Estimating Neighborhood Effects: Evidence from War-time Destruction in London*

Stephen J. Redding
Princeton University, NBER & CEPR†

Daniel M. Sturm
London School of Economics & CEPR‡

July 1, 2016

Preliminary and Incomplete

Abstract

We use Second World War destruction in London as a natural experiment to provide evidence on neighborhood effects. We use a newly-collected and remarkable dataset on thousands of locations within London that records wartime destruction and the economic and social characteristics of locations from the late-nineteenth to late-twentieth centuries. We combine these data with a quantitative model of the sorting of heterogeneous groups of agents across locations that differ in productivity, amenities and transport infrastructure. We find that both own and neighbors' destruction affect patterns of spatial sorting and that the effects of neighbors' destruction are highly localized (0-200 meters). These findings provide evidence for spatial sorting as a mechanism through which neighborhood effects occur.

JEL CLASSIFICTION: F16, N9, R23

KEYWORDS: Agglomeration Economies, Cities, Neighborhood effects, Second World War

*Redding and Sturm thank Princeton University and the European Research Council (ERC) for financial support respectively. We are grateful to the London Metropolitan Archives (LMA) for sharing the London County Council (LCC) bomb damage maps and to the British Library of Political and Economic Science (BLPES) at LSE for sharing the Booth and New London Survey maps. We thank Esteban Rossi-Hansberg and participants at the International Growth Center (IGC) Cities conference for helpful comments. We are grateful to Iain Bamford, Dennis Egger and Daniela Glocker for outstanding research assistance. The usual disclaimer applies.

†Department of Economics and WWS, Fisher Hall, Princeton, NJ 08540. 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 large social sciences literature emphasizes neighborhood effects, including the "Chicago School" in sociology and models of urban externalities in the economics literature. However, there remains substantial debate over the size of these neighborhood effects; the spatial scale over which they operate; the mechanisms underlying them; and the relevance of non-linearities and tipping points. One reason for this continuing debate is the theoretical and empirical challenge of distinguishing spillovers between agents from correlated individual effects. Agents with particular characteristics could choose to cluster close together either because spillovers between them or because of unobserved characteristics that are similarly valued by them. To empirically disentangle spillovers from such correlated individual effects requires exogenous variation in the characteristics of neighboring locations.

In this paper, use Second World War destruction in London to provide evidence of neighborhood effects through spatial sorting. We use a newly-collected and remarkable dataset on thousands of locations within London that contains information about the extent of wartime destruction and the economic and social characteristics of locations from the late-nineteenth to the late-twentieth centuries. This dataset combines post-war Census data with measures of the war-time destruction of individual buildings from Saunders (2005), and street-level data on economic and social characteristics from Booth (1891) and London School of Economics and Political Science (1930).

Our use of wartime destruction as a source of variation has a number of advantages. First, we show that wartime destruction is uncorrelated with pre-war characteristics within small geographical units, such as wards (e.g. Aldersgate or Bishopsgate), which is consistent with the primitive bombing technologies available in the Second World War. Although the East End of London was more heavily bombed by German aircraft during the Blitz of 1940-41 than the West End, whether an individual building or street within a ward was destroyed was random. As an additional source of variation, we report results using only flying bomb (V1) and rocket (V2) destruction from the latter stages of WWII. These missiles were targeted on Tower Bridge, but fell randomly throughout London and the surrounding area, depending on idiosyncratic variation in prevailing winds, atmospheric conditions, defensive measures and manufacturing quality.

Second, we have detailed data at a fine spatial scale and over a long time period on the characteristics of treated and untreated locations, both before and after the Second World War. Both the fine spatial scale and the long time horizon are important, because neighborhood effects can be localized and the gentrification and decline of neighborhoods can occur over extended periods of time. Third, we find substantial heterogeneity across the treated locations in the extent and concentration of destruction, the characteristics of the buildings destroyed, and the geographical position of the treated locations relative to untreated locations. We use this heterogeneity to shed new light on the size and spatial scale of neighborhood effects, the mechanisms underlying them and the relevance of non-linearities and tipping points.

Finally, we combine the exogenous variation from war-time destruction and our rich sources of data on location characteristics with a quantitative model of neighborhood effects. This quantitative model incorporates the sorting of heterogeneous groups of workers across an arbitrary number of locations within the city

that differ in terms of productivity, amenities, the density of development and transport infrastructure. Despite incorporating multiple worker groups and many asymmetric locations, the model remains tractable and amenable to quantitative analysis, because of our modeling of heterogeneity in worker employment-residence decisions and the productivity of locations for alternative land uses. Our primary measure of worker groups is an index of socioeconomic status measured on a comparable basis in Booth (1891), London School of Economics and Political Science (1930) and modern census data. But we also examine other possible measures of segregation and fractionalization, such as for example those based on ethnicity. We allow for differences across worker groups in production externalities (e.g. externalities can be more or less important in production in different occupations), amenity externalities (e.g. externalities can be positive within groups but negative across groups), and commuting costs (e.g. non-homothetic preferences for commuting). Neighborhood effects arise in the model because of the endogenous sorting of workers within and across groups in the presence of production and amenity externalities.

Our research is related to a number of existing literatures. First, our paper contributes to a large theoretical literature on neighborhood effects and the costs and benefits of agglomeration, as reviewed in Duranton and Puga (2004), Moretti (2004), Rosenthal and Strange (2004), and Ioannides (2013).[1] Studies highlighting particular mechanisms for neighborhood effects include human capital externalities (e.g. Rauch 1993), crime (e.g. Glaeser, Sacerdote, and Scheinkman 1996), schooling (e.g. Benabou 1993), social housing (e.g. Currie and Yelowitz 2000), housing externalities (e.g. Rossi-Hansberg, Sarte, and Owens 2010), and knowledge spillovers, input-output linkages and pooling of specialized skills (e.g. Ellison, Glaeser, and Kerr 2010). Our contribution relative to this literature is to combine exogenous variation from wartime destruction, detailed data on location characteristics over a long historical time period, and a quantitative spatial equilibrium model to provide empirical evidence for the size and nature of neighborhood effects.

Second, our paper is related more broadly to research on the persistence of place and place-based policies. In sociology, the endurance of poverty and other neighborhood characteristics has been emphasized in a long line of work including Dorling, Mitchell, Shaw, Orford, and Davey Smith (2000), Glennerster, Hills, Piachaud, and Webb (2004), Dorling, Rigby, Wheeler, Ballas, Thomas, and Fahmy (2007) and Sampson (2012). In economics, a growing body of research has examined place-based politics, including Busso, Gregory, and Kline (2013) and Kline and Moretti (2014a), as reviewed in Neumark and Simpson (2014) and Kline and Moretti (2014b). Relative to this literature, we use war-time destruction as an exogenous source of variation to examine the strength, spatial scale and mechanisms for neighborhood effects.

Third, our work connects with a recent literature that has used wartime bombing as a source of exogenous variation, including Davis and Weinstein (2002), Davis and Weinstein (2008), Brakman, Garretsen, and Schramm (2004), Bosker, Brakman, Garretsen, and Schramm (2007), Koster, Van Ommeren, and Rietveld (2011) and Miguel and Roland (2011). While these papers mostly use data across cities or regions, our analysis exploits variation at a fine spatial scale across locations within a city and makes use of detailed data on the socioeco-

[1] One strand of this literature on agglomeration emphasizes the interaction of costly trade in goods and factor mobility across cities or regions, as in Allen and Arkolakis (2014), Fujita, Krugman, and Venables (1999), Monte and Rossi-Hansberg (2015) and Redding (2012). Another strand of this literature focuses on the internal organization of economic activity within cities, as in Lucas and Rossi-Hansberg (2002), Ahlfeldt, Redding, Sturm, and Wolf (2015) and Allen, Arkolakis, and Li (2016).

nomic characteristics of those disaggregated locations.

Third, our analysis is part of a wider literature that has used natural experiments to provide empirical evidence on the predictions of economic geography models, including the division of Germany after the Second World War (e.g. Redding and Sturm 2008, Redding, Sturm, and Wolf 2011 and Burchardi and Hassan (2012)), the Dust Bowl (Hornbeck 2012) portage (e.g. Bleakley and Lin 2012), natural amenities as a source of persistence in spatial income distributions (Lee and Lin 2015), the Boston and San Francisco Fires (Hornbeck and Keniston (2012) and Siodla (2015)) and the flooding of cities (e.g. Kocornik-Mina, McDermott, Michaels, and Rauch 2014). In contrast to all of these papers, we use a quantitative spatial model and exogenous variation from war time bombing within a city to provide evidence on the empirical relevance of neighborhood effects.

The remainder of the paper is structured as follows. Section 2 discuss the historical background. Section 3 develops the theoretical framework. Section 4 discusses the data. Section 5 presents reduced-form evidence on the impact of Second World War destruction. Section 6 undertakes a quantitative analysis of the model. Section 7 concludes.

2 Historical Background

Although the Second World War started in September 1939 in Poland, it was not until 10 May 1940 that German forces invaded Belgium and France. Their main armored thrust through the Ardennes cut off and surrounded the British Expeditionary Force (BEF) and led to its evacuation from Dunkirk in late May and early June. As further German armored penetration outflanked the main French forces that were organized around the defensive Maginot Line, the French government signed an armistice with Germany on 22 June 1940.[2]

Following the fall of France, German military planning turned to the invasion of Britain codenamed Operation Sea Lion ("Seelöwe"). In preparation, the German air force ("Luftwaffe") began a series of concentrated aerial attacks in August 1940 (referred to as the Battle of Britain), aimed at the destruction of the Royal Air Force (RAF) and establishing air superiority over Britain.[3] Initially, these attacks were concentrated on RAF airfields and infrastructure. However, on 24 August 1940 night bombers aiming for RAF airfields drifted off course and accidentally destroyed several London homes and killed a number of civilians. After Winston Churchill ordered the immediate bombing of Berlin in response the following night, Adolf Hitler responded with a strategic bombing campaign on British cities concentrated on London.[4]

The intense bombing of London (the "Blitz") lasted from 7 September 1940 to 21 May 1941. Starting on 7 September 1940, London was bombed for 57 consecutive nights. Between September and November alone, almost 30,000 bombs were dropped. Heavy day-time aircraft losses led to a concentration on night-bombing from October 1940 onwards. In total, around 18,291 tons of high explosives were dropped on London during the Blitz, approximately 60 percent of the total for all British cities during this period. More than one million London houses were destroyed or damaged and around 20,000 civilians were killed.[5]

[2]For the history of the Fall of France, see Jackson (2004).

[3]Sea Lion and the Battle of Britain receive detailed historical treatments in Mckinstry (2014) and Holland (2012) respectively.

[4]In the face of the continuing resistance of the RAF and the shift towards a strategic bombing campaign, Operation Sea Lion was postponed indefinitely on 17 September 1940.

[5]These figures are taken from Ray (2004), which provides further historical detail on the London Blitz. In 127 Luftwaffe attacks

With the start of preparations for the German invasion of the USSR in June 1941 ("Barbarossa"), conventional air attacks on London were greatly reduced. However, as the Second World War progressed and in part in response to the Allied bombing of German cities, the German airforce and army ("Wehrmacht") developed long-range retaliatory weapons ("Vergeltungswaffen") for strategic bombing purposes.[6] The first of these weapons, the V-1, was a pulsejet predecessor of the cruise missile (commonly referred to as a "Buzz bomb" or "Doodlebug" because of its characteristic noise). The second, the V-2, was the world's first long-range ballistic missile (sometimes referred to by its technical name of the A-4).[7]

Following the Allied landings in Normandy on 6 June 1944, the first V-1 was launched at London on 13 June 1944. The V-1 had a range of 250km, carried an 850 kg warhead, and flew at a speed of 640 km/hr. It was launched from an fixed starting ramp and guided by a gyrocompass that controlled altitude and direction. An odometer driven by a vane anemometer on the V-1's nose determined when the target had been reached. Before launch, the counter was set to a value that would reach zero upon arrival at the target (Tower Bridge for London) in the prevailing wind conditions. When the count reached zero, two detonating bots were fired, which put the V-1 into a steep dive on to the target. Overall, only about 25 per cent of the V-1's are estimated to have hit their target area, with the majority being lost because of a combination of defensive measures, mechanical unreliability or guidance errors.[8] As a result of these factors, and fluctuations in prevailing winds and atmospheric conditions, V-1 impacts are randomly distributed throughout London and the surrounding area in a circle centered on Tower Bridge, as shown below.[9]

Development of the V-2 lagged somewhat behind that of the V-1 and it was not until September 1944 that the first missile was launched against London. The V-2 had a range of 320 km, carried a 1,000 kg warhead, travelled at up to 5 times the speed of sound during the powered phase of its trajectory, and dropped to earth from an altitude of 100km at nearly 3 times the speed of sound. Power was supplied by a liquid-propellant rocket engine and the V-2 was launched from a mobile launcher. Distance and azimuth to the target (again Tower Bridge for London) were set at the launch site. The guidance system consisted of two gyroscopes (a horizontal and a vertical) to stabilize the rocket and an accelerometer to control engine cutoff at a specified velocity. Once the engine cut out, the missile continued to follow its ballistic trajectory on to the target. Unlike the V-1, the V-2's speed and trajectory made it practically invulnerable to anti-aircraft guns and fighter interception. Nonetheless variation in manufacturing quality and technical malfunctions resulted in considerable inaccuracy.[10]

Even individual V-1 and V-2 impacts could create considerable destruction. For example, on 14th January 1945, twenty houses in South London were demolished by a single missile, with another 50 suffering serious damage. Impact craters could be more than thirty feet wide and damage might extend for up to one quarter of a

involving more than 100 tons of bombs from 7 September 1940 to 21 May 1941, an estimated total of 30,098 tons of bombs were dropped on British cities. Of these attacks, 71 were targeted on London with an estimated total of 18,291 tons of bombs dropped.

[6] For discussion of the allied bombing of German cities, see for example Friedrich (2008).

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

[8] Defensive measures included barrage balloons, a band of anti-aircraft guns South of London, and fighter interception.

[9] British Intelligence leaked false information to the Germans implying that the rockets were overshooting their London targets, which is believed to have shifted some of the concentration of V1-impacts towards less-populated areas South of London.

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

mile.[11] According to official estimates, some 32,000 V-1s were manufactured. Around 10,492 were launched at London, of which 2,419 reached the target area, killing 6,184 and injuring 17,981. In comparison, approximately 6,000 V-2s were manufactured, of which a little more than half were fired operationally. As a result of the 1,358 V-2 that landed in the London civil defense region (which extended substantially beyond the LCC area), 2,754 civilians were killed and 6,500 injured.[12] In total, 107,000 houses were destroyed and over 1.5 million damaged as a result of V-weapons attacks.[13] Although smaller in magnitude than bomb damage from conventional aircraft, V-weapon destruction was extensive, and its idiosyncratic variation around the target point of Tower Bridge provides a useful source of quasi-experimental variation.

3 Theoretical Framework

To guide our empirical analysis, we develop a model in which neighborhood effects arise from externalities that can vary by location and type of land use. We distinguish between commercial land use and several forms of residential land use that correspond to the different socioeconomic categories observed in our data. We interpret these socioeconomic categories in the model as corresponding to residences for workers in different occupations (e.g. manager, skilled white collar worker etc). We assume that workers from each occupation derive sufficiently low utility from living in residences designed for another occupation that they never choose to do so in equilibrium (hence each manager lives in a managerial residence etc).[14] We model land use as a dynamic decision to capture persistence in land use over time and to allow for the possibility that the impact of an exogenous unanticipated shock (e.g. wartime destruction) can depend on initial patterns of land use.

Time is continuous and indexed by $t \in (0, \infty)$. We consider a city embedded within a wider economy. The city consists of a set of discrete locations indexed by $n \in \{1, \ldots, N\}$ that correspond to neighborhoods. Each neighborhood consists of a continuum of land plots that each have a unit measure of land area. We denote the set of land plots in each neighborhood n by $\mathcal{L}_n$; we index individual land plots within that neighborhood by $\ell \in \mathcal{L}_n$; and we denote the total land area of each neighborhood by $\mathcal{K}_n = |\mathcal{L}_n|$. Each land plot can be used either commercially or for one of the categories of residential land use. Within a neighborhood, different land plots can be allocated to different uses (some commercial, some residential), but a given land plot only can be allocated to one use at a given time.

The city is populated by workers from a number of different occupations indexed by $o \in \{1, \ldots, O\}$. Workers from each occupation are perfectly mobile within the city and the larger economy, which provides a reservation level of utility $\bar{U}^o$ and offers a reservation wage $\bar{w}^o$ for workers from occupation o. Workers choose where to live and where to work. They face iceberg commuting costs of $\kappa^o_{\text{in}} > 1$ across land plots within the city and commuting costs of $\kappa^o_{\text{out}} > 1$ between the city and the larger economy, where we allow these commuting

[11] These figures are taken from Johnson (1981), pages 132 and 155.

[12] Although London was the main target for both V-weapons, they were launched at a number of other targets (in particular Antwerp), especially after the V-1 launch site in range of London had been overrun by Allied forces.

[13] In early December 1944, the American General Clayton Bissell completed a report in which he argued that the V-1 compared favorably in terms of destruction achieved relative to cost to conventional bombers. See also Irons (2003).

[14] We adopt this model structure to connect with the data available to us, but in principle the model could be extended to allow workers to substitute across residences designed for other occupations.

costs to differ across occupations.[15] Firms produce a single final good, which is costlessly traded within the city and the larger economy, and is chosen as the numeraire ($p = 1$).

The owner of an undeveloped land plot decides whether to develop that land plot for commercial use or one of the residential uses. We capture dynamics in land use by assuming that the decision to develop land for a particular use is irreversible, but with probability $0 < \delta < 1$ a land plot that has already been developed can be re-developed either for the same or a different use (e.g. one interpretation of δ is the depreciation of durable structures). Land plots within each neighborhood differ in terms of their suitability for alternative uses. We model these differences as variation in effective units of land for each use of a given land plot. These differences have a common component that is the same across all land plots within a neighborhood and an idiosyncratic component. The common component depends on the exogenous characteristics of neighborhoods (e.g. scenic views) and the endogenous fraction of land plots within each neighborhood that are allocated to each use (neighborhood effects). The idiosyncratic component is drawn randomly for each land plot when it is being prepared for development or re-development.

3.1 Workers

The utility of a worker i from an occupation o who chooses to live in land plot ℓ and work in land plot $\jmath$ at time t ($U^o_{i\ell\jmath t}$) depends on her consumption of the final good ($c^o_{i\ell\jmath t}$) and her quality-adjusted residential land use ($l^o_{i\ell\jmath t}$), and is assumed to take the Cobb-Douglas form:[16]

$$U^o_{i\ell\jmath t} = \left(\frac{c^o_{i\ell\jmath t}}{\beta}\right)^{\beta} \left(\frac{l^o_{i\ell\jmath t}}{1-\beta}\right)^{1-\beta}, \qquad 0 < \beta < 1, \tag{1}$$

where we model heterogeneity in amenities and residential externalities (neighborhood effects) through the supply of effective units of land (which determines quality-adjusted residential land use $l^o_{i\ell\jmath t}$), as discussed below. Since a given land plot cannot be allocated to both commercial and residential use simultaneously, all workers commute between land plots ($\ell \neq \jmath$ for all i), where these land plots could be in the same or different neighborhoods.

Each worker chooses where live to maximize her utility, taking as given prices and the location decisions of firms and other workers. Labor mobility implies that workers from a given occupation must obtain the same utility across all residential plots populated by that occupation, equal to the reservation level of utility for that occupation in the larger economy ($\bar{U}^o$). Utility maximization implies that a worker i from occupation o living in land plot ℓ and working in land plot $\jmath$ allocates constant shares of her residential income ($v^o_{i\ell\jmath t}$) to expenditure on the final good and residential land. Additionally, population mobility implies that equilibrium utility must be the same for all workers from a given occupation across all pairs of land plots and equal to the reservation level of utility in the wider economy ($\bar{U}^o$). Combining these two results, we obtain the following expression

[15] Commuting costs are assumed to take a common value across locations within the city (κ^o_{in}) and another common value to the wider economy (κ^o_{out}) for a given occupation to simplify the determination of equilibrium wages. In principle, the model can be extended to allow for additional variation in commuting costs.

[16] For empirical evidence using U.S. data in support of the constant housing expenditure share implied by the Cobb-Douglas functional form, see Davis and Ortalo-Magné (2011).

for this common level of utility for all workers from a given occupation o:

$$U^o_{i\ell\jmath t} = v^o_{i\ell\jmath t} \left(Q^o_{\ell t}\right)^{\beta-1} = \bar{U}^o. \tag{2}$$

where $Q^o_{\ell t}$ denotes the quality-adjusted land rent for residences for workers from occupation o in land plot ℓ and we have used our choice of the final good as numeraire ($p = 1$).

This indifference condition imposes a restriction on the quality-adjusted land rents and residential income consistent with population mobility. The quality-adjusted residential land rent ($Q^o_{\ell t}$) corresponds to the rent per effective unit of land for residential use o, where variation in these effective units of land for residential use o across plots captures differences in floor space, building quality, amenities and residential externalities. Observed land rents in a plot ℓ at time t that is allocated to residential use o equal the quality-adjusted land rent ($Q^o_{\ell t}$) times effective units of land for that use, as discussed further below.

Labor mobility between the city and the larger economy implies that the wage for each worker i in a given occupation o in each employment plot $\jmath$ at time t ($w^o_{i\jmath t}$) is equal to the wage in the larger economy adjusted for commuting costs:

$$w^o_{i\jmath t} = \bar{w}^o / \kappa^o_{\text{out}}. \tag{3}$$

Labor mobility within the city implies that residential income for each worker i in a given occupation o in each residential plot is equal to the common wage in each employment plot within the city adjusted for commuting costs:

$$v^o_{i\ell\jmath t} = w^o_{\jmath t} / \kappa^o_{\text{in}} = \bar{w}^o / \left(\kappa^o_{\text{in}} \kappa^o_{\text{out}}\right) = v^o. \tag{4}$$

Therefore labor mobility implies a common level of residential income (v^o) for a given occupation across all residential plots used by that occupation. This common level of residential income is increasing in the reservation wage in the larger economy and decreasing in commuting costs. Although we model commuting costs in terms of forgone labor income, the indirect utility function (2) is linear in labor income, which implies that the commuting costs have an isomorphic interpretation in terms of a reduction in utility.

Combining no-arbitrage in the labor market (4) with population mobility and utility maximization (2), we can solve for the equilibrium value of the quality-adjusted residential land rent for occupation o in each plot ℓ at time t ($Q^o_{\ell t}$) as a function of the reservation wage ($\bar{w}^o$), commuting costs (κ^o_{in}, κ^o_{out}) and the reservation utility in the wider economy for that occupation ($\bar{U}^o$):

$$Q^o_{\ell t} = \left(\frac{\bar{w}^o}{\kappa^o_{\text{in}} \kappa^o_{\text{out}} \bar{U}^o} \right)^{\frac{1}{1-\beta}} = Q^o. \tag{5}$$

Therefore utility maximization and labor mobility together imply that the quality-adjusted residential land rent for workers from a given occupation o is the same across all land plots ℓ developed for that occupation ($Q^o_{\ell t} = Q^o$). This common quality-adjusted residential land rent (Q^o) for a given occupation o, together with the common residential income for that occupation (v^o), implies common values of consumption of the final good ($c^o_{i\ell\jmath t} = c^o = \beta v^o$) and of residential land ($l^o_{i\ell\jmath t} = l^o = (1-\beta) v^o / Q^o$).

Although quality-adjusted residential land rents take the same value for all land plots developed for the same use ($Q^o_{\ell t} = Q^o$), observed residential land rents vary across these plots, because of differences in effective

units of land (differences in floor space, building quality, amenities and residential externalities). Additionally, quality-adjusted residential land rents differ across land plots developed for different occupations ($Q^o \neq Q^m$ for $m \neq o$).

A higher reservation wage in the larger economy ($\bar{w}^o$) for an occupation increases residential income and hence bids up the common quality-adjusted residential land rent for that occupation. Higher commuting costs (κ^o_{in}, κ^o_{out}) for an occupation reduce residential income and hence bid down the common quality-adjusted residential land rent for that occupation. A higher reservation utility for an occupation ($\bar{U}^o$) leads to a population outflow from the city until the common quality-adjusted residential land rent falls such that utility for that occupation equals its reservation utility in the wider economy.

3.2 Production

The final good is produced under conditions of constant returns to scale and perfect competition and is costlessly traded within the city and the larger economy. Output of the final good in a commercial land plot $\jmath$ at time t ($y_{\jmath t}$) depends on labor input from each occupation o ($h^o_{\jmath t}$) and quality-adjusted commercial land use ($x_{\jmath t}$). For simplicity, we assume that the production technology takes the Cobb-Douglas form:

$$y_{\jmath t} = \prod_{o=1}^{O} \left(h^o_{\jmath t}\right)^{\alpha^o} \left(x_{\jmath t}\right)^{1-\sum_{o=1}^{O} \alpha^o}, \qquad \alpha^o > 0 \; \forall \; o \; , \; 0 < \sum_{o=1}^{O} \alpha^o < 1, \tag{6}$$

where we model heterogeneity in productivity and production externalities (neighborhood effects) through the supply of effective units of land (which determines quality-adjusted commercial land use $x_{\jmath t}$), as discussed below. From the first-order conditions for profit maximization, employment of each occupation per unit of quality-adjusted commercial land use depends solely on relative factor prices:

$$\frac{h^o_{\jmath t}}{x_{\jmath t}} = \left(\frac{\alpha^o}{1 - \sum_{o=1}^{O} \alpha^o}\right) \frac{q_{\jmath t}}{w^o_{\jmath t}}, \tag{7}$$

where $q_{\jmath t}$ is the quality-adjusted commercial land rent, which corresponds to the rent per effective unit of land for commercial use. Variation in effective units of land for commercial use across plots captures differences in floor space, building quality, natural advantages for production and production externalities. Observed land rents in a plot ℓ at time t that is used for commercial use equal the quality-adjusted land rent ($q_{\jmath t}$) times effective units of land for that use, as discussed further below.

From this zero-profit condition (7), the lower the wage for an occupation relative to the quality-adjusted commercial land rent, the more intensively is that occupation used in production. Combining the first-order conditions for profit maximization and zero profits, the equilibrium quality-adjusted commercial land rent consistent with positive production in a plot $\jmath$ is:

$$q_{\jmath t} = \left(1 - \sum_{o=1}^{O} \alpha^o\right) \prod_{o=1}^{O} \left(\frac{\alpha^o}{w^o_{\jmath t}}\right)^{\frac{\alpha^o}{1-\sum_{o=1}^{O} \alpha^o}}. \tag{8}$$

Intuitively, the higher the wage for each occupation, the lower the quality-adjusted commercial land rent consistent with zero equilibrium profits.

As discussed above, labor mobility between the city and the larger economy (3) implies that the wage for a given occupation o in each employment location $\jmath$ at time t ($w^o_{\jmath t}$) is equal to the wage in the larger economy adjusted for commuting costs ($\bar{w}^o/\kappa^o_{\text{out}}$). Using this result in the zero-profit condition (8), the equilibrium quality-adjusted commercial land rent takes a common value across all plots with positive production that is determined by the reservation wage and commuting costs for each occupation:

$$q_{\jmath t} = \left(1 - \sum_{o=1}^{O} \alpha^o\right) \prod_{o=1}^{O} \left(\frac{\alpha^o}{\bar{w}^o/\kappa^o_{\text{out}}}\right)^{\frac{\alpha^o}{1-\sum_{o=1}^{O}\alpha^o}} = q. \tag{9}$$

Although quality-adjusted commercial land rents (q) are the same across all land plots used commercially, observed commercial land rents vary across these land plots, because of differences in effective units of land (differences in floor space, building quality, natural advantages for production and production externalities), as discussed further below.

3.3 Land Use Allocation

Recall that land can be used either commercially or as a residence for workers from one of the occupations. We index these alternative uses of land by s, where commercial land use is denoted by $s = 0$ and residential land use for each occupation is indicated by $s \in \{1, \ldots, O\}$. We denote the set of land plots allocated to each use s at time t by $\mathcal{L}^s_{nt}$ and the land area allocated to each use by $\mathcal{K}^s_{nt} = |\mathcal{L}^s_{nt}|$, such that $\sum_{s=1}^{S} \mathcal{K}^s_{nt} = \mathcal{K}_n$. When landowners prepare a plot of land ℓ for development in neighborhood n at time t, we assume that they draw effective units of land for each use s (z^s_ℓ) from a Fréchet distribution, which remain fixed thereafter until the plot is redeveloped:

$$F^s_{nt}(z) = e^{-A^s_{nt} z^{-\epsilon}}, \tag{10}$$

where the scale parameter A^s_{nt} determines the average effective units of land for each use within each neighborhood n at time t and the shape parameter ϵ controls for the dispersion in effective units of land.

The idiosyncratic realizations for effective units of land (z^s_ℓ) capture heterogeneity across land plots in their suitability for production or residence. The scale parameter (A^s_{nt}) controls average productivity for commercial land use ($s = 0$) and the average amenities for each category of residential use ($s \in \{1, \ldots, O\}$) for neighborhood n at time t. We allow this scale parameter (A^s_{nt}) to have an exogenous component (a^s_n) and an endogenous component (Λ^s_{nt}) that depends on the share of land allocated to that use within the neighborhood ($\xi^s_{nt} = \mathcal{K}^s_{nt}/\mathcal{K}_n$):

$$A^s_{nt} = a^s_n \Lambda^s_{nt}(\xi^s_{nt}). \tag{11}$$

The exogenous component (a^s_n) captures location fundamentals that determine productivity for commercial land use (e.g. access to natural water) and amenities for each category of residential land use (e.g. scenic views that may be valued differentially by workers from different occupations). The endogenous component ($\Lambda^s_{nt}(\xi^s_{nt})$) captures neighborhood effects that influence productivity for commercial land use (e.g. knowledge spillovers) or amenities for each category of residential land use (e.g. local public goods). We assume that location fundamentals (a^s_n) and externalities ($\Lambda^s_{nt}(\xi^s_{nt})$) are determined at the neighborhood level. They therefore

take the same value across land plots ℓ within neighborhood n. Nonetheless, realizations for effective units of land for each use vary stochastically across land plots within each neighborhood.[17]

After observing the realized effective units of land for each use, the landowner allocates the plot of land to the use that offers the highest net present value of returns. This land allocation decision is irreversible until the plot of land becomes available for re-development (with probability δ). If a plot of land ℓ is allocated to use s in neighborhood n at time t, it generates a constant flow return given by observed land rents ($\mathbb{Q}_{\ell t}^s$), which equal the (common) quality-adjusted land rent for that land use (Q^s) times the realization for effective units of land for that land use (z_ℓ^s):

$$\mathbb{Q}_{\ell t}^s = \mathbb{Q}_\ell^s = Q^s z_\ell^s, \tag{12}$$

where commercial land use corresponds to $s = 0$ (so that $Q^0 = q$) and residential land use corresponds to $s \in \{1, \ldots, O\}$.

The constant flow return (12) over time from allocating a given land plot to a given use (until that plot is redeveloped) substantially simplifies each landowner's dynamic land allocation decision. This property reflects two features of the model discussed above. First, effective units of land (z_ℓ^s) for each use s are drawn when a land plot ℓ is developed and remain fixed thereafter (until the plot is subsequently re-developed with probability δ). Second, utility maximization and labor mobility imply that quality-adjusted land rents take the same constant value (Q^s) across all plots allocated to the same use s.

The Bellman equation defining the net present value of returns from allocating the plot of land ℓ to use s over a period of time dt satisfies the following relationship:

$$V_{\ell t}^s = \mathbb{Q}_\ell^s dt + (1 - \delta dt) V_{\ell t}^s + \delta dt \max_r \left\{ V_{\ell t}^r \right\}, \tag{13}$$

where we have normalized the discount rate to zero; we have used the fact that $e^{-\delta dt} = (1 - \delta dt)$ for dt small; and we have exploited the fact that the flow return from land use ($\mathbb{Q}_\ell^s$) is constant until a plot is redeveloped. The value of allocating the plot of land ℓ to use s is therefore:

$$V_{\ell t}^s = \frac{\mathbb{Q}_\ell^s}{\delta} + \max_r \left\{ V_{\ell t}^r \right\}, \tag{14}$$

where the re-development probability (δ) and the continuation value ($\max_r \{V_{\ell t}^r\}$) are the same across alternative land uses s. Therefore the constancy of the flow return for each land use ($\mathbb{Q}_\ell^s$) and the common continuation value across alternative land uses ensure that the landowner's problem of allocating the plot of land to the highest net present value of returns ($V_{\ell t}^s$) reduces to the problem of allocating the plot of land to the highest flow rate of return ($\mathbb{Q}_\ell^s$).

To characterize this land allocation decision, we use the monotonic relationship (12) between effective units of land (z_ℓ^s) and observed land rents ($\mathbb{Q}_\ell^s$), which implies that the distribution of flow returns for land use s also has a Fréchet distribution:

$$F_{nt}^s(\mathbb{Q}^s) = e^{-A_{nt}^s (\mathbb{Q}^s / Q^s)^{-\epsilon}}. \tag{15}$$

[17] While our assumption that fundamentals and externalities are determined at the neighborhood level enables us to model neighborhood effects in a simple way, this assumption can be relaxed to allow both fundamentals and externalities to also vary across land plots within each neighborhood.

Since land is allocated to the use with the highest flow return, and the maximum of Fréchet distributed random variables also has a Fréchet distribution, the distribution of flow returns across all possible land uses is given by:

$$F_{nt}^{s}(\mathbb{Q}^{s}) = e^{-\sum_{s=0}^{S} A_{nt}^{s}(\mathbb{Q}^{s}/Q^{s})^{-\epsilon}}. \tag{16}$$

Using these distributions of flow returns, the probability that a re-developed plot of land ℓ in neighborhood n is allocated to land use s is as follows:

$$\lambda_{nt}^{s} = \frac{(Q^{s})^{\epsilon} A_{nt}^{s}}{\sum_{r=0}^{S} (Q^{r})^{\epsilon} A_{nt}^{r}} = \frac{(Q^{s})^{\epsilon} a_{n}^{s} \Lambda_{nt}^{s}(\xi_{nt}^{s})}{\sum_{r=0}^{S} (Q^{r})^{\epsilon} a_{n}^{r} \Lambda_{nt}^{r}(\xi_{nt}^{r})}, \tag{17}$$

which varies across neighborhoods n and over time t, but is the same across land plots ℓ within a given neighborhood at a given point in time.

Therefore the higher the quality-adjusted land rent for a given land use s (Q^{s}), the more favorable location fundamentals for that use (a_{n}^{s}), and the larger the fraction measure of land plots within a neighborhood already allocated to that use (ξ_{nt}^{s}), the more likely a re-developed land plot is to be allocated to that use. Both quality-adjusted land rents (Q^{s}) and location fundamentals (a_{n}^{s}) are constant over time, which implies that the neighborhood effects ($\Lambda_{nt}^{s}(\xi_{nt}^{s})$) are the sole source of dynamics in these choice probabilities (17).

3.4 Land Use Dynamics

Having characterized the land allocation decision for re-developed land plots, we are now in a position to characterize the laws of motion for each land use over time. Given that developed land commands a positive rate of return, any undeveloped land is immediately developed. Thereafter, the evolution of land use over time is determined by patterns of redevelopment. Each period, there is an outflow of existing land plots from use s, because a constant fraction δ of these land plots are re-developed. But there is also an inflow of land plots re-developed for use s, because a fraction λ_{nt}^{s} of all re-developed land plots are allocated to use s at time t. Hence the equation of motion for the measure of land allocated to use s in neighborhood n is:

$$\dot{\mathcal{K}}_{nt}^{s} = \lambda_{nt}^{s} \delta \mathcal{K}_{n} - \delta \mathcal{K}_{nt}^{s}, \tag{18}$$

Dividing through by $\mathcal{K}_{n}$, we obtain the following system of first-order differential equations for the share of land ($\xi_{nt}^{s} = \mathcal{K}_{nt}^{s}/\mathcal{K}_{n}$) allocated to each use $s \in \{1, \dots S\}$:

$$\dot{\xi}_{nt}^{s} + \delta \xi_{nt}^{s} = \lambda_{nt}^{s} \delta. \tag{19}$$

We first characterize the solution to this system of differential equations for the special case of the model without neighborhood effects. In this special case, there is a unique steady-state equilibrium allocation of land across alternative uses within each neighborhood (ξ_{n}^{s*}), which is determined by the (common) quality-adjusted land rents for each use (Q^{s}) and the neighborhood's location fundamentals for each use (a_{n}^{s}). The economy converges monotonically from any initial allocation of land across alternative uses (ξ_{n0}^{s}) to this steady-state allocation (ξ_{n}^{s*}). Therefore the steady-state allocation of land across alternative uses depends solely on model parameters (we solve for Q^{s} as a function of model parameters above) and is invariant with respect to the neighborhood's initial conditions (ξ_{n0}^{s}).

Proposition 1 *Consider the special case of the model with no neighborhood effects ($\Lambda^s_{nt}(\xi^s_{nt}) = 1$ for all n, s, t). In this special case, there exists a unique steady-state equilibrium, in which a constant share of land plots within each neighborhood are allocated to each use ($\xi^s_{nt} = \xi^{s*}_n$). Given initial values for the shares of land plots allocated to each use (ξ^s_{n0}), land allocation within each neighborhood converges monotonically to its steady-state allocation (ξ^{s*}_n).*

Proof. See the appendix. ■

We next examine the implications of neighborhood effects for the steady-state allocation of land across alternative uses. To illustrate these implications, we consider a simple specification, in which the strength of neighborhood effects depends on whether the share of land allocated to each use is above or below a threshold:

$$\Lambda^s_{nt} = \begin{cases} \Lambda^s_{nH} & \text{if } \xi^s_{nt} \geq \bar{\xi}^s \\ \Lambda^s_{nL} & \text{if } \xi^s_{nt} < \bar{\xi}^s \end{cases}, \qquad \Lambda^s_{nH} > \Lambda^s_{nL} \tag{20}$$

In the presence of such neighborhood effects, the steady-state equilibrium land allocation within each neighborhood (ξ^{s*}_n) depends on initial conditions (ξ^s_{n0}) as well as on the (common) quality-adjusted land rents for each use (Q^s) and the neighborhood's location fundamentals for each use (a^s_n). Therefore a given neighborhood can converge towards a different steady-state allocation of land across alternative uses (ξ^{s*}_n) depending on these initial conditions (ξ^s_{n0}).

Proposition 2 *Suppose that neighborhood effects ($\Lambda^s_{nt}(\xi^s_{nt})$) depend on whether the share of land allocated to each use (ξ^s_{nt}) is above or below the threshold ($\bar{\xi}^s$) in (20). In the presence of these neighborhood effects, the steady-state equilibrium allocation of land across alternative uses (ξ^{s*}_n) can depend on the initial allocation (ξ^s_{n0}).*

Proof. See the appendix. ■

We interpret wartime bombing as a shock to the initial shares of land allocated to each use (ξ^s_{n0}), whereby previously developed land plots within a neighborhood are destroyed and can be redeveloped. Landowners make decisions about redeveloping these destroyed plots as well as the fraction δ of all other plots that become available for redevelopment. If wartime destruction is uneven across the different land uses within a neighborhood, it changes the relative importance of each land use within the neighborhood. Therefore the strength of neighborhood effects for each land use will differ before and after the wartime destruction. If this change in the strength of neighborhood effects is sufficiently large relative to the difference in location fundamentals across alternative uses of land within the neighborhood, wartime destruction can shift the neighborhood's land allocation between different steady-state equilibria.

4 Data

We use a newly-collected dataset on thousands of locations within London that records wartime destruction and the economic and social characteristics of locations from the late-nineteenth to late-twentieth centuries. Our data covers the area of the London County Council (LCC), which was the principal local government body

for the County of London throughout its existence from 1889 to 1965. The County of London comprised the entire of Central London and much of its surrounding suburbs, with an area of just over 300km^2 and a 1931 population of 4.4 million.[18]

Our main source of data on war-time destruction is the London County Council (LCC) bomb damage maps from Saunders (2005). These maps were compiled as a comprehensive assessment of war-time damage by the LCC and are based on pre-war Ordinance Survey (OS) maps that show individual buildings (see Figure 1). Buildings are color-coded by level of destruction: Yellow (blast damage minor in nature); orange (general bast damage – not structural); light red (seriously damaged but repairable at cost); dark red (seriously damaged – doubtful if repairable); purple (damaged beyond repair); and black (total destruction). We use as our main measure of war-time destruction the fraction of the existing built up area that experienced serious repairable damage (light red) or worse.[19] We also use a linear index of destruction, in which minor blast damage (yellow) is scored as one, and one is added to this score for each successive level of destruction (so orange is scored two, light red is scored three, and so on). The impact of each V-1 or V-2 missile in London is shown on the bomb damage maps by a circle centered on the point of impact. We georeferenced these maps, drew the outline of the pre-war built-up area, color-coded destruction, recorded whether the built-up area today has the same footprint as before WWII, and recorded the impact of each V-1 or V-2.

Our main sources of contemporary data on economic and social characteristics are the Population Census and the Land Registry. The Population Census reports population, demographics, education and income for spatial units at a number of different levels of spatial aggregation. We use consistent spatial units over time based on the 2001 Population Census. Our baseline specification uses Output Areas (also refereed to as enumeration districts), which are the most disaggregated spatial unit for which Census data are reported (at least 40 households and 100 persons with a target size of 125 households). We control for the geographical location of Output Areas within London using fixed effects defined at higher levels of spatial aggregation, including Lower Layer Super Output Areas (LSOAs) with a typical population of 1,500 in 2011, Middle Layer Super Output Areas (MSOAs) with a typical population of 7,200 in 2011, wards (e.g. Bishopsgate), and Metropolitan Boroughs (e.g. City of London).[20] The Land Registry reports property transactions data on house price paid, postcode and a range of house characteristics for each house sale for the period 1995-2015. Postcodes are even more disaggregated than output areas, corresponding typically to either a single building or a group of houses on the same segment of street. We match house prices to Output Areas using the centroid of each postcode. We measure log house prices conditional on observed house characteristics as the Output Area fixed effect from a regression of the log price paid on year dummies and house characteristics, including type (detached, semi-detached, terraced or flat), whether the house was newly built, and whether it was free or leasehold.

[18] Prior to its incorporation into the Greater London Authority (GLA) in 1965, the County of London included the following Metropolitan Boroughs: City of London, Battersea, Bermondsey, Bethnal Green, Camberwell, Chelsea, Deptford, Finsbury, Fulham, Greenwich, Hackney, Hammersmith, Hampstead, Holborn, Islington, Kensington, Lambeth, Lewisham, Paddington, Poplar, St Marylebone, St Pancras, Shoreditch, Southwark, Stepney, Stoke Newington, Wandsworth, Westminster and Woolwich.

[19] We exclude minor and general blast damage, because these are explicitly non-structural, and hence are unlikely to have any permanent effect on building structures. We include both repairable and unrepairable damage, because repaired structural damage could have a permanent effect on building structures, and whether a building is deemed to be repairable or unrepairable could be endogenous to economic considerations.

[20] The LCC area includes 8,746 Output Areas, 1,682 LSOAs, 354 MSOAs, 231 wards, and 29 pre-war Metropolitan Boroughs.

We combine these contemporary data on economic and social characteristics with unique historical data at the level of individual streets from Booth (1891) and London School of Economics and Political Science (1930). Charles Booth was a sociologist who undertook a pioneering study in seventeen volumes called the "Labor and Life of the People of London" (henceforth LLPOL), which analyzed the living and working conditions of the people of London. As part of this analysis, Booth produced a series of street maps of London, in which individual streets or segments of streets are color-coded according to socioeconomic status, based on the occupation of the residents (see Figure 2). Forty years later, one of Booth's assistants, Hubert Llewellyn Smith directed a follow-up study by the London School of Economics called "The New Survey of London Life and Labour" (henceforth NSOL). This study also produced a series of street maps of London, in which individual streets or segments of streets are color-coded according to a comparable classification, again based on the occupation of the residents (see Figure 3). We georeferenced these maps and allocated each color-coded street segment to the census Output Area within which it falls. We also used the modern census data to construct a comparable classification of socio-economic status based on the occupation of the residents of each Output Area.[21] We aggregate the LLPOL, NSOL and modern census data into a common classification of socio-economic status: poor, middle and rich.[22] For each output area, we compute the average fraction of residents in the poor, middle and rich categories. We also use a linear index of socio-economic status, in which the lowest socio-economic category is scored as one, and one is added to this score for each higher socio-economic category (so poor equals one, middle equals two, and rich equals three). We first compute the average value of this socio-economic index across residents within an output area. We next convert this average value into a percentile of the distribution of the average socio-economic index across output areas.

We combine these data on wartime destruction and the economic and social characteristics of locations with a variety of other Geographical Information Systems (GIS) data, including administrative boundaries and transport infrastructure (e.g. underground and overground railways).

5 Reduced-Form Evidence

In this section, we provide reduced-form evidence on the evolution of socio-economic status across neighborhoods and over time and its relationship to war-time bombing. We begin by characterizing patterns of war-time bombing and socio-economic status within London. We next show that bomb damage during the Second World War is uncorrelated with pre-existing socio-economic characteristics before the war. In contrast, we find a strong and statistically significant relationship between socio-economic characteristics after the Second World War and war-time bomb damage. Finally, we provide evidence on a range of potential mechanisms for the causal effect of Second World War destruction on socio-economic characteristics.

[21] Dorling, Mitchell, Shaw, Orford, and Davey Smith (2000) within the sociology literature find that contemporary health outcomes across locations are correlated with historical socio-economic status as measured in Booth (1891).

[22] In LLPOL, poor includes black (lowest class; vicious and semi-criminal) and blue (very poor; casual; chronic want); middle includes light blue (18-21 shillings per week for a moderate family), dark red (mixed, some comfortable, others poor) and soft red (fairly comfortable, good ordinary earnings); and rich includes red (middle class, well-to-do) and yellow (upper middle and upper classes, wealthy). For further details and the aggregation of the NSOL and modern census data, see the data appendix.

5.1 Wartime Destruction and Socioeconomic Status

In Figure 4, we display the distribution of Second World War bomb damage in the LCC area by the color-coded level of destruction. This figure takes into account all Second World War bomb damage, including the Blitz of 1940-1, later attacks by conventional aircraft, and the V-1 and V-2 missile attacks in the later stages of the war. As apparent from the figure, although the port areas to the East were the initial focus of the attacks, war-time damage was widely spread across the LCC area, with considerable idiosyncratic variation in the extent of destruction within a given neighborhood of the city. This pattern is consistent with both the primitive nature of the bomb-aiming technology and the increasing focus over time on strategic bombing to destroy civilian morale. In Figure 5, we display the distribution of V-1 and V-2 missile impacts in the LCC area. Although both missiles were targeted on tower bridge, we find that these impacts are distributed in a dartboard fashion throughout the LCC area. This dartboard distribution is in line with the engineering challenges faced in ensuring the reliability of these new technologies, the variation in manufacturing quality and the fluctuations in atmospheric conditions that influenced the missiles' points of impact.

In Table 1, we report summary statistics on the distribution of streets across our three categories of socio-economic status in both the LLOL (1890) and NSOL (1930) data. In both the LLOL and NSOL data, we find that the poor middle and rich categories comprise around 3, 65 and 32 percent of streets respectively. This similarity is consistent with the use of a consistent method between the two studies and the chief researcher for the NSOL study being one of Charles Booth's assistants for the LLOL study. In Figure 6, we display the value of our linear index of socioeconomic status for each output area, which averages the value of the linear index across each street within that output area. As apparent from the figure, socioeconomic status varies systematically within the city, with the East End on average having lower socioeconomic status than the West End. However, we also find substantial idiosyncratic variation in socioeconomic status within a given neighborhood. We examine the relationship between this idiosyncratic variation in socioeconomic status and bomb damage within a given neighborhood, both before and after the Second World War in our empirical analysis below.

5.2 Randomness of Second World War Destruction

We now use our NSOL data on socio-economic characteristics immediately prior to the Second World War to show that subsequent bomb damage during the Second World War is uncorrelated with the pre-existing characteristics of locations, once we focus variation within relatively small geographical areas such as the 231 wards. We run the following cross-section regression of the NSOL socio-economic status of Output Area i (S_i^{1930}) on war-time bomb damage ($D_i^{1939\text{-}45}$):

$$S_i^{1930} = \beta D_i^{1939\text{-}45} + \eta_k + u_i \tag{21}$$

where η_k are fixed effects for more aggregated spatial units k (typically wards) and u_i is stochastic error. We report heteroskedasticity robust standard errors clustered on wards to allow for spatial correlation in the errors across enumeration districts within wards.[23]

[23] Bertrand, Duflo, and Mullainathan (2004) examine several approaches to control for serial correlation. They show that clustering the standard errors performs well i n settings with at least 50 clusters as in our application.

Table 2 reports the regression results. Each cell in the table corresponds to a separate regression. The columns of the table consider different measures of socio-economic status. Columns (1)-(3) use the fraction of streets in the rich, middle and poor categories respectively; column (4) uses our linear index of socio-economic status. As this linear index need not have natural cardinal units, we convert it into a percentile score across Output Areas.[24] The panels of the table report reports for two different measures of war-time bomb damage. The top panel uses the fraction of the 1939 built up area that experienced serious repairable damage or worse. The bottom panel uses our linear index of bomb damage. As this linear index again need not have natural cardinal units, we convert it into a percentile score across Output Areas.[25] Within each panel, the first row reports results with no fixed effects; the second row presents estimates using fixed effects for the historical Metropolitan Boroughs; and the third row gives results using fixed effects for wards.

As apparent from the first row of the top panel, when we include no fixed effects, we find a correlation between previous socio-economic characteristics and subsequent bomb damage. Output areas with higher fractions of poor and middle-class streets were more likely to experience subsequent war-time damage than output areas with higher fractions of poor streets. This pattern of results is consistent with bombing being more concentrated in the East and center of London area, which was poorer than the West and outlying areas of London. As shown in the second row, once we include fixed effects for the 29 historical Metropolitan Boroughs, the estimated coefficients already fall in magnitude by more than half. As evident from the third row, once we include fixed effects for 226 wards, the estimated coefficients fall by an order of magnitude relative to the first row, are close to zero and entirely statistically significant. Therefore, once we control for geographical location within London using ward fixed effects, we find that subsequent war-time damage is uncorrelated with the pre-existing socio-economic characteristics of locations. This pattern of results is consistent with the idea that war-time bomb damage provides an exogenous shock to output areas within wards and is in line with the relatively primitive bombing technology discussed above.

As shown in the bottom panel of the table, we find a similar pattern of results using our linear index for war-time damage. When no fixed effects are included, poor and middle-class streets are more likely to experience war-damage. As we include progressively more spatially disaggregated fixed effects, these estimated effects become weaker and weaker. Once we condition on ward fixed effects, we again find estimated coefficients that are an order of magnitude smaller, close to zero and entirely statistically significant. Therefore we again find no relationship between subsequent war-time damage and pre-existing socioeconomic characteristics.

5.3 Causal Estimates of the Direct Impact of War-time Damage

We now use the idiosyncratic variation in war-time bomb damage within wards to provide evidence on its causal effects on subsequent socio-economic characteristics. We begin by considering house prices as a summary statistic for the relative attractiveness of a location. We run the following cross-section regression of the log of contemporary house prices in Output Area i ($S_i^{1995\text{-}2000}$) on Second World War bomb damage ($D_i^{1939\text{-}45}$):

$$S_i^{1995\text{-}2000} = \beta D_i^{1939\text{-}45} + \eta_k + u_i \tag{22}$$

[24] We also find a similar pattern of results using the raw linear index of socio-economic status instead of the the percentile score.

[25] Again we find a similar pattern of results if we use the raw linear index of war-time bomb damage instead of the percentile score.

where η_k are fixed effects for more aggregated spatial units k (typically wards) and u_i is stochastic error. We again report heteroskedasticity robust standard errors clustered on wards to allow for spatial correlation in the errors across enumeration districts within wards.

Table 3 reports the estimation results. Again each cell in the table corresponds to a separate regression; the columns of the table present results for house prices for different time periods; the panels of the table use two different measures of war-time bomb damage; and each row of each panel reports results with a different set of fixed effects. As discussed in the data section above, we measure log measure log house prices conditional on observed house characteristics as the Output Area fixed effect from a regression of the log house price on year dummies and house characteristics, including type (detached, semi-detached, terraced or flat), whether the house was newly built, and whether it was free or leasehold.

As shown in the first row of the top panel, we find that Output Areas that experienced more Second World War bomb damage have statistically significantly lower house prices today. This finding in the first row is not surprising, because it is influenced by the fact that the Eastern parts of the LCC that experienced more war-time bomb damage are on average poorer than the Western parts of the LCC. Once we include fixed effects to control for geographical location within London, the estimated effects become smaller in magnitude, but they remain highly statistically significant. Therefore, in contrast to our findings prior to the Second World War, even once we include ward fixed effects, we continue to find a negative and statistically significant coefficient, which is only around one third smaller than in the specification with no fixed effects. Hence, while there was no relationship between socio-economic characteristics and war-time bomb damage prior to the Second World War, we find a strong and statistically significantly negative relationship after the Second World War, consistent with a causal effect of war-time bomb damage in reducing house prices.

Comparing across the columns of the table, we find a consistent pattern of results using the house price data for different time periods. We find an estimated coefficient on the fraction of houses seriously damaged of around -0.4 unconditionally and around -0.11 after conditioning on ward fixed effects. To interpret these magnitudes, the mean fraction of houses seriously damaged is 0.159 with a standard deviation of 0.205. Hence a one standard deviation increase in war-time damage within wards reduces contemporary house prices by around $2.23 = 0.11 \times 0.205 \times 100$ percent, where we have controlled for any effect on observed house characteristics by using the Output Area fixed effect from a house price regression that conditions on observed house characteristics.[26] Comparing the top and bottom panels of the table, we find a similar pattern of results whether we use the fraction of houses seriously damaged or our linear index of damage. Therefore, across a range of different specifications, we find a causal effect of war-time bomb damage in reducing house prices within wards after the Second World War, which is both statistically significant and economically large.

5.4 Causal Estimates of the Spillover Effect of War-time Damage

So far, we have focused on the direct effect of war-time bomb damage in an Output Area on the socio-economic characteristics of that Output Area. We now examine the extent to which there are spillover effects of war-

[26] The fraction of houses seriously damaged or worse varies substantially across Output Areas from 0.000 at the 25th percentile, 0.078 at the 50th percentile, 0.234 at the 75th percentile, 0.600 at the 95th percentile, and 0.906 at the 99th percentile.

time bomb damage, as suggested by the neighborhood effects in the model. We run the following cross-section regression of the log of contemporary house prices in Output Area i ($S_i^{1995\text{-}2000}$) on own bomb damage ($D_i^{1939\text{-}45}$) and neighbors bomb damage ($N_i^{1939\text{-}45}$):

$$S_i^{1995\text{-}2000} = \beta D_i^{1939\text{-}45} + \gamma N_i^{1939\text{-}45} + \eta_k + u_i \tag{23}$$

where η_k are fixed effects for more aggregated spatial units k (typically wards) and u_i is stochastic error. To measure neighbors bomb damage, we construct 100 meter buffers around each Output Area (as shown for an example output area in Holborn in Figure 7) and measure the fraction of the 1939 built up in each buffer that experienced serious damage or worse. We again report heteroskedasticity robust standard errors clustered on wards to allow for spatial correlation in the errors across enumeration districts within wards.

Table 4 reports the estimation results. We focus on the fraction of houses that experienced serious repairable damage or worse as our baseline measure of war-time destruction. Each column of the table corresponds to a separate regression. Each column uses house prices for a different time period. All columns include ward fixed effects. In Column (1), we reproduce our results for the direct effect of war-time damage on house prices from Table 3 above, with an estimated coefficeint of around -0.11. In Columns (2)-(5), we add measures of neighbors bomb damage for each successive 100 meter buffer from 0-100 meters to 300-400 meters. As apparent from the table, we find negative and statistically significant effects not only from own war-time damage but also from neighbors war-time damage. Output areas whose immediate neighbors experienced more Second World War bomb damage have statistically significantly lower house prices today. These spillover effects are large in magnitude, with the estimated effect for the 0-100 meter buffer of around the same magnitude as the direct effect. Controlling for neighbors' war-time damage reduces slightly the estimated coefficient on own war-time damage. This pattern is consistent with own and neighbors' destruction being positively correlated, because neighboring locations can be affected by collateral damage, and because sticks of bombs dropped by a single aircraft tend to fall close together. These spillover effects are also highly localized, with little evidence of spillover effects from neighbors' destruction beyond 100-200 meters. This pattern of results provides causal evidence of spillovers from neighbors' bomb damage on own house prices and suggests that these spillovers operate at a small spatial scale within neighborhoods.

5.5 Mechanisms

We now provide further evidence on the economic mechanisms underlying the direct and spillover effects from war-time bomb damage. First, we examine the extent to which these changes in house prices reflect the spatial sorting of different socio-economic characteristics across locations, as in the theoretical model above. We re-estimate the spillover regression (23) using our linear index of social status from the 2001 Census instead of the log of contemporary house prices. We again we include both own and neighbors' bomb damage using 100 meter buffers around each Output Area as well as ward fixed effects.

Table 5 reports the regressions results and has the same structure as Table 4. Each column corresponds to a separate regression using the fraction of houses that experienced serious repairable damage or worse as our baseline measure of war destruction. As apparent from Column (1), we find that Output Areas within wards

that experienced more bomb damage during the Second World War have statistically significantly lower socio-economic status today. This pattern contrasts with our findings prior to the Second World War when we found no relationship between subsequent war-time damage and pre-existing social status. Therefore we find that the negative direct effect of bomb damage in reducing house prices operates at least in part through a change in the social composition of Output Areas, consistent with the spatial sorting mechanism in the model.[27] These effects are not only statistically significant but also economically large. The mean index of social status is 50.0 with a standard deviation of 28.8, while the mean own war-time damage is 0.159 with a standard deviation of 0.205. Hence a one standard deviation increase in own war-time bomb damage reduces an Output Area's percentile score by $2.88 = -14.04 \times 0.205$. Although, for brevity, we focus on the results using the index of social status, we find a similar pattern of results if we instead use fractions of poor, middle and rich as above.

In Columns (2)-(5), we add measures of neighbors bomb damage for each successive 100 meter buffer from 0-100 meters to 300-400 meters. Across all four columns, we find that Output Areas whose neighbors experienced more bomb damage during the Second World War have statistically significantly lower socio-economic status today, even after controlling for own bomb damage. This pattern of results again provides support for the model, in which changes in the characteristics of a location's neighbors affect patterns of spatial sorting, and hence lead to changes its own socio-economic composition. Consistent with our results for house prices above, these spillover effects are large, with the estimated coefficient on neighbors bomb damage within 0-100 meters around the same magnitude as the estimated coefficient on own bomb damage. Also consistent with our results for house prices above, we find that these spillover effects are highly localized, with little evidence of any effects beyond 200 meters. Therefore our results using socio-economic composition confirm that these spillovers operate at a small spatial scale within neighborhoods.

Taken together, our results so far imply that own bomb damage reduces own house prices and socio-economic status, and that neighbors' bomb damage reduces own house prices and socio-economic status. These findings provide causal evidence of spillovers from war-time bomb damage that change patterns of spatial sorting, but they do not by themselves establish the mechanism through which such spillovers occur. We distinguish four main types of spillover mechanisms. First, damage to nearby neighbors may have motivated large scale restructuring of a larger area ("correlated rebuilding"). As part of this process, areas bordering a bombed areas may have been demolished to make space for new developments. Such large-scale redevelopment of not just the bombed areas but also undamaged areas adjacent to them could mechanically generate an effect on own house prices and socio-economic status from neighbors being bombed. Second, another channel for spillovers could be changes in land use in neighboring bombed areas ("changes in land use"). There could, for example, be changes in the amount of open space or the road layout in neighboring areas. To the extent that these nearby changes in land use affect the production or amenity value of a location, this is reflected in own house prices and socio-economic status.

Third, bombing to nearby neighbors mechanically changes the composition of buildings in those neighbors, as repaired or newly-built structures could differ from pre-existing structures along a number of dimensions

[27] Consistent with spatial sorting, we find a strong correlation between log contemporary house prices and social status percentile across Output Areas, as reflected in a univariate regression R-squared of 0.489.

("building composition"). To the extent that these repaired or newly-built structures have a different production or amenity value from the original structures, this affects own house prices and socio-economic status. Fourth, if bombing affects the production or amenity value of nearby neighbors, this affects the pattern of spatial sorting across locations, and hence changes the socio-economic composition of those neighbors. To the extent that individuals value the socio-economic composition of their neighbors ("neighborhood effects"), this in turn affects own house prices and socio-economic status. Distinguishing these third and fourth effects is challenging, because in a model of spatial sorting any change in the physical characteristics of neighbors affects socio-economic composition. Therefore, in the presence of spatial sorting, it is hard to determine whether own socio-economic characteristics are directly affected by a change in the physical characteristics of neighbors or indirectly affected by a change in the socio-economic characteristics of neighbors.

Table 6 provides further evidence on the role of these different mechanisms by incorporating information on a range of observed characteristics. Columns (1) and (2) report results using the fraction of the non-white population; Columns (3) and (4) consider the fraction of residents living in social housing; Columns (5) and (6) examine the fraction of houses that are not in the same building footprint as in 1939; and Columns (7) and (8) use information on the average height of buildings. For each observed outcome, the first of each pair of columns focuses solely on the direct effect of war-time bomb damage on the own location, while the second of each pair of columns introduces our spillover variables for war-time bomb damage in neighboring 100 meter buffers. As apparent from Columns (1) and (2), we find that both own and neighbors war-time bomb damage increases the fraction of the non-white population, providing further evidence that war-time bomb damage influences patterns of spatial sorting. As shown in Columns (3)-(8), own war-time bomb damage increases the fraction of residents living in social housing, the fractions of houses that have a different building footprint from 1939, and the average height of buildings. This pattern of results confirms that war-time bomb damage unsurprisingly affects building composition. All of these effects are statistically significant at conventional critical values and economically large. In contrast, we find no evidence that neighbors war-time bomb damage affects the propensity to live in social housing, the likelihood that building structures lie within a different footprint, or the average height of buildings.

This pattern of results suggests that our spillover estimates are not driven by correlated rebuilding. Such such redevelopment of a larger area would be expected to affect own building composition, which would be reflected in spillover effects for our measures of building composition. Yet we find no evidence of spillover effects for the prevalence of social housing or changes in building footprint and height. This combination of strong direct and spillover effects for house prices and socio-economic composition but only strong direct effects for building composition is consistent with both our third and fourth mechanisms. When a location is bombed and experiences a change in its building composition, this could affect house prices and socio-economic composition in neighboring locations either directly (because of changes in nearby production or amenity values) or indirectly (because of changes in nearby socio-economic composition).

6 Quantitative Analysis

[XXX To be completed XXX]

7 Conclusions

The relevance of neighborhood effects is a central question in the social sciences literature. We use WWII destruction in London as a natural experiment to provide evidence on neighborhood effects. We show that WWII destruction is uncorrelated with pre-war characteristics within small geographical areas (wards). We find that both own and neighbors' WWII destruction reduce modern house prices. We find that both own and neighbors' WWII destruction change patterns of spatial sorting. We find that these effects are highly localized (within around 100 meters). Our results highlight the role of spatial sorting in shaping the spatial distribution of economic activity within cities

References

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

Allen, T., and C. Arkolakis (2014): "Trade and the Topography of the Spatial Economy," *Quarterly Journal of Economics*, 129(3), 1085–1140.

Allen, T., C. Arkolakis, and X. Li (2016): "Optimal City Structure," Yale University, mimeograph.

Benabou, R. (1993): "Workings of a City: Location, Education and Production," *Quarterly Journal of Economics*, 108(3), 619–652.

Bertrand, M., E. Duflo, and S. Mullainathan (2004): "How Much Should We Trust Differences-in-Differences Estimators?," *Quarterly Journal of Economics*, 119(1), 249–275.

Bleakley, H., and J. Lin (2012): "Portage: Path Dependence and Increasing Returns in U.S. History," *Quarterly Journal of Economics*, 127(2), 587–644.

Booth, C. (1891): *Life and Labour of the People in London*. Williams and Norgate, London.

Bosker, M., S. Brakman, H. Garretsen, and M. Schramm (2007): "Looking for Multiple Equilibria when Geography Matters: German City Growth and the WWII Shock," *Journal of Urban Economics*, 61, 152–169.

Brakman, S., H. Garretsen, and M. Schramm (2004): "The Strategic Bombing of German Cities during WWII and its Impact on City Growth," *Journal of Economic Geography*, 4, 201–218.

Burchardi, K., and T. Hassan (2012): "The Economic Impact of Social Ties: Evidence from German Reunification," *Quarterly Journal of Economics*, 128(3), 1219–1271.

Busso, M., J. Gregory, and P. Kline (2013): "Assessing the Incidence and Efficiency of a Prominent Place-Based Policy," *American Economic Review*, 103, 897–947.

Campbell, C. (2012): *Target London*. Little-Brown, London.

Currie, J., and A. Yelowitz (2000): "Are Public Housing Projects Good for Kids," *Journal of Public Economics*, 75, 99–124.

Davis, D. R., and D. E. Weinstein (2002): "Bones, Bombs, and Break Points: The Geography of Economic Activity," *American Economic Review*, 92(5), 1269–1289.

——— (2008): "A Search for Multiple Equilibria in Urban Industrial Structure," *Journal of Regional Science*, 48(1), 29–65.

Davis, M. A., and F. Ortalo-Magné (2011): "Housing Expenditures, Wages, Rents," *Review of Economic Dynamics*, 14(2), 248–261.

Dorling, D., R. Mitchell, M. Shaw, S. Orford, and G. Davey Smith (2000): "The Ghost of Christmas Past: Health Effects of Poverty in London in 1896 and 1991," *British Medical Journal*, 7276(23-30), 1547–1551.

Dorling, D., R. Rigby, B. Wheeler, D. Ballas, B. Thomas, and E. Fahmy (2007): *Poverty, Wealth and Place in Britain, 1968 to 2005*. Policy, Bristol.

Duranton, G., and D. Puga (2004): "Micro-Foundations of Urban Agglomeration Economies," in *Handbook of Regional and Urban Economics*, ed. by J. V. Henderson, and J.-F. Thisse, vol. 4, chap. 48, pp. 2063–2117. Elsevier, Amsterdam.

Ellison, G., E. L. Glaeser, and W. R. Kerr (2010): "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns," *American Economic Review*, 100(3), 1195–1213.

Friedrich, J. (2008): *The Fire: The Bombing of Germany, 1940-1945*. Columbia University Press, New York.

Fujita, M., P. Krugman, and A. J. Venables (1999): *The Spatial Economy: Cities, Regions and International Trade*. MIT Press, Cambridge.

Glaeser, E. L., B. Sacerdote, and J. A. Scheinkman (1996): "Crime and Social Interactions," *Journal of Political Economy*, 111, 507?548.

Glennerster, H., J. Hills, D. Piachaud, and J. Webb (2004): *One Hundred Years of Poverty and Policy*. Jospeh Rowntree Foundation, York.

Holland, J. (2012): *The Battle of Britain: Five Months That Changed History; May-October 1940*. St. Martin's Griffin.

Hornbeck, R. (2012): "The Enduring Impact of the American Dust Bowl: Short- and Long-run Adjustments to Environmental Catastrophe," *American Economic Review*, 102(4), 1477–1507.

Hornbeck, R., and D. Keniston (2012): "Great Fires: Disasters, Spillovers, and Urban Growth in 19th Century America," *NBER Working Paper*, 20467.

Ioannides, Y. (2013): *From Neighborhoods to Nations*. Princeton University Press, Princeton.

Irons, R. (2003): *Hitler's Terror Weapons: The Price of Vengeance*. Harper Collins, New York.

Jackson, J. (2004): *The Fall of France: The Nazi Invasion of 1940*. Oxford University Press, Oxford.

Johnson, D. (1981): *V-1 V-2: Hitler's Vengeance on London*. Stein and Day, New York.

Kline, P., and E. Moretti (2014a): "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority," *Quarterly Journal of Economics*, 129(1), 275–331.

——— (2014b): "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs," *Annual Review of Economics*, 6(1), 629–662.

Kocornik-Mina, A., T. McDermott, G. Michaels, and F. Rauch (2014): "Flooded Cities," London School of Economics, mimeograph.

Koster, H. R. A., J. Van Ommeren, and P. Rietveld (2011): "Bombs, Boundaries and Buildings: A Regression Discontinuity Approach to Measure the Costs of Housing Supply Restrictions," VU University, Amsterdam.

Lee, S., and J. Lin (2015): "Natural Amenities, Neighborhood Dynamics, and Persistence in Spatial Income Distribution within Cities," *Review of Economic Studies*, forthcoming.

London School of Economics and Political Science (1930): *The New Survey of London Life and Labour*. P. S. King and Son Ltd, London.

Lucas, R. E., and E. Rossi-Hansberg (2002): "On the Internal Structure of Cities," *Econometrica*, 70(4), 1445–1476.

Mckinstry, L. (2014): *Operation Sea Lion*. The Overlook Press, London.

Miguel, E., and G. Roland (2011): "The Long Run Impact of Bombing Vietnam," *Journal of Development Economics*, 96(1), 1–15.

Monte, Ferdinando, S. R., and E. Rossi-Hansberg (2015): "Commuting, Migration and Local Employment Elasticities," *NBER Working Paper*, 21706.

Moretti, E. (2004): "Human Capital Externalities in Cities," in *Handbook of Regional and Urban Economics*, ed. by J. V. Henderson, and J. Thisse, vol. 4, pp. 2244–2289. Elsevier North Holland, Amsterdam.

Neumark, D., and H. Simpson (2014): "Place-based Policies," in *Handbook of Regional and Urban Economics*, ed. by J. V. Henderson, and J.-F. Thisse, vol. 4, chap. 18, pp. 1197–1288. Elsevier, Amsterdam.

Rauch, J. E. (1993): "Productivity Gains from Geographic Concentration of Human Capital," *Journal of Urban Economics*, 34(3), 380–400.

Ray, J. (2004): *The Night Blitz: 1940-1941*. Booksales.

Redding, S. J. (2012): "Goods Trade, Factor Mobility and Welfare," *NBER Working Paper*, 18008.

Redding, S. J., and D. M. Sturm (2008): "The Costs of Remoteness: Evidence from German Division and Reunification," *American Economic Review*, 98(5), 1766–1797.

Redding, S. J., D. M. Sturm, and N. Wolf (2011): "History and Industry Location: Evidence from German Airports," *Review of Economics and Statistics*, 93(3), 814–831.

Rosenthal, S. S., and W. C. Strange (2004): "Evidence on the Nature and Sources of Agglomeration Economics," in *Handbook of Regional and Urban Economics*, ed. by J. V. Henderson, and J. Thisse, vol. 4, chap. 49. Elsevier North Holland, Amsterdam.

Rossi-Hansberg, E., P.-D. Sarte, and R. I. Owens (2010): "Housing Externalities," *Journal of Political Economy*, 118(3), 485–535.

Sampson, R. J. (2012): *Great American City: Chicago and the Enduring Neighborhood Effect*. University of Chicago, Chicago.

Saunders, A. (2005): *London County Council Bomb Damage Maps 1939-45*. London Topographical Society, London.

Siodla, J. (2015): "Razing San Francisco: The 1906 Disaster as a Natural Experiment in Urban Redevelopment," *Journal of Urban Economics*, forthcoming.

A Proof of Proposition 1

Proof. In the special case with no neighborhood effects ($\Lambda_{nt}^s(\xi_{nt}^s) = 1$ for all n, s, t), the probability that re-developed land is allocated to each use is time-invariant:

$$\lambda_n^s = \frac{(Q^s)^\epsilon a_n^s}{\sum_{r=0}^S (Q^r)^\epsilon a_n^r}. \tag{24}$$

Setting $\dot{\xi}_{nt}^s = 0$ and $\lambda_{nt}^s = \lambda_n^s$ in the system of differential equations (19), the steady-state equilibrium allocation of land plots to each use is given by:

$$\xi_n^{s*} = \lambda_n^s. \tag{25}$$

Using the time-invariant probability that re-developed land is allocated to each use ($\lambda_{nt}^s = \lambda_n^s$), the system of differential equations (19) has the following general solution:

$$\xi_{nt}^s = [\xi_{n0}^s - \lambda_n^s]\, e^{-\delta t} + \lambda_n^s. \tag{26}$$

Therefore land allocation within each neighborhood converges monotonically from its initial condition (ξ_{n0}^s) to the steady-state allocation (ξ_n^{s*}). Note that the general solution (26) satisfies the requirement that the land market clear at each point in time, namely $\sum_{s=0}^S \xi_{nt}^s = 1$ for all t, since $\sum_{s=0}^S \xi_{n0}^s = 1$ and $\sum_{s=0}^S \lambda_n^s = 1$. ■

B Proof of Proposition 2

Proof. To establish the dependence of the steady-state equilibrium land allocation (ξ_n^{s*}) on the initial land allocation (ξ_{n0}^s), consider the following example.

(I) First, suppose that the initial land allocation (ξ_{n0}^s) is below the threshold ($\bar{\xi}^s$) for all land uses $s \in \{1, \ldots, S\}$

but above this threshold for land use $s = 0$. Consider the following candidate equilibrium evolution of land use over time. The probability that land is redeveloped takes the following time-invariant value:

$$\lambda_n^{s*} = \frac{(Q^s)^\epsilon \, a_n^s \Lambda_{nH}^s}{(Q^0)^\epsilon \, a_n^0 \Lambda_{nH}^0 + \sum_{r=1}^{S} (Q^r)^\epsilon \, a_n^r \Lambda_{nL}^r}, \qquad \text{for } s = 0. \tag{27}$$

$$\lambda_n^{s*} = \frac{(Q^s)^\epsilon \, a_n^s \Lambda_{nL}^s}{(Q^0)^\epsilon \, a_n^0 \Lambda_{nH}^0 + \sum_{r=1}^{S} (Q^r)^\epsilon \, a_n^r \Lambda_{nL}^r}, \qquad \text{for } s \in \{1, \ldots, S\}. \tag{28}$$

Setting $\dot{\xi}_{nt}^s = 0$ and $\lambda_{nt}^s = \lambda_n^{s*}$ in the system of differential equations (19), the candidate steady-state equilibrium allocation of land plots to each use is given by:

$$\xi_n^{s*} = \lambda_n^{s*}. \tag{29}$$

Using the candidate equilibrium probabilities that re-developed land is allocated to each use in (27)-(28), the system of differential equations (19) has the following candidate general solution:

$$\xi_{nt}^s = [\xi_{n0}^s - \lambda_n^{s*}] \, e^{-\delta t} + \lambda_n^{s*}. \tag{30}$$

A sufficient condition for (27)-(30) to constitute an equilibrium is that $\lambda_n^{0*} \geq \bar{\xi}^0$ in equation (27) and $\lambda_n^{s*} < \bar{\xi}^s$ for $s \in \{1, \ldots, S\}$ in equation (28). In this case, commercial land use is the high neighborhood effect activity ($\Lambda_{nt}^0 = \Lambda_{nH}^0$) in the initial allocation, along the transition path, and in the steady-state equilibrium. In contrast, each of the residential land uses are low neighborhood effect activities ($\Lambda_{nt}^s = \Lambda_{nL}^s$ for $s \in \{1, \ldots, S\}$) in the initial allocation, along the transition path, and in the steady-state equilibrium.

(II) Second, suppose that the initial land allocation (ξ_{n0}^s) is below the threshold ($\bar{\xi}^s$) for all land uses $s \in \{0, \ldots, S\}$. Consider the following candidate equilibrium evolution of land use over time. The probability that land is redeveloped takes the following time-invariant value:

$$\lambda_n^{s*} = \frac{(Q^s)^\epsilon \, a_n^s \Lambda_{nL}^s}{\sum_{r=0}^{S} (Q^r)^\epsilon \, a_n^r \Lambda_{nL}^r}, \qquad \text{for all } s. \tag{31}$$

Setting $\dot{\xi}_{nt}^s = 0$ and $\lambda_{nt}^s = \lambda_n^{s*}$ in the system of differential equations (19), the candidate steady-state equilibrium allocation of land plots to each use is given by:

$$\xi_n^{s*} = \lambda_n^{s*}. \tag{32}$$

Using the candidate equilibrium probability that re-developed land is allocated to each use (31), the system of differential equations (19) has the following candidate general solution:

$$\xi_{nt}^s = [\xi_{n0}^s - \lambda_n^{s*}] \, e^{-\delta t} + \lambda_n^{s*}. \tag{33}$$

A sufficient condition for (31)-(33) to constitute an equilibrium is that $\lambda_n^{s*} < \bar{\xi}^s$ for all s in (31). In this case, all uses of land are low neighborhood effect activities ($\Lambda_{nt}^s = \Lambda_{nL}^s$ for all s) in the initial allocation, along the transition path, and in the steady-state equilibrium.

Finally, both sets of sufficient conditions for equilibrium in **(I)-(II)** above can be satisfied simultaneously if Λ_{nH}^s is sufficiently large relative to Λ_{nL}^s. Thus we have established that the steady-state equilibrium land allocation can depend on the initial land allocation. ■

Figure 1: Excerpt of London County Council (LCC) Bomb Damage Map for Marylebone

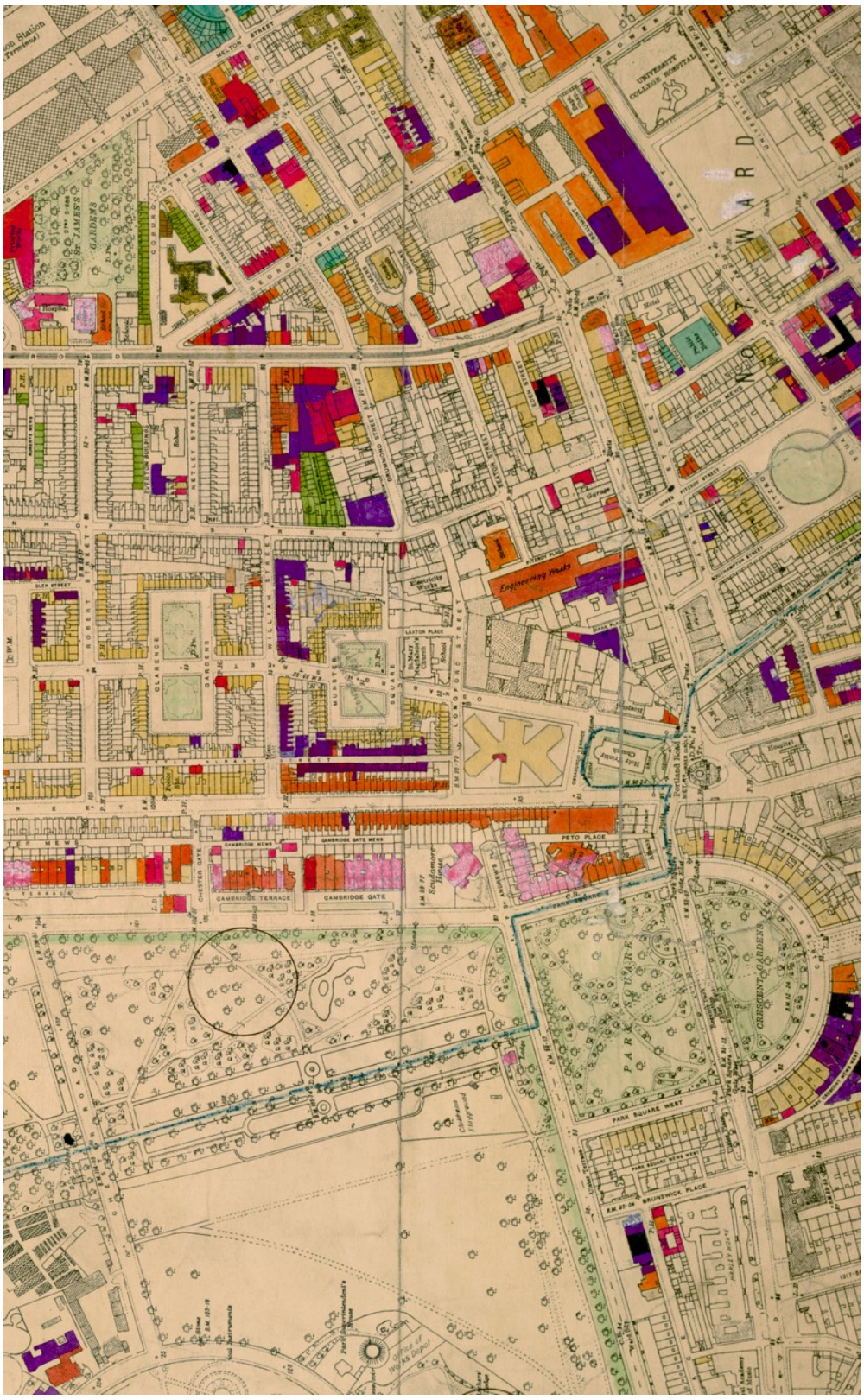

Figure 2: Excerpt from Booth (1891) Street Map, Sheet 4 (Marylebone)

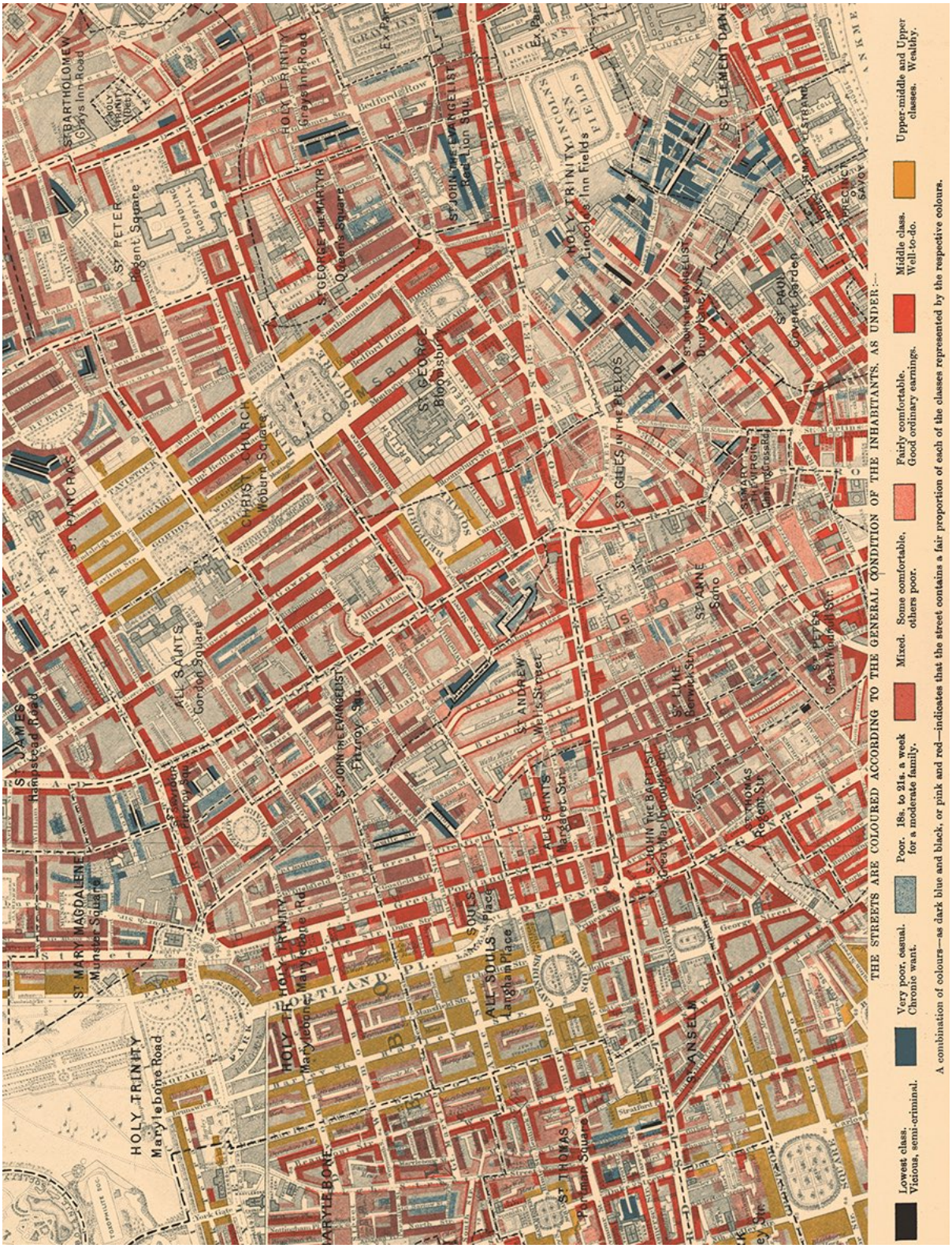

Figure 3: Excerpt from New London Survey (1930) Street Map, Sheet 8 (Inner North West)

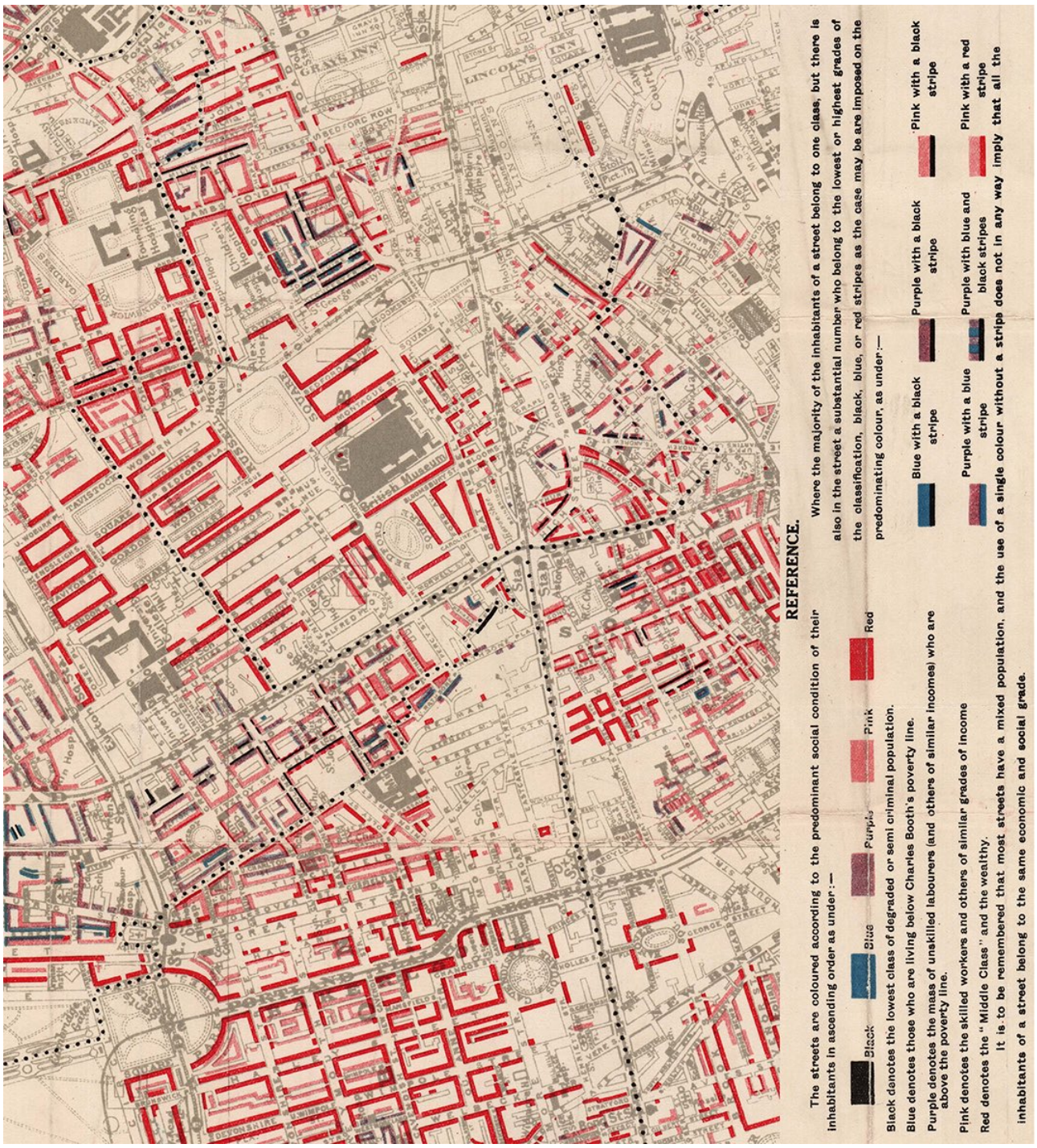

Figure 4: War-time Damage in London County

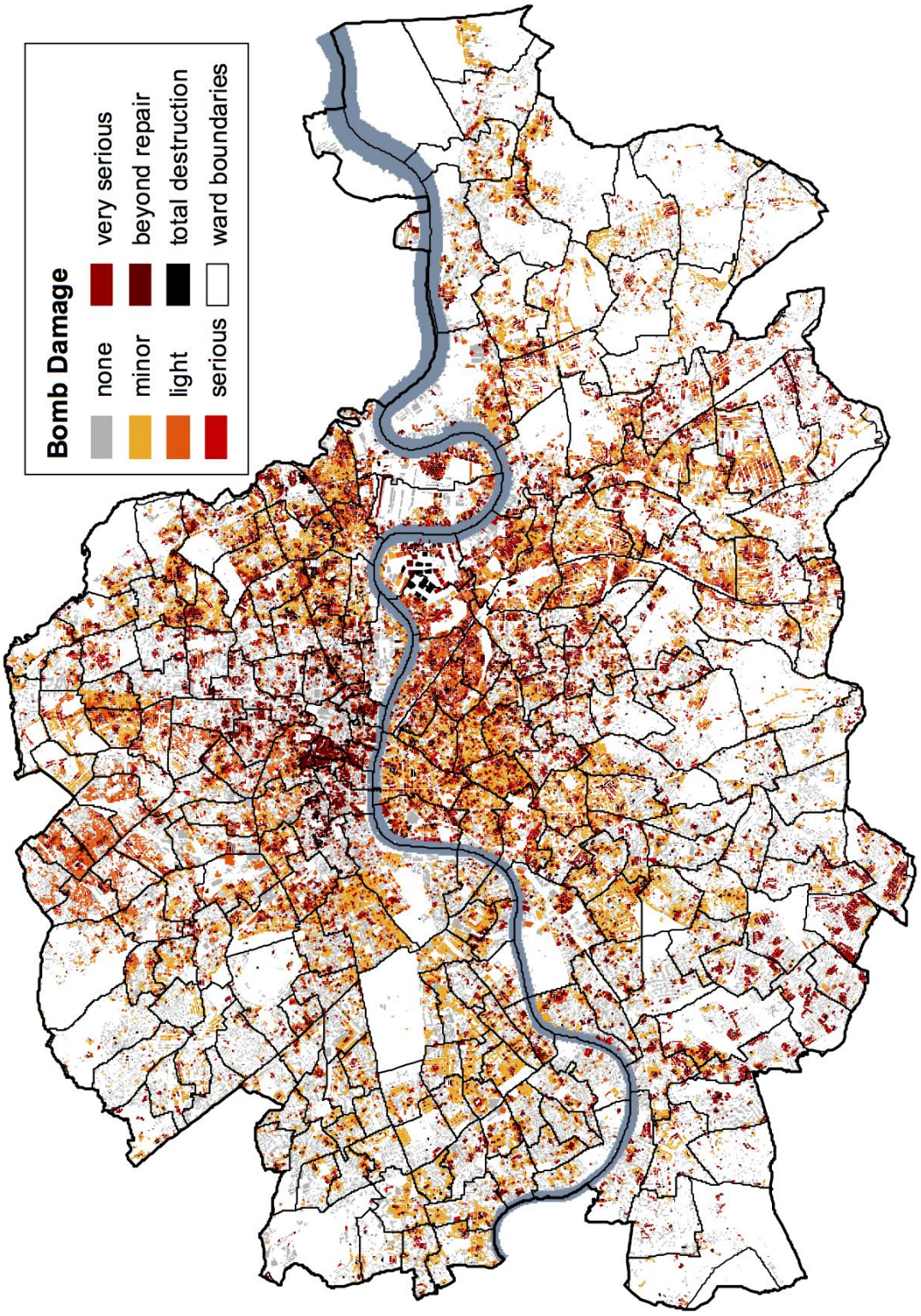

Figure 5: V1 and V2 Impacts in London County

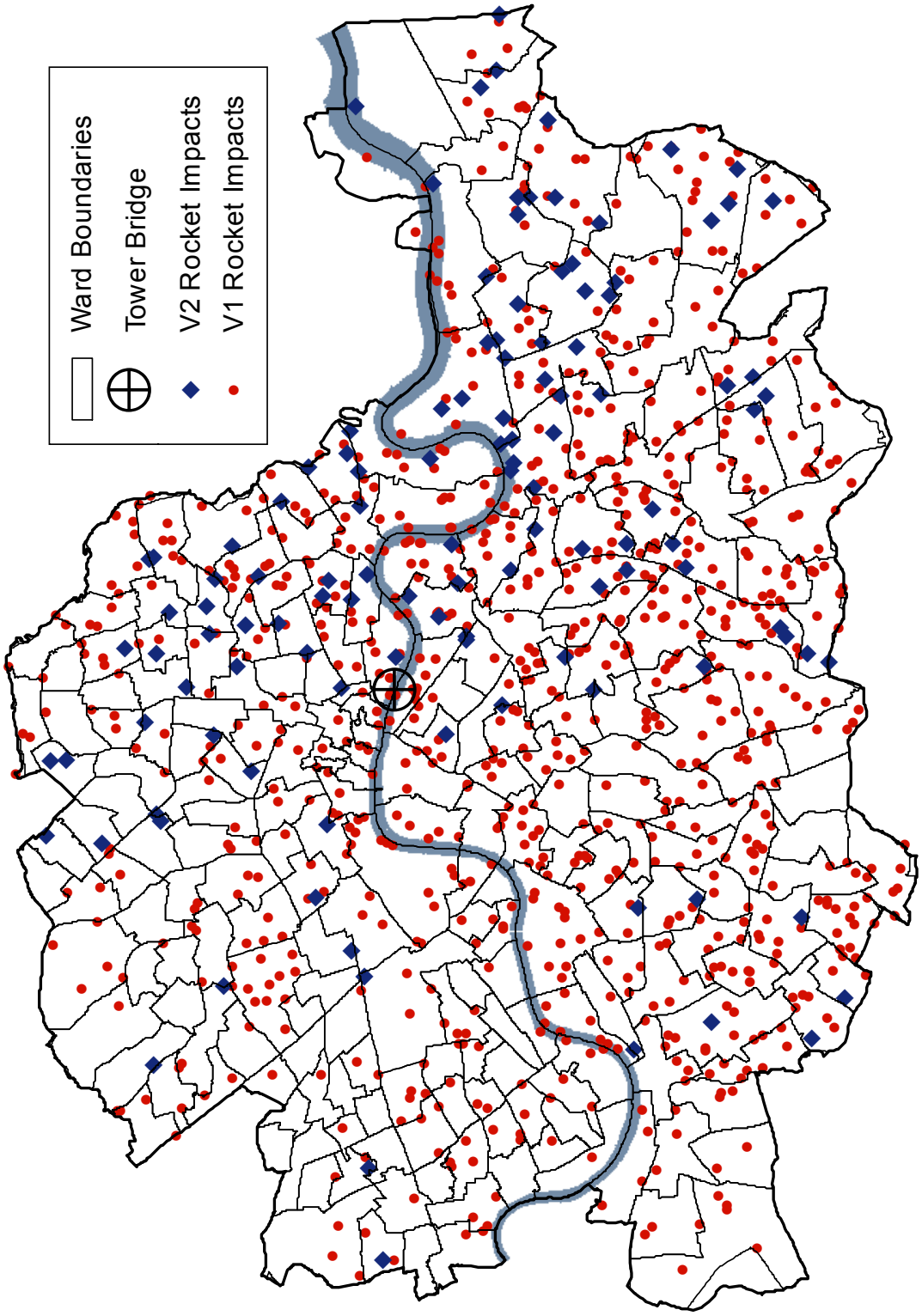

Figure 6: Linear Index of Socioeconomic Status for each Output Area

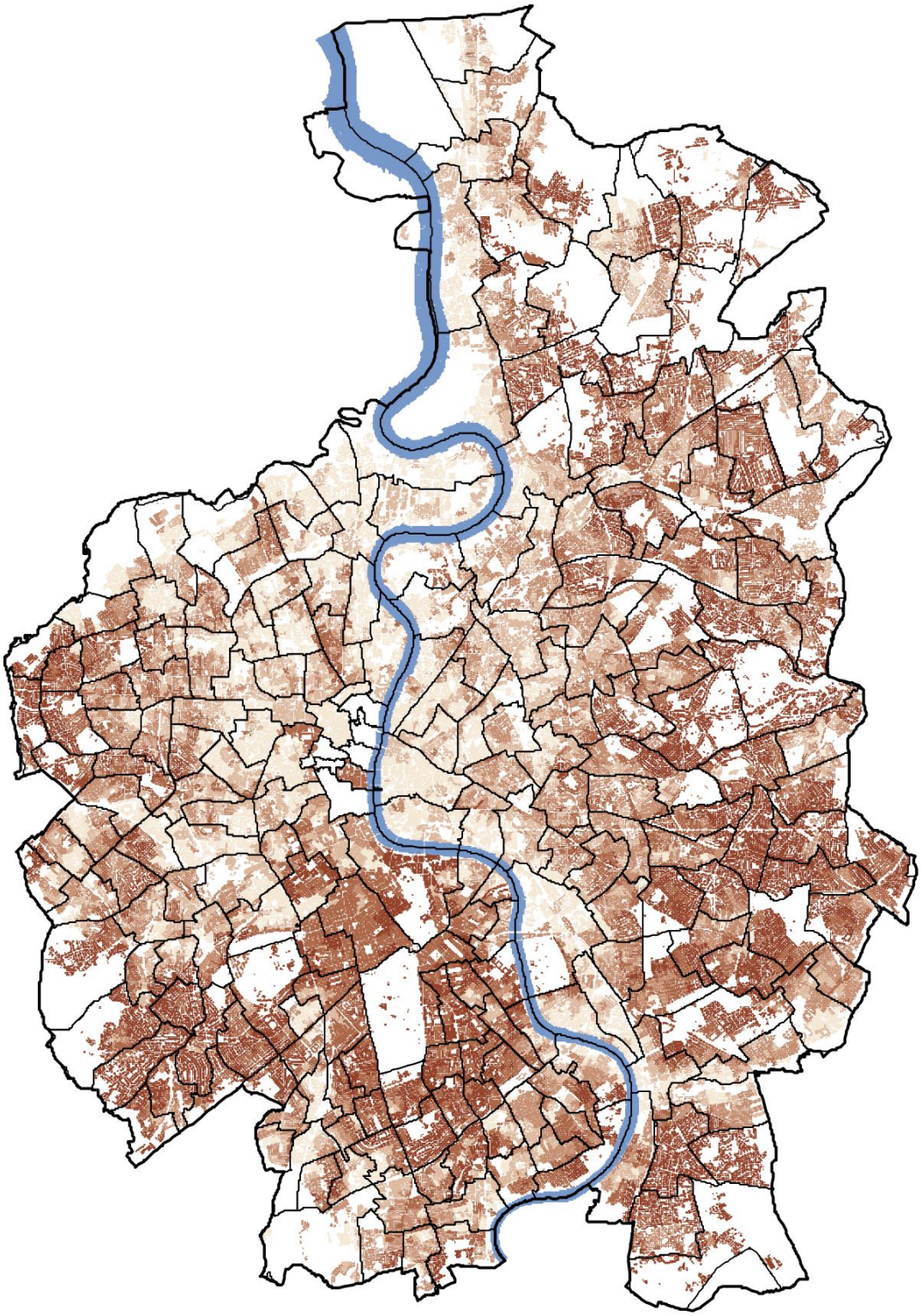

Figure 7: Example of 100 meter Buffers around an Output Area

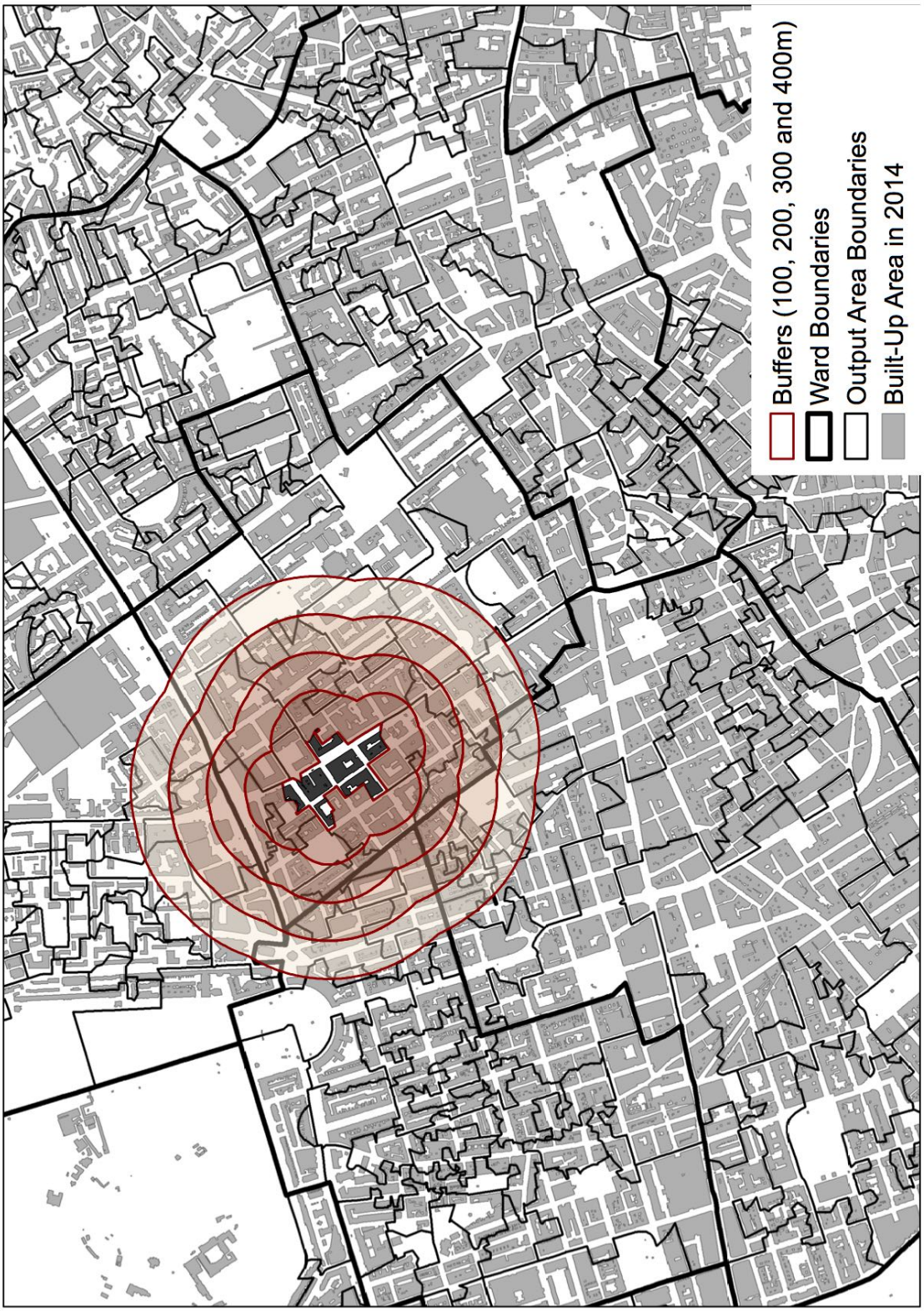

Table 1: Percentage of Streets in Each Category of Socio-economic Status

Socio-economic Status	Map Color	Description	Percent
Booth 1890			
Poor	Black	Lowest class. Vicious, semi-criminal	3.1%
	Blue	Very poor. Casual, chronic want	
Middle	Light blue	18-21s a week for a moderate family	65.2%
	Dark red	Mixed. Some comfortable, others poor	
	Soft red	Fairly comfortable. Good ordinary earnings	
Rich	Red	Middle class. Well-to-do	31.8%
	Yellow	Upper middle and upper classes. Wealthy	
NSOL 1930			
Poor	Black	Lowest class. Degraded, semi criminal	3.0%
	Blue	Below Charles Booth's poverty line	
Middle	Purple	Unskilled laborers. Above poverty line	66.9%
	Pink	Skilled workers	
Rich	Red	Middle class	30.1%

Measure of Destruction	Type of fixed effect included	(1) Fraction rich streets	(2) Fraction middle income streets	(3) Fraction poor streets	(4) Index of social status
Fraction houses seriously damaged	None	-0.284***	0.245***	0.038***	-25.46***
		(0.042)	(0.039)	(0.009)	(3.58)
	Districts (29)	-0.100***	0.098***	0.002	-9.22***
		(0.028)	(0.027)	(0.008)	(2.40)
	Wards (226)	-0.023	0.032	-0.009	-1.99
		(0.020)	(0.021)	(0.008)	(1.74)
Index of damage	None	-0.410***	0.357***	0.052***	-35.22***
		(0.057)	(0.054)	(0.013)	(4.79)
	Districts (29)	-0.128***	0.129***	-0.001	-10.65***
		(0.039)	(0.038)	(0.012)	(3.29)
	Wards (226)	-0.029	0.046	-0.017	-1.64
		(0.027)	(0.028)	(0.012)	(2.45)

Note: Each cell reports the results of a separate regression of a measure of social status from the New Survey of London (fraction of rich, middle income and poor streets and an index of social status) on a measure of destruction (percentage of houses seriously damaged and a damage index) from the London Bomb Damage Maps. The damage index is a linear combination of the different levels of damage. Percentiles of social status are based on ranking output areas according to a linear combination of the fraction of streets in each social class within them. Each specification includes different levels of spatial fixed effects as indicated in the second column. See the main text for more detail. Each regression has 8202 observations. Standard errors are clustered at the level of the ward. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: The Impact of Destruction on House Prices 1995-2015

Measure of Destruction	Type of fixed effect included	(1) Logarithm of house prices 1995 - 2000	(2) Logarithm of house prices 2000 - 2005	(3) Logarithm of house prices 2005 - 2010	(4) Logarithm of house prices 2010 - 2015	(5) Logarithm of house prices 1995 - 2015
Fraction houses seriously damaged	None	-0.487***	-0.410***	-0.405***	-0.484***	-0.436***
		(0.064)	(0.057)	(0.058)	(0.068)	(0.061)
	Districts (29)	-0.137***	-0.115***	-0.111***	-0.126***	-0.118***
		(0.032)	(0.026)	(0.026)	(0.030)	(0.028)
	Wards (231)	-0.122***	-0.108***	-0.107***	-0.118***	-0.106***
		(0.023)	(0.019)	(0.018)	(0.021)	(0.020)
Index of damage	None	-0.602***	-0.518***	-0.511***	-0.606***	-0.550***
		(0.086)	(0.077)	(0.078)	(0.091)	(0.082)
	Districts (29)	-0.145**	-0.125**	-0.121**	-0.131**	-0.128**
		(0.043)	(0.035)	(0.035)	(0.042)	(0.038)
	Wards (231)	-0.148***	-0.135***	-0.132***	-0.139***	-0.130***
		(0.031)	(0.025)	(0.026)	(0.030)	(0.027)

Note: Each cell reports the results of a separate regression of the logarithm of average house prices in each 2001 output area for different time periods (calculated on the basis of transactions data from the UK Land Registry) on a measure of destruction (percentage of houses seriously damaged and a damage index). Each specifications includes a different level of spatial fixed effects as indicated in the second column. The damage index is a linear combination of the different levels of damage. See the main text for more detail. Each regression has between 8092 and 8495 observations, depending on house price availability. Standard errors are clustered at the ward level. * significant at 10%; ** significant at 5%; *** significant at 1%.

	(1) Logarithm of house prices 1995 - 2015	(2) Logarithm of house prices 1995 - 2015	(3) Logarithm of house prices 1995 - 2015	(4) Logarithm of house prices 1995 - 2015	(5) Logarithm of house prices 1995 - 2015
Destruction in own spatial unit	-0.105***	-0.073***	-0.079***	-0.079***	-0.079***
	(0.020)	(0.017)	(0.018)	(0.018)	(0.018)
Destruction in 0-100 meter buffer		-0.112**	-0.077**	-0.083**	-0.083**
		(0.043)	(0.037)	(0.038)	(0.038)
Destruction in 100-200 meter buffer			-0.102*	-0.082*	-0.080
			(0.053)	(0.049)	(0.050)
Destruction in 200-300 meter buffer				-0.052	-0.061
				(0.062)	(0.052)
Destruction in 300-400 meter buffer					0.025
					(0.067)
Fixed effects	Ward	Ward	Ward	Ward	Ward
Observations	8494	8494	8494	8494	8494
R-squared	0.775	0.775	0.775	0.775	0.775

Note: Each column reports a different regression. The dependent variable is the logarithm of average house prices in each 2001 output area (calculated on the basis of transactions data from the UK Land Registry). The explanatory variable is a measure of destruction (percentage of houses seriously damaged) in each 2001 output area and buffers of 100 meter width around each output area. Standard errors are clustered at the ward level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Social Composition of Neighbourhoods in 2001 Census

	(1) Index of social status	(2) Index of social status	(3) Index of social status	(4) Index of social status	(5) Index of social status
Destruction in own spatial unit	-14.04***	-10.89***	-11.46***	-11.43***	-11.42***
	(1.96)	(1.63)	(1.68)	(1.68)	(1.68)
Destruction in 0-100 meter buffer		-11.05***	-8.02**	-8.40**	-8.40**
		(3.88)	(3.28)	(3.40)	(3.40)
Destruction in 100-200 meter buffer			-8.96*	-7.59*	-7.34*
			(4.60)	(4.20)	(4.28)
Destruction in 200-300 meter buffer				-3.58	-4.59
				(5.40)	(4.77)
Destruction in 300-400 meter buffer					2.77
					(5.80)
Fixed Effects	Ward	Ward	Ward	Ward	Ward
Observations	8625	8625	8625	8625	8625
R-squared	0.473	0.474	0.474	0.474	0.474

Note: Each column reports the results of a separate regression. The dependent variable is a linear index of social status for each 2001 output area constructed using 2001 census data on occupations. See the main text for details. The explanatory variable is a measure of destruction (percentage of houses seriously damaged) in each 2001 output area and buffers of 100 meter width around each output area. Standard errors are clustered at the ward level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Further Results on Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fraction of non-white population	Fraction of non-white population	Fraction living in social housing	Fraction living in social housing	Fraction of post-war houses	Fraction of post-war houses	Average height of buildings	Average height of buildings
Destruction in own spatial unit	0.075***	0.057***	0.153***	0.139***	0.295***	0.301***	0.773***	0.873***
	(0.011)	(0.010)	(0.021)	(0.017)	(0.024)	(0.023)	(0.291)	(0.315)
Destruction in 0-100 meter buffer		0.063***		0.041		-0.012		-0.508
		(0.019)		(0.038)		(0.044)		(0.609)
Destruction in 100-200 meter buffer		0.006		0.049		-0.090		0.822
		(0.024)		(0.043)		(0.057)		(1.020)
Destruction in 200-300 meter buffer		0.047*		-0.020		0.063		-0.572
		(0.026)		(0.047)		(0.060)		(0.849)
Destruction in 300-400 meter buffer		-0.011		-0.037		-0.131*		-0.910
		(0.028)		(0.052)		(0.068)		(1.225)
Fixed effects	Ward	Ward	Ward	Ward	Ward	Ward	Ward	Ward
Observations	8625	8625	8625	8625	8625	8625	8625	8625
R-squared	0.517	0.519	0.371	0.372	0.391	0.392	0.319	0.320

Note: Each column reports the results of a separate regression. The dependent variable in columns (1) and (2) is the fraction of people in each 2001 output area who report their ethnic background as non-white; in columns (3) and (4) it is the fraction of people living in accommodation provided by the local council; in columns (5) and (6) it is the fraction of 2014 houses that did not exist with the same footprint in the 1930s; in columns (7) and (8) it is the average height of buildings in 2014 in meters. The explanatory variable is a measure of destruction (percentage of houses seriously damaged) in each 2001 output area and buffers of 100 meter width around each output area. Standard errors are clustered at the ward level. * significant at 10%; ** significant at 5%; *** significant at 1%.