research. Our paper connects to the large literature on neighborhood effects, including Glaeser et al. (1996), Kling et al. (2007), Ellison et al. (2010), Rossi-Hansberg et al. (2010), Ioannides (2013), Galiani et al. (2015), Bayer et al. (2016), Chetty et al. (2016), Chetty et al. (2018), Fogli and Guerrieri (2019), Ambrus et al. (2020), Chyn and Katz (2021), Eckert and Kleineberg (2021) and Bayer et al. (2022). Part of this literature examines social housing, including Diamond and McQuade (2019), Davis et al. (2019b), Blanco (2021), Almagro et al. (2023) and Staiger et al. (2024). We provide new evidence on neighborhood effects using exogenous variation from wartime destruction in London.

We also contribute to the broader literature on the internal organization of economic activity within cities, including Fujita et al. (1999), Lucas and Rossi-Hansberg (2002), Ahlfeldt et al. (2015), Allen et al. (2016), Monte et al. (2018), Davis and Dingel (2019), Heblich et al. (2020), Owens et al. (2020) and Gechter and Tsivanidis (2023), as reviewed in Duranton and Puga (2004), Rosenthal and Strange (2004), and Redding (2023). One strand of this research has been concerned with the spatial sorting of heterogeneous agents, including Tsivanidis (2023), Fajgelbaum and Gaubert (2020), Davis and Dingel (2020), Balboni et al. (2023), Gaubert and Robert-Nicoud (2023), and Weiwu (2023). Another related vein of this research has analyzed endogenous amenities, such as Couture (2016), Davis et al. (2019a), Almagro and Domínguez-lino (2020), Allen et al. (2022), and Couture et al. (2023). Our main contribution is to combine a quantitative urban model with the exogenous variation from wartime destruction to estimate neighborhood effects.

Our paper also contributes to the literature that has used natural experiments to examine the determinants of economic development, including Peru's Mining Mitra (Dell 2010), the division of Germany (Redding and Sturm 2008, Redding et al. 2011 and Burchardi and Hassan 2012), the Dust Bowl (Hornbeck 2012), the Tennessee Valley Authority (Kline and Moretti 2014), portage (Bleakley and Lin 2012), natural amenities as a source of persistence (Lee and Lin 2018), and the Boston fire (Hornbeck and Keniston 2017). One strand of this literature has used wartime bombing as a source of exogenous variation, including Davis and Weinstein (2002), Brakman et al. (2004), Bosker et al. (2007), Miguel and Roland (2011), Dell and Querubin (2018), Dericks and Koster (2021), Harada et al. (2022), and Takeda and Yamagishi (2022). Our main contribution relative to this research is to develop a quantitative model of spatial sorting that can be used together with our spatially-disaggregated data to structurally estimate neighborhood effects.

The remainder of the paper is structured as follows. Section 2 discusses the historical background. Section 3 introduces our data. Section 4 presents reduced-form evidence on the impact of Second World War destruction. Section 5 develops our theoretical framework. Section 6 undertakes a quantitative analysis of the model. Section 7 reports our counterfactuals for wartime bombing and the role of neighborhood effects in explaining variation in socioeconomic outcomes across locations. Section 8 summarizes our conclusions.

2 Historical Background

With London's rapid growth during the 19th century, an increasing awareness emerged of the great disparity in living standards between its most and least prosperous districts. Motivated by this disparity, Charles Booth undertook a pioneering inquiry of the standard of living in London, published as Booth (1902). As part of this inquiry, he recorded the socioeconomic status of the households in each street segment in London on a series of maps, using seven discrete categories based on occupation and income, which ranged from extreme poverty to the wealthy.

By the early 1930s, more than forty years had elapsed since Booth's original inquiry, a period of considerable urban development in London. To examine the implications of this urban development for the disparity in living standards, one of Booth's assistants, Hubert Llewellyn Smith at the London School of Economics, replicated his analysis as the *New Survey of London Life and Labor (NSOL)*, published as Smith (1930). Using the same methodology, he again classified street segments based on occupation and income on a series of maps, as illustrated in Figure F.12 in Online Appendix F3. These maps provide rich spatially-disaggregated data on socioeconomic composition in London in the period immediately before the Second World War.

London experienced heavy aerial bombardment during the Second World War.[2] After the Fall of France in May 1940, initial attacks by the German air force sought to destroy the British Royal Air Force (RAF). But there was a shift over time to a strategic bombing campaign aimed at breaking the will of the British people to resist. The resulting intense bombardment of London (the "Blitz") lasted from 7 September 1940 to 21 May 1941. Destruction occurred from high-explosive bombs (which directly damaged buildings) and incendiary bombs (which caused fires that damaged buildings). In the face of heavy day-time aircraft losses, the German air force switched to night-bombing from October 1940 onwards.[3]

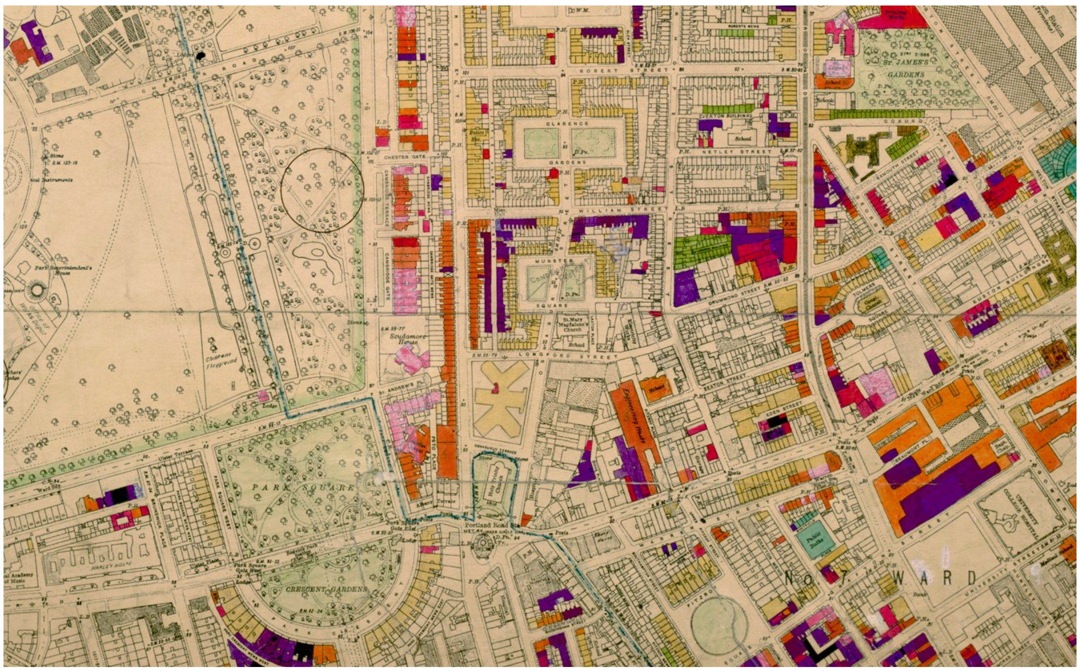
After Germany's invasion of the Soviet Union in June 1941, conventional air attacks on London were greatly reduced, but continued periodically. By the closing stages of the war, the German military had developed long-range missiles. The first of these weapons, the V-1 ("Doodlebug"), was a pulsejet predecessor of the cruise missile. The second, the V-2, was the first ballistic

[2]By comparison, there was little bombing or destruction during the First World War from 1914-8, because of the limitations of the aircraft and airship technology available at that time, as discussed in White (2008).

[3]For further discussion of the London Blitz, see for example Ray (2004) and White (2021).

missile.[4] These missiles caused destruction in a dartboard pattern throughout the LCC area (and Southern England), reflecting the primitive targeting system, variation in atmospheric conditions, the challenges of developing this new technology, and problems of manufacturing quality.[5]

Figure 1: Excerpt from a LCC Bomb Damage Map for an Area Around Regent's Park



Notes: Excerpt from London Sheet V.5 of the LCC Bomb Damage Maps. Buildings color-coded by level of bomb damage: minor blast damage (yellow); general blast damage (orange); seriously damaged but repairable at cost (light red); seriously damaged and doubtful if repairable (dark red); damaged beyond repair (purple); and total destruction (black). Large black circle in Regent's Park shows a V-1 missile impact.

To keep a record of the destruction of the built-up area, the LCC Architects' Department used detailed pre-war Ordinance Survey (OS) maps at 1:2,500 scale to record bomb damage to individual buildings. These buildings were color coded with 7 discrete levels of bomb damage ranging from minor blast damage (yellow) to total destruction (black).[6] The maps also indicated the point of impact of each V-1 and V-2 missile, with a V-1 strike denoted by a large black circle and a V-2 strike shown by a smaller black circle. In Figure 1, we display part of one of these maps for an area around Regent's Park in Central London. We observe substantial variation in the extent of destruction, even for buildings in close proximity, consistent with the idea that the differences in destruction at a fine spatial scale largely reflect idiosyncratic factors, such as the difficulties of accurate targeting and wind direction and speed.

[4]For the history of the development of the V-1 and V-2, see Johnson (1981) and Campbell (2012).

[5]V-2 rockets were produced in the Mittelwerk factory using forced labor from the Mittelbau-Dora concentration camp, with documented heroic acts of sabotage to manufacturing components.

[6]The LCC bomb damage maps were recently re-published in Ward (2016).

As the Second World War progressed, three separate plans were commissioned for post-war rebuilding for the historical City of London (the Square Mile or old Roman city), the LCC area (which included most of the built-up area), and the larger Greater London region.[7] However, after the end of the Second World War, these abstract plans ran up against the reality of the severe financial burden of Britain's war debt, a desperate need to quickly construct housing to replace destroyed dwellings, and a scarcity of raw materials.[8] Private-property owners received war damage compensation from the government for the repair of existing building structures. More than 80 percent of the new housing units constructed in the LCC area up until the end of the 1970s were government-owned council housing units.[9]

3 Data

We construct a new spatially-disaggregated dataset that combines property values and socioeconomic composition before and after the Second World War together with information on wartime destruction. A detailed exposition of the data sources and definitions is contained in Online Appendix F. Our data cover the administrative area of London County Council (LCC), which encompassed the city center and inner suburbs, with a total geographical area of just over 300 kilometers squared, and a total population of 4.4 million in 1931.[10] We measure the pre-war built-up area and wartime destruction using the LCC Bomb Damage maps, which are based on pre-war Ordinance Survey (OS) maps at 1:2,500 scale, and delineate individual buildings. We use a variety of other sources of pre-war data, as discussed further below. For the post-war period, we use data on socioeconomic composition from the 2001 and 2011 censuses and property values from transactions data from 1995-2020, assuming that by then economic activity has reached a new steady-state following the destruction during the Second World War.[11]

Spatial Units We use Output Areas (OAs) from the 2001 population census as our main spatial unit of analysis. These Output Areas have a target size of 125 households in 2001 and there are 9,041 of them within the LCC area. Output Areas can be aggregated to wards and boroughs (e.g., City of Westminster), where wards and boroughs differ substantially in geographical area. To construct consistent spatial aggregations of the Output Areas, we overlay hexagonal grids of

[7] See Holden and Holford (1951), Forshaw and Abercrombie (1943) and Abercrombie (1945), respectively. Urban planning in London began with the Barlow Commission of 1940, as discussed in Foley (1963).

[8] The rationing that was introduced in Britain during the war did not end until 1954 (see Kynaston 2008).

[9] Online appendix F8 shows a time series of completed housing units in the LCC area from 1946 onwards broken down into private construction, council housing and construction by housing associations.

[10] London County Council (LCC) was the principal local government body for London from 1889 to 1965.

[11] The 2001 census is the first post-war population census for which detailed data on socioeconomic status was enumerated for the full population, rather than for a 10 percent sample in earlier post-war censuses. Most rebuilding occurred in the 1950s and 1960s, although some construction on former bomb sites from the Second World War continued to occur into the 1970s, as discussed for example in Clapson and Larkham (2013).

different sizes over the LCC area, with hexagon diameters varying from 1 km (380 hexagons) to 4km (34 hexagons), as discussed further in Online Appendix F1.[12]

Property Values We measure residential and commercial property values before the Second World War using data on rateable values, which correspond to "The annual rent which a tenant might reasonably be expected, taking one year with one another, to pay for a hereditament, if the tenant undertook to pay all usual tenant's rates and taxes ... after deducting the probable annual average cost of the repairs, insurance and other expenses." These rateable values have a long history in England and Wales, dating back to the 1601 Poor Relief Act, and were used to raise revenue for local public goods.

We use data from the handwritten valuation list for the LCC area from 1936, which runs to approximately 50,000 pages. Each valuation entry on the list reports a street and street number, brief description of the property characteristics (e.g., house, flat, factory, wharf, shop, etc.), and the rateable value. In a first step, we photographed and digitized the 1936 valuation list. In a second step, we used historical maps showing each building and its corresponding street number to geolocate and assign the more than 1 million valuations to buildings. In a third step, we distinguish between commercial, residential and mixed use buildings using the reported property characteristics. For mixed use buildings, we allocate the total rateable value of the building between commercial and residential use based on the reported property characteristics. In a fourth and final step, we estimate a commercial and residential property value for each output area as the location fixed effect in a hedonic regression including property characteristics.

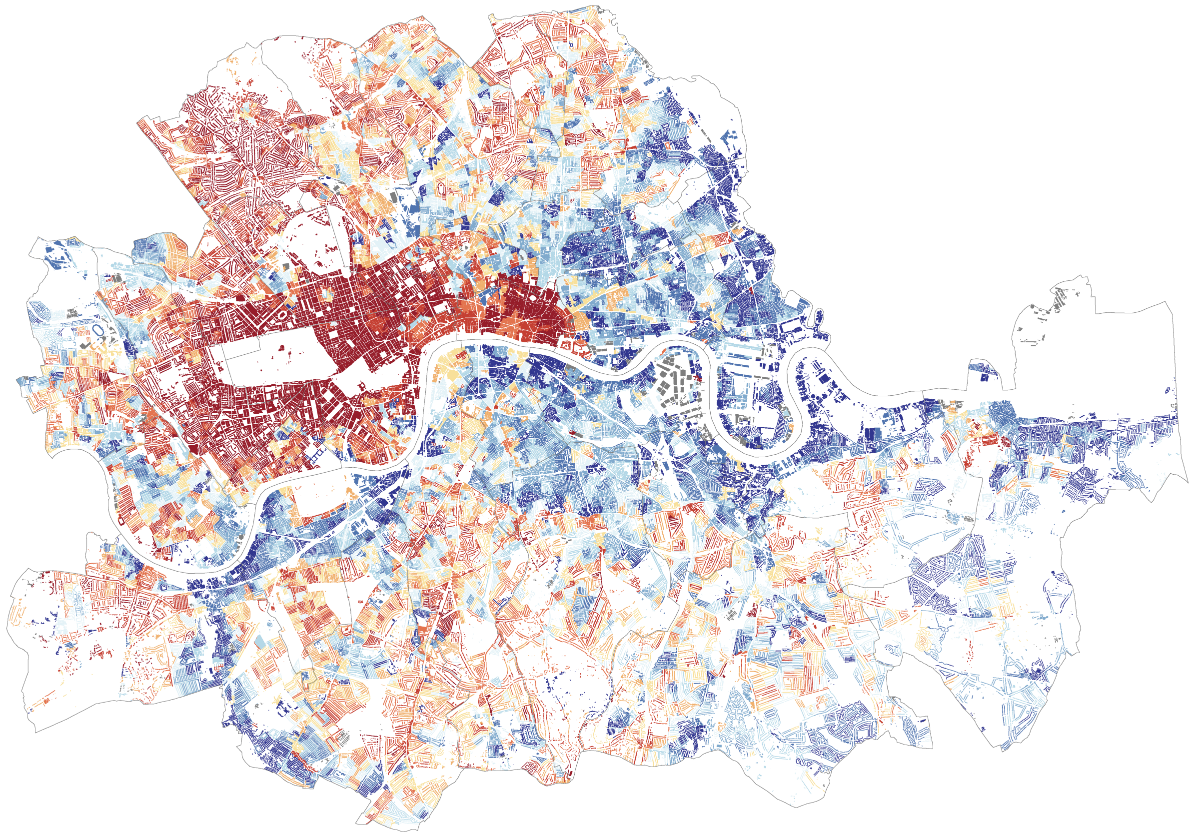
In Figure 2, we show the distribution of pre-war residential property values in the LCC area. We find the highest property values in the most central parts of London and a clear East-West gradient, with higher property values in the West End than in the East End, but substantial variation even within narrow geographical areas.

We measure residential property values after the Second World War using property transactions data from the U.K. Land Registry, which reports prices paid, postcodes and property characteristics. For the period 1995 to 2020, there are 1,186,317 transactions registered within the LCC area. We match each property transaction to our 2001 Output Areas using the centroid of the property's postcode, where there are an average of 133 transactions per Output Area. We estimate a residential property value for each Output Area as the location fixed effect in a hedonic regression including the property characteristics.

Population We measure pre-war population using the 1931 population census of England and Wales. The smallest spatial units for which population is reported in the 1931 census are the 316 wards of the LCC area. We allocate population across residential buildings within wards using

[12]We choose hexagons (rather than squares or triangles) because of their advantages for partitions of geographical space, as discussed for example in Carr and Pickle (2010).

Figure 2: Pre-War Residential Property Values by LCC Output Area



Notes: Property values in the LCC area in 1936 based on the market rental value (rateable value) of property for tax purposes. The property values are the Output Area fixed effects from a hedonic regression of the logarithm of rateable values on observed property characteristics. Red denotes high values; blue denotes low values.

their shares of the total residential built-up area within wards. As a specification check on this procedure, we implement an analogous procedure for boroughs and wards, where population is reported in the population census for both of these levels of aggregation. Allocating borough population across wards using their shares of the total residential built-up area within boroughs, we show that the resulting estimated ward population closely approximates the ward population reported in the population census, as discussed further in Online Appendix F4.

Socioeconomic Status We measure socioeconomic status before the Second World War using the New Survey of London (NSOL) maps. We digitized and georeferenced the more than 25,000 street segments. We assign a socioeconomic status to each residential and mixed use building based on the socioeconomic status of its street segment. Combining this information with the population data for each building discussed above, we obtain the total number of people with that socioeconomic status at the building level. Summing across buildings within Output Areas, we obtain the total number of people with each socioeconomic status at the Output Area level. To construct consistent measures of socioeconomic status before and after the Second World War, we aggregate the NSOL socioeconomic categories into three groups of low, middle and high-income. The income thresholds separating these three groups in the NSOL data are weekly-family incomes of £3 and £5 per week, as summarized in Table F.7 in Online Appendix F3.

We also construct an index of socioeconomic status at the Output Area level following Orford et al. (2002). We first assign a score ($\$^o$) to each socioeconomic group $o \in \{L, M, H\}$, which equals the mid-point of the cumulative distribution of residents for the entire LCC area. We next calculate the socioeconomic status ($\$_i$) of each Output Area i as the weighted average of these scores, using the shares of residents in each group for each Output Area (R_i^o/R_i) as weights:

$$\$_i = \left(\frac{R_i^L}{R_i} \times \$^L\right) + \left(\frac{R_i^M}{R_i} \times \$^M\right) + \left(\frac{R_i^H}{R_i} \times \$^H\right). \tag{1}$$

Finally, we rescale this socioeconomic index such that it varies between zero (all residents are low income) to one (all residents are high income).

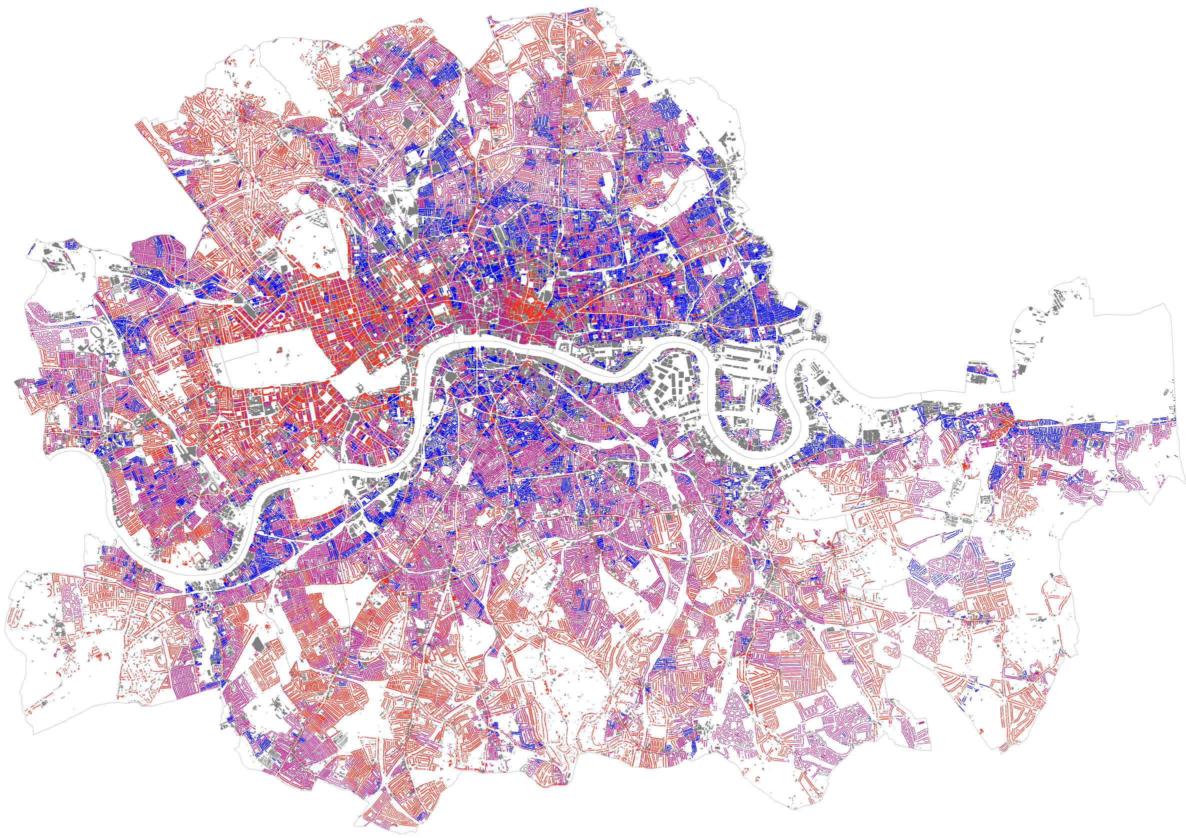
In Figure 3, we show the distribution of this index of socioeconomic status in the LCC area. We find a strong pattern of spatial sorting, with the areas characterized by higher property values in Figure 2 typically exhibiting higher socioeconomic status in Figure 3. As a result, we find a clear East-West gradient in socioeconomic status, with higher values in the West End than in the East End. Nevertheless, we again observe substantial variation in socioeconomic status even within narrow geographical areas.

We measure socioeconomic status after the Second World War using the population census for 2001, which reports the number of people in each disaggregated occupation at the Output Area level. We aggregate these disaggregated occupations into the same three categories of low, middle and high-income, as documented in Online Appendix F6. We find a relatively similar population distribution across these three categories before and after the Second World War, which is consistent the fact that the socioeconomic classification in the population census was heavily influenced by the Booth and NSOL studies. The low and high-income categories make up 24 and 28 percent of the population, respectively, in the pre-war period, which compares with 22 and 20 percent, respectively, in the post-war period. In robustness checks, we also use data on socioeconomic status from the population census for 2011.

Second World War Destruction We measure wartime destruction using the LCC bomb damage maps. We georeferenced the 110 map sheets, drew the outline of the 1939 built-up area for each map sheet, and recorded the level of damage to each building, as indicated by the color-coding on the maps. This measure of destruction includes damage caused by both conventional aircraft and V-1 and V-2 missiles.[13] As our baseline measure of war destruction, we use the frac-

[13] We employed research assistants to draw the built-up area and damage to each building on georeferenced versions of the bomb damage maps. In contrast, Fetzer (2023) applies automated color-recognition algorithms to digital scans of these maps to construct an instrument for building energy efficiency based on wartime destruction. Our

Figure 3: Pre-War Index of Socioeconomic Status by Building in the LCC Area



Notes: Socioeconomic status by building in the LCC area based on the New Survey of London Life and Labor 1928-31. The color of each building corresponds to the socioeconomic index of the residents of the building with red denoting high and blue low socioeconomic status. Non-residential buildings such as factories or churches are shown in gray.

tion of the pre-war built-up area in each Output Area that experienced serious repairable damage (light red) or worse. We construct this measure for the overall built-up area, residential built-up area, and commercial built-up area. We exclude minor and general blast damage, which are non-structural, and unlikely to permanently affect building structures. We do not distinguish between repairable and unrepairable damage, because what is deemed repairable could be endogenous. Finally, as a robustness check, we construct an overall index of war destruction. We first score levels of damage to each building from 0 to 6 (from no to total destruction). We next compute our index of war destruction for each Output Area as the weighted average of these scores, using the shares of its pre-war built-up area with each level of destruction.

In Figure 4, we show each building in the LCC area and its level of destruction, using the same color scheme as the original bomb damage maps. We find that war destruction was ex-

data from the bomb damage maps differ substantially from the BombSight data used in Dericks and Koster (2021), which claims to record the locations where German bombs landed. The BombSight data does not record building damage. Furthermore, we find many areas where destruction occurred, but no bomb impacts are recorded in the Bombsight data (in part because of the spread of fire), as shown in Online Appendix F2.5.

Figure 4: Second World War Destruction by Building in the LCC Area

Notes: The map shows the bomb damage for each building in the LCC area using the color scheme used by the original bomb damage maps: minor blast damage (yellow); general blast damage (orange); seriously damaged but repairable at cost (light red); seriously damaged and doubtful if repairable (dark red); damaged beyond repair (purple); and total destruction (black). Buildings that suffered no damage are shown in grey and clearance areas (1.3 percent of the pre-war built-up area) are in green.

tensive: more than 40 percent of the pre-war built-up area experienced some damage (yellow or worse), and around 17 percent experienced serious damage according to our measure.[14] There is a clear East-West gradient, with Eastern areas experiencing more destruction. But the extent of idiosyncratic variation within narrow geographic areas is striking, with substantial destruction in the Western parts of London. This pattern of idiosyncratic variation is consistent with our identifying assumption that war destruction is exogenous within narrow geographic areas.

Other Geographical Data We combine our data on property values, socioeconomic status and Second World War destruction with a variety of other census and geographical data, including the height of buildings, the fraction of people of living in council housing, and travel time using the transport network.

[14]Clearance areas (green) were areas assigned for post-war development (1.3 percent of the pre-war built-up area), and typically included both bombed areas and nearby areas with no destruction. We exclude these areas from our war destruction measures, since the choice to label parts of the city as clearance areas is endogenous.

4 Reduced-Form Evidence

We now present reduced-form evidence on the economic impact of wartime destruction that guides our theoretical model. In Subsection 4.1, we show that Second World War destruction is uncorrelated with pre-war socioeconomic status and property values within small geographical grid cells, supporting the idea that it provides an exogenous source of variation. In Subsection 4.2, we report estimates of the causal effect of Second World War destruction on post-war socioeconomic status and property values. In Subsection 4.3, we show that these causal effects of bomb damage spill over to neighboring locations. Finally, in Subsection 4.4, we provide further evidence on the mechanisms through which these effects of wartime destruction occur.

4.1 Randomness of Second World War Destruction

We begin by validating wartime destruction as an exogenous source of variation. We estimate the following regression specification between socioeconomic outcomes *before* the Second World War and *subsequent* wartime destruction:

$$Y_{i,\text{pre-war}} = \beta D_{i,\text{war}} + \varrho_k + u_i, \tag{2}$$

where i indexes Output Areas and k indexes hexagonal grid cells; $Y_{i,\text{pre-war}}$ is either pre-war socioeconomic status or property values; $D_{i,\text{war}}$ is a measure of wartime destruction; ϱ_k are fixed effects for hexagonal grid cells; and u_i is stochastic error. In our baseline specification, we report standard errors clustered by 1 km hexagons, which allows spatial correlation across Output Areas within these hexagons. As a robustness test, Table E.5 in Online Appendix E2 reports Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors following Conley (1999).[15]

Table 1 reports estimation results using our baseline measure of wartime destruction, the fraction of the built-up area seriously damaged. Online Appendix E1 documents a similar pattern of results using our damage index. Each cell of the table corresponds to a separate regression. The columns report results using different socioeconomic outcomes as left-hand side variables. Columns (1)-(3) use the fraction of the population who are high, middle and low income, respectively; Column (4) uses our index of socioeconomic status; Column (5) uses the unconditional average property value; Column (6) uses the average property value conditional on a set of observed property characteristics, as described in more detail in Online Appendix F5. The panels report results using different types of war destruction as right-hand side variables. Panel A uses overall damage; Panel B uses residential damage; and Panel C uses commercial damage. Within each panel, the first row reports results with no fixed effects; the second row presents estimates

[15] Bertrand et al. (2004) examine several approaches to control for serial correlation. They show that clustering the standard errors performs well in settings with at least 50 clusters as in our application.

using fixed effects for hexagons of 4 km diameter; and the third row gives results using fixed effects for hexagons of 1 km diameter.

Table 1: Randomness of Wartime Destruction: Bomb Damage Index

Fixed Effects	(1) Fraction High Status	(2) Fraction Middle Status	(3) Fraction Low Status	(4) Socio-Economic Index	(5) Log of Property Value	(6) Log of Property Value
			Panel A - All Damage			
None	-0.235^{***}	0.039^{*}	0.196^{***}	-0.215^{***}	-0.473^{***}	-0.481^{***}
	(0.031)	(0.023)	(0.025)	(0.026)	(0.057)	(0.066)
4 km Hexagons	-0.061^{***}	0.020	0.042^{**}	-0.051^{***}	-0.094^{**}	-0.094^{**}
	(0.020)	(0.018)	(0.017)	(0.016)	(0.041)	(0.044)
1 km Hexagons	−0.007	−0.004	0.011	−0.009	−0.017	−0.024
	(0.014)	(0.013)	(0.012)	(0.012)	(0.033)	(0.033)
			Panel B - Residential Damage			
None	-0.207^{***}	0.023	0.184^{***}	-0.195^{***}	-0.435^{***}	-0.453^{***}
	(0.028)	(0.021)	(0.023)	(0.023)	(0.052)	(0.058)
4 km Hexagons	-0.051^{***}	0.005	0.046^{***}	-0.049^{***}	-0.089^{**}	-0.095^{**}
	(0.018)	(0.016)	(0.015)	(0.014)	(0.036)	(0.038)
1 km Hexagons	−0.003	−0.015	0.017	−0.010	−0.015	−0.023
	(0.013)	(0.012)	(0.011)	(0.010)	(0.030)	(0.030)
			Panel C - Commercial Damage			
None	-0.170^{***}	0.033^{**}	0.136^{***}	-0.152^{***}	-0.321^{***}	-0.304^{***}
	(0.023)	(0.017)	(0.019)	(0.019)	(0.044)	(0.049)
4 km Hexagons	-0.046^{***}	0.018	0.028^{**}	-0.037^{***}	-0.075^{**}	-0.065^{*}
	(0.015)	(0.013)	(0.013)	(0.012)	(0.031)	(0.034)
1 km Hexagons	−0.016	0.011	0.006	−0.011	−0.025	−0.024
	(0.011)	(0.010)	(0.009)	(0.008)	(0.026)	(0.026)

Notes: Each cell in the table reports the results of a separate regression and the unit of observation is an output area as defined in the 2001 UK Census. Dependent variables in columns (1) to (4) are measures of socioeconomic composition from the New Survey of London (fraction of population that has low, middle and high income and an index of socioeconomic status). In column (5) the dependent variable is the logarithm of the average property value of buildings without any hedonic controls, while we control for a set of building characteristics in column (6). The explanatory variable in Panel A is the percentage of the built-up area seriously damaged and in Panel B and C the fraction of the residential and non-residential built-up area serious damaged respectively. We refer to the non-residential built-up area for simplicity as the commercial built-up area. Regressions include no fixed effects, fixed effects for 1 km hexagons, or fixed effects for 4 km hexagons, as indicated in the first column. Numbers of observations vary slightly across specifications depending on whether Output Areas had commercial and residential built-up area pre-war and therefore could experience destruction. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

In the specification with no fixed effects in the top row of each panel, we find a correlation between pre-war socioeconomic outcomes and subsequent wartime destruction. Output areas that had larger pre-war shares of the population with lower socioeconomic status and lower pre-war property values experienced more destruction during the Second World War. This pattern of results is consistent with Figures 2-4 above, where there is a West-East gradient in property values, socioeconomic status and wartime destruction. Once we include fixed effects for 4 km hexagons in the middle row of each panel, much of this correlation goes away, such that the regression coefficients fall by more than one half in absolute magnitude. Nevertheless, 4 km hexagons still cover a relatively large geographical area, and are still likely affected by the West-East gradients noted above. Once we include fixed effects for 1 km hexagons in the bottom row of each panel, the coefficients fall close to zero and are entirely statistically insignificant.

Therefore, once we focus on variation within narrow geographical grid cells, wartime damage is entirely unrelated to pre-war socioeconomic status and property values. We find the same pattern whether we use overall damage, residential damage or commercial damage. This pattern of results is consistent with the primitive bomb-aiming technology and night-time bombing, which precluded the precise targeting of locations.[16] Overall, these results provide strong support for the idea that wartime destruction within narrow geographical areas is as good as randomly assigned and provides an exogenous source of variation.

4.2 Direct Effects of Second World War Destruction

We next provide evidence on the causal impact of wartime destruction. We estimate the following regression specification for the direct effect of a location being bombed during the war on its own post-war outcomes:

$$Y_{i,\text{post-war}} = \beta D_{i,\text{war}} + \varrho_k + u_i \tag{3}$$

where $Y_{i,\text{post-war}}$ is a socioeconomic outcome after the end of the Second World War; the other variables are defined as in the previous subsection; and our baseline specification again reports standard errors clustered by 1 km hexagons.

Table 2 reports the estimation results. The structure of the table is similar to Table 1 above, except that we focus on our baseline specification with fixed effects for 1 km hexagons for brevity. The columns report results using different post-war outcomes ($Y_{i,\text{post-war}}$) as left-hand side variables. The panels report results using different types of wartime destruction as right-hand side variables ($D_{i,\text{war}}$). Panel A uses overall damage, while Panel B includes both residential and commercial damage.

In Panel A, we find statistically significant effects of wartime destruction on post-war outcomes, even after controlling for fixed effects for 1km hexagons. Output Areas that experienced more wartime destruction have lower shares of the post-war population who are high and middle income (Columns (1) and (2)); higher shares of the post-war population who are low income (Column (3)); a lower value for our index of post-war socioeconomic status (Column (4)); and

[16] Given the primitive bomb-aiming technology, the British Royal Air Force (RAF) largely gave up trying to strike specific targets in Germany and instead pursued the area bombing of German cities. Only with the development of more advanced bomb sights by the American Army Airforce (AAAF) later in the war was a degree of success achieved in striking specific targets by day, although even then accuracy was poor (e.g., Overy 2013).

lower post-war property values, both without and with hedonic controls for property characteristics (Columns (5) and (6)). We find smaller estimated coefficients in Column (6) including hedonic controls than in Column (5) without these controls, which is consistent with wartime destruction leading to a downgrading in property characteristics.

Table 2: The Direct Effect of Wartime Destruction

	(1) Fraction High Status	(2) Fraction Middle Status	(3) Fraction Low Status	(4) Socio-Economic Index	(5) Log of Property Value	(6) Log of Property Value
Panel A - All Damage						
All Damage	−0.039***	−0.023***	0.062***	−0.051***	−0.180***	−0.112***
	(0.006)	(0.005)	(0.009)	(0.007)	(0.022)	(0.018)
Hexagon Fixed Effects	1 km	1 km	1 km	1 km	1 km	1 km
Observations	8912	8912	8912	8912	8797	8797
R-squared	0.505	0.280	0.439	0.483	0.637	0.782
Panel B - Residential and Commercial Damage						
Residential Damage	−0.038***	−0.024***	0.062***	−0.050***	−0.193***	−0.111***
	(0.006)	(0.004)	(0.008)	(0.007)	(0.025)	(0.020)
Commercial Damage	−0.003	0.001	0.003	−0.003	0.003	−0.007
	(0.005)	(0.004)	(0.006)	(0.005)	(0.019)	(0.016)
Hexagon Fixed Effects	1 km	1 km	1 km	1 km	1 km	1 km
Observations	8511	8511	8511	8511	8423	8423
R-squared	0.518	0.290	0.455	0.498	0.645	0.786

Notes: The dependent variables in columns (1) to (4) consist of a measure of socioeconomic status from the 2001 UK census (fraction of population that has low, middle and high income and an index of socioeconomic status). In column (5) the dependent variable is the logarithm of the average property transaction price while in column (6) it is the logarithm of the average property transaction price conditional on a set of property characteristics. In Panel A, the explanatory variable is the fraction of the total built-up area seriously damaged, while the explanatory variables in Panel B are the fraction of the residential and commercial built-up area seriously damaged. The unit of observation for all regressions is an output area as defined in the 2001 UK Census and all regressions include fixed effects for 1 km hexagons. Numbers of observations vary slightly across specifications due to the availability of modern housing transaction prices and whether Output Areas had both commercial and residential built-up area pre-war. Standard errors are clustered at the 1 km hexagon level. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

These estimates are not only statistically significant but also economically relevant. Comparing undamaged to completely destroyed output areas, the estimated coefficients in Panel A imply a decline in property values from 11-18 percent; a decrease in the share of high-income residents of 4 percentage points; an increase in the share of low-income residents of 6 percentage points; and a decline of 5 percent in our index of socioeconomic composition.[17]

In Panel B, we show that these estimated effects of wartime destruction on post-war outcomes are entirely driven by damage to residential buildings. When we include both residential and commercial damage separately, we find coefficients on residential damage that are statisti-

[17] We also explored heterogeneity in the treatment effects of wartime destruction with respect to pre-war socioeconomic status. We consistently find negative estimated treatment effects of wartime destruction, which are only marginally smaller for the top quintile of pre-war socioeconomic status.

cally significant and close in magnitude to those for overall damage above. In contrast, we find coefficients on commercial damage that are entirely statistically insignificant and close to zero in magnitude. This pattern of results is consistent with the mechanism in our model, in which wartime destruction to residential buildings reduces the amenities from living in those buildings, and hence in turn leads to a change in socioeconomic composition. These results also cast doubt on potential alternative explanations that do not operate through residential composition, such as a direct negative amenity effect from looking at post-war buildings, which would imply a similar pattern of estimated coefficients for commercial and residential damage.

In the online appendix, we show that this pattern of results is robust across a wide range of different specifications. In Table E.2 of Online Appendix E1, we corroborate these findings using our index of wartime destruction. In Table E.6 of Online Appendix E2, we demonstrate the robustness of our results to using Conley (1999) Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors. In Table E.9 of Online Appendix E3, we show that we find similar socioeconomic composition results using the population census for 2011 instead of 2001, which is consistent with wartime destruction having an impact on steady-state outcomes. In Table E.12 of Online Appendix E4, we break out our post-war property prices data from 1995-2020 into sub-periods, and demonstrate similar results within each sub-period, which is again consistent with persistent long-run impacts. In Table E.14 of Online Appendix E5, we establish the same pattern of results if we exclude the Cities of London and Westminster as the main centers of commercial activity, again highlighting that our results are capturing effects through residential activity.

4.3 Spillover Effects of Second World War Destruction

We next provide evidence on the extent to which wartime destruction not only directly affects bombed locations, but also spills over to neighboring locations. We measure these spillovers using buffers of 100-meter width around the built-up area of each Output Area. These buffers exclude the Output Area itself and the area of the next smallest buffer, such that they form a set of hollow concentric rings around each Output Area.[18]

Using this definition of buffers, we estimate the following regression specification between a location's socioeconomic outcomes after the Second World War, its own wartime destruction, and the wartime destruction in surrounding areas:

$$Y_{i,\text{post-war}} = \beta D_{i,\text{war}} + \sum_{g=1}^{G} \gamma_g D_{ig,\text{war}} + \varrho_k + u_i \tag{4}$$

where we index buffers by $g \in \{1, \ldots, G\}$; $D_{ig,\text{War}}$ is the fraction of the built-up area seriously damaged in the buffer g surrounding location i; the other variables are defined above; and our

[18]We provide an example of these 100-meter buffers in Figure F.2 in Online Appendix F1.

baseline specification again reports standard errors clustered by 1 km hexagons.

In Table 3, we report the estimation results for our preferred specification including fixed effects for 1 km hexagons. Columns (1)-(2) measure post-war outcomes ($Y_{i,\text{post-war}}$) using our index of socioeconomic composition, while Columns (3)-(4) use property values controlling for observed property characteristics. Columns (1) and (3) use overall damage, while Columns (2) and (4) include separate measures of residential and commercial damage. To conserve space, we display the estimated coefficients on residential and commercial damage next to one another underneath the labels for Columns (2) and (4), even though these coefficients are estimated from a single regression. In each column, the first row gives the coefficient estimates for own destruction (β), and the remaining rows give results for surrounding destruction (γ_g).

Table 3: The Spillover Effect of Wartime Destruction

	Socio-Economic Index			Log of Property Value		
	(1)	(2)		(3)	(4)	
Destruction in own area	−0.042***	−0.045***	−0.001	−0.095***	−0.096***	−0.002
	(0.006)	(0.007)	(0.005)	(0.017)	(0.020)	(0.016)
Destruction in 100m buffer	−0.030**	−0.024*	−0.009	−0.072*	−0.086**	0.000
	(0.013)	(0.013)	(0.010)	(0.038)	(0.038)	(0.033)
Destruction in 200m buffer	−0.026	−0.022	−0.004	−0.110**	−0.119**	0.006
	(0.018)	(0.019)	(0.013)	(0.045)	(0.051)	(0.040)
Destruction in 300m buffer	−0.026	−0.027	−0.002	−0.092*	−0.075	−0.002
	(0.018)	(0.018)	(0.013)	(0.052)	(0.054)	(0.045)
Destruction in 400m buffer	0.004	−0.024	0.027*	−0.055	−0.110**	0.052
	(0.026)	(0.020)	(0.015)	(0.069)	(0.055)	(0.048)
Damage Type	Total	Res	Com	Total	Res	Com
Hexagon Fixed Effects	1 km	1 km		1 km	1 km	
Observations	8910	8500		8795	8412	
R-squared	0.485	0.500		0.782	0.787	

Notes: The unit of observation is an output area as defined in the 2001 UK Census. The dependent variable in columns (1) and (2) is an index of socioeconomic status and in columns (3) and (4) the logarithm of the average property transaction price conditional on a set of property characteristics. The explanatory variables in columns (1) and (3) are the percentage of the built-up area seriously damaged in each Output Area and in four buffers of 100 meter width around each Output Area. Columns (2) and (4) break down overall damage into damage to residential and commercial buildings. As indicated in the table, the left hand side of the column reports the estimates for residential destruction while the right hand side reports the estimates for commercial destruction. All regressions include fixed effects for 1 km hexagons. Numbers of observations vary slightly across specifications due to the availability of modern housing transaction prices and whether Output Areas had both commercial and residential built-up area pre-war. Standard errors are clustered at the 1 km hexagon level. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

We find statistically significant spillover effects from destruction in neighboring locations. These spillover effects are large in magnitude, with estimated coefficients within 100 meters that are substantial relative to the own effects. These spillover effects are also highly localized, with no estimates of statistically significant spillovers beyond 300 meters. We find marginally smaller coefficients on own destruction once we control for destruction in neighboring locations. From Columns (2) and (4), we find that these spillover effects are entirely driven by destruction of the residential built-up area, with estimated coefficients for destruction of the commercial built-up area that are close to zero and almost always statistically insignificant. This pattern of results provides further support for the mechanism in our model, in which these spillover effects between locations are driven by changes in surrounding residential composition.

In Online Appendix E, we show that these findings of spillover effects are robust across the same set of specifications considered for the direct effect of wartime destruction above.

4.4 Mechanisms for Second World War Destruction

We now provide further evidence on the mechanisms through which the direct and spillover effects of wartime destruction occur. In Table 4, we estimate the same regression specification (4) as in the previous subsection using additional left-hand side variables. For brevity, we focus on destruction of the pre-war overall built-up area.

First, we provide evidence that wartime destruction has a persistent impact on the type of buildings, which affects the residential amenities from living in those buildings. Column (1) uses the share of buildings within the pre-war building footprint; Column (2) considers the height of modern buildings; Column (3) examines the share of the land area that is built up. As reported in the first row, we find substantial direct effects of wartime destruction on each of these building outcomes. Wartime destruction substantially reduces the probability that buildings lie within the pre-war building footprint. Wartime destruction also increases the height of buildings by around 7.8 percent, and reduces the share of the land area that is built up by 4.1 percent, which is in line with post-war architectural trends towards high-rise tower blocks surrounded by open areas. As reported in the second to fourth rows, we find no systematic evidence of spillover effects of wartime destruction on these building outcomes. Therefore, destruction in neighboring locations does not change the types of buildings in the own location. This pattern of results suggests that the spillover effects in the previous subsection are not capturing the demolition of undamaged buildings in neighboring areas in response to wartime destruction.

Second, we provide further evidence on the changes in socioeconomic composition caused by wartime destruction. Column (4) uses the share of households living in council housing in the 2001 population census. We find that areas that experienced more own destruction have higher council housing shares in 2001. This pattern is consistent with the space created by wartime destruction being used to accommodate the large post-war expansion in council housing. As shown in Figure F.23 in Online Appendix F8, over 80 percent of all housing units constructed in the LCC area from 1945-80 were council housing. In 1980, Margaret Thatcher's Housing Act gave council tenants the "right to buy" their properties at considerable discounts on the market price, which led to a large large-scale transfer to private ownership. To capture the impact of wartime destruction on council housing before this large-scale transfer, Column (5) repeats the

Table 4: Mechanisms for Wartime Destruction

	(1) Fraction Buildings Surviving	(2) Log of Height of Buildings	(3) Fraction Land Area Built-Up	(4) Fraction Council in 2001	(5) Fraction Council in 1981	(6) Log of Empl. Density
Destruction in Own Area	−0.300***	0.078***	−0.041***	0.135***	0.246***	−0.209***
	(0.023)	(0.019)	(0.005)	(0.017)	(0.030)	(0.064)
Destruction in 100m Buffer	0.020	−0.019	0.004	0.028	0.036	−0.014
	(0.043)	(0.039)	(0.012)	(0.034)	(0.058)	(0.130)
Destruction in 200m Buffer	0.055	0.033	0.007	0.031	0.071	0.154
	(0.053)	(0.052)	(0.015)	(0.046)	(0.076)	(0.160)
Destruction in 300m Buffer	−0.035	−0.078	0.017	−0.017	0.035	0.066
	(0.058)	(0.050)	(0.016)	(0.045)	(0.075)	(0.169)
Destruction in 400m Buffer	0.131**	−0.129**	0.021	−0.069	−0.206**	0.119
	(0.064)	(0.064)	(0.019)	(0.056)	(0.094)	(0.201)
Hexagon Fixed Effects	1 km	1 km	1 km	1 km	1 km	1 km
Observations	8910	8910	8910	8910	6698	8910
R-squared	0.407	0.473	0.464	0.396	0.444	0.479

Notes: Each column reports the results of a separate regression. The unit of observation are Output Areas from the 2001 UK Census except column (5), which uses enumeration districts from the 1981 UK Census. The dependent variable in column (1) is the fraction of pre-war buildings that exist in the same footprint in 2014; in column (2) the logarithm of the average building height; in column (3) the fraction of total area of an Output Area that is built up; in columns (4) and (5) the fraction of households that reside in council housing in 2001 and 1981 respectively and in column (6) the logarithm of employment density. The explanatory variables in all columns are the fraction of the built-up area seriously damaged within the unit of observation as well as four buffers of 100 meter width around each unit of observation. Observations differ in column (5) due the different spatial units used in the 1981 census. All regressions include fixed effects for 1 km hexagons. Standard errors are clustered at the 1 km hexagon level. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

same regression using data from the 1981 census, and finds an even larger effect on the share of households living in council housing.[19]

In both Columns (4) and (5), we find no systematic evidence of spillover effects of wartime destruction on the share of households living in council housing. Therefore, destruction in neighboring locations does not change the likelihood that council housing is constructed in the own location, providing further evidence that spillover effects are not occurring through the demolition of undamaged buildings in neighboring areas in response to wartime destruction.

Third, we provide evidence on the impact of wartime destruction on the specialization of areas in commercial versus residential activity. Column (7) uses the log of employment density (employment by workplace per land area). We find a negative and statistically significant direct effect of wartime destruction, with no evidence of statistically significant spillover effects. This pattern of results suggests that if anything wartime destruction shifted economic activity towards

[19] Although "right to buy" sales transferred ownership to the private sector, demolitions were relatively rare, with only 140,000 council units demolished in England since 1997, when official data on demolitions were first published. The 1988 Housing Act reduced the barriers for local authorities to transfer council housing units to housing associations and led to a number of such transfers. To control for this policy change, we re-estimated Columns (4) and (5) in Table 4 counting housing association tenants as council tenants, and find similar results.

residential use, which together with our earlier findings of no effects for commercial destruction supports our focus on residential externalities. In Table E.8 of Online Appendix E2, we show that these findings are robust to using HAC standard errors. In Table E.11 of Online Appendix E3, we show that we find similar results using data from the 2011 census.

Taken together, the findings of this section provide further evidence in support of the mechanism of our model. Wartime destruction changes the types of buildings, and hence socioeconomic composition in neighboring locations, and residential decisions for the own location are affected by the socioeconomic composition of neighboring locations.

5 Theoretical Framework

Guided by these empirical findings, we now develop our theoretical model of neighborhood effects.[20] We consider a setting in which workers from different socioeconomic groups (low, middle and high-income) endogenously sort across residences and workplaces. Residential choices for each group of workers depend on amenities, which are determined by location characteristics (including building quality) and neighborhood effects (the socioeconomic composition of the surrounding population). We suppose that higher income workers value high-quality buildings and socioeconomic composition more than lower-income workers. We interpret wartime destruction as an exogenous shock that permanently changes building quality, which affects patterns of spatial sorting, both directly (through preferences for building quality), and indirectly (though preferences over the resulting changes in socioeconomic composition). We focus on steady-state comparisons of a pre-war equilibrium (during the 1930s) and a post-war equilibrium (during the 2000s), in line with the availability of our data for these two time periods.

We consider a city (London) that is embedded in a wider economy (Britain). The city consists of a discrete set of locations $n, i \in \mathbb{N}$, which correspond to the Output Areas in our data, where the total number of these locations is $N = |\mathbb{N}|$. Time is discrete and is indexed by t. There are two types of agents: workers and landlords. Workers belong to three occupations indexed by $o \in \mathbb{O} = \{L, M, H\}$: low-income ($L$), middle-income ($M$) and high-income ($H$). Workers are geographically mobile within the city and choose a residence and workplace to maximize utility. We consider both a closed-city (an exogenous supply of workers in each occupation ($\overline{E}_t^o$)) and an open-city (the supply of workers in each occupation ($\overline{E}_t^o$) is endogenously determined by population mobility with the wider economy that provides a reservation utility for each occupation ($\overline{U}_t^o$)). The floor space in each location is owned by a local landlord.

Firms produce a single final good under conditions of perfect competition and constant returns to scale. This final good is costlessly traded and chosen as the numeraire ($P_{nt}^Y = 1$). We allow

[20] See Online Appendix B for the derivation of all theoretical results in this section of the paper.

locations to differ from one another in terms of their attractiveness for production and residence, as determined by productivity, amenities, the supply of floor space, and transport connections, where each of these location characteristics can change over time. Throughout the following, we use bold math font to denote vectors or matrices.

5.1 Preferences

The indirect utility for worker ψ from occupation o residing in location n and working in location i is assumed to depend on her wage (w_{it}^{o}), the price of the homogenous final consumption good (P_{nt}^{Y}), the price of residential floor space (Q_{nt}), bilateral commuting costs (κ_{nit}^{o}), amenities that are common for all workers from an occupation (B_{nt}^{o}), and an idiosyncratic amenity draw ($z_{nit}^{o}(\psi)$) for each worker, according to the following Cobb-Douglas functional form:

$$u_{nit}^{o}(\psi) = \frac{B_{nt}^{o} z_{nit}^{o}(\psi) w_{it}^{o}}{\kappa_{nit}^{o} \left(P_{nt}^{Y}\right)^{\alpha^{o}} \left(Q_{nt}\right)^{1-\alpha^{o}}}. \qquad 0 < \alpha^{o} < 1, \tag{5}$$

where we allow residential floor space to account for a smaller share of expenditure for higher-income workers: $0 < \alpha^{L} < \alpha^{M} < \alpha^{H} < 1$.

We assume that common amenities for each occupation (B_{nt}^{o}) depend on three components: (i) the fraction of the pre-war built-up area destroyed ($D_{nt} \in [0,1]$); (ii) neighborhood effects ($\mathbb{B}_{nt}$); (iii) exogenous fundamentals such as scenic views (b_{nt}^{o}):

$$B_{nt}^{o} = e^{\eta_{D}^{o} D_{nt}} \mathbb{B}_{nt}^{\eta_{R}^{o}} b_{nt}^{o}, \qquad \mathbb{B}_{nt} \equiv \left[\sum_{i \in \mathbb{N}} \mathbb{I}_{nit}^{B} \times \mathbb{S}_{it}\right], \tag{6}$$

where the exponential specification for wartime destruction ($e^{\eta_{D}^{o} D_{nt}}$) ensures that log amenities is defined for all $D_{nt} \in [0,1]$; $\mathbb{I}_{nit}^{B}$ is a measure of the geographical proximity of location i to location n; and $\mathbb{S}_{it}$ is our index of socioeconomic status from equation (1).

The parameter η_{D}^{o} captures the impact of wartime destruction on residential amenities through building quality. While for simplicity we assume a direct relationship between residential amenities and wartime destruction in equation (6), we derive this relationship from a construction sector technology in Online Appendix B6. The parameter η_{R}^{o} controls the relative importance of neighborhood effects for residential amenities. We allow these parameters (η_{D}^{o}, η_{R}^{o}) to differ across occupations, such that high-income residents can care more about building quality and socioeconomic status than low-income residents.

Idiosyncratic amenities ($z_{nit}^{o}(\psi)$) are assumed to be drawn from an independent extreme value (Fréchet) distribution each period for each worker ψ, occupation o, residence n and workplace i:

$$G_{nit}^{o}(z) = e^{-z^{-\epsilon^{o}}}, \qquad \epsilon^{o} > 1, \tag{7}$$

where we normalize the Fréchet scale parameter in equation (7) to one, because it enters worker choice probabilities isomorphically to common amenities (B^o_{nt}) from equation (5). A larger value for the Fréchet shape parameter ϵ^o implies less dispersion in idiosyncratic amenities, such that location decisions are more responsive to economic variables relative to idiosyncratic amenities. We again allow this parameter to vary across occupations, such that low-income residents can be more sensitive to differences in real income than high-income residents.

We assume that floor space in each location is owned by a local landlord, who receives expenditure on floor space as income, and for simplicity consumes only the final good.

5.2 Production

Production occurs under conditions of perfect competition and constant returns to scale. We assume that the single tradable final good is produced using labor and commercial floor space according to a Cobb-Douglas technology. Therefore, the following zero-profit condition must hold in each location with positive production of this tradable final good:

$$1 = \frac{1}{A_{it}} \mathbb{W}_{it}^{\beta} q_{it}^{1-\beta}, \qquad 0 < \beta < 1, \tag{8}$$

where A_{it} is productivity; q_{it} is the price of commercial floor space; and $\mathbb{W}_{it}$ is a Cobb-Douglas labor cost index that depends on wages for each occupation (w^o_{it}):

$$\mathbb{W}_{it} = \left(w^L_{it}\right)^{\gamma^L} \left(w^M_{it}\right)^{\gamma^M} \left(w^H_{it}\right)^{\gamma^H}, \qquad \gamma^L + \gamma^M + \gamma^H = 1. \tag{9}$$

We allow productivity (A_{it}) to depend on three components: (i) the fraction of the pre-war built-up area destroyed ($D_{it} \in [0, 1]$); (ii) agglomeration forces ($\mathbb{A}_{it}$); (iii) exogenous production fundamentals such as access to natural water (a_{it}):

$$A_{it} = e^{\chi_D D_{it}} \mathbb{A}_{it}^{\chi_E} a_{it}, \qquad \mathbb{A}_{it} \equiv \left[\sum_{n \in \mathbb{N}} \mathbb{I}^A_{nit} \times \frac{E_{nt}}{K_n}\right], \tag{10}$$

where the exponential specification for wartime destruction ($e^{\chi_D D_{it}}$) again ensures that log productivity is defined for all $D_{it} \in [0, 1]$; $\mathbb{I}^A_{nit}$ is a measure of the geographical proximity of location i to location n, and (E_{nt}/K_n) is total employment (E_{nt}) per unit of land area (K_n). The parameter χ_D captures any impact of wartime destruction on productivity through changes in the local built environment; and χ_E controls the relative importance of agglomeration forces.

5.3 Residence and Workplace Decisions

Workers from each occupation choose their residence and workplace to maximize their utility. Using the properties of the Fréchet distribution, the probability that a worker from occupation o

chooses to live in location n and work in location i is given by:

$$\lambda_{nit}^{o} = \frac{E_{nit}^{o}}{\overline{E}_{t}^{o}} = \frac{\left(B_{nt}^{o} w_{it}^{o}\right)^{\epsilon^{o}} \left(\kappa_{nit}^{o} Q_{nt}^{1-\alpha^{o}}\right)^{-\epsilon^{o}}}{\sum_{k \in \mathbb{N}} \sum_{\ell \in \mathbb{N}} \left(B_{kt}^{o} w_{\ell t}^{o}\right)^{\epsilon^{o}} \left(\kappa_{k\ell t}^{o} Q_{kt}^{1-\alpha^{o}}\right)^{-\epsilon^{o}}}, \qquad n, i \in \mathbb{N}, \tag{11}$$

where E_{nit}^{o} is the measure of commuters from residence n to workplace i in occupation o; we have used our choice of numeraire ($P_{nt}^{Y} = 1$); and the term $\left(B_{nt}^{o} w_{it}^{o}\right) / \left(\kappa_{nit}^{o} Q_{nt}^{1-\alpha^{o}}\right)$ in the numerator and denominator captures amenity-adjusted real income.

Therefore, bilateral commuting flows satisfy a gravity equation, consistent with a wide range of empirical evidence.[21] In our specification, this gravity equation holds by occupation, such that workers from different occupations sort endogenously across residence-workplace pairs, based on differences in amenities (B_{nt}^{o}), wages (w_{nt}^{o}), the price of residential floor space (Q_{nt}), commuting costs (κ_{ni}^{o}), expenditure shares ($1 - \alpha^{o}$), and the preference dispersion parameter (ϵ^{o}).

Summing across workplaces i in equation (11), we obtain the share of workers from occupation o who live in residence n ($\lambda_{nt}^{Ro} = R_{nt}^{o}/\bar{E}_{t}^{o}$), where R_{nt}^{o} is the measure of residents from occupation o in location n. Summing across residences n in equation (11), we obtain the share of workers from occupation o who are employed in each workplace i ($\lambda_{it}^{Eo} = E_{it}^{o}/\bar{E}_{t}$), where E_{it}^{o} is the measure of employment from occupation o in location i. With a continuous measure of workers, there is no uncertainty in the supply of either residents or workers for each location.

Finally, expected utility conditional on choosing a residence-workplace pair for each occupation (U_{t}^{o}) is equalized across all residence-workplace pairs:

$$U_{t}^{o} = \mathbb{E}_{t}\left[u_{t}^{o}\right] = \vartheta^{o} \left[\sum_{k \in \mathbb{N}} \sum_{\ell \in \mathbb{N}} \left(B_{kt}^{o} w_{\ell t}^{o}\right)^{\epsilon^{o}} \left(\kappa_{k\ell t}^{o} Q_{kt}^{1-\alpha^{o}}\right)^{-\epsilon^{o}} \right]^{\frac{1}{\epsilon^{o}}}, \tag{12}$$

where $\mathbb{E}_{t}$ is the expectation operator with respect to the distribution of idiosyncratic amenities; $\vartheta^{o} \equiv \Gamma\left(\frac{\epsilon^{o}-1}{\epsilon^{o}}\right)$; and $\Gamma(\cdot)$ is the Gamma function. Intuitively, bilateral pairs with more desirable economic characteristics (e.g., low commuting costs) attract commuters with lower realizations for idiosyncratic amenities, until expected utility (including idiosyncratic amenities) is the same across all bilateral residence-workplace pairs.

Commuter market clearing requires that employment in each occupation in each workplace (E_{it}^{o}) equals the measure of workers from that occupation commuting to that workplace:

$$E_{it}^{o} = \sum_{n \in \mathbb{N}} \lambda_{nit|n}^{Ro} R_{nt}^{o}, \qquad \lambda_{nit|n}^{Ro} \equiv \frac{\lambda_{nit}^{o}}{\lambda_{nt}^{Ro}} = \frac{\left(w_{it}^{o}/\kappa_{nit}^{o}\right)^{\epsilon^{o}}}{\sum_{\ell \in \mathbb{N}} \left(w_{\ell t}^{o}/\kappa_{n\ell t}^{o}\right)^{\epsilon^{o}}}, \tag{13}$$

where $\lambda_{nit|n}^{Ro}$ is the conditional probability that workers in occupation o commute to workplace i, conditional on living in residence n.

[21] See for example McFadden (1974), Fortheringham and O'Kelly (1989), and McDonald and McMillen (2010).

Commuter market clearing also implies that income per capita in each residence n for each occupation o (v_{nt}^{o}) is a weighted average of the wages in all locations, where these weights are given by the above conditional commuting probabilities by residence ($\lambda_{nit|n}^{Ro}$):

$$v_{nt}^{o} = \sum_{i \in \mathbb{N}} \lambda_{nit|n}^{Ro} w_{it}^{o}. \tag{14}$$

We assume that commuting costs are a power function of travel times (τ_{nit}) using the transport network ($(\kappa_{nit}^{o})^{-\epsilon^{o}} = \tau_{nit}^{-\epsilon^{o}\kappa} = \tau_{nit}^{-\phi^{o}}$); $\phi^{o} \equiv \epsilon^{o}\kappa$ is the product of the elasticity of commuting flows to commuting costs (ϵ^{o}) and the elasticity of commuting costs to travel time (κ).

5.4 Floor Space Market Clearing

Given the supplies of floor space allocated to residential (H_{it}^{R}) and commercial use (H_{it}^{E}), the prices of residential (Q_{it}) and commercial (q_{it}) floor space are determined by the equalities between the demands and supplies for each use of floor space:

$$Q_{it} = \frac{\sum_{o \in \mathbb{O}} \left(1 - \alpha^{o}\right) v_{it}^{o} R_{it}^{o}}{H_{it}^{R}}, \tag{15}$$

$$q_{it} = \frac{1-\beta}{\beta} \frac{\left[\sum_{o \in \mathbb{O}} w_{it}^{o} E_{it}^{o}\right]}{H_{it}^{E}}. \tag{16}$$

In our estimation of the model's parameters, we are not required to make assumptions about how the supplies of residential and commercial floor space (H_{it}^{R}, H_{it}^{E}) are determined. Instead, we use the structure of the model to back out their implied values given the observed data on the other endogenous variables. When we undertake counterfactuals, our baseline specification holds these supplies of residential and commercial floor space fixed, which is motivated by our empirical setting, in which the reallocation of land between residential and commercial use was heavily restricted following the Town and Country Planning Act of 1942. In robustness checks, we undertake counterfactuals allowing for endogenous responses in the supply of floor space.

5.5 General Equilibrium

We now characterize the general equilibrium of the model. The spatial distribution of economic activity is determined by the model parameters (α^{o}, β, γ^{o}, η_{D}^{o}, η_{R}^{o}, χ_{D}, χ_{E}, ϵ^{o}, κ) and the following location characteristics: residential fundamentals for each occupation (b_{nt}^{o}), production fundamentals (a_{nt}), wartime destruction (D_{nt}), land area (K_{n}), travel times (τ_{nit}), and the supplies of residential (H_{nt}^{R}) and commercial (H_{nt}^{E}) floor space.

Given these parameters and location characteristics, the open-city general equilibrium is referenced by the residence and workplace choice probabilities for each occupation (λ_{nt}^{Ro}, λ_{nt}^{Eo}), wages for each occupation (w^o_{nt}), the prices for residential and commercial floor space (Q_{nt}, q_{nt}), and the total city population for each occupation ($\overline{E}^o_t$). Given these equilibrium variables, all other endogenous variables of the model can be determined. We now provide a sufficient condition for the existence of a unique equilibrium in the special case of the model with no neighborhood effects and no agglomeration forces, following the approach of Allen et al. (2024).

Proposition 1 *Assume no neighborhood effects and no agglomeration forces ($\eta^o_R = \chi_E = 0$). Given the location characteristics (b^o_{nt}, a_{nt}, D_{nt}, K_n, τ_{nit}, H^R_{nt}, H^E_{nt}), a sufficient condition for the existence of a unique general equilibrium (λ^{Ro}_{nt}, λ^{Eo}_{nt}, w^o_{nt}, Q_{nt}, q_{nt}, $\bar{E}^o_t$) (up to scale) is that the spectral radius of a coefficient matrix of model parameters (α^o, β, γ^o, η^o_D, χ_D, ϵ^o, κ) is less than or equal to one.*

Proof. See Online Appendix B5.1. ■

In general, with sufficiently strong neighborhood effects and agglomeration forces, there is the potential for multiple equilibria in the model. An important feature of our estimation approach is that it is robust to the presence of multiple equilibria, because it conditions on the observed equilibrium in the data, as discussed further below.

Under our assumption $0 < \alpha^L < \alpha^M < \alpha^H < 1$, housing accounts for a larger share of expenditure for lower-income workers. Additionally, for $\epsilon^L > \epsilon^M > \epsilon^H$, lower-income workers are more sensitive to differences in amenity-adjusted real income across residence-workplace pairs. When both of these conditions are satisfied, locations with higher equilibrium prices for residential floor space will tend to have larger equilibrium shares of high-income workers, other things equal. Nevertheless, this spatial sorting is imperfect because of the idiosyncratic preference shocks, which ensure that all locations with strictly positive residential fundamentals (b^o_{nt}) for all three occupations have positive shares of residents from all three occupations.

Wartime destruction affects the spatial distribution of economic activity in the model through four mechanisms. First, wartime destruction leads to a temporary reduction in the supply of residential and commercial floor space, until reconstruction occurs. In our baseline specification, we assume that the supply of residential and commercial floor space is rebuilt to its pre-war values, such that there is no permanent impact through this channel. In robustness specifications, we allow for endogenous changes in the supply of floor space.

Second, wartime destruction affects residential amenities for each occupation in bombed locations through a reduction in building quality ($\eta^o_D < 0$ in equation (6)). If higher-income workers care more about building quality ($|\eta^H_D| > |\eta^M_D| > |\eta^L_D|$), this lower building quality leads them to sort out of bombed locations, and induces lower-income workers to sort into these locations. Third, wartime destruction can directly affect productivity in bombed locations, which changes wages and employment for each occupation ($\chi_D \neq 0$ in equation (10)). In our baseline specification, and again motivated by our empirical application, we focus on effects through residential amenities, holding productivity constant ($\chi_D = \chi_E = 0$). In robustness specifications, we allow for endogenous changes in productivity through agglomeration forces.

Fourth, the changes in patterns of spatial sorting in response to the direct effects of wartime destruction on amenities ($\eta_D^o < 0$ in equation (6)) have indirect effects through neighborhood effects ($\eta_R^o > 0$ in equation (6)). Since neighborhood effects decay spatially, changes in socioeconomic composition in bombed locations spill over to affect their unbombed neighbors. If higher-income workers care more about socioeconomic status ($|\eta_R^H| > |\eta_R^M| > |\eta_R^L|$), the decline in socioeconomic status from reduced building quality in bombed locations makes surrounding areas relatively less attractive to higher-income workers. The resulting change in patterns of spatial sorting shapes the impact of wartime destruction on the amenity-adjusted real income of workers from each occupation and the prices for residential floor space received by landlords.

6 Quantitative Analysis

In this section, we estimate the model's structural parameters for the strength of neighborhood effects. Our quantitative analysis has a sequential structure, such that we undertake our analysis in a number of steps. Each step uses results from the previous one and imposes the minimal set of additional assumptions relative to the previous step. We provide further details on each step of our estimation procedure in Online Appendix C.

Two key advantages of our estimation procedure are as follows. First, we are not required to make assumptions about the impact of wartime destruction on productivity or agglomeration forces in production to estimate the neighborhood effects parameters, because we condition on observed variables that directly control for these production characteristics. Second, we are not required to make assumptions about whether the model has a unique equilibrium or multiple equilibria in this estimation, because we condition on the observed equilibrium in the data. Given this observed equilibrium and the structure of the model, we are able to estimate the neighborhood effects parameters, regardless of whether there could have been another (unobserved) equilibrium for the same parameter values.

6.1 Preference and Production Parameters (Step 1)

We begin by calibrating the model's standard preference and production technology parameters using historical data from our empirical setting. We calibrate the housing expenditure shares ($1 - \alpha^o$) for each group of workers using a British Ministry of Labor household expenditure survey from 1937-8. We distinguish low, middle and high-income households using the £3 and £5 thresholds for weekly-family income that separate these three groups in our NSOL data. We set the household expenditure share for each group equal to the mean across households within that group, which yields $(1-\alpha^L) = 0.26$, $(1-\alpha^M) = 0.22$, and $(1-\alpha^H) = 0.16$. Therefore we find an intuitive pattern, in which housing expenditure accounts for a lower share of expenditure for higher-income workers, which acts to make lower-income workers' location decisions more sensitive to differences in the price of residential floor space.[22]

We assume a value for the share of labor in production costs of $\beta = 0.55$, which lies in the middle of the range of 0.43-0.63 reported in Antràs and Voth (2003), and is close to the labor share reported for Britain in 1913 in Matthews et al. (1982). The remaining share of production costs of $(1-\beta) = 0.45$ is attributed to commercial floor space, including both capital (machinery, equipment, buildings and structures) and land.

We calibrate the labor cost shares (γ^o) for the three groups of workers using two properties of our model. First, the commuter market clearing condition implies that the sum of income by workplace ($w_i^o E_i^o$) across all locations equals the corresponding sum of income by residence ($v_n^o R_n^o$). Second, under our assumption of Cobb-Douglas preferences, income by residence for each occupation and location is a constant multiple ($1/(1-\alpha^o)$) of payments for residential floor space, which equal observed residential rateable values by occupation ($\mathbb{V}_n^o$). Combining these two properties, and assuming that the LCC area was approximately a closed commuting market before the Second World War, we calibrate the labor cost shares for the three groups using their observed shares in residential rateable values for the LCC area as a whole.[23]

We thus measure labor cost shares as $\gamma^o = \frac{\sum_{\ell \in \mathbb{N}} w_\ell^o E_\ell^o}{\sum_{h \in \mathbb{O}} \sum_{\ell \in \mathbb{N}} w_\ell^h E_\ell^h} = \frac{\sum_{k \in \mathbb{N}} v_k^o R_k^o}{\sum_{h \in \mathbb{O}} \sum_{k \in \mathbb{N}} v_k^h R_k^h} = \frac{\sum_{k \in \mathbb{N}} \mathbb{V}_k^o/(1-\alpha^o)}{\sum_{h \in \mathbb{O}} \sum_{k \in \mathbb{N}} \mathbb{V}_k^h/(1-\alpha^h)}$, which yields $\gamma^L = 0.17$, $\gamma^M = 0.38$ and $\gamma^H = 0.46$. As a point of comparison, the respective pre-war population shares are 0.24 (low), 0.47 (middle) and 0.28 (high). Therefore we again find an intuitive pattern in which higher-income workers account for a larger share of labor payments than of population. As a robustness check on this procedure, we obtain similar results if we instead proxy income with expenditure, and calibrate the labor cost shares using the shares of the three worker groups in household expenditure, as discussed in Online Appendix C1.

6.2 Commuting Parameters (Step 2)

We next estimate the model's commuting parameters using data on bilateral commuting flows. Pre-war commuting data are not disaggregated by worker group and are only available for the

[22] We find a similar pattern using a later British Ministry of Labor household expenditure survey from 1953-4 and an earlier survey of 30,000 workers in the LCC area in 1887, as discussed further in Online Appendix C1.

[23] In our pre-war commuting data for 1921, we find that out-commuting beyond the LCC boundaries was negligible, because the surrounding areas were largely agricultural or residential at that time. We find that in-commuting to the LCC area was also small for most boroughs, with the main exceptions being the Cities of London and Westminster. Our calibration of γ^o is robust to this in-commuting if occupation wage bill shares are similar for in-commuters as for commuters within the LCC area. We include an explicit correction for in-commuting in Section 6.3 below.

relatively aggregated spatial units of the 29 LCC boroughs. Therefore, we use post-war data on bilateral commuting flows by worker group, which are available for 356 Middle Super Output Areas in the LCC area from the 2011 Population Census. We compare our model's predictions for pre-war commuting patterns to the available data in overidentification checks below.

Re-writing the commuting probabilities (11), we estimate the following gravity equation for each group of workers separately:

$$\lambda_{nit}^{o} = \eta_{nt}^{Ro} \eta_{it}^{Lo} \tau_{nit}^{-\phi^{o}} \zeta_{nit}^{o}, \tag{17}$$

where recall $((\kappa_{nit}^{o})^{-\epsilon^{o}} = \tau_{nit}^{-\epsilon^{o}\kappa} = \tau_{nit}^{-\phi^{o}})$; η_{nt}^{Ro} are residence fixed effects that capture amenities (B_{nt}^{o}) and the cost of living ($Q_{nt}^{-(1-\alpha^{o})}$) and vary by occupation; η_{it}^{Lo} are workplace fixed effects that capture wages (w_{nt}^{o}) and again vary by occupation; we use the property that the denominator in equation (11) equals expected utility (U_{t}^{o}) from equation (12) to absorb this denominator into the fixed effects; and ζ_{nit}^{o} is a stochastic error. We cluster the standard errors by residence and workplace to allow for correlated error components by residence and workplace.

In our baseline specification, we estimate this gravity equation (17) in levels using the Poisson pseudo maximum likelihood (PPML) estimator to allow for zero bilateral flows and granularity at small spatial scales following Santos Silva and Tenreyro (2006) and Dingel and Tintelnot (2023). An empirical challenge in this estimation is that travel time depends on the transport network, which is likely to be endogenous, because railway lines in London were constructed by profit-seeking private-sector companies. In particular, bilateral pairs that have more commuters for unobserved reasons in the error term (ζ_{nit}^{o}) could have more bilateral transport connections, and hence lower bilateral travel times (τ_{nit}). To address this concern, we follow Heblich et al. (2020) in instrumenting bilateral travel times (τ_{nit}) with straight-line distance, and use a control function approach for the PPML estimator following Wooldridge (2014). Conditional on the residence and workplace fixed effects, our identifying assumption is that the unobserved factors that affect commuting in the error term (ζ_{nit}^{o}) are orthogonal to the straight-line distance between locations. In our empirical setting, the LCC area is relatively homogeneous in terms of other economic and geographic features that could be correlated with straight-line distance conditional on the workplace and residence fixed effects.

Columns (1)-(3) of Table 5 report our baseline estimation results without instrumenting for bilateral travel time for low, middle and high-income workers, respectively. We find a strong negative and statistically significant relationship between bilateral commuting flows and bilateral travel times for all three groups. Columns (4)-(6) report the corresponding instrumental variables (IV) estimates. We find a similar pattern of results. The estimated commuting elasticities are marginally larger in absolute magnitude once we instrument, which suggests that a greater incentive to invest in routes with more commuters for unobserved reasons in the error term may have been offset by other factors. In particular, the historical literature emphasizes the noncooperative behavior of the private-sector railways, and their attempts to carve out geographical territories of dominance through a proliferation of branch lines. This struggle for areas of geographic dominance could have led to overinvestment in routes that were less attractive in terms of their unobserved characteristics in the error term, thereby resulting in IV coefficients that are marginally larger in absolute magnitude.

In Online Appendix C2, we show that we find similar results if we re-estimate the gravity equation (17) in logs using the linear fixed effects estimator, and instrument bilateral travel times (τ_{nit}) with straight-line distance using two-stage least squares. We show that bilateral straight-line distance is a strong predictor of bilateral travel times in the first-stage regression, with a first-stage F-statistic well above the conventional threshold of ten.

Table 5: Commuting Gravity Equation by Occupation

	(1)	(2)	(3)	(4)	(5)	(6)
	λ_{nit}^{L}	λ_{nit}^{M}	λ_{nit}^{H}	$\log \lambda_{nit}^{L}$	$\log \lambda_{nit}^{M}$	$\log \lambda_{nit}^{H}$
Travel time	-2.788^{***}	-2.303^{***}	-1.791^{***}	-2.923^{***}	-2.411^{***}	-1.873^{***}
	(0.037)	(0.078)	(0.087)	(0.041)	(0.097)	(0.104)
Control function	–	–	–	1.122^{***}	0.901^{***}	0.717^{***}
				(0.097)	(0.192)	(0.231)
Occupation	Low	Mid	High	Low	Mid	High
Estimator	PPML	PPML	PPML	PPML IV	PPML IV	PPML IV
Workplace FEs	Yes	Yes	Yes	Yes	Yes	Yes
Residence FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126,380	126,380	126,380	126,380	126,380	126,380

Notes: Table reports the results of estimating the gravity equation (17) using data on bilateral commuting flows between Middle Super Output Areas (MSOAs) in the LCC area for low, mid and high-income occupations from the 2011 population census; Columns (1)-(3) report results using PPML; Columns (4)-(6) report results instrumenting bilateral travel times with straight-line distance using the control function approach for PPML following Wooldridge (2014); all regressions include workplace and residence fixed effects (FEs) that vary by occupation; standard errors in parentheses are clustered by residence and workplace; *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

Looking across Columns (1)-(6), we find that lower-income workers have elasticities of commuting flows to commuting costs that are larger in absolute magnitude, which reflects the net effect of several forces. On the one hand, lower-income workers could have lower opportunity costs of time, which implies commuting elasticities that are smaller in absolute magnitude. On the other hand, lower-income workers' commuting decisions are plausibly more sensitive to differences in real income relative to idiosyncratic preferences, which implies commuting elasticities that are larger in absolute magnitude. We find that the second of these forces dominates, which is in line with the empirical findings in Kreindler and Miyauchi (2023) and Tsivanidis (2023). We use the estimated commuting elasticities from our preferred instrumental variables PPML specification in Columns (4)-(6) as our baseline parameter values: $\phi^{L} = 2.92$, $\phi^{M} = 2.41$, and $\phi^{H} = 1.87$.

Finally, we separate the composite elasticity of commuting flows to travel times ($\phi^o = \epsilon^o \kappa$) into its two components. We allow the commuting decisions of high, middle and low-income workers to respond differentially to commuting costs (through variation in ϵ^o), which reflects for example differences in real income across the three occupations. But we assume that travel time affects commuting costs in the same way for all three groups of workers (common κ). Given these assumptions, we calibrate the preference dispersion parameter for middle-income workers as $\epsilon^M = 5.25$, based on the estimate using the construction of London's 19th-century railway network in Heblich et al. (2020). We then recover the implied preference dispersion parameters for low and high-income workers from our estimated commuting elasticities above, using our assumption of a common κ: $\epsilon^L = (\phi^L/\phi^M)\epsilon^M = 6.36$ and $\epsilon^H = (\phi^H/\phi^M)\epsilon^M = 4.07$.[24]

6.3 Wages, Commuting and Employment (Step 3)

Given our estimated commuting parameters, we now use the structure of the model to recover the unobserved values of wages (w_{it}^o), commuting flows (E_{nit}^o) and employment (E_{it}^o) for each occupation in the initial pre-war equilibrium, which are inputs into our counterfactuals below.

From our Cobb-Douglas production structure, labor payments by workplace for each occupation ($w_{it}^o E_{it}^o$) are a constant multiple ($\beta\gamma^o/(1-\beta)$) of payments for commercial floor space ($\mathbb{V}_{it}^E$). Using this property and our estimates of commuting costs ($(\kappa_{nit}^o)^{-\epsilon^o} = \tau_{nit}^{-\phi^o}$), we can re-write the commuter market clearing condition (13) for each occupation as:

$$\frac{\beta\gamma^o}{1-\beta}\mathbb{V}_{it}^E = \sum_{n\in\mathbb{N}} \frac{\left(w_{it}^o\right)^{\epsilon^o} \tau_{nit}^{-\phi^o}}{\sum_{\ell\in\mathbb{N}} \left(w_{\ell t}^o\right)^{\epsilon^o} \tau_{n\ell t}^{-\phi^o}} w_{it}^o R_{nt}^o. \tag{18}$$

Residential income on the right-hand side of this equation is the sum of the income of workers from an occupation o employed in location i and living in any location n within the LCC area. Commercial rateable values ($\mathbb{V}_{it}^E$) on the left-hand side are a multiple of workplace income ($w_{it}^o E_{it}^o$), which equals the income of workers from occupation o employed in location i, regardless of where they live. To ensure that workplace and residential income are both measured for workers living within the LCC area, we scale down the observed commercial rateable values on the left-hand side by the share of workers that in-commute from outside the LCC area to each borough in our 1921 pre-war commuting data. Given these adjusted commercial rateable values ($\mathbb{V}_{it}^E$), and observed residents (R_{it}^o) and travel times (τ_{nit}), this commuter market clearing condition (18) determines unique pre-war wages (w_{it}^o) by occupation for each Output Area.

Given these solutions for pre-war wages by occupation (w_{it}^o), we compute pre-war conditional commuting probabilities for each occupation ($\lambda_{nit|n}^{Ro}$) using equation (13) and our estimates

[24] These values for the preference dispersion parameters lie within the range of existing empirical estimates from 2.18 to 8.3 in Ahlfeldt et al. (2015), Dingel and Tintelnot (2023), Severen (2023) and Kreindler and Miyauchi (2023).

of commuting costs ($(\kappa_{nit}^{o})^{-\epsilon^{o}} = \tau_{nit}^{-\phi^{o}}$). Finally, using these solutions for pre-war conditional commuting probabilities ($\lambda_{nit|n}^{Ro}$), together with observed residents (R_{nt}^{o}) and total city population by occupation ($\bar{E}_{t}^{o}$), we calculate pre-war unconditional commuting probabilities ($\lambda_{nit}^{o} = \lambda_{nit|n}^{Ro} R_{nt}^{o} / \overline{E}_{t}^{o}$) and employment ($E_{it}^{o} = \sum_{n \in \mathbb{N}} \lambda_{nit|n}^{Ro} R_{nt}^{o}$) for each occupation.

In Online Appendix C3, we report two overidentification checks, in which we compare our model's predictions to the available pre-war data on employment by workplace and commuting. We aggregate across the three occupations and report results for boroughs, because our pre-war bilateral commuting data are not disaggregated by occupation and are only available for the 29 LCC boroughs. Our model predictions are based on the commuter market clearing condition (18) using our data on residents and commercial rateable values during the 1930s. Therefore, there is no necessary reason why these model predictions should exactly equal the observed data on employment and bilateral commuting, in part because these observed data are for the earlier year of 1921. Nonetheless, we find a strong and approximately log linear relationship between our model's predictions and the observed data, with a correlation coefficient of 0.94 for employment by workplace, and 0.87 for bilateral commuting flows.

For the post-war period, we solve for wages using a similar a procedure. We use our observed data on employment (E_{it}^{o}) and residents (R_{nt}^{o}) by Output Area and occupation and the commuter market clearing condition (13) to solve for unique values for wages (w_{it}^{o}) for each Output Area and occupation (up to a choice of units in which to measure wages).

6.4 Amenities (Step 4)

Given these solutions for wages (w_{nt}^{o}) by location and occupation, we next use the structure of the model to recover residential amenities (B_{nt}^{o}) by location and occupation.

Summing across workplaces in the commuting probabilities (11) and using expected utility (12), we obtain the following closed-form expression for residential amenities for each occupation (B_{nt}^{o}) in terms of the observed shares of residents (λ_{n}^{Ro}), observed residential floor space prices (Q_{n}) and a measure of residents' commuting market access (RMA_{nt}^{o}):

$$\ln B_{nt}^{o} = \ln\left(\frac{U_{t}^{o}}{\delta^{o}}\right) + \frac{1}{\epsilon^{o}} \ln\left(\lambda_{nt}^{Ro}\right) + (1-\alpha^{o}) \ln Q_{nt} - \ln RMA_{nt}^{o}. \tag{19}$$

Residents commuting market access (RMA_{nt}^{o}) for each occupation is a travel time weighted average of wages in each workplace for that occupation:

$$RMA_{nt}^{o} = \left[\sum_{\ell \in \mathbb{N}} (w_{\ell t}^{o})^{\epsilon^{o}} \, \tau_{n\ell t}^{-\phi^{o}}\right]^{\frac{1}{\epsilon^{o}}}, \tag{20}$$

where we have again used our estimates of commuting costs ($(\kappa_{nit}^{o})^{-\epsilon^{o}} = \tau_{nit}^{-\phi^{o}}$).

Intuitively, locations with high shares of residents (λ_{nt}^{Ro}), and yet high prices for residential floor space (Q_{nt}) and low residents market access (RMA_{nt}^{o}), must have high amenities (B_{nt}^{o}) in order for many residents to live there. We thus recover unique values for amenities for each location and occupation (B_{nt}^{o}) from equations (19) and (20), up to a choice of units in which to measure expected utility (U_{t}^{o}). We can solve for these amenities by location and occupation (B_{nt}^{o}) without making any assumptions about the relative importance of the different components of amenities in equation (6): wartime destruction (D_{nt}), neighborhood effects ($\mathbb{B}_{nt}^{o}$) and residential fundamentals (b_{nt}^{o}). In specification checks, we separate out residential amenities into these components, using our estimates of the wartime destruction and neighborhood effects parameters (η_{D}^{o}, η_{R}^{o}) from the next section. We find that our model's predictions for residential fundamentals are strongly correlated with observable proxies, such as access to parks.

6.5 Wartime Destruction and Neighborhood Effects (Step 5)

Given post-war amenities (B_{nt}^{o}) from the previous step, we next estimate our structural parameters for wartime destruction (η_{D}^{o}) and neighborhood effects (η_{R}^{o}) by occupation, using the exogenous variation from wartime destruction. We instrument for post-war neighborhood effects ($\mathbb{B}_{nt}$) using wartime destruction in neighboring locations. We use the fact that wartime destruction makes these neighboring locations less attractive to higher-income workers, and hence leads to a change in socioeconomic composition, which spills over geographically to make the own location less attractive to higher-income workers.

Using our specification for residential amenities in equation (6), we estimate the following second-stage regression between post-war amenities (B_{nt}^{o}), wartime destruction (D_{nt}) and neighborhood effects ($\mathbb{B}_{nt}$) for each occupation:

$$\ln B_{nt}^{o} = \eta_{Dt}^{o} D_{nt} + \eta_{R}^{o} \ln \mathbb{B}_{nt} + \varrho_{kt}^{o} + d_{nt}^{o}, \tag{21}$$

where ϱ_{kt}^{o} are fixed effects for 1 kilometer hexagons and d_{nt}^{o} is a stochastic error.

From our reduced-form regressions in Section 4, we find no evidence of spillover effects of wartime destruction beyond 300 meters. Therefore, we model neighborhood effects as depending on socioeconomic composition within 300 meters of a location. In particular, we define $\mathbb{B}_{nt}$ as the unweighted average of the socioeconomic composition ($\mathbb{S}_{nt}$) of the own location and its first three 100-meter buffers. As a robustness exercise, we also exclude the own location n from this average, such that it is only computed across the first three buffers.

In the first-stage regression, we instrument neighborhood effects ($\mathbb{B}_{nt}$) using wartime destruction in neighboring locations (D_{nt}^{neigh}):

$$\ln \mathbb{B}_{nt} = \varkappa_{D}^{o} D_{nt} + \varkappa_{N}^{o} D_{nt}^{\text{neigh}} + \varpi_{kt}^{o} + u_{nt}^{o}, \tag{22}$$

where D_{nt}^{neigh} is the unweighted average of wartime destruction in the first three buffers (excluding the own location n); ϖ_{kt}^{o} are fixed effects for 1-kilometer hexagons; and u_{nt}^{o} is a stochastic error.

We estimate our instrumental variables (IV) specification separately for each occupation to allow the war destruction and neighborhood effects parameters (η_D^o, η_R^o) to differ across occupations. Our exclusion restriction is that conditional on a location's own wartime destruction and the fixed effects for 1 km hexagons, the only way in which wartime destruction in neighboring locations affects residential amenities is through surrounding socioeconomic composition. This identifying assumption is consistent with our earlier reduced-form findings that wartime destruction is uncorrelated with pre-war economic outcomes; only residential wartime destruction affects post-war socioeconomic composition, whereas commercial destruction does not; and wartime destruction in neighbors does not directly affect the type of post-war buildings in the own location. We provide further specification checks on this identifying assumption below.

Table 6 reports the results of estimating equation (21) for post-war amenities. The top, middle and bottom panels display results for high, middle and low-income workers, respectively. Column (1) estimates this relationship using OLS, including wartime destruction of the overall built-up area (D_{nt}) and the fixed effects for 1 kilometer hexagons (ϱ_{kt}^{o}). We find negative and statistically significant coefficients on wartime destruction for high and middle-income workers, which are larger in absolute magnitude for high-income workers. In contrast, the estimated coefficient for low-income workers is positive, but close to zero and only statistically significant at the 10 percent level. This pattern of results provides direct support for the mechanism in our model, in which wartime destruction reduces amenities by more for higher-income workers than for lower-income workers.

Column (2) augments this specification with our measure of post-war neighborhood effects ($\mathbb{B}_{n,\text{post-war}}$) based on average socioeconomic status in the own location and the first three 100-meter buffers. After controlling for neighborhood effects, we find direct effects of wartime destruction (η_D^o) that are smaller in absolute magnitude but display a similar pattern. The estimated coefficients for high and middle-income workers are negative and significant, whereas the estimated coefficient for low-income workers is close to zero and statistically insignificant. Additionally, we find evidence of neighborhood effects (η_R^o), with positive and significant coefficients for high and middle-income workers, which are again larger in absolute magnitude for high-income workers. In contrast, the estimated coefficient for low-income workers is negative and statistically significant. Although this pattern of results is consistent with higher-income workers caring more about surrounding socioeconomic status than lower-income workers, this OLS specification is hard to interpret, because surrounding socioeconomic status is endogenous. High, middle and low-income workers sort endogenously across locations in response to differences in amenities. Therefore, there could be unobserved factors in the error term in equation

Table 6: Post-war Amenities, Wartime Destruction and Neighborhood Effects

	(1)	(2)	(3)	(4)	(5)	(6)
(A) High-income	$\ln B_n^H$	$\ln B_n^H$	$\ln B_n^H$	$\ln B_n^H$	$\ln B_n^H$	$\ln B_n^H$
$D_{n,\text{war}}$	-0.102***	-0.036***	-0.055***	-0.067***	-0.068***	-0.090***
	(0.014)	(0.009)	(0.011)	(0.010)	(0.010)	(0.010)
$\ln \mathbb{B}_{n,\text{post-war}}$		1.514***	1.081***	0.963***	0.919***	0.900***
		(0.032)	(0.205)	(0.167)	(0.185)	(0.209)
$\ln \mathbb{B}_{n,\text{pre-war}}$					0.0811***	0.0722**
					(0.030)	(0.034)
Estimation	OLS	OLS	IV	IV	IV	IV
Observations	8,780	8,778	8,776	8,594	8,594	8,594
R-squared	0.556	0.794	0.497	0.465	0.462	0.191
First-stage F	–	–	10.08	21.41	19.98	24.57
(B) Middle-income	$\ln B_n^M$	$\ln B_n^M$	$\ln B_n^M$	$\ln B_n^M$	$\ln B_n^M$	$\ln B_n^M$
$D_{n,\text{war}}$	-0.046***	-0.020***	-0.021***	-0.030***	-0.030***	-0.044***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
$\ln \mathbb{B}_{n,\text{post-war}}$		0.610***	0.585***	0.600***	0.581***	0.566***
		(0.021)	(0.162)	(0.129)	(0.140)	(0.137)
$\ln \mathbb{B}_{n,\text{pre-war}}$					0.035	0.031
					(0.023)	(0.022)
Estimation	OLS	OLS	IV	IV	IV	IV
Observations	8,795	8,793	8,791	8,609	8,609	8,609
R-squared	0.614	0.719	–	–	–	–
First-stage F	–	–	10.08	21.33	19.89	24.57
(C) Low-income	$\ln B_n^L$	$\ln B_n^L$	$\ln B_n^L$	$\ln B_n^L$	$\ln B_n^L$	$\ln B_n^L$
$D_{n,\text{war}}$	0.014*	0.003	0.023**	0.015*	0.016*	0.008
	(0.008)	(0.007)	(0.010)	(0.008)	(0.008)	(0.007)
$\ln \mathbb{B}_{n,\text{post-war}}$		-0.258***	0.206	0.326	0.338	0.327
		(0.027)	(0.244)	(0.204)	(0.225)	(0.209)
$\ln \mathbb{B}_{n,\text{pre-war}}$					-0.023	-0.022
					(0.038)	(0.036)
Estimation	OLS	OLS	IV	IV	IV	IV
Observations	8,776	8,774	8,772	8,591	8,591	8,591
R-squared	0.466	0.483	–	–	–	–
First-stage F	–	–	9.961	21.17	19.78	24.45

Note: The dependent variables ($\ln B_n^H$, $\ln B_n^M$, $\ln B_n^L$) are post-war amenities for high, middle and low-income workers, respectively; $D_{n,\text{war}}$ is the percentage of the pre-war overall built-up area seriously damaged in Columns (1)-(3) and the percentage of the pre-war residential built-up area seriously damaged in Columns (4)-(6); $\mathbb{B}_{n,\text{post-war}}$ is post-war neighborhood effects as defined as the unweighted average of the post-war socioeconomic composition ($\mathbb{S}_{nt}$) of the own location and its first three 100-meter buffers; $\mathbb{B}_{n,\text{pre-war}}$ is pre-war neighborhood effects, measured as the average of the pre-war socioeconomic composition of the own location and its first three 100-meter buffers; instrument in Column (3) is average overall war-time destruction in the first three 100-meter buffers around the built-up area of location n (excluding the own location n); instrument in Columns (4)-(6) is average residential war-time destruction in the first three 100-meter buffers (excluding the own location n); Column (6) excludes the own location n from the measures of post-war and pre-war neighborhood effects ($\mathbb{B}_{n,\text{post-war}}$ and $\mathbb{B}_{n,\text{pre-war}}$, respectively), such that these measures are based on average socioeconomic composition in the first three 100-meter buffers only; all specifications include fixed effects for 1 kilometer hexagons; First-stage F is first-stage F-statistic; R-squared not reported for the IV specifications, because it does not have a meaningful interpretation; standard errors in parentheses clustered by 1 kilometer hexagons; *, ** and *** denote significance at the 10, 5 and 1 percent levels, respectively.

(21) that directly affect amenities (B_n^o) and also influence surrounding socioeconomic status, and hence neighborhood effects ($\mathbb{B}_{n,\text{post-war}}$).

To overcome this challenge, Column (3) reports our instrumental variables (IV) estimates, in which we instrument for post-war neighborhood effects using average wartime destruction of the overall built-up area in the first three 100-meter buffers (excluding the own location). We continue to find the most negative effects of wartime destruction and the largest neighborhood effects for high-income workers. Therefore, even when we focus on exogenous variation in surrounding socioeconomic composition from wartime destruction in neighboring locations, we continue to find strong evidence of neighborhood effects that are largest for high-income workers. Comparing Columns (2)-(3), our IV estimates of the neighborhood effects parameters for high-income workers are smaller than those using OLS. This is the expected pattern of results if attractive residential fundamentals both directly raise amenities, and induce high-income workers to sort into a location, thereby raising surrounding socioeconomic status. We find that wartime destruction in neighboring locations is a powerful instrument for surrounding socioeconomic composition, with a first-stage F-statistic of around ten. In Table C.2 of Online Appendix C5, we report the full first-stage regressions for each specification in Table 6.

In our reduced-form findings in Section 4, we found that only residential wartime destruction matters for socioeconomic composition and property values, with little evidence of any effects from commercial wartime destruction. Therefore, in Column (4), we re-estimate our IV specification, using average wartime destruction of the residential built-up area in the first three 100-meter buffers (again excluding the own location). We continue to find a similar pattern of estimated coefficients for both wartime destruction and neighborhood effects. Consistent with our mechanism of lower residential amenities from living in buildings reconstructed after bombing, we find that residential destruction in neighboring locations is a more powerful instrument than overall destruction, with the first-stage F-statistic approximately doubling.

In Column (5), we report a robustness check, in which we include pre-war neighborhood effects ($\mathbb{B}_{n,\text{pre-war}}$) as an additional control besides the fixed effects for 1 kilometer hexagons. We find that the pattern of estimated coefficients for post-war neighborhood effects ($\mathbb{B}_{n,\text{post-war}}$) is virtually unchanged when we include this additional control. This pattern of results provides further support for the idea that wartime destruction provides an exogenous source of variation that is uncorrelated with pre-war location characteristics. We find the estimated coefficients on pre-war neighborhood effects are small in magnitude for all three groups of workers, which is consistent with our post-war neighborhood effects measure fully capturing surrounding socioeconomic composition.

In Column (6), we present a further robustness check, in which we exclude the own location from our measures of both post-war and pre-war neighborhood effects, such that average surrounding socioeconomic status is only computed across the first three 100-meter buffers. We again find that the estimated coefficients on both wartime destruction and neighborhood effects are virtually unchanged. This pattern of results provides further support for the idea that our instrument is uncorrelated with own location characteristics.

In Table C.2 of Online Appendix C5, we report the results of estimating the reduced-form relationship between post-war amenities and own and neighbors's destruction implied by the first and second-stage regressions. Consistent with the results discussed above, we find that the effects of both own and neighbors' wartime destruction are more negative for higher-income workers. As a final placebo specification check, in Table C.4 of Online Appendix C5, we re-estimate this reduced-form relationship for pre-war amenities and subsequent war-time destruction. Consistent with our reduced-form findings in Section 4 above, we find no evidence of any relationship between pre-war amenities and subsequent wartime destruction. Again these findings provide further support for the idea that wartime destruction provides an exogenous source of variation within hexagonal grid cells.

Taken together, the results of this section provide strong evidence of neighborhood effects. Wartime destruction changes residential amenities and socioeconomic composition in neighboring locations, and residential decisions for the own location are affected by the socioeconomic composition of neighboring locations.

7 Counterfactuals

In this section, we use our estimated model to undertake two sets of counterfactuals. First, we examine the aggregate and distributional consequences of wartime destruction. Second, we evaluate the role of neighborhood effects versus differences in residential fundamentals in determining the observed differences in socioeconomic outcomes across locations.

We report the results of these counterfactuals for both closed and open-city specifications. In the closed-city specification, we hold the total population of each occupation in the LCC area constant, such that wartime destruction affects the expected utility of workers in each occupation. In the open-city specification, we hold the reservation level of utility for workers in each occupation constant, which implies that wartime destruction affects the total population of each occupation, but leaves the expected utility of workers in each occupation unchanged. In both specifications, wartime destruction has distributional consequences across locations for landlords.

In our baseline specification, we report results for the case of exogenous productivity and perfectly inelastic supplies of commercial and residential floor space. In robustness specifications, we report results allowing for agglomeration forces (such that productivity responds to local employment density) and an imperfectly elastic supply of residential floor space (such that the supply of residential floor space responds to changes in its price). Throughout the remainder of this section, we suppress the implicit dependence on time to reduce notational clutter.

7.1 Counterfactual Equilibrium

We follow an exact-hat algebra approach from the international trade literature, in which we use the values of the model's endogenous variables in the initial pre-war equilibrium to control for initial differences in location characteristics. We use the model's predictions for pre-war bilateral commuting flows based on our PPML gravity equation estimation, which allows for zero commuting flows and granularity for small spatial units. We denote the value of a variable in the counterfactual equilibrium by a prime (x_n'), the value of variable in the initial equilibrium without a prime (x_n), and the relative change in a variable by a hat ($\widehat{x}_n = x_n'/x_n$).

Given an exogenous change in residential amenities by occupation ($\widehat{B}_n^o$), we solve the system of general equilibrium conditions of the model for the counterfactual equilibrium, as discussed further in Online Appendix D. Under the conditions for the existence of an unique equilibrium in Proposition 1, we obtain unique counterfactual predictions for the impact of the exogenous change in residential amenities by occupation on the spatial distribution of economic activity. In the presence of sufficiently strong neighborhood effects and agglomeration forces, there can be multiple equilibria in the model. When we solve for counterfactuals, we solve for a counterfactual equilibrium starting with initial values from the observed pre-war equilibrium, which implicitly searches for the closest counterfactual equilibrium to this observed pre-war equilibrium.

7.2 Wartime Destruction

We begin by undertaking our counterfactuals to assess the role of neighborhood effects in shaping the impact of wartime destruction. We use the estimated coefficients from Column (5) of Table 6, which identifies neighborhood effects using the variation in residential destruction in neighboring locations, after controlling separately for pre-war socioeconomic status. These regressions use quasi-experimental variation to isolate the causal effects of wartime destruction. By themselves, they do not capture its general equilibrium impact on the spatial distribution of economic activity, which is absorbed into the intercept and fixed effects. In contrast, our counterfactuals use the structure of the model to solve for this general equilibrium impact, starting from the observed pre-war equilibrium in the data, and holding all else constant.

We first undertake a counterfactual for the direct effects of wartime destruction under the assumption of no neighborhood effects ($\eta_R^o = 0$). In this first counterfactual, the change in residential amenities from equation (6) is exogenously determined by the estimated wartime destruction coefficients (η_R^o) and the variation in wartime destruction across Output Areas (D_n): $\widehat{B}_n^o = e^{\eta_D^o D_n}$. We next undertake a counterfactual for the full effect of wartime destruction, incorporating endogenous neighborhood effects. In this second counterfactual, the change in residential amenities from equation (6) depends on both the estimated coefficients on wartime destruction (η_D^o), the exogenous variation in wartime destruction (D_n), the estimated parameters for neighborhood effects (η_R^o), and the endogenous change in neighborhood effects ($\widehat{\mathbb{B}}_n$):

$$\widehat{B}_n^o = e^{\eta_D^o D_n} \widehat{\mathbb{B}}_n^{\eta_R^o}, \tag{23}$$

where we again define neighborhood effects ($\mathbb{B}_{nt}$) as the unweighted average of the socioeconomic composition ($\mathbb{S}_{nt}$) of the own location and its first three 100-meter buffers.

In this second counterfactual for the full effect, we allow for the endogenous feedback of residential amenities to the endogenous change in patterns of spatial sorting induced by wartime destruction through neighborhood effects. Wartime destruction directly reduces residential amenities in bombed locations for high-income workers relative to low-income workers. In response, high-income workers sort out of these bombed locations, which reduces the price of residential floor space, and induces low-income workers to sort into these locations. Neighborhood effects magnify these direct effects of wartime destruction. As high-income workers sort out and low-income workers sort into bombed locations, there is a decline in socioeconomic status. Since high-income workers value socioeconomic status more than low-income workers, this induces further sorting out of these bombed locations by high-income workers, and further sorting into these bombed locations by low-income workers. Finally, since neighborhood effects depend on socioeconomic status in both the own and surrounding locations, these impacts of wartime destruction spill over from bombed locations to their unbombed neighbors.

In Figure 5, we display the results of both counterfactuals. Each panel of the figure uses a histogram to show the distribution of counterfactual changes in a variable across Output Areas in the LCC area. The black-hollow bars show our first counterfactual for the direct effects of wartime destruction alone. The gray-shaded bars show our second counterfactual for the full effects of wartime destruction, incorporating neighborhood effects.

Panels A-C show that there is substantial variation in the impact of wartime destruction on residential amenities, both across Output Areas, and across occupations. In our first counterfactual (black-hollow bars), the uneven effects of wartime destruction on residential amenities for workers from a given occupation ($\log \widehat{B}_n^o = \eta_D^o D_n$) are driven solely by the substantial variation across Output Areas in the share of the built-up area destroyed (D_n). The effects are much larger for high-income workers (Panel A) than for middle-income workers (Panel B), with only small effects for low-income workers (Panel C), because the absolute value of the estimated coefficients on wartime destruction (η_D^o) are substantially larger for higher-income workers.

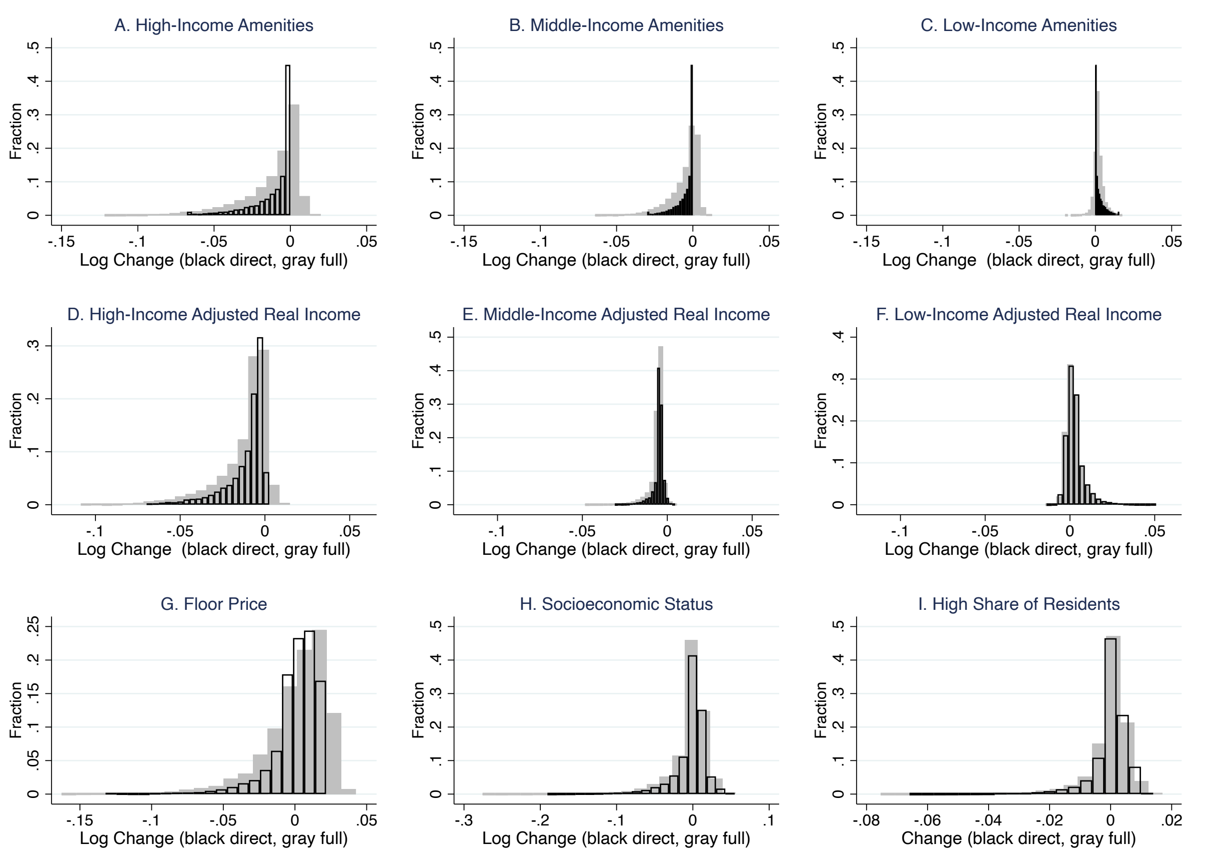
For our second counterfactual (gray-shaded bars), the log changes in residential amenities

($\log \widehat{B}_n^o = \eta_D^o D_n + \eta_R^o \log \widehat{\mathbb{B}}_n$) also depend on the general equilibrium response in patterns of spatial sorting to wartime destruction through endogenous neighborhood effects ($\widehat{\mathbb{B}}_n$). Comparing results for the two counterfactuals (gray-shaded versus black-hollow bars in Panels A-C), we find substantially more dispersion in log changes in residential amenities once we incorporate neighborhood effects. This pattern of results highlights how neighborhood effects magnify the impact of wartime destruction. High-income workers are the most sensitive to both wartime destruction and neighborhood effects. Therefore, as wartime destruction has a larger negative impact on residential amenities, and induces high-income workers to sort out of bombed locations, the resulting decline in socioeconomic composition further reduces the attractiveness of these locations to high-income workers. In Panels A and B, the direct effects of wartime destruction on residential amenities (back-hollow bars) are always negative. In contrast, the full effects (gray-shaded bars) are sometimes positive, which again reflects spatial sorting in response to wartime destruction. As high-income workers sort out of bombed locations into unbombed locations, this increases socioeconomic status in those unbombed locations, which raises residential amenities through neighborhood effects.

Panels D-F examine the distributional consequences of wartime destruction for high, middle and low-income workers. Under our assumption of population mobility within the LCC area, there is a common change in expected utility across all Output Areas for workers from a given occupation ($\widehat{U}^o$). Nevertheless, there are uneven changes across locations in amenity-adjusted real income ($\log[\widehat{B}_n^o \widehat{w}_n^o \widehat{Q}_n^{-(1-\alpha^o)}]$), excluding idiosyncratic amenities, because each location faces an upward-sloping supply function for residents from each occupation. We find that these general equilibrium responses are substantial relative to the impact of wartime destruction on residential amenities. For example, there is a longer right tail of positive changes for amenity-adjusted real income (Panel F) than for amenities (Panel C) for low-income workers, which reflects these general equilibrium forces. As high and middle-income workers sort out of bombed locations, this reduces the price of residential floor space, thereby increasing amenity-adjusted real income for low-income workers.

Despite these substantial changes in amenity-adjusted real income, we find only small effects of wartime destruction on the expected utility of workers, averaging across the distribution of idiosyncratic amenities, which are less than 2 percent for all three occupations. These small effects on expected utility reflect the combination of four forces. First, our counterfactuals evaluate the long-run effects of wartime destruction on residential amenities after reconstruction has occurred. Second, some of the decline in residential amenities in response to wartime destruction is capitalized in lower prices for residential floor space, thereby dampening its impact on the expected utility of workers. Third, many Output Areas experience little or no destruction, which allows workers to relocate away from bombed locations. Fourth, for our standard values

Figure 5: Counterfactuals for Wartime Destruction



Note: Counterfactuals for the impact of wartime destruction based on the estimated coefficients (η_D^o, η_R^o) from Column (5) of Table 6 and starting from the pre-war equilibrium observed in the data; each panel shows a histogram of counterfactual changes in a variable across Output Areas in the LCC area; black-hollow bars show our first counterfactual for the direct effects of wartime destruction alone; gray-shaded bars show our second counterfactual for the full effects of wartime destruction incorporating endogenous neighborhood effects; Panels A, B and C show log changes in amenities ($\log(\widehat{B}_n^o)$) for high, middle and low-income workers, respectively; Panels D, E and F show log changes in amenity-adjusted real income ($\log(\widehat{B}_n^o \widehat{w}_i^o \widehat{Q}_n^{-(1-\alpha^o)})$) for high, middle and low-income workers, respectively; Panel G shows log changes in the price of residential floor space ($\log \widehat{Q}_n$); Panel H shows log changes in our index of socioeconomic status ($\log \hat{\mathbb{S}}_n$); Panel I shows changes in the share of high-income residents in total residents ($R_n^{H\prime}/R_n^{\prime} - R_n^H/R_n$).

for the preference dispersion parameters (ϵ^o from 4.23 – 6.90), Output Areas are relatively good substitutes for one another.[25]

Panel G shows that the distributional consequences of wartime destruction on landlord income are larger than those on the amenity-adjusted real income of workers in Panels D-F. Under our baseline assumption of an inelastic supply of residential floor space, these log changes in landlord income equal the log changes in the price of residential floor space, which range from around −15 to 5 percent. Therefore, landlords were highly unevenly affected by wartime destruc-

[25] As a result, we find only a small impact of wartime destruction on total city population in our open-city specification in Online Appendix D4.3 of less than 1 percent. Therefore, our findings suggest that wartime destruction can lead to substantial changes in neighborhood composition, with limited impact on total city population, which is consistent with the existing evidence on the aggregate effects of wartime destruction on total city population.

tion, depending on whether they owned floor space in locations that were severely destroyed or largely unscathed. Again we find that neighborhood effects magnify the direct effects of wartime destruction, with substantially more dispersion for the gray-shaded histogram.

The remaining two panels quantify the changes in spatial sorting in response to wartime destruction, with panel H showing log changes in our index of socioeconomic status ($\log(\widehat{\mathbb{S}}_n)$), and Panel I displaying changes in the share of high-income residents ($R_n^{H\prime}/R_n' - R_n^H/R_n$). We find substantial changes in both measures of socioeconomic status, with the change in the share of high-income residents ranging from −8 to 2 percentage points. A long left-tail of locations experience large declines in both measures of socioeconomic status in response to wartime destruction. Again neighborhood effects magnify the direct effects of wartime destruction, with a substantially longer left tail once we incorporate neighborhood effects (gray-shaded bars).

7.3 Neighborhood Effects and Spatial Sorting

We next return to our central question of the role of neighborhood effects versus location fundamentals in explaining the large observed differences in socioeconomic outcomes across locations. Starting from the observed pre-war equilibrium in the data, we evaluate the impact of removing neighborhood effects, such that variation in residential amenities across locations in the counterfactual equilibrium is driven solely by exogenous residential fundamentals. Using our specification of residential amenities as $B_n^o = e^{\eta_D^o D_n} \mathbb{B}_n^{\eta_R^o} b_n^o$, we have:

$$\widehat{B}_n^o = \frac{B_n^{o\prime}}{B_n^o} = \frac{b_n^o}{b_n^o \left(\mathbb{B}_{n,\text{pre-war}}\right)^{\eta_R^o}} = \frac{1}{\left(\mathbb{B}_{n,\text{pre-war}}\right)^{\eta_R^o}}, \tag{24}$$

where we start from the pre-war equilibrium, such that $D_n = 0$ and hence $e^{\eta_D^o D_n} = 1$; we set $\eta_R^o = 0$ in the counterfactual equilibrium, which implies a common value of counterfactual neighborhood effects of one across all locations ($\left(\mathbb{B}_n'\right)^{\eta_R^o} = 1$); and pre-war neighborhood effects ($\mathbb{B}_{n,\text{pre-war}}$) are defined as the unweighted average of the pre-war socioeconomic composition ($\mathbb{S}_{n,\text{pre-war}}$) of the own location and its first three 100-meter buffers.

This counterfactual is conceptually distinct from that in the previous subsection, in the sense that we now assess the importance of neighborhood effects for cross-sectional patterns of spatial sorting, which is a question that can be asked completely separately from wartime destruction. However, the reason that we can address this separate question is that we have estimated the model's structural parameters for neighborhood effects (η_R^o) using the exogenous variation in wartime destruction. We again use the estimated coefficients from Column (5) of Table 6, which identifies neighborhood effects using the variation in residential destruction in neighboring locations, after controlling separately for pre-war socioeconomic status. From equation (24), this second counterfactual removes neighborhood effects ($\mathbb{B}_n$) evaluated at the observed socioeconomic composition in the initial pre-war equilibrium ($\mathbb{S}_{n,\text{pre-war}}$), which implies that the change in residential amenities ($\widehat{B}_n$) is exogenously determined by the pre-war data.

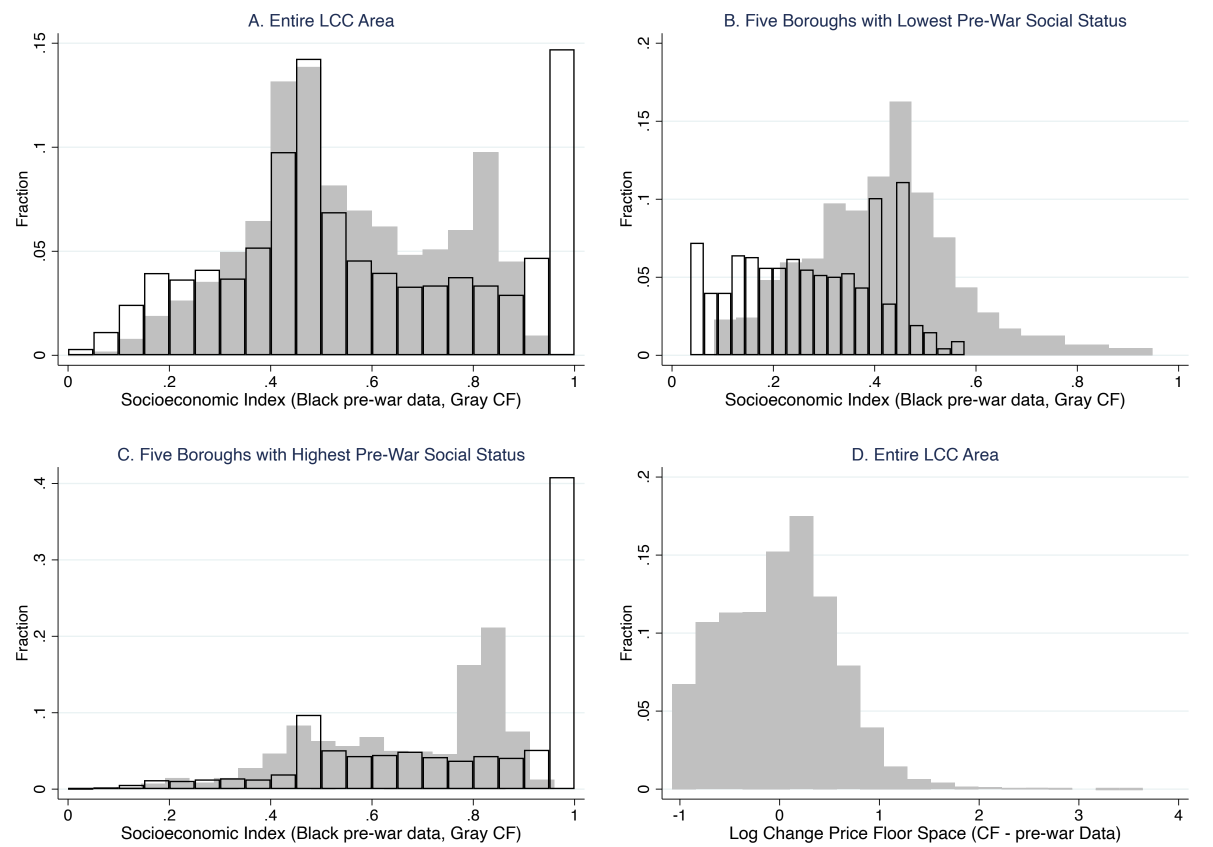
In the initial pre-war equilibrium, higher-income workers have lower shares of expenditure on residential floor space and care more about socioeconomic status. Therefore, higher-income workers are more willing to pay the higher prices of residential floor space in locations with attractive residential amenities and higher surrounding socioeconomic status. As we remove neighborhood effects, these locations with higher socioeconomic status become relatively less attractive to higher-income workers, which induces them to sort out of these locations, and sort into locations with lower socioeconomics status. As some higher-income workers move out of the most desirable locations, this bids down the price of residential floor space, making these locations more attractive to lower-income workers. Similarly, as some higher-income move into the least desirable locations, this bids up the price of residential floor space, making these locations less attractive to lower-income workers.

In Figure 6, we display the results of this counterfactual. Each panel of the figure uses a histogram to show the distribution of a variable across Output Areas. In Panels A-C, the black-hollow bars show the distribution in the initial equilibrium in the pre-war data, while the gray-shaded bars show the distribution in the counterfactual equilibrium. In Panel D, the gray-shaded bars show log changes between the initial and counterfactual equilibria.

We find substantial changes in patterns of spatial sorting in this counterfactual, highlighting the quantitative relevance of neighborhood effects in driving the observed differences in socioeconomic outcomes across locations. Panel A shows the distribution of our socioeconomic index for the LCC area as a whole; Panel B shows this distribution for the five boroughs with the lowest pre-war socioeconomic status; and Panel C shows this distribution for the five boroughs with the highest-pre-war socioeconomic status. Removing neighborhood effects makes locations with low initial socioeconomic status (Panel B) more attractive to higher-income workers, thereby raising the mass of the distribution at high socioeconomic status (towards the right on the horizontal axis in Panel B). As higher-income workers move into these locations, this bids up the price of residential floor space, thereby inducing lower-income workers to sort out of these locations, and reducing the mass of the distribution at low socioeconomic status (towards the left on the horizontal axis in Panel B).

In contrast, removing neighborhood effects makes locations with high initial socioeconomic status (Panel C) less attractive to higher-income workers, thereby reducing the mass of the distribution at high socioeconomic status (towards the right on the horizontal axis in Panel C). As higher-income workers move out of these locations, this bids down the price of residential floor space, thereby inducing lower-income workers to sort into these locations, and raising the mass of the distribution at low socioeconomic status (towards the left on the horizontal axis in Panel

Figure 6: Counterfactual Removing Neighborhood Effects



Note: Counterfactual for removing neighborhood effects ($\widehat{B}_n^o = 1/\left(\mathbb{B}_{n,\text{pre-war}}\right)^{\eta_R^o}$) based on the estimated coefficients from Column (5) of Table 6 and starting from the pre-war equilibrium observed in the data; each panel shows a histogram across Output Areas in the LCC area; black-hollow bars show a histogram for the observed pre-war data; gray-shaded bars show a histogram for the counterfactual removing neighborhood effects; Panel A shows the distribution of our index of socioeconomic status ($\mathbb{S}_n$) across all Output Areas within the LCC boundaries; Panel B shows this distribution across Output Areas in the five boroughs with the lowest pre-war socioeconomic status (Bethnal Green, Bermondsey, Poplar, Shoreditch and Stepney); Panel C shows this distribution across Output Areas in the five boroughs with the highest pre-war socioeconomic status (Hampstead, Kensington, St. Marylebone, Stoke Newington, and Wandsworth); and Panel D shows log changes in the price of residential floor space between the counterfactual and pre-war equilibria.

C). The net effect is that the distributions of socioeconomic status become more similar to one another in poor and rich boroughs (comparing the black-hollow and gray-shaded bars in Panels B and C), which leads to a compression in the overall distribution of socioeconomic status (comparing the black-hollow and gray-shaded bars in Panel A). This compression is particularly evident in a decline in the mass of the distribution at high socioeconomic status in Panel A, highlighting the role of neighborhood effects in the emergence of the most exclusive neighborhoods.

We find that these large-scale changes in patterns of spatial sorting have substantial income distributional consequences for landlords in different locations. We find log changes in the price of residential floor space that range from declines of over 1 log point to increases of more than 2 log points (Panel D). The distribution of these log changes in the price of residential floor space has a long right-tail, driven by locations with low initial levels of socioeconomic status that experience large percentage increases in the price of residential floor space, as they become more attractive to higher-income workers when neighborhood effects are eliminated.

Taken together, these results highlight the importance of neighborhood effects for observed differences in socioeconomic outcomes across locations. A substantial part of why some locations are prosperous and others are poor is not down to immutable features of physical geography but rather endogenous neighborhood effects from patterns of spatial sorting.

7.4 Robustness

We find that this pattern of counterfactual results is robust across a range of different specifications, as discussed further in Online Appendix D4. We replicate both our wartime destruction and neighborhood effects counterfactuals for the following alternative specifications: (i) Agglomeration forces in production, using standard estimates for the elasticity of productivity with respect to employment density; (ii) Endogenous responses in the supply of residential floor space, using standard estimates for the elasticity of the supply of floor space with respect to changes in its price; (iii) An open-city specification, in which the supply of workers from each group is endogenously determined by a constant reservation level utility in the wider economy. Across all of these different specifications, we find that neighborhood effects are quantitatively important in magnifying the impact of wartime destruction and explaining observed differences in socioeconomic outcomes across locations.

8 Conclusions

An enduring source of economic debate is the relevance of neighborhood effects, according to which individual behavior is influenced by the surrounding socioeconomic composition of the population. We use the German bombing of London during the Second World War as an exogenous source of variation to estimate the strength of these neighborhood effects.

We begin by providing reduced-form evidence on wartime destruction. We show that wartime destruction is uncorrelated with the pre-war characteristics of locations within narrow geographical grid cells in London, which is consistent with the primitive bomb-aiming technology at the time, and supports its use as an exogenous source of variation. We next show that wartime destruction has a long-run causal impact on building structures in bombed locations, which reduces property values and leads to a shift in socioeconomic composition towards lower-income residents. Finally, we show that bombing in neighboring locations does not affect building structures in the own location, but does reduce property values and shift socioeconomic composition towards lower-income residents in the own location. We find that these spillover effects extend beyond the immediately contiguous buffer of 0-100 meters, but are highly localized, with no evidence of any effects beyond 300 meters. We show that these findings only hold for damage to residential buildings, and not for damage to commercial buildings, consistent with them being driven by changes in residential composition.

To rationalize these empirical findings, we develop a theoretical model in which workers from different socioeconomic groups (low, middle and high-income) endogenously sort across residences and workplaces. Residential choices for each group of workers depend on amenities, which are determined by location characteristics (including building quality) and neighborhood effects (the socioeconomic composition of the surrounding areas). We suppose that higher income workers value high-quality buildings and high-socioeconomic status more than lower-income workers. We interpret wartime destruction as an exogenous shock that permanently changes building quality, which affects patterns of spatial sorting, both directly (through preferences for building quality), and indirectly (though preferences over the resulting changes in socioeconomic composition). As higher-income workers sort out of bombed locations, this reduces property values and socioeconomic status in those locations, which makes surrounding locations less attractive to higher-income workers, and leads to declines in property values and socioeconomic status in these surrounding locations.

We estimate the strength of neighborhood effects by using wartime destruction in neighboring locations to instrument for surrounding socioeconomic composition. We find that higher-income workers are substantially more sensitive to wartime destruction and surrounding socioeconomic composition. We use our estimated model to undertake counterfactuals to assess the importance of neighborhood effects for the impact of wartime destruction and cross-sectional differences in socioeconomic outcomes across locations. We find that neighborhood effects magnify the impact of wartime destruction on spatial sorting and property values. We find that they make a substantial contribution towards explaining observed differences in socioeconomic outcomes across locations, and are particularly important for the emergence of exclusive enclaves of high socioeconomic status and high prices of residential floor space.

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