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Research Paper

The impact of public transportation and commuting on urban labor markets: Evidence from the *New Survey of London Life and Labour*, 1929–1932

Andrew J. Seltzer[a,*], Jonathan Wadsworth[b]

[a] Royal Holloway, LSE, IZA, UK
[b] Royal Holloway, CEP, IZA, LOWER, UK

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ABSTRACT

The growth of public transport networks in the late-nineteenth and early-twentieth centuries had profound effects on commuting in the industrialized world, yet the consequences for labor markets during this important period of historical development remains largely unstudied. This paper draws on a unique dataset combining individual commuting and wage information for working-class residents of London, circa 1930, to analyze, for the first time, the nature of and returns to commuting shortly after when networks were first built. A sizeable majority of working-class Londoners worked within a short walk of their residence in 1890. By 1930, over 70 percent commuted at least one kilometer. Commuting allowed workers to search for jobs over a wider geographic area and across a larger number of potential employers. This, in turn, potentially increased workers' bargaining power and improved employer-employee matching. We show that wage returns to commuting were on the order of 1.5–3.5 percent per kilometer travelled. Access to public transport increased both the probability of commuting and distance commuted but had little or no direct effect on the probability of being employed or on earnings. We argue that these results are consistent with a search and matching framework; commuting led to workers finding jobs more suited to their skills and to better matches with employers. We also provide descriptive evidence from contemporary sources to describe the impact of commuting on improving quality of life by reducing urban crowding.

1. Introduction

Did near-universal access to low-cost public transport have consequences for the efficiency of working-class labor markets? At the end of the nineteenth century, low-cost bus, tram, and subway networks began to appear throughout the industrialized world. By the early-twentieth century the widespread adoption of these urban transport networks meant that many workers were travelling distances to work that would have seemed unthinkable to their counterparts one or two generations earlier. Despite the scale of this change, the economic determinants of commuting and, importantly, the rewards for commuting during this important period of history have not yet been addressed. This paper draws on a unique dataset combining individual commuting and wage information for working-class residents of London, circa 1930, to analyze this issue. So, for the first time, we can obtain a sense of the nature of and returns to

* Corresponding author.
E-mail address: a.seltzer@rhul.ac.uk (A.J. Seltzer).

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working-class commuting in an important period of historical development.

Urban and labor economists have long recognized that public transport and commuting have the potential to transform labor markets. Competitive theory suggests that identical workers would be paid identical wages regardless of commute – or that unobserved worker attributes underlie any difference in earnings. However, it also allows for the possibility that employers could pay higher wages as a compensating differential to attract workers into a central business district or a remote location (Gibbons and Machin, 2006). Other models suggest that commuters or those with the ability to commute will be paid more than local workers. Search theory emphasizes that productivity often depends on the specific match between workers and firms (Mortensen and Pissarides, 1994; Rogerson et al., 2005). Public transport reduces the travel cost for employees and thus allows them to search across and commute to more potential employers, leading to better matches between workers and firms (Gibbons and Machin, 2006). Manning (2003b) suggests that the number of acceptable job offers may rise with distance commuted, generating a positive relationship between distance commuted and wages. Improved public transport may also reduce employers' monopsony power (Bhaskar and To, 1999; Bhaskar et al., 2002; Manning, 2003a). Workers may be willing to accept lower wages to avoid the disutility of longer commuting time. As such, travel costs create a wedge between net wages (wages minus commuting costs) earned at local and distant employment. This wedge may give employers local monopsony power, as workers' threat to switch employers is constrained by their commuting costs. Monopsony power may also derive from differentiated worker preferences over non-wage attributes across employers. Employers who need large numbers of workers, particularly non-local workers, will need to offer higher wages. High-speed, low-cost public transport reduces employers' monopsony power by increasing workers' outside options, e.g., reducing the cost of commuting to more distant positions.

Prior to the development of high-speed, low-cost transport, virtually all workers lived near their place of work (Heblich et al., 2020). Nineteenth century observers and subsequent economic historians have noted that this created a major crowding problem in larger urban areas (Booth, 1902; Steckel, 1995). From the mid-nineteenth century, the development of railway networks meant that it was increasingly possible for wealthier workers to live away from their place of work and commute. The subsequent development of bus, tram, and underground networks in the early-twentieth century made regular travel between inner-city locations feasible for a larger fraction of the working population. As a result, commuting became increasingly common (Ponsonby and Ruck, 1930).

At the time of our study, London had among the most extensive public transport systems in the world (London Transport Museum, 2020). As we show below, by 1930 virtually everyone residing within 15 kms of the city center lived within a few hundred meters of public transport. Moreover, a modest-distance commute cost only a small share of typical working-class earnings. Although London was an early adaptor of public transport, it was hardly unique in having public transport networks by 1930. Virtually all major population centers in the UK also had some sort of public transport network by the early-twentieth century. Major cities worldwide also developed extensive rail, tram, and bus networks around this time, with the largest cities (New York, Chicago, Boston, Buenos Aires, Madrid, Paris, Tokyo, and Berlin) also having extensive underground networks.

To explore the consequences of comprehensive low-cost public transport networks on working-class labor markets, we construct a unique GIS-based commuting data set using the individual responses contained in the publicly available N*ew Survey of London Life and Labour* (henceforth *New Survey* or NSLLL). The *New Survey,* conducted between 1928 and 1932, contains approximately two percent of working-class households in 29 London Metropolitan Boroughs and 9 adjacent Municipal and County Boroughs. Crucially for our purposes, the data combine individual wages and two important indicators of commuting: 1) weekly expenditures on work-related travel and 2) residential and work addresses, a combination rarely seen even in modern survey datasets. We generate GIS co-ordinates for each unique street or place name in the sample and for the rail, Underground, tram, and bus network of the entire London metropolis. We use this to calculate crow-flies distances between residence, workplace, public transport, and two central points – the Bank of England and Charing Cross Station.

We show that commuting moderate distances was common at the time; the mean one-way commuting distance was about three kilometers and over 70 percent of workers commuted at least one kilometer. We use the distance variables to examine the returns to commuting; running Mincer-type regressions on labor force status and earnings, with distance commuted, distance to public transport, and distance to the center included as independent variables. A naïve OLS regression of the effect of commuting distance on earnings is likely to suffer from bias caused by reverse causality, as workers had a degree of choice over both where to work and where to live. We address this using three separate identification strategies: first, restricting our sample to individuals for whom residence was plausibly exogenous; second, introducing fixed effects that control for unobserved heterogeneity at the household level; and, third, instrumenting distance commuted with the distance between birthplace and the center of London.

We find that the probability of employment was higher for individuals residing closer to the center but was not affected by proximity to public transport. We also find that a one-kilometer increase in distance commuted increased earnings by about 1.5 to 2.0 percent in the OLS and fixed effects specifications and 3.0 to 3.5 percent in the IV specifications. These estimated effects are robust to the inclusion of workplace fixed effects but decline (although not to zero) as we introduce finer-grained controls for occupation. We interpret this as consistent with a search and matching framework.

Finally, we offer some thoughts on the broader implications of commuting. Using descriptive evidence from the earlier *Life and Labour of the People of London* (henceforth LLPL) of 1886–1903, we show that increased commuting distances increased earnings by about 4.1 – 9.4 percent between the 1890s and 1930s. Commuting also facilitated movement away from the center into outlying areas which had lower population densities and larger dwellings.

The results from this paper provide new insights into improvements in quality of life in the early twentieth century. It has long been recognized that both GDP per capita and income per worker were increasing, albeit slowly, in early-twentieth century Britain, despite a sharp decline in hours worked after the First World War (Maddison, 1964; Crafts, 2021; Huberman and Minns, 2007). Clark (2020) calculates real earnings increased by 35.6 percent over the period 1895–1930. Similarly, Crafts (2021) estimates British GDP per capita increased by 0.84 percent per annum over the period 1899–1913 and 0.70 percent per annum over the period 1924–37. Crafts' estimates suggest that TFP (total factor productivity) growth accounts for about half of all growth in 1899–1913 and more than 100 percent of growth in 1924–37. TFP growth is estimated as a residual in the growth accounting framework, and thus its sources are something of a "black box". Typically, within-country TFP growth is attributed to technological progress and increases in the level of human capital (Benhabib and Spiegel, 2005). The results from this paper suggest another important source of historical TFP growth, namely the improvements in the ability of workers to commute resulted in better employer/employee matching and thus increased the utilization of existing human capital. Our finding of a commuting wage premium of 1.5–3.3 percent per kilometer travelled implies that a substantial share of increased worker productivity and earnings between 1890 and 1930 resulted from this mechanism.

Our results also speak to a second literature on improved living standards, namely improved health and life expectancy in the early twentieth century (Crafts, 1997; Hatton and Martin, 2010). In the nineteenth century, a large share of urban mortality can be attributed to diseases that were caused or exacerbated by crowding. Hatton and Martin (2010) show that crowding within dwellings (defined by more than two people per room) was associated with shorter stature and with higher incidence of contagious diseases. Scholars have argued that the urban health penalty decreased substantially in the late nineteenth and early twentieth centuries (Kearns, 1988; Chapman, 2019). This paper suggests a hitherto largely neglected contributor to improvements in urban health, namely reduced urban overcrowding resulting from public transport systems. There were three likely mechanisms for this relationship. First, housing was a normal good and increased income due to commuting allowed workers to rent larger dwellings. Second, public transport facilitated the growth of outer suburbs where housing was cheaper and generally higher quality. Third, the population of the most crowded inner-London boroughs began to decline after the expansion of the transport network.

2. Historical background: the London metropolis and its commuting infrastructure

The *New Survey* area comprised 429.9 square kilometers in 29 Metropolitan Boroughs of the County of London and nine outer boroughs (officially County Boroughs, Municipal Boroughs, and Urban Districts) in the neighbouring counties of Surrey, Middlesex, Essex and Kent, which contained about 27 percent of the total area of what is now Greater London.[1] The 1928 population was 5686,000, approximately 72.4 percent of the total population of the London metropolis.[2] While the are no official figures on distribution of residences for working-class people, the *New Survey* area was selected specifically based on having a high working-class population (Llewellyn-Smith, 1930a, b). Within the *New Survey* area, population density tended to be highest near the center. It is also likely that the predominantly working-class areas surveyed in the *New Survey* contained much higher population densities than other areas within the same boroughs.[3]

As with most modern cities, London at that time was characterized by economies of agglomeration and a resulting industrial concentration. As we will show, working-class employment was geographically concentrated within the *New Survey* area, with the highest densities overall, then, as now, in and around the City of London. This concentration of employment in central areas implies that residential areas would also have been crowded unless workers were able to live away from their employment and commute into work.

During the early-nineteenth century, most employees worked near their residence, as travel was slow and expensive (Heblich et al., 2020). The development of the rapid public transport infrastructure needed for longer-distance commutes occurred from the mid-nineteenth through to the early-twentieth centuries. Railways were first built in London in 1836. Trams, buses, and London Underground began to follow several decades later but there did not exist comprehensive, fast, reliable, and inexpensive networks until the early-twentieth century. Table 1 shows some statistics on speed, coverage, and cost of the four modes of public transport in 1900–07, 1913, and 1929. The decline in cost per kilometer is particularly noteworthy, because, as we will show later, by 1930 commuting by public transport was well within the means of a large majority of working-class employees.

Most of the modern rail network in London was complete by the end of the nineteenth century. In 1907, the average scheduled speed for commuting trains into central London terminal stations was 32.3 kms an hour (London Statistics, 1907).[4] The availability of rail transport led to the growth of residential suburbs and outwards migration of the middle-class from the mid- to late-nineteenth century (Bowley, 1930, pp. 74–5).

Fig. 1, panel A, shows the railway network circa 1930 and the borders of the County of London and the *New Survey* area. The map shows two important features of rail travel. First, there was extensive coverage of the exterior of the metropolis. Virtually all built up

[1] Throughout this paper we refer to Metropolitan, Municipal, County Boroughs and Urban Districts as of the time of the *New Survey*, established under the London Government Act, 1899. The LGA was amended in 1963 and the Boroughs and Districts were replaced by the much larger London Boroughs which exist today.

[2] *UK Census* data, reprinted in *London Statistics* and Llewellyn-Smith (1930a).

[3] We are unaware of data on population density for geographic areas smaller than Metropolitan Boroughs. However, one of the initial reasons for undertaking both the LLPL and NSLLL was a perception of working-class crowding (Booth, 1902; Llewellyn-Smith, 1930b).

[4] *London Statistics* (1907) provides the inward speed for 20 suburban train routes which terminated at a central London station between 8:00 and 9:00 a.m. The figure of 32.3 kilometers per hour is the average across these routes, weighted by the number of trains on each route. This is similar to other estimates of rail speed.

Table 1
Public Transportation Statistics for 1900–07, 1913, and 1929.

		1900–07	1913	1929
Local and Underground railways	Route kilometers	153.2	178.0	194.1
	Train kilometers (1000,000 s)	8.06	29.7	38.8
	Passengers (1000,000 s)	214.5	474.7	648.8
	Average fare per kilometer (1930 pence)	0.71	0.61	0.49
	Average scheduled speed (in kilometers per hour)	24.1	28.8	31.1
Mainline railways	Route kilometers	903.2	898.3	859.6
	Daily trains	2097	NA	2799
	Average scheduled speed (kilometers per hour)	32.35	NA	NA
	Passengers (1000,000 s)	233	250	415
Buses	Route kilometers	482.8	751.6	1882.9
	Car kilometers (1000,000 s)	67.6	177.0	347.1
	Average scheduled speed (kilometers per hour)	8.0	13.7	15.3
	Passengers (1000,000 s)	264.5	735.7	1912.1
	Average fare per kilometer (1930 pence)	1.17	0.66	0.60
	Average seats per vehicle	23	34	50
Tramways	Kilometres of roadway	356.8	563.8	556.0
	Car kilometers (1000,000 s)	77.1	154.3	167.9
	Average scheduled speed (kilometers per hour)	NA	14.2	16.1
	Passengers (1000,000 s)	340.2	812.1	1076.3
	Average fare per kilometer (1930 pence)	0.66	0.56	0.42
	Average seats per vehicle	38	67	67

Notes: The figures for the first column are from 1900, 1905, 1906, and 1907. See Ponsonby and Ruck (1930), p. 194 for details. Figures for fares are converted into 1930 prices using O'Donoghue, et al. (2004). The reported scheduled speed for the London Underground is for the Metropolitan and District Line.
Sources: Ponsonby and Ruck (1930), p. 194 and Munby (1978), p. 537.

locations were connected to the center by rail. Second, rail commuting *across* the central areas of the metropolis was difficult, as the terminal stations of the network were built at what was the outskirts of the central area in the mid-nineteenth century and there were few direct connections between the terminal stations.[5] These two characteristics meant that rail travel was typically used for longer-distance commutes from the suburbs to the center or, less frequently, reverse commutes out from the center to industrial suburbs (Ponserby and Ruck, 1930).

Although rail commuting transformed the lives of the wealthy and middle classes, most scholars have argued that, with the exception of a small number of relatively high earners, few working-class employees commuted by rail in the nineteenth century (Ponsonby and Ruck, 1930; Dyos, 1953; Polasky, 2010). Ponsonby and Ruck (1930) argue that even around 1930, rail was a relatively infrequent mode of commuting for the working-class, typically used only for very long commutes (over 16 kms) or as a substitute for the Underground in the south and east of the metropolis.

In the early-twentieth century, new infrastructure and technology, most notably the development of the Underground network and the replacement of horse-drawn buses and trams by their motorized counterparts, reduced the cost and increased access to and the speed and reliability of travel, making it practical to commute between inner-city locations.[6] Although its first underground train line was opened in 1863, the core of the modern London Underground network was built in the early-twentieth century. The Central London Railway (the modern Central Line), Baker Street & Waterloo Railway (the Bakerloo Line), Piccadilly & Brompton Railway (the Piccadilly Line), and Charing Cross, Euston & Hampstead Railway (the Northern Line) opened in 1900, 1906, 1906, and 1907, respectively.[7] The Underground ran at similar speeds to mainline rail. However, unlike the rail network, the Underground network crossed the inner city on multiple routes, thus making it feasible to commute between most locations in the central, north, and west regions of the NSLLL area. A limiting factor on Underground usage for some was its cost, particularly for short journeys. In 1930, 58 percent of Underground journeys cost 2d or more (Ponsonby and Ruck, 1930, p. 187), although the average fare per kilometer was lower than the bus (Table 1).[8] Ponsonby and Ruck (1930) argue that circa 1930 the Underground was the primary mode of

[5] The opening of the Metropolitan Underground Line in 1863 provided limited connections between the terminal rail stations in the central areas of London. However, coverage was limited, and the cost of an additional ticket would have been beyond the means of most working-class employees in the late-nineteenth century.

[6] In addition to public transport, bicycles were an important form of transport for the working-class. Aldred (2014) argues that bicycles were relatively cheap and widely used for commuting in 1930. It is not possible to determine the exact number of workers commuting by bicycle, as the *New Survey* recorded transport expenses rather than mode of transport. Nevertheless, commuting by bicycle is specifically mentioned for 288 individuals and it is likely that many individuals with zero or missing commuting expenditures cycled to work. Private cars and motorcycles were beyond the means of almost all workers in our sample.

[7] By 1907, the routes that would become the Central, District, Metropolitan, Central, Bakerloo, Piccadilly, and Northern Lines were all largely completed. Although the outer termini of these lines would be extended between 1907 and 1930, no new lines were opened from 1907 until the opening of the Victoria Line in 1969.

[8] All prices in this paper are reported in "old" pounds sterling, where one pound (£) equals 20 shillings (s) and one shilling equals 12 pence (d).

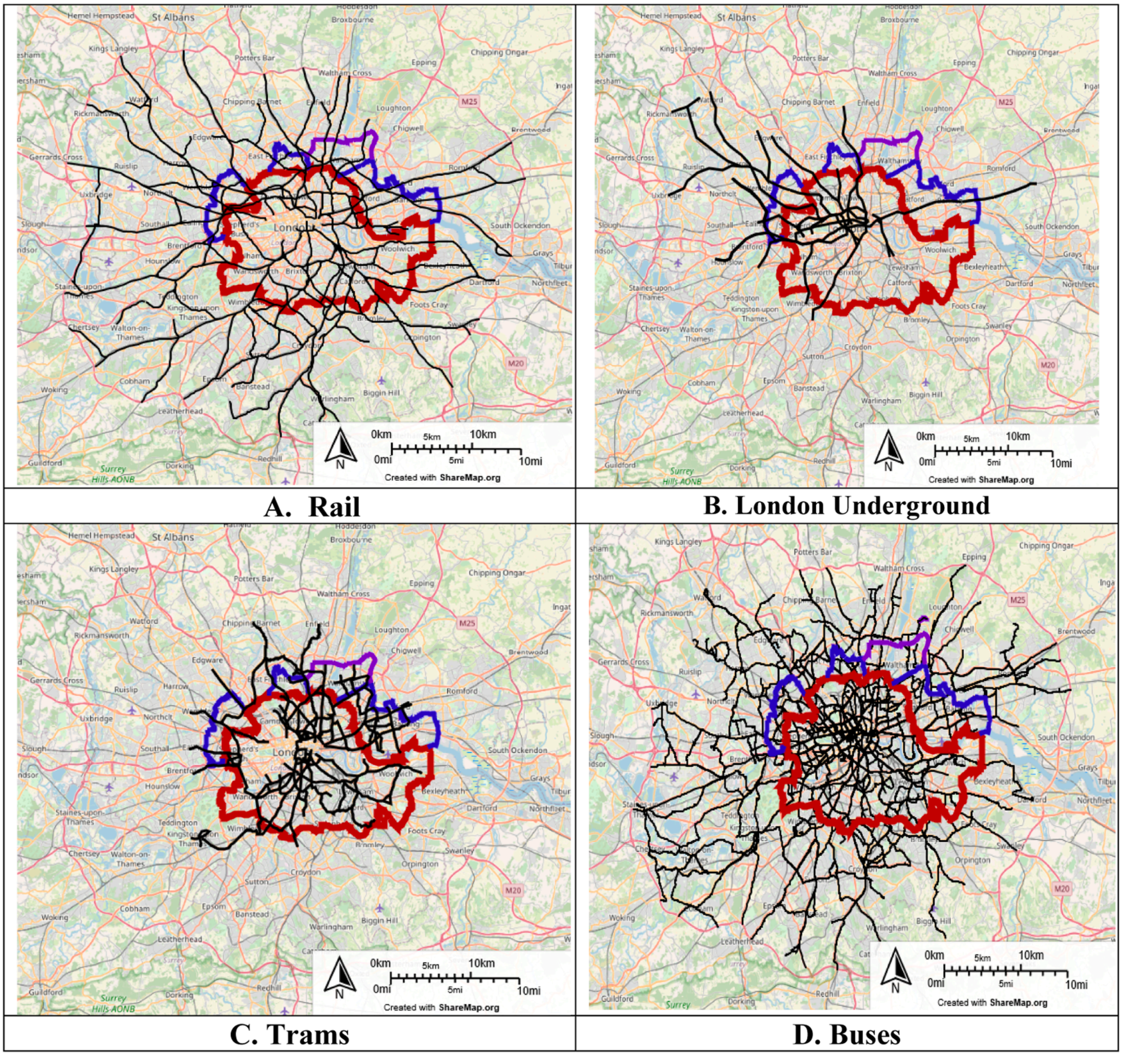

Fig. 1. Public Transport Networks, Circa 1930.

Notes: The maps show the transport networks (circa 1931) within the London metropolis (inside the modern ring road, the M25). The borders of the County of London and the *New Survey* catchment area are shown to provide scale. Scalable versions of these maps can be found at Seltzer (2020a, b, c, d).

Sources: National Library of Scotland, Map Images, https://maps.nls.uk/geo/explore/side-by-side; Omnibus Society, *Motor Omnibus Routes in London*, vol 10a, 1930–31; http://sharemap.org/public/Trams_in_London#!webgl; https://londonist.com/2016/05/the-history-of-the-tube-map.

working-class travel for distances between 3.2 and 19.3 kms.

Fig. 1, panel B shows the Underground network in 1930. Unlike the rail network, the Underground network was geographically concentrated, with over 80 percent of stations located north of the River Thames and west of the eastern boundary of the City of London. This concentration occurred for both geological and economic reasons. North of the Thames, the soil near the surface is predominantly "London clay", which is comparatively easy and inexpensive to tunnel through and is largely impermeable to water (Paul, 2016). In most areas south of the Thames, the London clay is covered by sand and silt, which is porous and difficult to tunnel through. Even today, virtually all the deep underground rail network is in areas where the London clay is near the surface. The boroughs east of the City of London were poorer than those to the west, and the Underground was generally not extended to this area, regardless of geological suitability (Heblich et al., 2021).[9] The outer parts of the metropolis, with the exception of a few wealthier areas to the north and west, were generally not serviced by the Underground because the density of traffic would not have been sufficient to justify the initial investment.

Horse-drawn omnibuses open to the public were first run in 1829 (London Transport Museum, 2020). Horse-drawn trams date back

[9] The entire area east of the City of London contained only one Underground line (District) and 9 stations.

to 1860. Electric, diesel, and petrol engines replaced horses in the early-twentieth century (London Transport Museum, 2020). Around 1930, buses and trams were similar in terms of design, speed, and cost, with the only major difference being that trams ran on fixed lines, whereas buses could run on any road (Ponsonby and Ruck, 1930; London Transport Museum, 2020). Both were substantially slower than rail or the Underground but were also cheaper on short routes, with fares starting at ½d. In addition to slower average speeds, buses and trams shared the roadways with other vehicles and could be held up by traffic, whereas trains and the Underground had their own dedicated tracks. This almost certainly meant that workers travelling by bus or tram would have had to allow for extra travel time to guarantee their arrival at work by a specific time. Ponsonby and Ruck (1930) argue that workers used buses and trams interchangeably, but only on short journeys of up to 3.2 kms.

The bus and tram networks in 1930 are shown in Fig. 1, panels C and D. Trams were contained within inner-London, with few routes extending beyond the boundaries of the *New Survey* area. Tram density was highest in areas without Underground lines. On the other hand, buses were the most widely distributed form of public transport. There were 209 bus routes within the London metropolis in 1931, covering virtually all built-up areas. Virtually all residents of the *New Survey* area had access to at least one bus route, and only a few households in the outer boroughs were located more than a few hundred meters from a route.

3. Data

Our primary source of data are records from the *New Survey*, a household survey of working-class residents of the 29 Metropolitan Boroughs and nine outer boroughs conducted between 1928 and 1932. Most of the original record cards have survived intact and were encoded in the 1990s by the team of Roy Bailey, Dudley Baines, Timothy Hatton, Paul Johnson, Anna Leith, and Angela Raspin (Johnson et al., 1999). The original cards from the Municipal Boroughs of Walthamstow and Tottenham, the two northernmost boroughs in the sample, have been lost.[10] The records contain 26,915 households, 94,137 individuals, and 49,445 income earners, about two percent of the working-class population of London.

The *New Survey* was a follow-up to the LLPL survey, which influenced both the sample and the questions. The LLPL focused on poverty amongst working-class Londoners in the late-Victorian period. It surveyed residents, employers, and union representatives of the 29 Metropolitan Boroughs of the County of London, excluding the City of London, which had few working-class residents by the 1890s. The LLPL was designed to be comprehensive, rather than systematic; enumerators typically visited streets, households, or factories and wrote down impressions. To the best of our knowledge, there are no machine-readable data sets extracted from these notebooks. Rather what survives are digital scans of the original notebooks, a series of "poverty maps" based on street descriptions, and the extensive set of published volumes (Booth, 1902; London School of Economics, 2020).

The *New Survey* was designed to much more closely resemble a modern household survey. The NSLLL had a fixed set of questions and a more limited, but near-random sample. The NSLLL covered the County of London (again excluding the City of London). However, by the late-1920s there had been outward movement of working-class residences, thus the NSLLL also included nine adjacent outer boroughs.[11] Both the LLPL and NSLLL cover only working-class households, defined by the head of household not working in a white-collar occupation. The intent of the designers of the NSLLL was to make the coverage directly comparable to the LLPL, however, over the forty-year period there were structural changes in working-class employment, specifically the rise of the clerical sector.[12]

The NSLLL was structured by individual household and there is a single record card for each interviewed household. Each record card contains background information about each member of the household: age, gender, place of birth (for those aged 14 and over), relation to head of household, and different sources of non-wage income. The cards also contain the following additional information for each working member of the household: earnings in the previous week and in a full-time week, hours worked in the previous week and in a full-time week, occupation, employer name, place of work, and transport expenditures. A complete list of the information on the record cards and summary statistics for variables used in the paper are shown in Appendix I.[13]

For our purposes, the most important feature of the data is that it contains information about travel to work. The only direct information is on expenditures. However, using transport expenditure to measure commuting is problematic for our purposes. This information is missing for about 30.8 percent of workers with a positive number of working hours in the previous week and for 46.4

[10] The adjacent boroughs of Leyton and Hornsey comprised 4.2 percent of the total 1931 *Census* population of the NSLLL area and 4.0 percent of the sample. The missing boroughs comprised only 5.2 percent of the total 1931 *Census* population of the NSLLL area. Thus, it is likely that the share of records lost was fairly small.

[11] These were Acton, Barking, East Ham, Hornsey, Leyton, Tottenham, Walthamstow, West Ham, and Willesden. These boroughs contained the highest density of working-class residents outside the County of London (Llewellyn-Smith 1930a).

[12] In the 1890s, it would have been extremely uncommon for anyone in a working-class household to hold a white-collar position. However, approximately 6.8 percent of reported occupations in the NSLLL data were in white-collar occupations, the vast majority of whom were clerks. According to *Census* figures, the clerical sector increased from 370,433 workers in 1891 to 1,375,431 in 1931.

[13] The data, a codebook, and Stata code to construct all tables and figures are available at Seltzer and Wadsworth (2023).

percent who were assigned an earner number. In addition, many respondents did not supply easily quantifiable answers to the question about transport expenditures, e.g., “bicycle” or “it varies”. Moreover, it is possible that some non-commuting-related travel costs are included in the responses even though the question was clearly intended to cover commuting costs only (see Appendix I). For these reasons, we only use transport expenditures for robustness tests, rather than as the main indicator of commuting in our analysis.

As an alternative to travel expenditure, we construct crow-flies distances between individual residence and workplace using GIS coordinates and the Great Circle Distance formula.[14] We first generate GIS coordinates for each relevant point of interest using Streetmap.co.uk and National Library of Scotland (2020). For each unique location in the data, we generate GIS coordinates for a single centroid. Sometimes this centroid will be a specific address, but typically it will be the center of each street or place name. In addition to home and workplace coordinates, we generate GIS data for the entire public transport network within the London metropolis. We use these coordinates to construct variables for the distances between a) residence (workplace) and the geographic and commercial centers of London at Charing Cross and the Bank of England, and b) residence (workplace) and nearest available stop for each mode of public transport. Appendix II outlines the procedures used to obtain GIS coordinates and construct the distance variables and the potential sources of measurement error and bias in these variables.

Table 2 shows some summary statistics on distances. The first 8 rows show the mean distances from home and workplace to the nearest available point of embarkation for each of the four modes of public transport. As would be expected based on Fig. 1, the average distance from both home and work is largest for the Underground and smallest for buses. The variance is also much higher for the Underground, due to its incomplete coverage. Table 2 also shows the universality of access to at least some form of public transport. A household two standard deviations above the mean distance from the nearest bus stop, would nevertheless still be within easy walking distance (520 m). Only 0.02 percent of income earners in the sample lived more than one kilometer from the nearest available means of public transport.

The next 15 rows of Table 2 show the distribution of crow-flies distances between home and work. The mean and median distances were 3.21 and 1.94 kms, respectively; less than modern commutes, but considerably more than “working on the spot”, which was typical in the 1890s (Ponsonby and Ruck, 1930).[15] It is also evident that on average 1) men commuted greater distances than women, 2) commuting distance increased with skill, and 3) heads of households commuted further than others.

The construction of the sample and the loss of records from two outer boroughs almost certainly implies that the average commute for the entire London workforce was greater than the figures shown in Table 2. There are three groups of London workers missing from the *New Survey*: working-class employees residing in Tottenham and Walthamstow (whose records were lost), working-class employees residing beyond the *New Survey* area, and middle- and upper-class employees. The non-surveyed and missing working-class employees resided much further out from the center on average than those in the *New Survey*. It is likely that each of these groups commuted further than the averages reported in Table 2.[16]

Table 2 also outlines the direction of commuting, divided into four mutually exclusive and collectively exhaustive categories: *inwards* – workplace is at least one kilometer closer to the center than home; *outwards* – home is at least one kilometer closer to the center than workplace; *local* – distance travelled is less than one kilometer, and *across* – distance travelled is at least one kilometer but there is less than one kilometer difference in home and workplace centrality. The largest share of workers, 38 percent, commuted inwards, followed by working locally, 29 percent. The remainder of workers in the sample were roughly evenly split between commuting outwards, 16.1 percent, or across London, 16.4 percent. Employment was not confined to the central zone. Just 13 percent of all employment in the sample lay within 1 kilometer of Charing Cross/Bank of England and 31 percent within 2 kms. Work was, however, more centrally located than residence. Only 1 percent of workers lived within 1 kilometer of one of the two London centres and 11 percent within 2 kms.

Fig. 2 shows net flow rates by borough, defined as the difference between the number employed and the number residing in the borough (from the sample data), divided by the number residing in the borough. The general pattern across all residential boroughs was that the largest share of workers either worked within their borough of residence or commuted inwards toward the center. Consistent with evidence from 1866, 1881, 1891, and 1901 *Day Censuses* and the *1921 UK Census*, the City of London was by far the largest net recipient of commuters, with 3412 employees, but no residents in the *New Survey* data (City of London, 1866). Wealthier boroughs north and west of the City, such as Westminster, St. Marylebone, and Holborn, were also net recipients. The exterior boroughs were typically “dormitory suburbs”, with far more residents than workers, although some had large employers that attracted many workers from other boroughs, such as the Arsenal at Woolwich or the docks at Bermondsey and Poplar.

[14] A potential alternative to crow-flies distances is to calculate travel times between residence and workplace. However, this is nearly impossible to do with any degree of reliability given the available records. The *New Survey* does not provide transport mode and is often missing travel expenses. Thus, any attempt to construct travel times would likely contain substantial measurement error. To determine how closely correlated crow-flies distances are to likely travel times, we have taken a one-percent sample from the data and obtained the travel time using the modern transport network from Google Maps. The correlation between crow-flies distances and modern travel times for commutes on public transport of at least one kilometer is 0.874. The correlation between crow-flies distances and walking times for commutes of up to two kilometers is 0.984. Thus, we believe that crow-flies distances are reliably proxying other measures of commuting.

[15] According to figures from the *2001 UK Census*, approximately 74.5 percent of workers in inner London commuted at least two kilometers and the median (mean) commute was approximately 5.0 (7.1) kilometers.

[16] A simple OLS regression of commuting distance on centrality and a dummy variable for white collar shows the following follows (with standard errors in parentheses): Distance Commuted = 0.30 (0.01) Distance from Center + 0.27 (0.09) white collar $R^2 = 0.02$, $F = 360.0$.

Table 2
Summary Statistics on Commuting.

	Mean (standard deviation)
Distance in km from home to nearest train station	0.64 (0.35)
Distance in km from home to nearest Underground station	1.17 (1.21)
Distance in km from home to nearest bus stop	0.20 (0.16)
Distance in km from home to nearest tram stop	0.35 (0.31)
Distance in km from workplace to nearest train station	0.60 (0.40)
Distance in km from workplace to nearest Underground station	0.95 (1.19)
Distance in km from workplace to nearest bus stop	0.16 (0.19)
Distance in km from workplace to nearest tram stop	0.39 (0.39)
Distance in km from home to work	
10th percentile	0.40
Median	1.94
Mean	3.21 (6.11)
75th percentile	4.17
90th percentile	7.29
95th percentile	9.44
99th percentile	15.14
by heads of household	3.34 (7.44)
by others	3.08 (4.35)
by men	3.42 (6.91)
by women	2.74 (3.68)
Skill category = professional	7.65 (10.25)
Skill category = middling	4.43 (6.75)
Skill category = skilled	3.61 (6.76)
Skill category = semi-skilled	2.75 (5.97)
Skill category = unskilled	2.84 (4.66)
Direction of commute	
Commutes inwards	37.9 %
Commutes outwards	16.0 %
Works locally, does not commute	29.4 %
Commutes across	16.7 %
Distance from nearest center	
Living < 1 km	0.9 %
Living < 2 km	11.2 %
Living < 5 km	50.0 %
Working < 1 km	12.7 %
Working < 2 km	30.7 %
Working < 5 km	63.3 %

Notes: All distances reported in kilometers. Standard deviations are shown in parentheses for continuous variables. Sample sizes: 49,361 with an earner number (used to estimate distances from home to public transportation), 34,972 with an identifiable workplace (used for all other figures). Distances from workplace to public transport is only reported for workers employed in the *New Survey* area. Approximately eight percent of workers who reported pay were itinerant, with no fixed place of work. We did not assign a commuting distance to these workers. See Appendix II for further details.
Source: Seltzer and Wadsworth (2023).

4. Empirical modelling – commuting, labor force participation, and earnings

To examine the importance of commuting for London's labor market, we run a series of regressions on 1) labor force participation, 2) commuting expenditures and distances, and 3) earnings. To examine labor force status, we run probit regressions of the general form:

$$EMP_I = a + BX_i + b_2DU_{H,i} + b_3DTRAIN_{H,i} + b_4DTRAM_{H,i} + b_5DBUS_{H,i} + b_6CENT_{H,i} + e_i$$

The dependent variable, *EMP*, is a dummy which takes a value of one if an individual is employed (defined either by having an earner number or reporting non-zero working hours in the previous week). *X* denotes a vector of control variables: age, age^2, age not reported, age > 14 (the school leaving age in 1930), sex, born in England, born in London, born in same borough as current residence, born in an adjacent borough to current residence, wage income of other family members, non-wage income of the household, and borough of residence. The main independent variables of interest are measures of crow flies distance (CFD) with: DU_{H} – denoting CFD between home and the nearest underground station; $DTRAIN_H$, home to train station; $DTRAM_H$, home to tram stop; $DBUS_H$, home to bus stop; and $CENT_{\mathrm{H}}$ denoting centrality, defined as MIN[CFD home to Charing Cross, CFD home to Bank of England]. The subscript, i, denotes the individual in the observation.

To examine distance commuted or use of public transport we run OLS regressions of the following general form:

$$COM_i = a + BX_i + b_2DU_{H,i} + b_3DTRAIN_{H,i} + b_4DTRAM_{H,i} + b_5DBUS_{H,i} + b_6CENT_{H,i} + e_i$$

The dependent variable, *COM*, indicates the extent of commuting: defined as CFD commuted, whether reporting positive

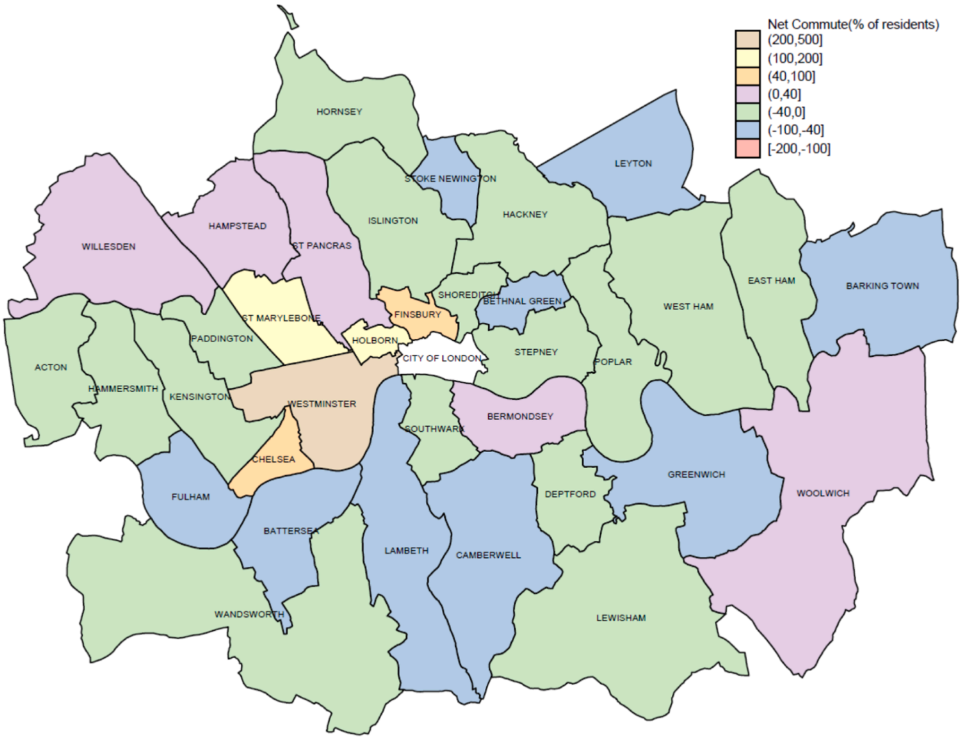

Fig. 2. Net Commuting Flows by Borough of Residence.
Notes: The map shows the net commuter flow by borough:
$\left(\frac{100^*(individuals\ employed\ in\ borough\ i - employees\ residing\ in\ borough\ i)}{employees\ residing\ in\ borough\ i}\right)$
The City of London is blank on the map as its residents were not included in the *New Survey*.
Source: Seltzer and Wadsworth (2023).

commuting expenditures, whether working locally, or whether commuting at least 3.2 kms.[17] The control variables in the X vector include age, age^2, age not reported, sex, hours worked last week, born in England, born in London, born in same borough as current residence, born in an adjacent borough to current residence, and borough.

To address the impact of commuting on earnings, we run modified Mincer-type wage regressions (Mincer, 1958 and 1974) of the general form:

$$\ln(W_i) = a + BX_i + b_1 DCOM_i + b_2 DU_{H,i} + b_3 DTRAIN_{H,i} + b_4 DTRAM_{H,i} + b_5 DBUS_{H,i} + b_6 CENT_{H,i} + b_7 DU_{W,i} + b_8 DTRAIN_{W,i} + b_9 DTRAM_{W,i} + b_{10} DBUS_{W,i} + b_{11} CENT_{W,i} + e_i$$

The dependent variable, W, indicates earnings in the previous week (reported in Johnson et al. (1999) in hundredths of old pence, where 240d = £1). The control variables in the X vector include age, age^2, age not reported, sex, hours worked last week, born in England, born in London, born in same borough as current residence, born in an adjacent borough to current residence, skill level, occupation, and dummy variables for boroughs of residence and workplace. In addition to the distance from home variables included in the previous regressions, the earnings regressions also include: $DCOM_i$, the CFD between home and workplace and a set of variables capturing distance from workplace to public transport and the city center – $DU_{W,i}$; $DTRAIN_{W,i}$; $DTRAM_{W,i}$; $DBUS_{W,i}$; $CENT_{W,i}$. The variables in the X-vector are determined by availability in the *New Survey* data; however, they comprise a fairly standard set of control variables for these sorts of labor market regressions. Our interest in this paper is in commuting, thus we focus on the coefficients on the distance variables, although complete results are shown in Appendix IV.

4.1. Endogeneity of location

Both residence and workplace were choice variables for individuals or households, thus in a naïve OLS regression of wages on the distance variables there exists the possibility of reverse causality. Income may determine commuting distance or the proximity to public transport by affecting the set of available residential choices for individual workers or potential workers. For example, a simple

[17] In the data, 92.1 percent of workers with non-missing expenditures commuting less than one kilometer reported zero expenditures. Among workers with non-missing expenditures commuting over 3.2 kilometers, 89.8 percent reported positive transport expenditures.

monocentric city model implies that self-selection will lead to wealthier households living further from the city center than poorer households, although this pattern will reverse if the poor can afford transport to the center or if the center contains particularly valued amenities (Mills, 1967; LeRoy and Sonstelie, 1983; Brueckner et al., 1999). Put simply, high earning individuals could choose to live either near their workplace or in relatively distant residential suburbs and commute into work. Reverse causation would imply that the estimated coefficients on the distance variables in an OLS regression would be biased. *A priori* the extent and even the direction of the bias is ambiguous. Llewellyn-Smith (1930b) argues that London housing rental markets were very tight circa 1930, and households would not have had the extent of residential choice as do modern urban residents. Nevertheless, it is likely that there was at least some degree of residential choice, and thus it is necessary to mitigate the associated potential biases.

We use three distinct approaches to addressing potential endogeneity of distance commuted: sample restrictions, household fixed effects, and instrumental variables estimation.[18] We run a variety of regression specifications for each approach to ensure the robustness of the results.

Our first approach is to restrict our sample to individuals who likely had the least choice of where to live and, thus, may have plausibly had an exogenously determined residential location. There exists a literature in urban economics which assumes that households' residential choices revolve around the primary income earner (Kain, 1962; O'Reagan and Quigley, 1993; Rees and Shultz, 1970). Non-relatives (such as lodgers) also likely had considerable choice over where to live.[19] Thus, our OLS regressions exclude heads of household and non-family members. Even among family members who were secondary earners within a household, there may have been differences in the extent of residential choice. Put simply, a son aged 28 could more easily leave home to be nearer to work than could a daughter aged 16.[20] There is no formal econometric test for the appropriate sample and thus we run multiple specifications, progressively restricting the sample based on the plausible extent of residential choice. As we show below, in practice the results are fairly robust to sample specification once heads of household and non-relatives are excluded.

For this strategy to identify a causal effect, it must be the case that there is no association between the workplace location of the head (who is excluded from the sample) and that of working relatives (who are in the sample). In such cases, the distance commuted variable would be proxying the real determinant of wages, household head influence. It is of course possible that some household heads may have been able to help secure employment at the same workplace for other family members. The evidence, however, suggests that this was rare. Baines and Johnson (1999) show that it was fairly rare for fathers and sons to even work within the same trade. We expand on this by using the information in the data on workplace address to further split the sample, excluding households for which one or more relatives were employed at the same workplace as the head. The estimates from these workers would be presumably more compromised by this type of endogeneity bias. In practice, only around 3 percent of individuals under the age of 25 worked with the same employer as the head and only 5 percent of individuals under the age of 25 lived in a household where someone had the same employer as the head. The removal of such a small group from the estimation sample is unlikely to make much difference to the OLS estimates and, thus, any estimation bias for the returns to commuting from this source is likely to be small.

Our second approach to controlling for endogeneity is to run a household fixed effects specification. Including household fixed effects means that the distance variables are identified by within-household differences in commuting, effectively different household members travelling to different work locations. This will reveal whether individuals in the same household (and by extension the same location) received higher wages with increases in distance travelled. This approach will also mitigate against biases associated with any unobserved household-level characteristics associated with location that also determine wages.

Our third approach to identification is to use an instrumental variable (IV) strategy. The *New Survey* data contains information on the place of birth of most individuals. We use the distance between birthplace and the nearest center as an instrument for the distance between home and work. Any IV must satisfy three exogeneity exclusion restrictions in order to produce consistent estimates: 1) relevance – the instrument must be "sufficiently" correlated with the endogenous regressors, 2) no direct influence – the instrument cannot plausibly influence the dependent variable directly through mechanisms other than its correlation with the endogenous variables, 3) monotonicity – the instrument should affect the endogenous variable of all individuals in the sample with the same sign (Angrist et al., 1996). We argue in Appendix III that each of these restrictions is met for our sample.

[18] Other studies have addressed endogeneity using exogenous variation in the routes of public transportation. These studies have 1) constructed an IV for transport routes based on geographic characteristics (Donaldson and Hornbeck 2016; Banerjee et al. 2020) or 2) analysed public transportation infrastructure which was planned but never built as a natural experiment (Donaldson, 2018). However, this sort of identification strategy (for example, using the London clay areas or planned, but never built Underground extensions) would not resolve the underlying endogeneity problem in our setting. Unlike the studies mentioned above, where the dependent variable is measured at the level of geographic area, our dependent variable is measured at the level of the individual worker. Thus, a suitable identification strategy must address workers' choices of where to live and work, not government planners' choices of where to build public transport.

[19] We use the relationship categories from Johnson et al. (1999) to determine whether individuals were related to the head of household. We assume that individuals were not related to the head if there is ambiguity in the reported relationship ("single", "bachelor", "spinster"), as well as if clearly unrelated ("lodger").

[20] Arguably wives of household heads would have had among the least residential choice. However, we do not focus on them because working spouses are found in less than 8 percent of households with a male head in work. In contrast, 60 percent of female household heads under the age of 60 and 82 percent of daughters of household heads (and 83 percent of sons) aged 14 and over were working.

5. Results

5.1. Effects of public transport on labour force status and commuting distance

Table 3 shows the main results of probit regressions on employment status and OLS regressions on distance commuted. The estimated marginal effects for the other explanatory variables are shown in Appendix IV, Table A.IV.1. The sample in the employment status regressions is restricted to individuals who were related to the head of household and at least 14 years old (the school-leaving age in 1930). The sample for the commuting distance regressions has the additional restriction that individuals must have an identifiable workplace. In Appendix IV, Table A.IV.2 we show results for a variety of alternative specifications as a robustness check.

The first two columns of Table 3 show the estimated marginal effects of centrality and access to public transport on the probability of being in work, where being in work is defined by either by having earnings in the previous week or having an earner number in the data. The last five columns show the estimated coefficients (OLS specifications) and marginal effects (probit specifications) of the centrality and access to public transport variables on commuting, defined as the distance commuted (columns 3 and 4), reporting positive transport expenses (column 5), having a workplace within one kilometer of home (column 6), and having a workplace at least 3.2 kms from home (column 7). In column 4, we jointly estimate the effects of employment and commuting distance using the Heckman correction (using the regression in Table 3, column 1 as the first stage). In this specification, the first stage is identified by the standard "labor supply" variables, wage income of other family members and non-wage income of the household.

The estimated coefficients on the main independent variables in the employment status regressions are similar across the two specifications. In both columns 1 and 2, the coefficient on distance from the nearer center is negative and significantly different from zero. Individuals residing more centrally were more likely to be employed, presumably because of the greater concentration of jobs in the central areas. However, we do not find any effects for proximity to public transport. In both specifications, the coefficients on all the distances from home to the nearest stop or station are near zero and statistically insignificant, perhaps because of the near universality of easy access to public transport.

The results of the commuting regressions are also consistent across specifications. Individuals residing near the two centers commuted shorter distances (columns 3 & 4), were less likely to incur transport expenses (column 5), were more likely to work locally (column 6), and were less likely to commute longer distances (column 7). As with the employment regressions, the logical interpretation of these results is that labor markets were thicker and there were more local employment opportunities near the center. Unlike in the participation regressions, access to public transport had some effect on distance commuted. Access to the Underground was associated with longer commutes, a higher probability of incurring transport expenses, a lower probability of working locally, and a higher probability of a longer commute (columns 3 to 7). There is a sharp contrast between access to the Underground and to the other transport modes. The coefficients on access to the train network are much smaller than for the Underground and are insignificant in all but one specification, suggesting either that commuting by train was uncommon or that local employment near train stations more-or-less offset longer-distance travel by train. The coefficients on distance to bus and tram stops are generally insignificant and the estimated marginal effects small. This again may reflect the near-universal access to these forms of public transport.

5.2. Effects of access to public transport and commuting on earnings

Table 4 shows the OLS estimates of distance effects for the earnings regressions. Results for the control variables are shown in Appendix IV, Table A.IV.3. In the main specification (column 1), we restrict the sample to relatives of the head of household, and thus exclude heads, lodgers, and other non-relatives. In column 2, we jointly estimate earnings and the probability of employment (using the regression in Table 3, column 1 as the first stage) and report the Heckman selectivity corrected earnings estimates on distance. As robustness tests, we further restrict the sample to relatives of the head under age 25 (column 3) and children of the head of household under age 25 (column 4).[21] We also run the regression using all individuals in the sample (column 5) and adding household fixed effects (column 6).

The strongest and most robust results in Table 4 pertain to the distance from home to work. The estimated coefficients on distance commuted and its square are large and strongly significant in every specification. The magnitude of the net effect is very similar across specifications and all household members. The coefficients can be interpreted as semi-elasticities and imply that a one-kilometer increase in distance to work is associated with between a 1 to 2 percent increase in earnings, depending on distance travelled, as the presence of a quadratic term allows the distance effect to be non-linear.[22] The coefficient on the quadratic term is negative,

[21] Children tended to live with their parents until their mid- to late-20s. Among individuals in the sample aged 25 or less, 78.6 percent lived in a household headed by one of their parents, 7.6 percent were the head of household, 10.1 percent were the spouse of the head, 2.9 percent lived in a household headed by another relative, and 0.1 percent lived in a household headed by a non-relative (usually as a lodger). At age 25, 45.4 percent of women and 54.5 percent of men in the sample were listed as the child of the head of household.

[22] The magnitude of these estimates is somewhat larger than those found in the (rather rare) literature on contemporary returns to commuting distance. Mulalic et al. (2014) report a wage-distance elasticity of around 0.015. If we estimate the wage equations using log of distance to work, the estimated wage-distance elasticities range from 0.04 (OLS) to 0.1 (IV).

Table 3
Effects of Distance on Labour Force Participation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	Hours > 0	Has earner num.	Dist. to work	Dist. to work	Trans. costs = 0	Dist. work < 1 km	Dist. work > 3.2 km
Estimation technique	Probit	Probit	OLS	Heckman	Probit	Probit	Probit
Distance home-center	−0.007*	−0.009*	0.459*	0.470*	−0.060*	−0.062*	0.066*
	(0.002)	(0.002)	(0.031)	(0.038)	(0.005)	(0.004)	(0.004)
Distance home-train	0.010	0.001	−0.165	−0.167	0.032*	0.013	−0.002
	(0.006)	(0.006)	(0.108)	(0.109)	(0.013)	(0.012)	(0.011)
Distance home-Underground	0.005	−0.003	−0.201*	−0.192*	0.052*	0.057*	−0.038*
	(0.004)	(0.004)	(0.070)	(0.068)	(0.009)	(0.007)	(0.007)
Distance home-tram	−0.007	−0.003	0.123	0.128	−0.016	−0.062*	0.001
	(0.008)	(0.007)	(0.145)	(0.136)	(0.017)	(0.015)	(0.014)
Distance home-bus	−0.007	−0.016	−0.028	−0.007	0.037	−0.027	−0.030
	(0.013)	(0.012)	(0.235)	(0.224)	(0.028)	(0.024)	(0.023)
Observations	41,319	41,319	16,910	41,319	14,212	16,901	16,901
R-squared	0.320	0.352	0.069		0.057	0.048	0.082
Sample mean	0.399	0.449	3.067	3.067	0.395	0.290	0.329
χ^2	11,568.6*	12,086.2*		1250.3*	1206.3*	864.5*	1613.4*
F			36.1*				

Notes: The sample consists of individuals aged 14 or more who were related to the head of household. Robust standard errors in brackets. *= significant at a 5 % level. Marginal effects evaluated at sample means reported for probit estimates. Pseudo-R^2 reported for all probits. The Heckman regression in column 4 uses the probit on reporting positive hours in the previous week (column 1) as the first stage. See Appendix IV, Tables A.IV.1 and A.IV.2 for additional results.
Source: Seltzer and Wadsworth (2023).

Table 4
Effects of Distance on Log Weekly Earnings.

	(1)	(2)	(3)	(4)	(5)	(6)
	Related to head: OLS	Related to head: Heckman	Related to head & Age<25	Children of head & Age<25	All	All: HH fixed effects
Distance to work	2.577*	2.574*	2.144*	2.017*	2.185*	2.134*
	(0.233)	(0.231)	(0.244)	(0.247)	(0.167)	(0.229)
Distance squared	−0.0489*	−0.0490*	−0.0486*	−0.0448*	−0.0605*	−0.0551*
	(0.0138)	(0.0137)	(0.0148)	(0.015)	(0.0113)	(0.0125)
Dist. home-center	−0.062	−0.066	−0.335	−0.156	1.105*	
	(0.355)	(0.354)	(0.351)	(0.357)	(0.236)	
Dist. home-train	1.659	1.510	2.133*	2.601*	0.736	
	(0.978)	(0.977)	(0.957)	(0.976)	(0.644)	
Dist. home-UG	0.768	0.763	0.701	0.792	−0.221	
	(0.614)	(0.612)	(0.615)	(0.620)	(0.384)	
Dist. home-tram	2.405	2.380	1.098	1.505	1.380	
	(1.255)	(1.250)	(1.222)	(1.236)	(0.773)	
Dist. home-bus	−2.882	−2.826	−1.687	−1.995	−1.620	
	(2.082)	(2.074)	(2.050)	(2.074)	(1.261)	
Dist. work-center	−0.139	−0.136	−0.213	−0.040	0.194	0.242
	(0.348)	(0.347)	(0.341)	(0.345)	(0.230)	(0.369)
Dist. work-train	−0.533	−0.529	−1.459	−1.171	0.513	−0.111
	(0.943)	(0.938)	(0.908)	(0.914)	(0.566)	(0.911)
Dist. work-UG	0.929	0.930	0.955	0.961	0.363	−0.025
	(0.483)	(0.481)	(0.539)	(0.543)	(0.298)	(0.558)
Dist. work-tram	0.773	0.774	0.444	0.213	0.552	−0.962
	(0.804)	(0.800)	(0.832)	(0.861)	(0.493)	(0.816)
Dist. work-bus	0.229	0.227	0.980	0.716	0.241	3.887*
	(1.120)	(1.112)	(1.302)	(1.296)	(0.707)	(1.195)
Observations	15,436	15,436	11,997	11,354	31,668	19,410
R-squared	0.572	.	0.632	0.645	0.687	0.891
Sample Mean	10.359	10.359	10.273	10.271	10.756	10.572
F statistic	173.123*	.	.	.	601.849*	370.387*

Notes: The dependent variable is the natural log of earnings (in hundredths of pence) in the previous week. All regression coefficients and standard errors multiplied by 100. The first stage controls in the Heckman regressions are as in Table 3, column 1. Household characteristics are omitted in the household fixed effects specification. Robust standard errors in brackets. *Indicates significance at a 5 % level. See Appendix IV, Tables A.IV.3, A.IV.4, A.IV.5 for additional results.
Source: Seltzer and Wadsworth (2023).

implying that the marginal gains to commuting fall with distance.[23] In Appendix II, we show that measured crow-flies distance commuted is likely to be an over-estimate. This implies that there will be attenuation bias in the regression and thus the estimated returns to distance should be interpreted as a lower bound of the true returns. While distance commuted has a strong effect on earnings, the effects of the other distance variables are far weaker. The coefficients on both home and workplace centrality are insignificant in nearly every specification. The coefficients on the access to public transport variables are small, mostly insignificant, and not robust to specification.

In column 6, we add household fixed effects to control for potential unobserved characteristics that might influence earnings. Individuals in the same household will, by definition, possess the same household characteristics and reside at the same location. In this specification, we do not include the distance from home to public transport variables, as these will be the same for all members of a given household. It can be seen in column 6 that the addition of household fixed effects does not change the estimated coefficients appreciably.[24]

We also run several additional regressions to examine the extent of heterogeneity in the estimated returns to distance. In these regressions we interact distance commuted with either direction of commuting or distance from home to Underground. Table 5 shows the coefficients on distance commuted and interactions for these additional regressions (with additional results in Appendix Table A.IV.6). White (1988) argues that the presence of employment centres outside the central zone can compromise estimated returns to distance. This implies that the returns to distance may depend on the direction travelled. The estimates in Table 4 are subject to this possible criticism as they use distance travelled as the primary independent variable, irrespective of the direction of commuting.

In columns 1 and 2 of Table 5, we test whether the estimated returns to distance commuted depend on direction of commuting by including the interactions of the distance travelled variables with dummy variables for commuting out and across London. There is no significant difference in the estimated returns to distance for the different commuting patterns. Another possible source of heterogeneity is differences in access to public transport; specifically, the Underground, which was concentrated in the north and west of the metropolis. In columns 3–5 we include the interaction of distance commuted and dummy variables indicating whether an individual resided within 500, 1000, or 2000 m of an Underground station. The results of these regressions show that the estimated returns to distance remains positive and strongly significant, independent of Underground access. However, the fifth column shows that the returns to distance travelled are slightly higher for those within two kilometers of an Underground station (perhaps the upper limit of walking distance) than for those with no access to the Underground (about twelve percent of the sample).

5.3. Instrumental variable estimates of earnings

Our third identification strategy is to instrument distance commuted with the distance between place of birth and the nearer of the two centers. Since we only have one instrument and several distance variables, we estimate the wage returns again solely as a function of the distance to work, along with age, gender, occupation, and workplace borough dummies. As the coefficients on the other distance variables were generally small and insignificant in Tables 4 and 5, it is highly unlikely that their omission will substantially bias other results. The main results are given in Table 6, and additional results are in Appendix IV, Table A.IV.7. We report OLS estimates for each distance group alongside their two stage least squares counterparts using the full sample of wage earners aged 14 and over. This enables us to determine the robustness of the IV estimates to different birth-distance thresholds in the results that follow.

The OLS point estimates are quite stable, at around 0.014, no matter the distance cut-off sample, indicative of a 1.4 percent wage premium for each kilometer commuted.[25] In addition to being quite stable, the point estimate of the effect of distance commuted is very similar to that shown in Table 4. The IV estimates are also quite stable for the sub-samples most likely to exhibit monotonicity behavior. The point estimates for the sub-samples born less than 6, 8, or 10 kms from the center of London are around 0.033 to 0.038, indicative that the average causal response wage effect may be somewhat higher than the OLS estimates suggest, at around 3.5 percent for each kilometer commuted. The instrument is highly relevant for these sub-samples. The first stage F-statistic of the significance of the instrument is above 190 in column 9, which implies a t-statistic of about 13.8 on the instrument. The estimated coefficient on the instrument in the first stage (not shown) suggests that distance commuted rises by around 0.2 km for every kilometer further from the center the individual was born. Extending the sample incrementally into sub-populations whose behavior is less likely to exhibit monotonicity and/or compliance regarding the instrument, the IV point estimates start to rise, (Table 6, columns 10 to 12). This is consistent with the idea that the identification conditions required of an IV estimator may indeed be less likely to hold across the full sample. However, for the majority of the sample born within 10 km of the center of London, the IV estimates may be closer to describing the average causal response of distance on wages.

[23] The implied distance before the marginal returns to commuting turn negative is around 20-25 kilometers depending on the sample used. Only about 0.4 percent of workers in the sample commuted 20 kilometers or more, thus the negative marginal returns is effectively an out-of-sample estimate.

[24] The addition of household fixed effects will change the sample size and composition, as households with only one earner will be excluded from the sample. To check that this does not substantively change the results, we have rerun the regression in column 5 (all workers) using the sample from column 6 (workers from households with multiple workers). The results are qualitatively very similar to those for other specifications.

[25] Since we remove the quadratic in distance, the estimated coefficient on the distance variable is effectively the average marginal return over all distances and so is in line with the estimates in Table 4. The removal of the other distance variables does not affect the estimate of distance to work in Table 4.

Table 5
Regressions to Identify Potential Heterogeneous Effects of Commuting.

	1	2	3	4	5
Specification	Table 4, column 1	Table 4, column 3	Table 4, column 1	Table 4, column 1	Table 4, column 1
Distance to work	2.81*	2.47*	2.59*	2.36*	1.95*
	(0.43)	(0.43)	(0.25)	(0.30)	(0.40)
Distance squared	−0.0719*	−0.0745*	−0.05*	−0.04*	−0.002
	(0.027)	(0.027)	(0.01)	(0.01)	(0.01)
Commutes out*distance	−0.32	−0.51			
	(0.56)	(0.57)			
Commutes out*distance squared	0.30	0.37			
	(0.29)	(0.29)			
Commutes across*distance	0.59	0.63			
	(0.47)	(0.47)			
Commutes across*distance squared	−0.007	−0.021			
	(0.04)	(0.040)			
Resides near Underground*distance			0.18	0.50	0.87*
			(0.38)	(0.35)	(0.41)
Resides near Underground *distance squared			−0.02	−0.03	−0.04*
			(0.02)	(0.02)	(0.01)
Resides near Underground, distance cut-off			<0.5 km	<1.0 km	<2.0 km
Observations	15,436	11,997	15,436	15,436	15, 436
R-squared	0.57	0.63	0.572	0.57	0.57
Mean Dep. Var.	10.36	10.27	10.36	10.36	10.36
F statistic	168.0*	.	170.0*	170.09*	170.47*

Notes: The dependent variable is the natural log of earnings (in hundredths of pence) in the previous week. Resides near Underground is a dummy variable taking a value of 1 if the individual resides within the relevant cut-off distance (500, 1000, or 2000 m) of the nearest Underground station. See Table A.IV.6 for additional results.
Source: Seltzer and Wadsworth (2023).

6. Discussion of results

6.1. Explaining the commuting premium

The main results on commuting and earnings in Tables 4-6 are fairly consistent across the different econometric specifications. In each specification, distance commuted has a significant positive effect on earnings. The magnitude of the point estimate is somewhat greater in the IV regressions than the OLS regressions, although measured with less precision. From Table 4, the proximity of individuals' residence and workplace to public transport has little or no effect on earnings.

The models described in the Introduction can be used to shed further light on these results. The mechanism by which commuting increased earnings is important, as whether increased earnings reflect higher productivity matters for the effect on the overall quality of life. In this section, we outline empirical predictions of the individual models and test these predictions with additional regressions. The four models and their empirical predictions for the commuting variables are briefly summarized below.

Local monopsony: Workers are equally productive at different employers. However, wages do not necessarily equal productivity and are influenced by workers' outside options. These, in turn, are determined by the density of local employment and commuting costs. If there are multiple nearby employers, workers can change employer at virtually no cost and thus their wage will be little different to what they would earn in a competitive labor market. Conversely, workers residing in a relatively remote location with high commuting costs and few local employers offering relevant vacancies will be paid substantially less than their competitive wage. In this context, access to public transport increases workers' bargaining power because it reduces the cost of switching employers and thus increases the value of outside options. The main empirical prediction of this model is that workers whose residence is near to public transportation will earn more than otherwise similar employees residing further away from public transport. This effect of *access to* public transport on wages is independent of whether an individual worker actually commutes by public transport.

Compensating differentials: Accessing a remote workplace is costly to workers in terms of both travel expenses and time costs. In a competitive labor market, a remote employer needs to reimburse this additional cost with higher wages. The main empirical prediction of this model is that wages will increase with employers' distance from public transport.

Search/matching: Workers have different productivity levels at different employers. Pay is equal to their productivity at each employer. Commuting increases the number of potential employers and thus facilitates better matches between workers and firms. This, in turn, leads to higher average productivity and wages for workers who commute than those who work near their residence. Thus, the main prediction of this model is that all else equal wages will increase with distance commuted.

Non-wage benefits/upward sloping labor supply curves: Employees differentiate between employers in terms of non-monetary attributes associated with individual workplaces (e.g., corporate culture, hours worked, etc.). Because workers differentiate between employers, the labor supply curve facing each employer will be upward sloping. All else equal, larger employers will need to recruit from further afield in any given location. Workers who have to commute will need to be compensated for the monetary and time cost. However, firms cannot differentiate between workers and thus firms which need to recruit from afar will pay higher wages to both

Table 6
Ordinary Least Squares and Instrumental Variable Estimates of the Wage Returns to Distance.

	OLS						IV					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sample dist. from center	< 6k	< 8k	< 10k	< 15k	< 30k	All	< 6k	< 8k	< 10k	< 15k	< 30k	All
Distance to work	1.54*	1.52*	1.39*	1.34*	1.33*	1.34*	3.87*	3.61*	3.33*	3.84*	4.33*	3.55
	(0.14)	(0.13)	(0.12)	(0.10)	(0.10)	(0.10)	(1.69)	(1.10)	(0.80)	(0.69)	(0.80)	(2.38)
Observations	12,430	15,131	17,035	18,233	18,581	19,680	12,430	15,131	17,035	18,233	18,581	19,680
R-squared	0.62	0.62	0.62	0.62	0.62	0.62	0.61	0.61	0.61	0.61	0.61	0.61
1st Stage F statistic							67.97*	130.78*	190.97*	193.04*	138.61*	25.67*
F statistic	303.4*	367.2*	420.1*	452.2*	458.1*	477.1*						
χ^2							21,796.0*	26,605.0*	30,411.1*	32,201.9*	32,073.9*	34,202.5*

Notes: The dependent variable is the natural log of earnings (in hundredths of pence) in the previous week. The sample includes everyone in paid work aged 14 and over who 1) reported earnings in the previous week and 2) had an identifiable birthplace. The dependent variable is the natural log of earnings (in hundredths of pence) in the previous week. All regression coefficients and standard errors multiplied by 100. Robust standard errors in brackets. *Indicates significance at 5 % level. The first stage F-statistic is for the relevance of the instrument net of controls. Additional regression results in Table A.IV.7.
Source: Seltzer and Wadsworth (2023).

commuters and local residents. As with the search model, the main empirical prediction of this model is that wages will increase with distance commuted.

The results in the previous section provide little support for the main predictions of either the local monopsony or compensating differential models outlined above. The coefficients on the proximity of residence and place of employment to all four modes of public transport in Table 4 are close to zero and statistically insignificant. Given that by 1930 almost no residences or workplaces were over a kilometer away from some form of public transportation, it is perhaps not surprising that variation in proximity to public transport did not drive wages.

On the other hand, the results in Tables 4-6 show robustly that earnings increased with distance commuted. This result is consistent with both the search and non-wage benefits models. To distinguish between these models, we need to explore the mechanism by which longer commuting distances led to higher wages. In the search model, match-specific productivity is a characteristic of individual employees. This implies that different employees can have different productivity and earnings at the same employer. On average, employees with longer commutes at a given employer will be better matches than those with shorter commutes, as additional earnings will be needed to offset the higher commuting costs. By contrast, the relationship between commuting distance and earnings in the non-wage benefits model is a workplace-level characteristic, caused by the fact that firms which need to recruit from further away must also offer higher wages. Similar workers at the same firm will be paid the same wages, and thus there is no within-firm commuting premium.

Our first empirical test to distinguish between the two models focuses on whether the relationship between commuting distance and earnings held within workplaces, as predicted by the search model but not the non-wage benefits model. We rerun the regressions from Table 4, adding workplace fixed effects. In the search model, the coefficient on distance commuted will be robust to the inclusion of workplace fixed effects, whereas the non-wage benefits model implies that this coefficient should decrease towards zero once these are included.

A second testable implication of the search model is that increased search may lead to workers being employed in higher-skilled, higher-pay occupations. A worker who is constrained to employment within walking distance from home may have a limited range of employers and job opportunities. Commuting increases the range of possible opportunities. In other words, a skilled worker may not be able to find skilled work within a short radius from their home but would have a higher probably of finding skilled work as this radius extends and the number of potential employers increases. The empirical prediction of this hypothesis is that some (or all) of the returns from commuting will be due to workers obtaining more skilled jobs. To test this, we add increasingly fine-grained occupation controls in the wage regressions. The search model implies that the coefficient on distance commuted will decrease as we add better controls for occupation. It does not necessarily decrease to zero, as there may be employer-employee match productivity effects in addition to the position-specific productivity effects. In the non-wage benefits model, occupation is simply a control variable and does not affect the correlation between distance commuted and earnings.

Table 7 shows the results of three additional sets of regressions – adding workplace fixed effects, increasingly fine-grained measures of position, and both. As the main empirical distinction between the two models pertains to distance commuted, we only report results for this variable and its square. Additional results are available in Appendix IV, Table A.IV.8. In the first set of tests, we add workplace fixed effects. In this context, workplaces are defined as employer/place of work pairs.[26] Of course, there is only a single employee observed for many (3981) workplaces in the data and these are dropped from the fixed effects specification. To ensure the robustness of our results, columns 1 and 2 report results from the original regression from Table 4, column 1 using the full sample of 15,436 observations and the 11,455 observations for which there are multiple employees at the same workplace. The results for these two samples are virtually identical, implying that any changes to the results after adding workplace fixed effects are not driven by changes in sample composition. In column 3 we add workplace fixed effects. The point estimate of the coefficient on distance commuted in this specification is strongly significant and is *greater than* those in specifications in columns 1 and 2, although its value lies within one standard deviation of these estimates. Thus, there is clearly no evidence that the addition of employer fixed effects reduces the coefficient on distance, as would be predicted by the non-wage benefits model.

The second set of estimates in columns 4, 5, 1, and 6 shows the results of a series of regressions with increasingly fined-grained position controls. In column 4, there are no position controls. Column 5 includes four Armstrong skill category dummy variables. Column 1 contains the original regression from Table 4, which has 29 *Census* occupational categories (roughly equivalent to a two-digit SOC code). Column 6 includes dummy variables for all 629 job titles in the data (roughly equivalent to a four-digit SOC code). Comparing columns 4, 5, 1, and 6, the estimated coefficient on distance commuted declines monotonically as we add increasingly fine-grained occupation dummies. This is consistent with the prediction of the search model that one consequence of extended search is that workers who commute will be able to obtain more skilled positions than observationally equivalent workers who work locally. Finally, in columns 7, 8, 3, and 9 we include both workplace fixed effects and increasingly fine-grained position controls. All of the results described above are robust to this specification.

These results suggest that search and matching is the most likely mechanism for the strong correlation between distance commuted and earnings. Workers with good access to public transport would have had more potential employers to choose between than those constrained to work locally. Those who used public transport would have been rewarded by being matched to either a more skilled job or to a more suitable employer. This mechanism implies that the higher wages associated with commuting reflect genuine productivity

[26] It is likely that in a small number of cases, employers operated multiple workplaces in the same borough and thus the place of work variable does not fully identify separate workplaces. We expect there will be few of these cases and thus their net effect on the estimated distance coefficients will be minimal.

Table 7
Additional Regressions on Earnings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance to work	0.026*	0.029*	0.061*	0.036*	0.030*	0.022*	0.059*	0.054*	0.044*
	(0.002)	(0.003)	(0.016)	(0.002)	(0.002)	(0.002)	(0.015)	(0.015)	(0.015)
Distance squared	-0.001*	-0.001*	-0.002*	-0.001*	-0.001*	-0.000*	-0.002*	-0.003	-0.002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)
Workplace fixed effects	NO	NO	YES	NO	NO	NO	YES	YES	YES
Occupation controls	2-digit	2-digit	2-digit	None	1-digit	4-digit	None	1-digit	4-digit
Observations	15,436	11,455	11,455	15,436	15,436	15,436	11,455	11,455	11,455
R-squared	0.572	0.572	0.906	0.534	0.553	0.628	0.901	0.905	0.923

Notes: The dependent variable is the natural log of earnings (in hundredths of pence) in the previous week. 1-digit = Armstrong skill categories, 2-digit = 29 *Census* occupations, 4-digit = 629 job titles in the *New Survey* data. * = significance at a 5 % level. See Table 4 and the associated discussion for a list of control variables. Additional regression results are in Appendix IV, Table A.IV.8.
Source: Seltzer and Wadsworth (2023).

effects, rather than merely some sort of transfer of income.

6.2. Commuting costs

Commuting has monetary and non-monetary costs in addition to the benefits shown in Tables 4-6. Table 8 shows some simple back-of-the-envelope calculations of the returns and costs of 8 stylized "standard" commutes. The table shows one-way commuting distances, typical mode of travel, estimated time, estimated monetary returns, and monetary and implied time costs for these commutes. We follow Ponsonby and Ruck (1930) in identifying the likely mode of travel based on distances. The monetary costs are typical costs taken from reported travel expenses in the *New Survey* data. We estimate the returns to commuting at the tenth, twenty fifth, and fiftieth percentiles of the weekly income distribution using the regression results from the first column of Table 4 and the ninth column of Table 6 (in parentheses). We calculate the implied time cost by estimating the time spent walking, waiting, and taking public transport for each commute and multiplying this by 50 or 100 percent of hourly earnings.[27] In these calculations we assume a walking speed of four kilometers an hour, public transport speeds shown in Table 1, and waiting times of five minutes for bus and tram and eight minutes for train and Underground. Full details of these calculations are described in Appendix V.

Table 8 shows that the monetary returns from commuting outweighed the monetary costs for all but the lowest earners (approximately the bottom 10–20 percent). Workers earning above this level of income would not have been prevented from commuting by income constraints, as their higher earnings due to commuting would have paid for the monetary costs of travel. Whether these workers would have chosen to commute would thus depend only on whether the total (monetary and non-monetary) returns outweighed the total costs. Table 8 also shows that time costs were substantial even for low earners, suggesting that most individuals would not have commuted unless there were non-monetary benefits, derived from greater choice over place of residence or non-pecuniary aspects of their job. We do not observe non-monetary costs or benefits for individuals, and it is likely that there was substantial heterogeneity in both. This is consistent with the high standard deviation of commuting distances and sizable share of workers working locally despite the monetary returns to commuting outweighing the monetary costs for all but the lowest earners.

For at least some workers in the bottom quintile of the earnings distribution, the monetary costs of commuting outweighed the monetary returns. If these workers were the primary source of income for their household, it is likely that they would have been income constrained and unable to afford to commute even if doing so would have generated substantial non-monetary returns. On the other hand, if these workers were secondary earners from wealthier households, it is much less likely that they would have faced income constraints. These workers would have been able to commute, so long as they received sufficient non-monetary benefits. To determine whether low earners were typically from poor households and thus potentially faced income constraints, we construct household-specific poverty lines using the approach outlined in Hatton and Bailey (1998). The poverty lines are based on minimum required expenditure on food and clothing, rent, and fuel given the structure of each household and actual expenditure on National Insurance and transport. Further details of the construction of the poverty line are available in the appendix of Hatton and Bailey (1998) and Appendix V of this paper. We estimate the share of workers in the bottom 10 percent of the earnings distribution who resided in households under the poverty line to be 25.2 percent. Although low earners were more likely than the sample as a whole to be below the poverty line, a substantial majority of low earners were secondary earners in wealthier households. These figures imply that less than five percent of workers in the *New Survey* data faced household income constraints that may have prevented commuting. As the *New Survey* only covered working-class households, this implies that the cost of using public transport was sufficiently low for commuting to be accessible to almost all Londoners by 1930.

[27] This is a fairly typical range of estimated values of time travel savings in the modern urban economics and geography literatures (Wardman, 1998; Zamparini and Reggiani, 2007).

Table 8
Costs and Returns of Commuting.

Crow-flies dist. (mtrs)	Trans. mode	Dist. walked	Dist. on public trans.	Walk time (mins)	Public trans. time (mins)	Implied return 10th percentile (d)	Implied return 25th percentile (d)	implied return median (d)	Monetary cost (d)	implied time cost, 10th percentile (d)	implied time cost, median (d)
500	Walk	625	0	9.38	0	2.3 (2.9)	3.9 (4.8)	7.5 (9.8)	0	3.5–7.0	11.4–22.8
1000	Walk	1250	0	18.75	0	4.6 (5.8)	7.7 (9.6)	14.9 (19.8)	0	7.0–14.1	22.8–45.6
2000	Bus	300	2200	4.5	8.62	9.2 (11.7)	15.3 (19.5)	29.7 (40.2)	6–12	6.5–13.0	21.1–42.2
2000	Tram	300	2200	4.5	8.20	9.2 (11.7)	15.3 (19.5)	29.7 (40.2)	6–12	6.4–12.7	20.6–41.2
4000	UG	600	4400	9	7.83	18.0 (24.2)	30.0 (40.3)	58.3 (83.1)	12–24	9.1–18.1	29.3–58.6
8000	UG	600	8800	9	15.66	34.4 (51.6)	57.3 (86.0)	111.5 (178.1)	18–30	11.7–23.4	38.0–76.0
8000	Train	600	8800	9	15.08	34.4 (51.6)	57.3 (86.0)	111.5 (178.1)	18–30	11.5–23.0	37.3–74.6
16,000	Train	600	17,600	9	30.17	59.9 (118.0)	99.8 (196.6)	194.0 (410.7)	30–36	16.7–33.3	54.0–108.0

Notes: The tenth, twenty fifth, and fiftieth percentile of weekly earnings were 180d, 300d, and 583.5d, respectively. Implied returns are estimated using Table 4, column 1 and (Table 6, column 9). See Appendix V for details on the calculations.
Sources: Ponsonby and Ruck (1930); Seltzer and Wadsworth (2023).

7. Further discussion – commuting and the quality of life

Although the formal results in the previous sections only directly address the working-class labor market of metropolitan London circa 1930, the effects of the commuter transport revolution were far broader. In this section, we provide informal evidence of the wider consequences of commuting on quality of life. We address changes in working-class commuting since the 1890s and non-labor market effects, specifically on crowding and health. All available evidence points to commuting having large and widespread effects on quality of life in the late-nineteenth and early-twentieth centuries. Finally, we also show that by 1930 similar commuting infrastructure was common throughout the developed world, thus the impacts shown in this paper almost certainly extended well beyond London.

7.1. Comparison to the 1890s

Ponsonby and Ruck (1930) argue that newly available modes of transport in the early-twentieth century led to fundamental changes in the working-class labor market, stating,

> “No change in the last generation has had more far-reaching effects upon the life of the whole community in London than the improvement of transport facilities. … It must be remembered, above all, in this connection that by far the greatest proportion of the increase [in commuting] is due to working-class travel. In [the 1890s] workmen travelled but little, being generally employed on the spot.” (pp. 171, 191).

Evidence on commuting in the companion volumes to the LLPL is largely indirect but strongly supports the claim that most working-class employees did not commute in the 1890s. There are only a few direct references to working-class commuting, generally pertaining to footloose occupations such as the building trades (Booth, 1902, Vol. IX, p. 17, Vol. V, p. 125).[28] However, the LLPL volumes do contain numerous mentions of outwork from home, the most extreme absence of commuting; of workshops located very nearby workers’ residences; and of neighbourhoods of specific groups of workers, such as dock laborers, being located nearby their workplace.[29] Booth was clearly aware of commuting, thus the absence of discussion in the LLPL strongly suggests that it was not an important part of working-class lives in the 1890s.

The primary reason for the absence of commuting in the late-nineteenth century was almost certainly under-developed infrastructure. As can be seen in Table 1, the bus, tram, and Underground networks all had fewer route kilometers, vehicle kilometers, and slower travel speeds in the first decade of the twentieth century than by 1930. These supply-side issues were almost certainly even greater in the 1890s than a decade later, as the figures in Table 1 already reflect the initial replacement of horse-drawn transport and extension of networks. In addition to improvements in infrastructure, public transport became much more affordable in the period between the two surveys. Table 1 also shows that the cost per kilometer for each mode of transport decreased substantially over the period. Moreover, real weekly earnings increased approximately 20 percent from the 1890s to circa 1930 (Llewellyn-Smith, 1930a, p. 19).[30] Based on this, it seems likely that in 1890 income constraints were binding and prevented commuting for a sizeable number of workers.

We can gauge the monetary importance of commuting by estimating additional earnings due to increased commuting distance

[28] The LLPL also refers to commuting by middle class workers, such as bankers and clerks (Booth 1902, vol. IX, p. 189), and to weekly or bi-weekly trips by working-class outworkers to pick up raw materials and drop off finished products.
[29] Booth (1902), Vol. IX, p. 204–205, Vol. IV, pp. 19, 41-42, 60, 71, 73, 79, 117, 149, 160–161, 174, 204, 278, 295.
[30] After adjusting for the decline in the workweek and making comparison between like-for-like workers, Lewellyn-Smith (1930a,b) concludes that real hourly earnings increased by about a third between 1895 and 1928. This is similar to recent estimates. Clark (2020) calculates real earnings increased by 35.6 percent for the entire UK over the period 1895-1930.

between 1890 and 1930. To do so, we answer a simple counterfactual question – what would earnings have been in 1930 if workers had commuted 1890s distances, but the earnings returns to commuting were as we have previously estimated? We estimate earnings for 1890 and 1930 using the mean commuting distances for each year and the returns from Tables 4 and 6, evaluated at the mean (mode) of the other continuous (discrete) variables. Table 2 shows that the average commute in 1930 was 3.21 kms. We do not have distance figures for 1890 but based on the discussion above, we believe a substantial majority of working-class employees would have worked locally. Thus, we believe that 200–500 m would have covered the range of typical crow-flies distances from home to work in the 1890s. This implies an increase in commuting distance of 2.7–3.0 kms each way. Using an increase in the average one-way commute of 2.7 kms and the estimated returns per kilometer of between 1.5 and 3.5 percent, we estimate an increase in earnings of about 4.05 to 9.45 percent due to commuting. This accounts for about 20–47 percent of the increase in real weekly earnings or 14.5–31.5 percent in real hourly earnings of the working-class between 1890 and 1930. The lower end of these figures is similar to Leunig's (2006) finding that social savings from railways accounted for about one sixth of economy-wide productivity growth during late-nineteenth and early-twentieth centuries.

7.2. Commuting, residential choice, and urban crowding

Although the focus of this paper is on labor markets, commuting likely also had additional consequences for the quality of life. Economic historians have generally accepted that living standards rapidly increased from the late-nineteenth century across a range of metrics including income, health, leisure time and education (Maddison, 1964; Horrell, 2000; Clark, 2005; Chapman, 2019). Our focus on labor markets has shown that commuting was an important contributor to increased income. It is also likely that the ability to commute led to movement of the population away from the center of the metropolis, which, in turn, reduced inner-city crowding. Much of the discussion in the summary volumes of the LLPL concerns crowding and subsequent economic historians have argued that nineteenth century crowding had substantial negative health externalities (Nicholas and Steckel, 1991; Steckel, 1995).

Public transport was widely perceived by contemporaries to have substantially reduced crowding. Llewellyn-Smith (1930a, b) states, "every increase in mobility arising from improved means of travel widens the area within which such a workman can exercise his choice of a residence. Imperfect mobility is at the root of the most serious overcrowding difficulties." Data on population by borough further suggests that the commuter transport revolution directly led to a reduction in crowding in the central areas. The population of the City of London reached its peak in the early-nineteenth century and declined rapidly from about 1850. The decline was rapid, from 130,117 in 1801, to 43,882 in 1891, and 15,758 in 1931 (*UK Census*), although employment continued to increase well into the twentieth century (Bowley, 1930, p. 74; *Day Census*, 1868,1881,1891, 1911 and *UK Census*, 1921).[31] The wealthier inner boroughs in the *New Survey* area – Finsbury, Holborn, St Marylebone, Westminster, and Shoreditch – also reached their peak population in the mid-nineteenth century (Bowley, 1930, pp. 74–5). By contrast, most of the predominantly working-class boroughs in the central and middle rings of the metropolis reached their maximum UK *Census* population in 1901. All but two outer boroughs reached their peak population in 1921 or later.

While it is beyond the scope of the paper to formally examine the causes of these movements of residential populations between boroughs, they are consistent with a simple explanation based on commuting first suggested by Llewellyn-Smith (1930a, b). The construction of rail networks in the nineteenth century facilitated the movement of the middle-class and wealthy away from the center, which was increasingly devoted to commercial purposes. Central areas which had been predominantly populated by comparatively wealthy households experienced comparatively early population declines. However, the working-class generally remained in the central areas and the population of central, predominantly working-class boroughs continued to increase into the twentieth century. The later construction of Underground, bus, and tram networks and the associated decline in transport costs made it feasible for these households to move away from the center. Furthermore, a dramatic decline in working hours following the First World War reduced the extent to which time constraints prevented commuting (Huberman and Minns, 2007). The outward movement of working-class households directly reduced the population density of the inner boroughs and thus reduced crowding in these areas. The most densely populated, predominantly working-class boroughs of Bethnal Green, Stepney, and Southwark had densities of 42,323.6, 41, 837.1, and 45,007.6 residents per kilometer in 1901, respectively. By 1928, these figures declined to 36,463.5, 34,281.3, and 39,545.5, respectively (*London Statistics*; Llewellyn-Smith, 1930a, b).

In addition to reducing crowding in central areas, it is likely that commuting also reduced crowding within dwellings. The income increases associated with commuting would have led to families consume more housing, leading to larger dwellings. In addition, the outwards movement of the working-class population described above, meant more were living in the outer ring of the metropolis where dwellings were typically larger, better maintained, and less expensive than in the central areas (Booth, 1902; Llewellyn-Smith, 1930a, b).

7.3. Commuting infrastructure in other locations

The UK, particularly London, was a pioneer in transport infrastructure in the nineteenth century, with both the first rail and underground networks. However, these technologies were quickly adopted elsewhere and cities throughout the more-developed world

[31] The *Reports of the Day Censuses* show that the number of non-residents entering the City every day increased over time. The estimated daytime population of the City of London grew from 261,061 in 1881 to 301,384 in 1891; 364,061 in 1911; and 436,721 in 1921 (*Day Census,* 1881, 1891, 1911 and *UK Census*, 1921).

built their own transport networks over the nineteenth and early-twentieth centuries. By 1930, all large and medium-sized cities throughout the UK, continental Europe, North America had extensive public transportation networks and thus it is virtually certain that the effects of the commuter transport revolution shown in this paper were simultaneously occurring elsewhere.

Rail networks in the UK had largely been completed by the end of the nineteenth century and connected cities to suburbs and all major population centers to each other (https://www.railmaponline.com/UKIEMap.php#). By the time of the *New Survey*, comprehensive rail networks also existed throughout Europe and North America and in parts of Asia and South America. It is likely that, by 1930, rail commuting was common in virtually all large cities in the UK and most worldwide. Underground systems were the most expensive to construct and hence were only viable in large, densely populated cities. At the time of the *New Survey*, there were extensive underground systems operating in only six cities worldwide: Berlin (opened 1902: 8 lines, 100 stations in 1930); Boston (opened 1901: 4 lines, 128 stations in 1930); Chicago (opened 1892: 7 lines, 85 stations in 1930); London (opened 1863: 7 lines, 208 stations in 1930); New York (opened 1904: 14 lines, 269 stations in 1930); and Paris (opened 1900: 12 lines, 202 stations in 1930) (Wikipedia, 2022a). Smaller systems with one or two lines and up to 41 stations operated in Istanbul, Budapest, Glasgow, Athens, Philadelphia, Hamburg, Buenos Aires, Madrid, Barcelona, and Tokyo. Tram systems were far more common. There were 196 separate tram networks in the UK in 1920. At its peak, the entire UK system contained over 4000 route kilometers, with the largest networks in London (556 kms), Manchester (262 kms), Glasgow (228 kms), Liverpool (145 kms), Birmingham (130 kms), and Leeds (116 kms) (Wikipedia, 2022b). Other Western European and North American countries had similar network densities (Wikipedia, 2022c). However, by the mid- to late-1920s, tram networks outside the largest UK cities were already in decline, with the total number of networks decreasing to 147 in 1930 and 45 in 1940. Virtually all discontinued tram networks were replaced by buses. In 1930, there was bus coverage operating *alongside* tram networks in all major cities and most large towns in the UK and also *instead of* tram networks in many towns.

8. Summary and conclusions

In the 1890s, the only available means of high-speed, low-cost urban transport was rail, which predominantly connected middle-class and professional workers from residential suburbs to the central areas. The working-class typically worked where they lived. By 1930, there were comprehensive bus, tram, and subway networks running fast and relatively inexpensive routes in major cities worldwide. Data from the *New Survey* show that these networks were widely used by the working-class of London. Over 70 percent of income earners in the data commuted at least one kilometer. Over twice as many workers reported positive transport expenditures as zero expenditures.

We have used the NSLLL data to examine the impact of access to public transport and commuting on working-class London labor markets, circa 1930. We GIS code home addresses and places of work and construct crow-flies distance commuted, distance from public transport, and distance from the metropolitan centres. We then use these distance variables in Mincer-type regressions on labor force participation and earnings. We control for the potential endogeneity of distance commuted by 1) restricting the sample to individuals' whose residence was plausibly exogenous, 2) using household fixed effects, and 3) instrumenting distance commuted with distance from birthplace to the center of London. Our main finding is that distance commuted had a strong impact on earnings, with a one-kilometer increase in commuting distance resulting in about a 1.5–3.5 percent increase in earnings. However, we find little evidence to suggest that proximity of home or workplace to public transport had an independent effect on labor force participation or earnings, perhaps because virtually all areas covered by the *New Survey* were within easy walking distance of some form of public transport. These results are robust to a variety of specifications. The most plausible explanation for the commuting earnings premium is that commuting allowed workers to extend their search and thus choose between more potential employers. This, in turn, led to better matches between employers and employees. Finally, we show that commuting was an important contributor to increasing quality of life in the early-twentieth century. In addition to increasing incomes, it contributed to reduced urban crowding.

Data availability

data and code available at https://www.openicpsr.org/openicpsr/workspace?goToPath=/openicpsr/193,991&goToLevel=project

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Appendix I. Information in the *New Survey of London Life and Labour*

Front of Card
Name (Not recorded in Johnson et al. (1999))
Address (street address)
Borough
For each wage earner
 Relationship to head of household
 Age
 Occupation – see Bailey and Leith (2002)
 Employer
 Place of work
 Cost of transport weekly
 Hours last week
 Hours full time
 Earnings last week (in s. and d.)
 Earnings full time (in s. and d.)
 State Insurance deductions (in s. and d.)
For each non-wage earner
 Sex
 Age
 Relationship to head of household
Income from other sources
 Source
 Amount (in s. and d.)
Date of interview
Interviewer

Back of Card
Birthplace of adults
Rent, weekly (includes rates)
Persons and accommodation
 No. of persons
 no. of bedrooms
parlor (yes or no)
Kitchen (number)
Scullery (yes or no)
Pantry or larder (yes or no)
Bath (yes or no)
Yard (yes or no)
Garden (yes or no)
Allotment (yes or no)
Remarks on accommodation

Table A.I.1

Table A.I.1
Summary Statistics.

A. Individual Characteristics		
	All individuals	Employed in the previous week
Male (%)	48.7	70.5
Age	28.4 (19.8)	32.6 (14.4)
Born outside England (%)	2.7	2.5
Born in London (%)	84.2	86.2
Living in borough of birth (%)	33.3	36.6
Living in borough adjacent to borough of birth (%)	11.8	11.4
N	93,891	35,282
B. Household/Dwelling Characteristics		
Persons in the household	3.5 (1.9)	
One-person household (%)	11.0	
Two-person household (%)	24.6	
Three-person household (%)	22.5	
Four-person household (%)	17.2	
Five + person household (%)	24.7	
Non-wage income (d per week)	0.38 (0.65)	
Minimum distance to a central point (km)	5.4 (2.8)	
Nearest central point = Charing Cross (%)	42.9	
Inner ring (%)	30.1	
Middle ring (%)	20.6	
Exterior ring (%)	49.3	
County of London (%)	81.8	

(*continued on next page*)

Table A.I.1 (*continued*)

B. Household/Dwelling Characteristics	
N	26,915
C. Employment Characteristics	
Hours working in previous week	46.1 (8.3)
% age 16–65 reporting hours in previous week > 0	54.9
Worked at least 40 h (%)	90.8
Worked at least 48 h (%)	57.1
Hours worked in a full-time week	46.9 (7.2)
% age 16–65 reporting hours in a full-time week > 0	56.1
Earnings in previous week (£)	2.34 (1.17)
Earnings in a full-time week (£)	2.38 (1.17)
Occupation = metal worker (%)	8.0
Occupation = electrical (%)	2.4
Occupation = makers of textile goods (%)	8.5
Occupation = food, drinks & tobacco (%)	3.1
Occupation = wood & furniture (%)	4.9
Occupation = printers & photographers (%)	2.5
Occupation = building trades (%)	4.4
Occupation = painters & decorators (%)	2.8
Occupation = transport and communications (%)	17.7
Occupation = commerce, finance, insurance (%)	8.6
Occupation = personal service (%)	11.4
Occupation = clerk (%)	5.5
Occupation = warehousemen, storekeepers (%)	4.7
Occupation = other or unknown (%)	15.5
Armstrong skill category = professional (%)	0.1
Armstrong skill category = middling (%)	0.7
Armstrong skill category = skilled (%)	49.0
Armstrong skill category = semi-skilled (%)	24.0
Armstrong skill category = unskilled (%)	26.1
N	35,353

Notes: Standard errors are reported in parentheses for continuous variables. Age is reported as zero in 9.2 percent of observations. We have excluded these observations from our calculations in Table A.I.1 and included a dummy variable for the regressions reported in Tables 3–7 and Appendix IV.
Source: Seltzer and Wadsworth (2023).

Appendix II. Coding GIS coordinates and distances

This appendix outlines our approach to GIS coding of home street addresses, workplace locations, and the public transport network. We also outline how we use these GIS coordinates to construct our measures of distance commuted, access to public transport, and centrality. Finally, we examine measurement error and biases that are likely to result from our approach and the likely implications for our results.

I. Residential addresses

Our approach to GIS coding home addresses is as follows. First, we have entered the street name into streetmap.co.uk. If there exists exactly one modern street with the same name that is located within the historic Metropolitan Borough listed on the original record, we assumed this to be the residential address. We then took the GIS coordinates from streetmap.co.uk. Occasionally there are multiple streets of the same name within the same historic borough, e.g., two towns have a "High St.". Normally in these cases, the records themselves indicate the correct street. For example, the streets may be listed as "High St., Woolwich" or "High St., Plumstead". In cases such as this, the street is clearly identified even though the official name of both streets is just "High St." and both Woolwich and Plumstead were in the Metropolitan Borough of Woolwich. In the small handful of cases where there remained ambiguity, we have looked at additional information from the record cards to determine the most likely correct address (e.g., whether household members were working in Plumstead or Woolwich).

For about a quarter of the observations, we were unable to find the address listed on the record card in streetmap.co.uk due to changes of street names or the urban layout. London was extensively bombed during the Second World War. Many homes and even entire neighbourhoods were damaged beyond repair (Ward, 2015). After the War, London's urban planners "cleared" many War-damaged areas and other urban slums. The clearances disproportionately affected working-class areas, as 1) housing in these areas was often old and poor quality and 2) wealthier areas which suffered minor bomb damage were quickly repaired whereas poorer areas often deteriorated to the point where clearances became necessary. The clearances often changed the physical layout of the area, for example replacing low-rise dwellings with high-rise council housing (Redding and Sturm, 2016).

To locate no-longer-extent streets, we began by searching the online indexed maps from the LLPL (London School of Economics, 2020). Because of the similarity of coverage between the two surveys, most residential streets within the County of London appearing in the NSLLL previously appeared in the LLPL. We were thus normally able to find residential streets on the LLPL map and obtain GIS coordinates from Ordinance Survey maps (National Library of Scotland, 2020).[32] In cases where a street was not included in the LLPL index (particularly in the outer boroughs not surveyed in the LLPL), we have searched other on-line resources such as *Medical Officer of Health Reports, Census Street Index*, and various genealogical web sites (Welcome Library, 2021; Family Search, 2021). We were often able to find an exact or at least an approximate location for a residential street, usually based on known locations for nearby streets that were listed in the same source. Once we found the location, we then found the GIS coordinates using Ordinance Survey maps (National Library of Scotland, 2020).

When entering GIS coordinates, we have used a single centroid for each home address in the data.[33] The centroid will either be the location used by Streetmap.co.uk (for still-extent streets) or at approximately the middle of the street (for no-longer-extent streets). The approach of using a single centroid facilitates checking for inconsistencies in the data. It also makes it possible to replicate our GIS coding procedure, as it avoids non-replicable *ad hoc* assumptions about individual locations.

We believe that home addresses were very accurately recorded by the NSLLL enumerators. The enumerators were instructed to visit each individual household; hence they actually set foot on the residential street. We have been able to locate well over 99 percent of home addresses in the data. Although our use of a single centroid for each address will inevitably create some measurement error, we believe that this measurement error is likely to be small because working-class residential streets tended to be fairly short.

II. *Workplace addresses*

Our approach to obtaining GIS coordinates for workplaces closely follows that of home addresses. We searched streetmap.co.uk, followed by the indexed LLPL maps, followed by other on-line sources to identify workplace streets or place names. If this failed to produce a likely match, we searched old Ordinance Survey maps (National Library of Scotland, 2020) for similarly named streets nearby the place of residence.[34]

There are several sources of measurement error for workplaces that are not present for residences. First, the survey question for workplace is less precise than residence, asking for "place of work" rather than "address". Accordingly, the responses were more varied than for home addresses, ranging from an exact address, to just a street name, to a broader place name. About half the responses are place names. Even place names can be imprecise. For example, "Greenwich" is the name of both a Metropolitan Borough and the main town within the borough. Where a place name is reported, we enter a common GIS coordinate using the centroid of the smallest plausible geographic unit (e.g., town, rather than borough). If the record card provides a general, but very broad area (e.g., "London" or "East End"), we treated place of work as missing unless we could identify a more specific location based on the employer.[35] The lack of precision in workplace locations implies that our GIS coordinates are inherently subject to more measurement error than for home

[32] National Library of Scotland (2020) contains a variety of scalable modern and historic street maps which can be uploaded side-by-side. Our GIS coding has primarily relied on OpenStreetMap; Ordinance Survey (OS), 25 inches, 1892–1914; and OS 1/2500, 1944–1967.

[33] We have used the street/borough pair when assigning centroids. We have assigned a set of GIS coordinates for each borough that a street passed through. However, most streets were entirely contained within a single borough, as street names tended to change at borough boundaries.

[34] Since enumerators relied on residents to provide workplace addresses, there were fairly frequent transcription errors or spelling mistakes on the original records. We were often able to find very similar (or identically pronounced) workplace street names by searching the map around the home address.

[35] Locations of larger employers often turned up in on-line searches, and we were often able to identify precise GIS coordinates using this information.

addresses. In addition, commercial streets tended to be longer than residential streets and thus there is likely to be more measurement error for workplaces than residences, even in cases where a street is listed for both. A final issue is that in about eight percent of observations with pay reported, the place of work is listed as "various" or "casual". We assume these workers to either be footloose (such as in the building trades) or itinerant. We do not assign workplace locations to these workers.

A second difficulty identifying workplaces is that, unlike the home addresses, the original record cards do not contain boroughs for workplace.[36] This makes it more difficult to identify the workplace location for common London street names, unless the location is given on the original record card, e.g. "High St., Plumstead". In cases where a workplace address was ambiguous, we used other data from the record such as home address, name of employer, and travel costs to identify the most plausible location.

A final issue results from the fact that enumerators never visited places of work, instead they relied on information supplied by interviewees. At best, this meant that the address was second-hand information from the worker, rather than directly from the enumerator. However, it is likely that the information was often supplied by another member of the household. Although the *New Survey* enumerators were explicitly instructed to make repeated visits to households to get employment information from the income earner themselves, it is known that Arthur Bowley, the overseer of the NSLLL, was willing to "sacrifice accuracy to speed and simplicity" (Abernethy, 2017; Hennock, 1991).[37] Responses from someone other than individual workers themselves were probably widely tolerated.[38]

Although the issues raised above imply that workplace addresses face greater measurement error than home addresses, we believe that they are nevertheless fairly accurate. We were able to obtain GIS coordinates for about 98 percent of observations where a street or place name is given for place of work. When we were unable to obtain workplace GIS coordinates, it was typically because either the worker was itinerant or the original respondent did not supply the necessary information. In about 12 percent of observations reporting earnings in the previous week the information is either missing or unusable ("X", "refused", "London", etc.).

III. Birthplaces

The *New Survey* data contains information on the place of birth of most individuals. We GIS code birthplace and use this to calculate the distance between place of birth centroid and Charing Cross/Bank of England.

Sometimes place of birth is recorded as a street. More often it is recorded as a local area. Much as with residential addresses, we use the centroid of the area as the basis for the distance calculation for the latter cases.

IV. Public transport

We have compiled a list of railway and London Underground stations in 1929 using historic Underground maps (Graham-Smith, 2018), historic Ordinance Survey maps (National Library of Scotland, 2020), and Wikipedia lists of current and historic stations (Wikipedia 2020a, b, c, d). Wikipedia usually provides GIS coordinates for rail and Underground stations and we cross-checked these using historical Ordinance Survey maps (National Library of Scotland, 2020). We thus believe that these coordinates are very accurate.

We obtained detailed information on bus and tram routes from London Historical Research Group (2014) and Public (2020), respectively. However, neither source indicates where vehicles stopped along the route. We have used OpenStreetMap to find the location of modern bus stops and assumed that these correspond to stops on the historic routes. Where the historic routes do not coincide with modern routes, we have assumed that stops were 300–500 m apart in central areas and slightly further apart in outer areas, as with modern routes. We start with a known stop on route, such as the route terminus or a railway station, and assign stops approximately equidistant from this point. In addition to official stops, it was generally possible for able-bodied passengers to board or leave a bus or tram at any point where the vehicle was stopped and thus we also classify major intersections as stops.[39] There will be some measurement error in this approach that is absent in our calculations for rail and Underground (for which we know the exact location for each station), but this is likely to be fairly small, as tram and bus stops were generally fairly close together.

[36] The Johnson et al. (1999) data contains a variable for workplace borough. However, this has been constructed by the researchers, not transcribed from the original record cards. We believe that there are numerous coding errors in this variable for observations in which only a street address is given for place of work. We have created a new variable for workplace borough by mapping the NSLLL area into approximately 500 square meter grids. We map each observation into a cell using the GIS coordinates. We then map the grid cells into boroughs. In cases where a grid cell is divided between more than one borough, we mapped workplace addresses within the cell into boroughs by hand using Ordinance Survey maps, OS 25 inches, 1892–1914 (National Library of Scotland, 2020).

[37] It was noted in the original instructions to enumerators that "vague estimates of husband's earnings by wife, of child's by parent, or of lodger's by landlady, should not be entered until an effort has been made to see the wage earner concerned" (*New Survey*, instructions issued to investigators, quoted in Abernethy, 2017).

[38] Missing or imprecise workplace information is much more common in the NSLLL data for lodgers than family members. It is difficult to reconcile this with earners supplying their own information, but consistent with a single (non-working) resident supplying information for all household members. In addition, the original record cards often provide relationships within households vis-à-vis someone other than the likely head of household (Bailey and Leith 2002). The fact that the head of household was frequently not correctly identified by the enumerators is strongly suggestive that they made a single visit to the household and collected all information from the person who answered the door.

[39] The buses and trams of the 1930s were "routemaster" design with an open entrance at the back. Passengers could embark or disembark at any point on route when the bus was stopped.

V. Calculating distances

We have used the GIS coordinates to calculate crow-flies distances between home, work, the city centres, and public transport for each employed individual in the sample. Conceptually, these distances are 1) the distance commuted (home to work), 2) the centrality of their home or workplace (minimum distance to Charing Cross or the Bank of England), and 3) access to public transport (distance to bus, tram, Underground, or train). Fig. A.II.1 shows these distances for one individual. On the map, the residence is denoted H, the workplace is denoted W, the nearest Underground stop to home is denoted U, and Charing Cross is denoted CX. The black line shows the crow-flies distance between home and work (commuting distance). The green line shows the distance between home and Charing Cross (centrality). The solid red line between H and U shows the distance from home to the nearest underground station. The dotted and solid red lines connecting H to W show the most plausible transport route to work (by underground for two stops and a short walk to the workplace at the end). For ease of exposition, we have not shown the other distances on this map.

To calculate distances, we use the great circle distance formula:

d = R*acos(sin(lat_a)*sin(lat_b) + cos(lat_a)*cos(lat_b)*cos(d_lon));

where: R = radius of the earth (6365 km); lat_a, lat_b = latitudes of points a and b; d_lon = difference in longitude between the two points.

There were a few exceptions to these principles in our calculations of distance. As mentioned above, if a worker was deemed to be itinerant, we did not fix workplace coordinates, and thus could not calculate distances. If the original record card listed workplace as some variant of “local” or “nearby”, we assume a commuting distance of 0.5 km and that workplace centrality is the same as home centrality. These cases account for approximately 2.4 percent of observations.

There are also observations for which the distances between home and workplace were very large. It is likely that these workers were stationed remotely and did not commute on a daily basis. Thus, in our main analysis, we exclude the 76 observations where the distance between home and work was over 50 km. We have also set the cut-off at 20 km (which excludes an additional 117 observations) and included long commutes in the analysis as robustness checks. Our results are not particularly sensitive to the rule used for exclusion of outliers.

VI. Measurement error and bias

For the most part, errors in our distance variables will simply be classical measurement error, resulting from our inability to identify precise locations for home, workplace, bus stops, and tram stops. Our assumption that residences and workplaces are at the center of the street (or broader location) implies that, on average, our GIS coordinates will be very close to correct, but there will be a variance around the point estimate. As noted above, the extent of this measurement error is likely to be larger for workplaces than for residences or public transport.

In addition, there exist two likely sources of systematic bias in our variable for distance commuted. First, we are less likely to find workplace locations for individuals who had longer commutes. When we could not find a workplace through other means, our final approach was to search the map in proximity to the worker’s residence. This approach helped locate numerous workplaces, but it also implies that we are more likely to be missing data for workplace location if a worker’s residence was further from home, and thus had a longer commute. This will bias the estimated travel distances in Section 6 downwards. However, we do not feel that this bias is likely to be large because we have been able to locate all but about two percent of workplaces named on the original record cards.

A more serious potential concern results from our use of a single centroid for each residential street and workplace location. As noted above, the use of a single centroid is likely to result only in measurement error for residential addresses or workplace locations, *taken individually*. However, in this context, the location of an individual’s workplace is not independent of their residence. For example, a worker who resides on a short north-south street that intersects a lengthy east-west workplace street near its eastern end is more likely to work around the corner at the eastern end of the workplace street than a couple kilometres away at the centroid of the street. Similarly, a worker whose workplace is reported as a borough adjacent to their borough of residence is more likely to be employed near the border of the two boroughs than at the centroid of the workplace borough. Consequently, it is possible that our approach will overestimate the distance commuted. In this case the measurement is not classical but instead the covariance between the measurement error and (true) distance commuted is positive. A positive covariance generally reinforces the attenuation bias stemming from classical measurement error (Bound et al., 2001).

Taken together, the likely consequence of these types of measurement error will be attenuation bias in our estimates of the effects of distances on earnings. In other words, our estimated returns to commuting in Section 7 are likely to be biased downwards. The extent of this bias is likely to be lower in the IV estimates of the returns to commuting (Table 6) than the OLS estimates (Table 4) because the birthplace location and nearest city center are much more likely to be independent of each other than residence and workplace. On the other hand, there is likely to be little bias in our estimated returns to access to public transport, as these GIS coordinates are measured with little error. As a result, we think our results in the OLS regressions in Tables 4 and Appendix IV represent a lower bound on the returns to distance commuted but are fairly accurate on the returns to access to public transport.

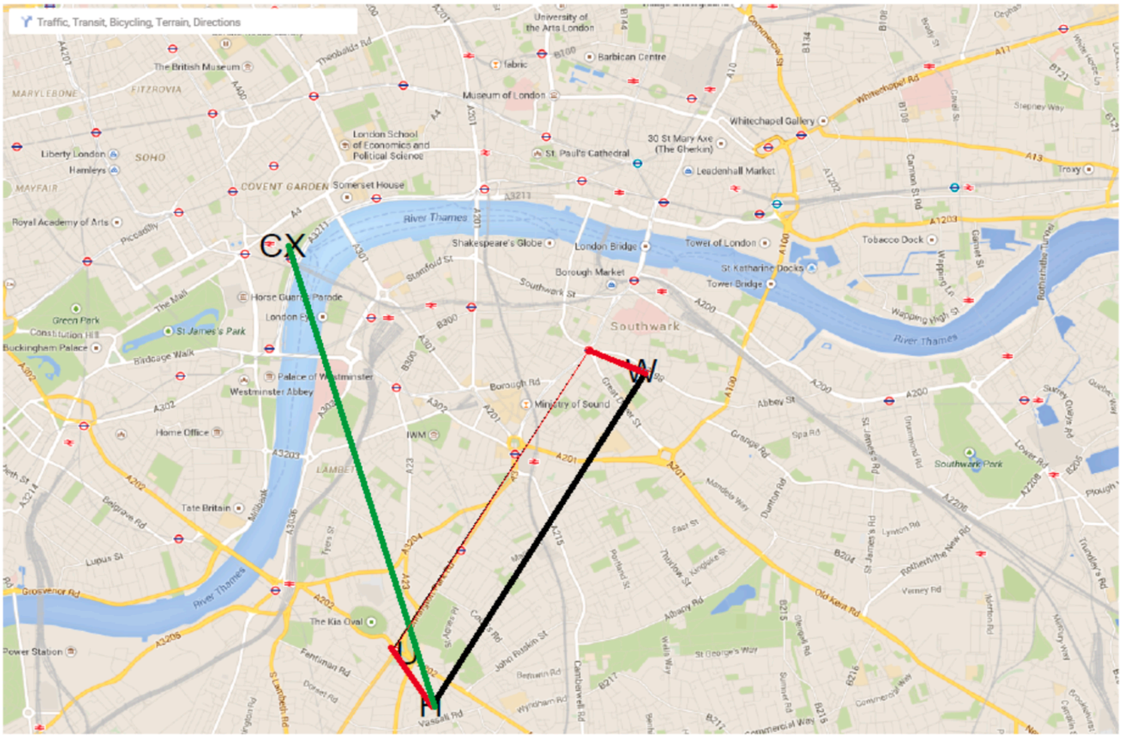

Fig. A.II.1. Distances for One Individual.

Appendix III. Identifying assumptions of the IV regressions

The logic behind the instrument's compliance with the "relevance" condition is that birthplace "fixes" residence and Charing Cross/ Bank of England "fixes" workplace. Intuitively, this will hold if, first, birthplace and current residential location are correlated and, second, if workers tended to commute inwards toward the two centers. Both conditions clearly hold. There is a strong relationship between place of birth and place of residence. Among all income earners in the sample born in the *New Survey* area, 31.5 percent lived in the same borough that they were born in, and 11.9 percent resided in an adjacent borough. As we have shown in Section 3, there also was a strong tendency to commute inwards.

There is no formal test for the "no direct influence" condition; however, it seems plausible that distance from birthplace to the nearest center does not affect earnings, except through commuting distance. Neither birthplace nor the location of the centers are choice variables for individual workers, thus there can be no concerns about reverse causation.[40]

"Monotonicity" implies in our case that those born further away from Charing Cross/Bank of England centroid commuted further. It is, however, possible that "local" London labor markets – concentrations of work outside the center – may lead to a population of "defiers" in our sample. A large population of defiers – e.g., individuals born some distance from the center of London who nevertheless

[40] One possible threat to the IV strategy would be if distance from birthplace to the center was an indicator of father's social status (e.g., the rich lived further from the center, as per the monocentric city model) and there was low intergenerational mobility. In this case, the IV would be proxying head of household influence and thus be correlated with the error term. However, the evidence for both conditions is very weak. London has rich and poor areas, but they are more correlated with direction (north and west are wealthier than south and east) than with distance from the center (Heblich et al., 2021). Moreover, Baines and Johnson (1999) show that there was a high degree of social mobility; sons rarely followed their fathers into a trade.

commute a short distance to work into one of these “local” labor markets – would undermine the IV strategy. In these circumstances, the IV estimates cannot be attributed as causal, local or otherwise.

The monotonicity assumption implies that commuting distance should be increasing with distance from birthplace to the nearest center. Strict monotonicity implies this should hold for all employees in the sample. More realistically, a stochastic version of monotonicity may hold, if there are more “compliers” than “defiers” or if the expected value of distance commuted is increasing with the distance of birthplace to the nearest center. We summarize the theory behind the monotonicity assumption and the relevant evidence in the *New Survey* data below.

There have been several recent attempts to address what instrumental variable regressions can estimate if the assumptions of strict monotonicity are violated. Small et al., (2017), re-purposed the idea of “stochastic monotonicity” to show that if there are more compliers than defiers in each sub-group of the population having the same value of the outcome variable then 2SLS estimates a weighted difference of the average treatment effect, where the weights reflect the size of compliers and defiers in the population. Chaisemartin (2017) argues that something close to a treatment effect can be identified if there are at least as many compliers as defiers and that the “treatment” variable has the same effect on both groups. In our case, this would require that a larger distance commuted has the same effect on wages for both compliers and defiers. If so, then the 2SLS estimates will give the local average treatment effect of the remaining (excess) compliers in the sample. Dahl et al. (2017) show that a local average treatment effect (LATE) for compliers (and defiers) can be estimated when there are only one or the other population in some range of the outcome variable for a given level of the instrument. Under this “local monotonicity” each LATE of the compliers is then locally identified in the range of the outcome variable where they are the only group.

Many of these results are, however, developed on the assumption of a binary endogenous variable and/or instrument. In our case, both the endogenous variable (commute distance) and the instrument (distance from birthplace to the nearest center) are continuous variables. As such any appeal to the weaker versions of monotonicity above can only be suggestive. Counting the numbers of compliers and defiers is harder when the endogenous variable is continuous rather than discrete. In a review of the recent literature, Fiorini and Stevens (2021) recommend looking at “stochastic dominance” of the instrument first proposed by Angrist and Imbens (1995) as a necessary but not sufficient condition for monotonicity. The idea here is to look at the cumulative distribution function of the endogenous variable conditional on the level of the instrument. If monotonicity holds, the *expected value* of the distance commuted for someone with a birthplace distance of $k + 1$ should be higher than the expected value of distance commuted for someone with a birthplace distance of k. Equivalently the (cumulative) probability of a given distance commuted should be lower among individuals with a lower value of the instrument than among those with a higher value of the instrument. With continuous variables this is a necessary but not sufficient test of deterministic monotonicity – since the continuous variables have to be drawn into discrete groups. A graph of distance commuted for each of the (banded) levels of the instrument is one way of assessing whether monotonicity is likely to hold. If the cumulative distances commuted for the sample with birthplace to the center distance k is always above the cumulative distances travelled for the sample born at distance $K + 1$ from the center, then this suggests monotonicity may hold.

The visual tests of stochastic dominance are given in Fig. A.III.1. When the instrument is banded into discrete distance intervals, the figure suggests that stochastic dominance holds for (banded) values of the instrument below 10 km from the center of London. At values of the instrument greater than 10 km, stochastic dominance no longer holds. Some individuals born outside the center of London may find work in more local labor markets, so that distance from birthplace to the center of London is negatively correlated with distance to work. This suggests that we may be able to identify something close to a local causal response for a restricted range of the instrument. In practice, some 85 percent of the sample of wage earners was born within 10 km of the London centroids.

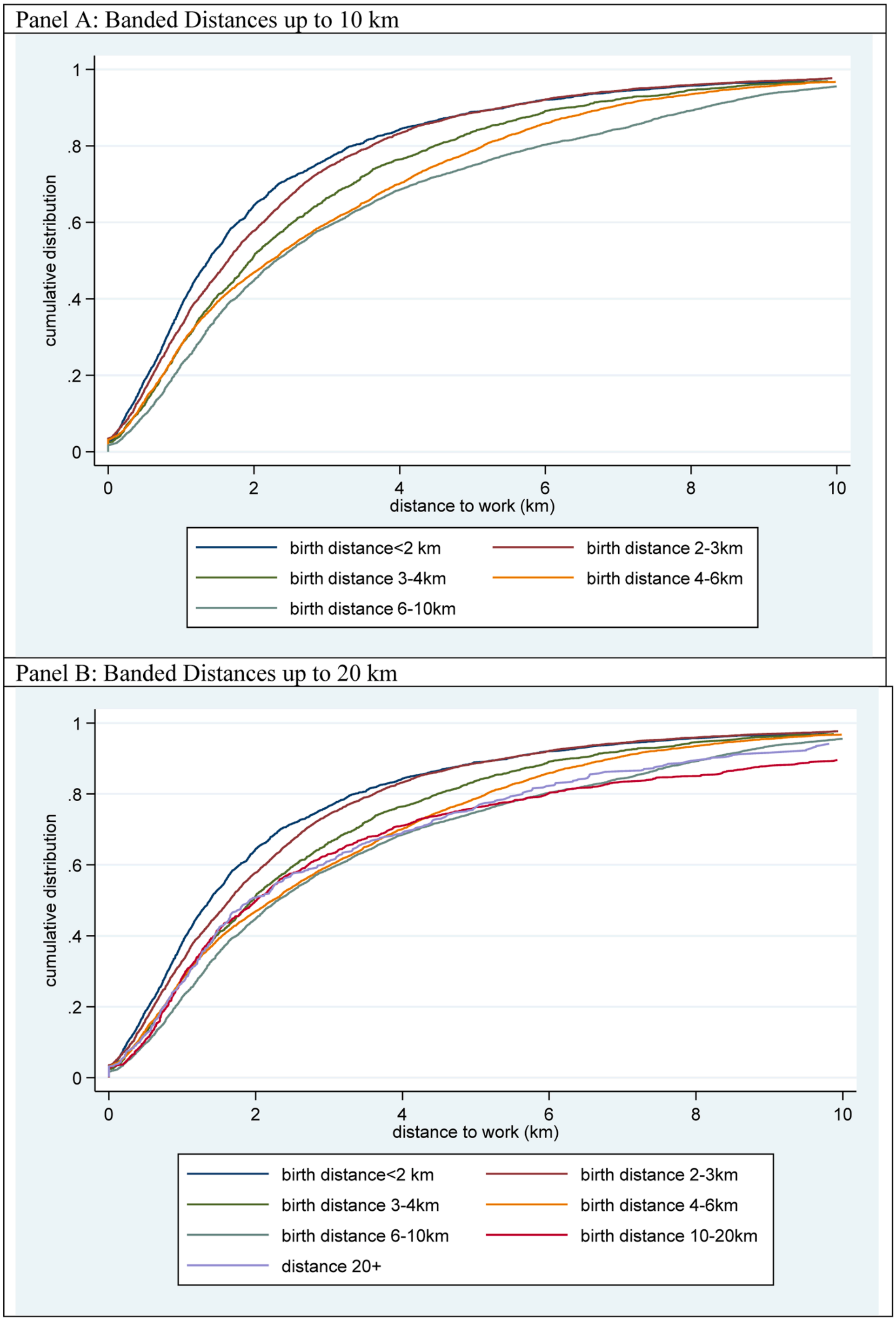

Fig. A.III.1. Stochastic Dominance Inspection Test: Distance to Work by Birthplace Distance Groups.
Source: Seltzer and Wadsworth (2023).

Appendix IV. Additional tables and figures

This appendix shows full results for all regression tables in the paper. It also shows the results of additional regressions undertaken as robustness checks. A brief summary of each table is below.

Table A.IV.1 – This table shows the estimated marginal effects for the control variables in Table 3.

Table A.IV.2 – This table shows robustness checks for Table 3. We have re-estimated the models using the full sample. We have also replaced the distance from public transport variables with the number of train/Underground stations and bus/tram stops in the same 500 m^2 grid (and one square kilometer grid) as the individual's residence. Finally, we have also included household fixed effects. The results in all cases are qualitatively similar to those shown in Table 3.

Table A.IV.3 – This table shows the estimated coefficients for the control variables in Table 4.

Tables A.IV.4 and A.IV.5 – This table shows robustness checks for Table 4. These regressions: 1) redefine the head to be the highest income earner in each household, 2) replace the distance to public transport variables with the number of stops/stations within the same one kilometer squared grid as workers' residences and workplaces, 3) include only heads of household, 4) replace distance commuted with discrete distance categories, 5) include very long commutes (50+ kilometers), 6) exclude occupation and workplace borough dummies, 7) replace occupation dummies with skill categories, 8) exclude observations collected by the most prolific enumerator, G.E. Bartlett, whose accuracy has been questioned in Abernethy (2017), 9) exclude individuals working for the same employer as the head of household, and 10) exclude all members of households where at least one other member works for the same employer as the head. In all cases, the main results are qualitatively similar to those presented in Table 4.

Tables A.IV.6 – This table shows the estimated coefficients for the control variables in Table 5.

Tables A.IV.7 – This table shows the estimated coefficients for the control variables in Table 6.

Tables A.IV.8 – This table shows the estimated coefficients for the control variables in Table 7.

Table A.IV.1
Estimated Effects of Control Variables on Labour Force Participation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Hours>0	In work	Distance	Distance (Heckman)	Transport costs=0	Distance< 1 km	Distance> 3.2 km
Age	−1.558*	−1.630*	10.195*	6.873*	−1.130*	−0.633*	1.104*
	(0.056)	(0.053)	(1.478)	(1.771)	(0.001)	(0.122)	(0.127)
Age^2	0.009*	0.009*	−0.144*	−0.129*	0.170*	0.011*	−0.016*
	(0.001)	(0.001)	(0.020)	(0.020)	(0.020)	(0.002)	(0.002)
Age = missing	−0.599*	−0.570*	1.825*	0.518	−0.131*	−0.064*	0.186*
	(0.012)	(0.011)	(0.276)	(0.484)	(0.028)	(0.024)	(0.024)
Female	−0.341*	−0.380*	−0.418*	−1.041*	−0.015*	0.027*	−0.046*
	(0.003)	(0.003)	(0.062)	(0.200)	(0.007)	(0.006)	(0.006)
Born in England	0.077*	0.070*	−0.176	−0.004	0.019	−0.001	−0.022
	(0.007)	(0.007)	(0.185)	(0.152)	(0.014)	(0.012)	(0.012)
Born in London	0.188*	0.192*	−0.214	0.163	−0.009	0.001	−0.014
	(0.006)	(0.006)	(0.139)	(0.159)	(0.011)	(0.009)	(0.009)
Born and lives in the same borough	−0.029*	−0.037*	−0.165*	−0.187*	0.031*	0.010	−0.023*
	(0.005)	(0.004)	(0.081)	(0.090)	(0.009)	(0.007)	(0.008)
Borough is adjacent to birth borough	−0.055*	−0.071*	−0.209*	−0.280*	−0.004	−0.019	0.009
	(0.006)	(0.006)	(0.102)	(0.138)	(0.013)	(0.011)	(0.012)
Other family pay	−0.000*	−0.001*					
	(0.000)	(0.000)					
Non-labor income household	−0.002*	−0.002*					
	(0.000)	(0.000)					
Observations	51,970	51,970	23,254	51,970	19,147	23,254	23,254

Notes: Coefficients on Age, Age^2, and Age = missing are multiplied by 100. See Table 3 for additional results and notes.
Source: Seltzer and Wadsworth (2023).

Table A.IV.2
Distance Effects on Labour Force Participation: All Family Members in a Household.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Hours > 0: probit	In work: probit	Dist. to Work: OLS	Dist. to work: Heckman	Trans. costs=0: probit	Dist. to work < 1 km: probit	Dist. to work > 3.2 km: probit
Distance home-center	−0.001	−0.005*	0.441*	0.410*	−0.052*	−0.057*	0.060*
	(0.002)	(0.002)	(0.035)	(0.038)	(0.003)	(0.003)	(0.003)
Distance home-train	0.024*	0.007	−0.100	−0.072	0.011	−0.010	−0.008
	(0.005)	(0.005)	(0.105)	(0.109)	(0.009)	(0.008)	(0.008)
Distance home-Underground	0.005	−0.003	−0.182*	−0.179*	0.039*	0.041*	−0.026*
	(0.003)	(0.003)	(0.080)	(0.067)	(0.006)	(0.005)	(0.005)
Distance home-tram	−0.007	−0.003	−0.063	−0.102	−0.007	−0.040*	0.001
	(0.006)	(0.006)	(0.129)	(0.133)	(0.012)	(0.010)	(0.010)
Distance home-bus	−0.004	−0.026*	−0.064	−0.060	−0.009	−0.043*	0.006
	(0.010)	(0.009)	(0.189)	(0.220)	(0.019)	(0.016)	(0.016)
Observations	67,584	67,584	34,342	67,584	28,880	34,294	34,294
R-squared	0.278	0.351	0.029		0.047	0.042	0.063
Sample mean	0.512	0.582	3.22	3.22	0.418	0.294	0.332

Notes: The sample in these regressions is the same as in Table 3, except heads of households and non-relatives are included. See other notes in Table 3.
Source: Seltzer and Wadsworth (2023).

Table A.IV.3
Estimated Effects of Control Variables on Earnings.

	(1)	(2)	(3)	(4)	(5)	(6)
	Related to head	Related to head: Heckman	Related to head: age<25	Children of head: age<25	All	All: HH fixed effects
Age	0.146*	0.146*	0.491*	0.495*	0.098*	0.110*
	(0.003)	(0.003)	(0.015)	(0.015)	(0.001)	(0.001)
Age^2	−0.002*	−0.002*	−0.010*	−0.010*	−0.001*	−0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age = missing	2.586*	2.595*	6.131*	6.246*	2.054*	2.187*
	(0.039)	(0.038)	(0.140)	(0.143)	(0.022)	(0.030)
Male	0.266*	0.266*	0.211*	0.202*	0.321*	0.272*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.008)
Born in England	0.042*	0.043*	0.006	0.007	0.039*	0.058*
	(0.016)	(0.016)	(0.018)	(0.019)	(0.008)	(0.014)
Born in London	−0.001	−0.001	0.016	0.018*	0.003	−0.024
	(0.010)	(0.010)	(0.009)	(0.009)	(0.007)	(0.014)
Born and lives in same borough	0.102*	0.102*	0.015	0.014	0.074*	0.161*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)	(0.010)
Lives in an adjacent borough	0.019	0.019	0.004	0.013	0.024*	0.082*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.007)	(0.014)
Hours last week	0.017*	0.016*	0.010*	0.009*	0.016*	0.018*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Hours missing	0.615*	0.615*	0.351*	0.305*	0.635*	0.672*
	(0.036)	(0.036)	(0.041)	(0.041)	(0.024)	(0.028)
Quarrying	0.056	0.056	0.136	0.129	0.167*	0.132
	(0.132)	(0.132)	(0.127)	(0.134)	(0.054)	(0.120)
Brick/glass worker	0.106	0.105	0.139	0.117	0.165*	0.198
	(0.099)	(0.099)	(0.087)	(0.089)	(0.048)	(0.084)
Chemicals	0.178	0.179	0.184	0.178	0.170*	0.196
	(0.095)	(0.094)	(0.080)	(0.082)	(0.042)	(0.078)
Metals	0.144	0.144	0.134	0.132	0.174*	0.165*
	(0.093)	(0.093)	(0.078)	(0.080)	(0.040)	(0.073)
Electro-plate	0.090	0.090	0.107	0.079	0.240*	0.144
	(0.121)	(0.120)	(0.111)	(0.116)	(0.062)	(0.099)
Electricians	0.115	0.115	0.103	0.095	0.185*	0.124
	(0.093)	(0.093)	(0.079)	(0.081)	(0.041)	(0.075)
Watchmakers	0.151	0.152	0.113	0.107	0.226*	0.096
	(0.115)	(0.114)	(0.090)	(0.092)	(0.055)	(0.098)

(*continued on next page*)

Table A.IV.3 (*continued*)

	(1) Related to head	(2) Related to head: Heckman	(3) Related to head: age<25	(4) Children of head: age<25	(5) All	(6) All: HH fixed effects
Leather	0.104	0.105	0.131	0.111	0.175*	0.130
	(0.095)	(0.094)	(0.079)	(0.081)	(0.043)	(0.077)
Textiles	0.036	0.035	0.047	0.038	0.092	0.102
	(0.096)	(0.096)	(0.083)	(0.085)	(0.048)	(0.085)
Dressmakers	0.108	0.108	0.112	0.101	0.166*	0.103
	(0.093)	(0.092)	(0.078)	(0.080)	(0.040)	(0.073)
Food/drink	0.131	0.132	0.148	0.142	0.169*	0.170
	(0.093)	(0.093)	(0.079)	(0.081)	(0.040)	(0.074)
Wood	0.157	0.158	0.168*	0.165*	0.240*	0.175*
	(0.094)	(0.093)	(0.079)	(0.081)	(0.040)	(0.073)
Paper	0.068	0.068	0.109	0.096	0.112*	0.106
	(0.094)	(0.093)	(0.079)	(0.081)	(0.042)	(0.075)
Printer	0.167	0.168	0.165*	0.156	0.300*	0.185*
	(0.094)	(0.094)	(0.079)	(0.081)	(0.041)	(0.075)
Builders	0.319*	0.320*	0.334*	0.327*	0.210*	0.247*
	(0.095)	(0.094)	(0.081)	(0.083)	(0.040)	(0.074)
Painters	0.245*	0.245*	0.236*	0.227*	0.253*	0.212*
	(0.095)	(0.095)	(0.080)	(0.082)	(0.041)	(0.075)
Other materials	0.088	0.089	0.082	0.059	0.131*	0.125
	(0.095)	(0.094)	(0.080)	(0.082)	(0.043)	(0.079)
Other	0.049	0.049	0.072	0.065	0.121*	0.072
	(0.095)	(0.095)	(0.081)	(0.083)	(0.044	(0.077)
Transport	0.084	0.085	0.136	0.131	0.127*	0.112
	(0.093)	(0.092)	(0.077)	(0.079)	(0.039)	(0.072)
Finance	0.074	0.075	0.098	0.099	0.109*	0.064
	(0.093)	(0.092)	(0.078)	(0.080)	(0.040)	(0.073)
Public admin.	0.556*	0.560*	0.728*	0.647*	0.453*	0.381*
	(0.136)	(0.136)	(0.207)	(0.208)	(0.042)	(0.095)
Professional	0.402*	0.402*	0.285*	0.259*	0.391*	0.343*
	(0.108)	(0.108)	(0.099)	(0.101)	(0.055)	(0.082)
Entertainment	0.178	0.178	0.214	0.211	0.180*	0.049
	(0.136)	(0.135)	(0.136)	(0.137)	(0.063)	(0.095)
Personal services	−0.148	−0.148	−0.032	−0.002	−0.124*	−0.125
	(0.093)	(0.093)	(0.078)	(0.080)	(0.040)	(0.073)
Clerks	0.279*	0.279*	0.249*	0.238*	0.333*	0.224*
	(0.093)	(0.092)	(0.078)	(0.080)	(0.040)	(0.073)
Warehouse	0.120	0.120	0.134	0.128	0.159*	0.136
	(0.093)	(0.093)	(0.078)	(0.080)	(0.040)	(0.073)
Drivers	0.297*	0.299*	0.269*	0.265*	0.167*	0.200*
	(0.101)	(0.101)	(0.094)	(0.098)	(0.041)	(0.077)
Other	0.126	0.127	0.141	0.137	0.108*	0.108
	(0.094)	(0.094)	(0.079)	(0.081)	(0.040)	(0.074)
Missing occ.	−0.090	−0.086	0.153	0.138	0.040	−0.034
	(0.308)	(0.307)	(0.175)	(0.182)	(0.121)	(0.142)
Observations	15,436	16,566	11,997	11,354	31,668	31,668

Notes: Coefficients on Age, Age^2, and Age = missing are multiplied by 100. The omitted occupation is agriculture. See Table 4 for additional results and notes.
Source: Seltzer and Wadsworth (2023).

Table A.IV.4
Robustness Checks on Distance Estimates in Pay Regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance to work	4.738*	3.359*	2.447*	2.451*	2.577*	1.858*	2.992*	2.540*
	(0.273)	(0.165)	(0.188)	(0.203)	(0.233)	(0.314)	(0.319)	(0.236)
Distance^2	−0.075*	−0.057*	−0.039*	−0.035*	−0.049*	−0.026	−0.083*	−0.046*
	(0.018)	(0.009)	(0.011)	(0.009)	(0.014)	(0.017)	(0.023)	(0.014)
Demographic	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Work location	No	No	No	Yes	Yes	Yes	Yes	Yes
Residence	No	No	No	Yes	Yes	Yes	Yes	Yes
Other distance	No	No	No	No	Yes	Yes	Yes	Yes
Household fixed effects	No	No	No	No	No	Yes	No	No
One km^2 grids	No	No	No	No	No	No	Yes	No
Excludes influential heads	No	No	No	No	No	No	No	Yes
Observations	15,436	15,436	15,436	15,436	15,436	15,436	15,185	14,679
R-squared	0.046	0.521	0.559	0.571	0.572	0.869	0.571	0.572
Mean dep. var.	10.359	10.359	10.359	10.359	10.359	10.359	10.355	10.355
F statistic	381.7*	1396.4*	482.6*	186.8*	173.1*	107.8*	167.7*	164.4*

Notes: Estimates based on sample of family members, excluding head of household (column 1, Table 4). See Table 4 for additional notes. Column 8 excludes workers in households with influential heads – e.g., households where at least one additional member works for the same employer as the head.
Source: Seltzer and Wadsworth (2023).

Table A.IV.5
Further Robustness Checks on Distance Estimates in Pay Regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unlimited distance	Armstrong skill	Exclude highest earner	No Bartlett sample	Discrete distance: non-head family	Discrete distance: all family	Only heads	Discrete distance: only heads
Distance to work	2.337*	2.999*	3.040*	2.595*			1.272*	
	(0.177)	(0.239)	(0.267)	(0.258)			(0.167)	
Distance^2	−0.0304*	−0.0600*	−0.0734*	−0.0506*			−0.0418*	
	(0.0093)	(0.0143)	(0.0154)	(0.0153)			(0.0118)	
Ref: distance<0.5 km								
Distance: 0.5–1 km					0.042*	0.029*		0.025*
					(0.014)	(0.009)		(0.010)
Distance: 1–2 km					0.058*	0.042*		0.041*
					(0.013)	(0.008)		(0.009)
Distance: 2–3 km					0.078*	0.061*		0.047*
					(0.014)	(0.009)		(0.010)
Distance: 3–4 km					0.083*	0.074*		0.062*
					(0.015)	(0.009)		(0.011)
Distance: 4–5 km					0.143*	0.102*		0.057*
					(0.017)	(0.010)		(0.012)
Distance: 5–10 km					0.176*	0.126*		0.071*
					(0.016)	(0.009)		(0.010)
Distance: 10+ km					0.237*	0.183*		0.117*
					(0.021)	(0.013)		(0.013)
Observations	15,441	15,436	12,480	13,298	13,298	31,195	15,758	15,758
R-squared	0.572	0.553	0.511	0.567	0.567	0.686	0.512	0.512
Mean dep. var.	10.359	10.359	10.259	10.349	10.349	10.754	11.141	11.141
F statistic	172.9*	199.8*	99.2*	147.6*	141.8*	574.5*	68.9*	67.4*

Notes: See notes in Table 4.
Source: Seltzer and Wadsworth (2023).

Table A.IV.6
Effects of Cross and Out-Commuting on Distance Effects on Pay.

	(1)	(2)	(3)	(4)	(5)
Age	0.1456*	0.4906*	0.1456*	0.1456*	0.1456*
	(0.0027)	(0.0148)	(0.0027)	(0.0027)	(0.0027)
Age^2	−0.0018*	−0.0098*	−0.0018*	−0.0018*	−0.0018*
	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)
Age = missing	2.5861*	6.1246*	2.5865*	2.5861*	2.5859*
	(0.0386)	(0.1403)	(0.0386)	(0.0386)	(0.0386)
Male	0.2658*	0.2105*	0.2661*	0.2661*	0.2661*
	(0.0069)	(0.0069)	(0.0069)	(0.0069)	(0.0069)
Born in England	0.0418*	0.0053	0.0423*	0.0423*	0.0422*
	(0.0157)	(0.0176)	(0.0157)	(0.0157)	(0.0157)
Born in London	−0.0005	0.0159	−0.0005	−0.0007	−0.0006
	(0.0095)	(0.0092)	(0.0095)	(0.0095)	(0.0095)
Born and lives in same borough	0.1019*	0.0146	0.1020*	0.1020*	0.1019*
	(0.0078)	(0.0083)	(0.0078)	(0.0078)	(0.0078)
Lives in an adjacent borough	0.0190	0.0038	0.0188	0.0189	0.0188
	(0.0128)	(0.0128)	(0.0128)	(0.0128)	(0.0128)
Hours last week	0.0165*	0.0104*	0.0165*	0.0165*	0.0165*
	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0006)
Hours missing	0.6168*	0.3512*	0.6157*	0.6157*	0.6172*
	(0.0361)	(0.0411)	(0.0361)	(0.0361)	(0.0361)
Dist. home-center	−0.0010	−0.0044	−0.0008	−0.0011	−0.0010
	(0.0042)	(0.0042)	(0.0036)	(0.0036)	(0.0036)
Dist. home-train	0.0165	0.0211*	0.0178	0.0166	0.0168
	(0.0098)	(0.0096)	(0.0099)	(0.0098)	(0.0098)
Dist. home-Underground	0.0082	0.0076	0.0100	0.0095	0.0082
	(0.0062)	(0.0062)	(0.0067)	(0.0073)	(0.0071)
Dist. home-tram	0.0246*	0.0117	0.0228	0.0239	0.0244
	(0.0126)	(0.0122)	(0.0126)	(0.0126)	(0.0125)
Dist. home-bus	−0.0292	−0.0174	−0.0291	−0.0296	−0.0291
	(0.0208)	(0.0206)	(0.0208)	(0.0208)	(0.0208)
Dist. work-center	−0.0011	−0.0013	−0.0010	−0.0010	−0.0011
	(0.0042)	(0.0042)	(0.0035)	(0.0035)	(0.0035)
Dist. work-train	−0.0062	−0.0152	−0.0056	−0.0069	−0.0082
	(0.0095)	(0.0090)	(0.0093)	(0.0094)	(0.0095)
Dist. work-Underground	0.0090	0.0092	0.0086	0.0081	0.0079
	(0.0048)	(0.0054)	(0.0049)	(0.0049)	(0.0048)
Dist. work-tram	0.0063	0.0025	0.0075	0.0072	0.0085
	(0.0082)	(0.0085)	(0.0081)	(0.0081)	(0.0081)
Dist. work-bus	0.0011	0.0080	0.0054	0.0054	0.0060
	(0.0114)	(0.0130)	(0.0115)	(0.0111)	(0.0108)
Observations	15,436	11,997	15,436	15,436	15,436
R-squared	0.572	0.632	0.572	0.572	0.572
Mean dep. var.	10.4	10.3	10.4	10.4	10.4
F statistic	167.9*	158.0*	170.0*	170.1*	170.5*

Notes: Coefficients on Age, Age^2, and Age = missing are multiplied by 100. See Table 5 for additional notes.
Source: Seltzer and Wadsworth (2023).

Table A.IV.7
Full Ordinary Least Squares and Instrumental Variable Estimates of the Wage Returns to Distance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS < 6k	2nd Stage IV < 6k	OLS < 8k	2nd Stage IV < 8k	OLS < 10k	2nd Stage IV < 10k	OLS < 15k	2nd Stage IV < 15k	OLS < 30k	2nd Stage IV < 30k	OLS: All	2nd Stage: IV All
Distance to work	1.540*		1.520*		1.393*		1.342*		1.331*		1.337*	
	(0.137)		(0.130)		(0.115)		(0.104)		(0.101)		(0.097)	
Distance to work IV (Birthplace centrality)		3.87*		3.61*		3.33*		3.84*		4.33*		3.55
		(1.69)		(1.10)		(0.80)		(0.68)		(0.80)		(2.38)
Age	0.0929*	0.0917*	0.0955*	0.0946*	0.0971*	0.0962*	0.0967*	0.0954*	0.0963*	0.0948*	0.0939*	0.0927*
	(0.0019)	(0.0021)	(0.0018)	(0.0019)	(0.0017)	(0.0017)	(0.0016)	(0.0017)	(0.0016)	(0.0017)	(0.0016)	(0.0020)
Age^2	−0.00107*	−0.00106*	−0.00111*	−0.00109*	−0.00113*	−0.00112*	−0.00112*	−0.00111*	−0.00112*	−0.00110*	−0.00109*	−0.00107*
	(0.00002)	(0.00003)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00003)
Age = missing	1.9121*	1.8820*	1.9540*	1.9309*	1.9830*	1.9629*	1.9760*	1.9483*	1.9703*	1.9370*	1.9305*	1.9061*
	(0.036)	(0.0428)	(0.0336)	(0.0360)	(0.0317)	(0.0330)	(0.0308)	(0.0321)	(0.0305)	(0.0321)	(0.0299)	(0.0391)
Male	0.4069*	0.3987*	0.4006*	0.3929*	0.3992*	0.3925*	0.4037*	0.3958*	0.4042*	0.3946*	0.4128*	0.4049*
	(0.0110)	(0.0122)	(0.0100)	(0.0107)	(0.0092)	(0.0096)	(0.0090)	(0.0092)	(0.0089)	(0.0093)	(0.0088)	(0.0123)
Head of household	0.1631*	0.1621*	0.1679*	0.1662*	0.1690*	0.1676*	0.1633*	0.1620*	0.1632*	0.1614*	0.1660*	0.1651*
	(0.0120)	(0.0122)	(0.0110)	(0.0112)	(0.0103)	(0.0104)	(0.0099)	(0.0100)	(0.0098)	(0.0010)	(0.0096)	(0.0098)
Observations	12,430	12,430	15,131	15,131	17,035	17,035	18,233	18,233	18,581	18,581	19,680	19,680
R-squared	0.618	0.610	0.617	0.610	0.620	0.614	0.622	0.610	0.622	0.605	0.622	0.613
F	303.37*		367.15*		420.14*		452.19*		458.07*		477.11*	
Wald χ^2		21,796.10*		26,605.01*		30,411.04*		32,201.95*		32,073.98*		34,202.49*
1st-stage F statistic		4.75*		12.64*		14.80*		16.68*		17.05*		9.24*

Notes: Coefficients on Age, Age^2, and Age = missing are multiplied by 100. See Table 6 for additional notes.
Source: Seltzer and Wadsworth (2023).

Table A.IV.8
Additional Regressions on Earnings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	0.108*	0.101*	0.089*	0.105*	0.104*	0.099*	0.099*	0.097*	0.090*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age^2	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age = missing	2.310*	2.173*	1.887*	2.227*	2.200*	2.122*	2.128*	2.093*	1.956*
	(0.019)	(0.036)	(0.049)	(0.019)	(0.019)	(0.020)	(0.037)	(0.036)	(0.038)
Male	0.364*	0.398*	0.348*	0.423*	0.428*	0.349*	0.445*	0.455*	0.378*
	(0.006)	(0.012)	(0.015)	(0.006)	(0.005)	(0.007)	(0.010)	(0.010)	(0.013)
Born in England	0.046*	0.048*	0.037*	0.050*	0.051*	0.036*	0.056*	0.058*	0.037*
	(0.008)	(0.013)	(0.015)	(0.008)	(0.008)	(0.007)	(0.014)	(0.013)	(0.013)
Born in London	0.007	−0.013	−0.020	0.008	0.017*	0.008	−0.012	−0.007	−0.008
	(0.007)	(0.013)	(0.015)	(0.007)	(0.007)	(0.007)	(0.013)	(0.013)	(0.012)
Born and lives in same borough	0.067*	0.075*	0.087*	0.069*	0.070*	0.062*	0.070*	0.077*	0.070*
	(0.005)	(0.009)	(0.010)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)
Lives in an adjacent borough	0.027*	0.034*	0.035*	0.023*	0.029*	0.023*	0.026*	0.039*	0.030*
	(0.007)	(0.012)	(0.014)	(0.008)	(0.007)	(0.007)	(0.013)	(0.012)	(0.012)
Hours last week	0.017*	0.017*	0.018*	0.017*	0.016*	0.016*	0.017*	0.016*	0.016*
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Hours missing	0.663*	0.618*	0.662*	0.671*	0.617*	0.607*	0.624*	0.557*	0.576*
	(0.024)	(0.042)	(0.049)	(0.026)	(0.025)	(0.026)	(0.044)	(0.043)	(0.047)
Dist. home-center	0.011*	0.012*	0.009	0.012*	0.011*	0.007*	0.013*	0.012*	0.007
	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)
Dist. home-train	0.007	0.000	0.009	0.013	0.009	0.006	0.010	0.008	−0.004
	(0.007)	(0.011)	(0.014)	(0.007)	(0.007)	(0.006)	(0.012)	(0.011)	(0.011)
Dist. home-Underground	−0.002	−0.005	−0.006	−0.003	−0.002	−0.000	−0.006	−0.007	−0.003
	(0.004)	(0.007)	(0.008)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)
Dist. home-tram	0.011	0.002	−0.004	0.014	0.009	0.005	0.005	−0.002	−0.002
	(0.008)	(0.013)	(0.016)	(0.008)	(0.008)	(0.007)	(0.014)	(0.013)	(0.013)
Dist. home-bus	−0.013	−0.020	−0.020	−0.021	−0.003	−0.009	−0.025	−0.012	−0.023
	(0.013)	(0.021)	(0.024)	(0.013)	(0.013)	(0.012)	(0.022)	(0.021)	(0.020)
Dist. work-center	0.002	0.010	0.011	−0.001	0.001	−0.000	0.007	0.006	0.001
	(0.002)	(0.005)	(0.007)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Dist. work-train	0.004	−0.013	−0.030	0.006	0.001	−0.001	−0.015	−0.022	−0.025*
	(0.005)	(0.011)	(0.016)	(0.006)	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)
Dist. work-Underground	0.004	0.006	−0.016	0.005	0.006	0.005	0.007	0.014	0.015
	(0.003)	(0.008)	(0.010)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)
Dist. work-tram	0.007	0.017	0.035*	0.007	0.007	0.011*	0.021	0.018	0.017
	(0.005)	(0.012)	(0.016)	(0.005)	(0.005)	(0.005)	(0.013)	(0.012)	(0.012)
Dist. work-bus	0.001	−0.003	−0.006	0.007	0.011	0.001	0.005	0.026	0.015
	(0.007)	(0.021)	(0.024)	(0.007)	(0.007)	(0.006)	(0.021)	(0.021)	(0.020)
Observations	15,436	11,455	11,455	15,436	15,436	15,436	11,455	11,455	11,455
R-squared	0.572	0.572	0.906	0.534	0.553	0.628	0.901	0.905	0.923
Mean dep. var.	10.4	10.3	10.3	10.4	10.4	10.4	10.3	10.3	10.3

Notes: Coefficients on Age, Age^2, and Age = missing are multiplied by 100. See Table 7 for additional notes.
Sources: Seltzer and Wadsworth (2023).

Appendix V. Costs and benefits of commuting and calculating poverty lines

I. Costs and benefits of commuting

Table 8 shows the costs and benefits of commuting. The calculations in this table are very much back-of-the-envelope but are informed by stylized facts from Ponsonby and Ruck (1930) and from the *New Survey* data. In this appendix, we describe the assumptions behind these calculations and examine their historical basis.

Crow-flies distances

The distances in the first column are arbitrary round numbers, which cover the range of typical distances commuted. The range of distances covers virtually all workers who were not working “on the spot” (the term used by Ponsonby and Ruck, 1930 to describe the proximity of employment to residence in the 1890s). Approximately 86 percent of income earners in the sample travelled at least 500 m; approximately 99 percent travelled at most 16 km.

Transport mode

Ponsonby and Ruck (1930) state that workers typically walked up to 1.6 km, buses and trams were used interchangeably for distances of 1.6 to 3.2 km, the Underground was typically used for distances of 3.2 to 19.3 km, and trains were used for longer distances or as a replacement for the Underground in places where it was not available. This is broadly supported in the data. Approximately

82.9 percent of workers with non-missing transport costs who travelled distances of up to 1.6 km, reported costs of exactly zero, and thus must have walked or cycled. Approximately 83.7 percent of individuals with non-missing transport costs who commuted at least 1.61 km, reported positive costs, and thus must have used public transport. We do not observe the mode of transport, but the relationship between proximity to the Underground and the probability of commuting over 3.2 kms shown in the regressions in Table 3 is consistent with this pattern.

Distance walked

We construct *as the crow-flies* distances, i.e., in a straight line. The urban layout rarely allows this to be the actual route, thus actual distance travelled must be greater than crow-flies distance. There exists a substantial literature in geography on the difference between crow-flies and actual distances (Rietveld et al., 1999 and Underhill 2020). We assume, somewhat arbitrarily, that walking-only journeys were 25 percent longer than the crow-flies distance. Any journey involving public transport would have also involved walking from home to transport and from transport to work. Table 2 shows the average distance from home and work to each public transport mode. However, workers would have chosen their mode of transport at least partly based on proximity, so the walking distance to the chosen mode of transport will have on average been less than for modes not used. We assume 300 m of total walking at both ends for a one-way bus journey, about 75 percent of the sum of average distances from the nearest bus stop to home and workplace. We also assume 300 m of walking for a one-way tram journey. This is considerably less than the average distance shown in Table 2; however, one would expect that the distance walked by tram users would have been approximately the same as bus users, as the two modes of transport travelled at about the same speed, cost similar amounts per kilometer travelled, and, according to Ponsonby and ruck (1930), were used interchangeably by commuters. We assume 600 m of walking at both ends for a one-way Underground or train journey, about 75 percent of the maximum distance that geographers have argued that commuters are willing to walk to these modes of transport (Daniels and Mulley 2013).

Distance on public transport

As with walking, public transport generally does not travel in a straight line and this adds to the total distance. On the other hand, in many cases workers can choose between stops which are approximately equidistant to home (work). If there are two approximately equidistant stops from home, a worker would have been more likely to use the one closer to their work to minimize total travel time. This will at least partly offset the effect of added distance due to non-linear transport routes, and thus we assume that the travel distance for public transport is only 10 percent more than the crow-flies distance of total travel.

With each of our assumptions about distance, there is likely to be considerable heterogeneity across individuals and locations. The assumptions are not verifiable in the data, so it is also possible that there is some error on average. However, it is unlikely that modest errors in either direction will have a substantial impact on our conclusions in Section 6.

Walking and public transport time

Time is calculated as distance (from columns 3 and 4 in Table 8) divided by speed. Following Leunig (2006), we use 4 km per hour as a typical urban walking speed. We take public transport speeds from Table 1. Neither Ponsonby and Ruck (1930) nor *London Statistics* provide train speeds after the First World War. However, rail was an established mode of transport by this time and thus we follow Leunig (2006) and assume that average speeds in 1930 were 10 percent faster than those reported in *London Statistics* for 1907–08.

Implied return

We use the regressions in Table 4, column 1 and Table 6, column 9 evaluated at the tenth, twenty fifth, and fiftieth percentiles of the weekly earnings distribution (180d, 300d, and 583.5d) to calculate the returns to commuting the distances shown in the first column. Specifically, we estimate the returns as:

$\mathrm{Exp}[\ln(WE) + 0.02577d - 0.000489d^2] - \mathrm{Exp}[\ln(WE)]$	OLS estimates
$\mathrm{Exp}[\ln(WE) + 0.0333d] - \mathrm{Exp}[\ln(WE)]$	IV estimates

where:

WE = weekly earnings (in pence), evaluated at the 10th, 25th, and 50th percentile

d = distance commuted, in kilometres

Monetary costs

We use reported transport expenses from the *New Survey* data and the description of travel costs from Ponsonby and Ruck (1930) to determine a "typical" cost for the journey in each row. Public transport fares were set according to travel zones, which were imperfectly correlated to distance. For any given distance and mode of transport there may have been multiple fares, depending on the embarkation and disembarkation stations. The monetary costs reported in Table 8 are the range of typical fares reported in the *New Survey* data for workers commuting distances within 500 m of the crow-flies distances in column 1.[41]

Implied time costs

The total time spent commuting is the sum of walking time, transport time, and waiting time. We assume five minutes waiting time for the bus and tram and eight minutes for the train and Underground. We assume a longer time for train and Underground because the platform was physically removed from the entrance to the station. Following an extensive literature on the value of travel time saved, we use values of 50 and 100 percent of salary as the lower and upper bounds of the implied cost of commuting time (Wardman 1998; Zamparini and Reggiani 2007). In the second column of Table 8, we assume a single mode of transport. In practice, some commuters, particularly those with longer commutes, may have needed to transfer between modes and thus incurred additional waiting time.

II. The Hatton-Bailey poverty line

The appendix in Hatton and Bailey (1998) outlines their approach to constructing household poverty lines. To briefly summarize, they allocate minimum required expenditures on food and clothing, rent, and fuel. The minimum required expenditure on food and clothing is based on age and sex of the individual and ranges from 36d per week for a child under age 1 to 102d per week for males aged 18 and over. The minimum required rental expenditure is based on a standard of no more than two individuals to a room and a cost of 60d per week for one room, 102d per week for two rooms, 126d per week for three rooms, and 30d per week for each additional room. The minimum required expenditure on fuel is 36d per week, plus an additional 2d in South London. A household is classified as poor if the sum of these minimum expenditures and actual household expenditures on transport and National Insurance is greater than their total income from all sources. Hatton and Bailey (1998) use income from the previous week for the poverty calculations. The estimated poverty lines using this approach are 198, 292, 392, 588 pence per week for a household with only a single adult male, a married couple, a couple with one child, and a couple with three children, respectively. They estimate that 12.11 percent of households and 12.0 percent of individuals fell below the poverty line.

We have made two adjustments to their calculations. First, approximately 9.2 percent of individuals in the *New Survey* have a reported age of exactly zero. This is implausibly large and almost certainly age was not reported in most of these observations. We have reclassified these individuals as adults and adjusted required expenditure on food and clothing if 1) they had an occupation or reported earnings or hours worked or 2) their relationship to the head of household indicates they must have been an adult (e.g., wife or grandfather). If the individual was not an income earner and was plausibly a child (e.g., son or nephew of the head), we use a value of zero for age and assign minimum expenditure accordingly. The reclassification of children reported as aged zero to adults (age 18+) increases the minimum expenditure on food and clothing from 38d per week to 102d per week for 3742 men and to 94d per week for 4792 women. It is likely that many of those we still classify as age zero were actually older than one year and thus would require greater expenditures than for an infant, so our upwards adjustment to the poverty line is a lower-bound. Secondly, both National Insurance contributions and transport expenses are frequently missing in the data. Among individuals reporting earnings or hours in the previous week, approximately 30 percent are missing transport costs and approximately 20 percent are missing National Insurance contributions. We have handled missing data in two ways: constructing a lower-bound poverty line where missing observations are replaced by a value of zero and an expected value poverty line where missing observations are replaced by the overall sample mean. These reclassifications increase the poverty line for 4730 households and increase the number of individuals classified as poor from 12.0 percent of the sample (Hatton and Bailey 1998, p. 584) to 16.7 percent of the sample (lower-bound poverty line) or 20.6 percent of the sample (expected value poverty line).

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[41] The *New Survey* data typically reports weekly expenditures on transport. We divide this by 12 to find one-way fares. In each case, the range reported in Table 8 covers both the median and modal fare.

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