sociological science

Commuting and Gender Differences in Job Opportunities

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Abstract: Women tend to commute shorter distances and earn lower wages. The theory suggests that more mobile workers are likely to command higher wages, in part because they have access to more job opportunities. We show how information on employment concentration and commuting patterns can be linked to build an index of labor market opportunities, using linked administrative and household survey data from the UK. Although labor markets are porous, commonly used measures of employment concentration require well-defined geographical boundaries. We overcome this problem by combining employment concentration indices calculated using areas of different sizes and using the individual commuting costs as weights. We show that women have higher commuting costs and, as a result, their labor markets are smaller and their job opportunities are more limited.

Keywords: commuting costs; gender; parenthood; job opportunities; labor market concentration

Reproducibility Package: The data used in this research include the Business Structure Database (DOI: 10.5255/UKDA-SN-6697-15); Understanding Society: Waves 1–11, 2009–2020 and Harmonised BHPS: Waves 1–18, 1991–2009: Special Licence Access, Census 2001 Lower Layer Super Output Areas (DOI: 10.5255/UKDA-SN-6670-13); and Understanding Society: Waves 1–11, 2009–2020 and Harmonised BHPS: Waves 1–18, 1991–2009 (DOI:10.5255/UKDA-SN-6614-16). All three are available free of charge via the UK Data Service. The syntax code for reproducing results can be found at: https://osf.io/zscpf/?view_only=ccb1d3bb40c1400cacfe55382dababd3

A well-established finding in the social science literature is that women have shorter commutes and earn lower wages (Le Barbanchon, Rathelot, and Roulet 2021; Meekes and Hassink 2022). Yet, when and how shorter commutes translate into lower wages is not well understood. In theory, willingness to commute longer distances increases the pool of available job opportunities, potentially leading to better job matches and higher pay. Yet, this effect is highly dependent on the spatial distribution of jobs. A different mechanism linking commuting, job opportunities, and wages is bargaining power (Hirsch 2009; Hirsch, König, and Möller 2013). Workers with better access to alternative job opportunities can credibly threaten to quit their current employer if they believe their rewards package is inadequate. Thus, in principle, commuting constraints can depress wages via both lower quality job matches and lower bargaining power.

The existing literature has to date not directly tested the relationship between commuting costs, job opportunities, and wages. Previous studies have relied on indirect approaches such as scrutinizing how the gender pay gap varies with population density and distance from an urban center (Nisic 2017; Phimister 2005; Semyonov and Lewin-Epstein 1991). While insightful, these indirect approaches cannot provide definitive evidence on the mechanisms linking commuting costs and

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lower wages. Instead, direct measures of job opportunities, the mediating factor, are needed. Direct measures of job opportunities are also required to better understand the relative importance of the two mechanisms, poor job matches versus weaker bargaining power, in bringing about lower wages for workers with high commuting costs. However, measuring job opportunities is not straightforward. The economics literature has typically relied on labor market concentration indices, such as the Herfindahl-Hirschman index (HHI), constructed based on employment or vacancy data (Azar, Marinescu, and Steinbaum 2019, 2022). HHI captures variation in the spatial distribution of jobs or vacancies, and it is relatively simple to compute and straightforward to interpret. However, it is insensitive to differences in commuting costs among workers. In this article, we propose a new method of constructing an index of job opportunities that incorporates information on individual commuting costs and the spatial distribution of employment. Using administrative and panel survey data from the UK, we show how traditional employment concentration indices such as HHI can be modified to incorporate individual heterogeneity in commuting costs. We then use this index to document gender and parenthood differences in job opportunities.

This article contributes to the literature in two major ways. First, it makes a methodological contribution by proposing a new index of job opportunities that is sensitive to variation in worker commuting costs. Second, it makes a substantive contribution by using this index to explore gender and parenthood differences. Understanding how job opportunities vary for men and women is crucial to explain the observed gender gaps in pay. However, traditional indices of labor market concentration such as HHI are inadequate as they reflect only gender differences in occupations/industries and cannot capture women's shorter commuting range. Using a newly developed job opportunities index, we show that gender differences in commuting costs generate large differences in job opportunities. Our results indicate that, abstracting from commuting costs, women are found in less concentrated labor markets, due to their higher propensity to work in services that tend to be more geographically dispersed. However, incorporating commuting costs reverses this result. Women, and especially mothers, face higher commuting costs and smaller and more concentrated labor markets with reduced job opportunities. The average index of job opportunities among women with children is approximately 600 points, or about a quarter of the threshold for severe concentration, higher than the average index for men without children.

Literature Review

Gender Differences in Commuting

Commuting is an important feature of the modern labor market. Most workers spend a significant amount of their day commuting to work and back. For example, in 2021, the average commuting time in the UK was around 27 minutes one way (ONS 2022). Economic models assume that workers can balance the benefits of commuting (e.g., a higher salary or better housing amenities) with the costs (financial costs, stress, opportunity cost of time, etc.). Despite this, most studies find a negative relationship between long commutes and general life satisfaction (Chatterjee et al. 2020; Stutzer and Frey 2008), or satisfaction with specific life domains such as leisure and/or family life (Clark et al. 2020; Lorenz 2018). In any case, the well-being costs of commuting can be significant, and they vary across the population.

A gender gap in commuting time and distance has been well documented in a variety of contexts (Casado-Díaz, Simón-Albert, and Simón 2023; Fuchs and Jost 2024; Madden 1981; Van Ommeren and Fosgerau 2009), with the majority of studies focusing on occupational segregation and social roles as likely explanations (Fernandez and Su 2004). Women are observed to more often work in public or service sector jobs, which tend to be geographically dispersed, so they may have less need to commute longer distances (Benson 2014; Fuchs and Jost 2024; Shauman 2010). Conversely, it is possible that women respond to constraints in commuting time by sorting themselves into occupations that are more geographically dispersed (Johnston-Anumonwo 1988).

Gendered social roles require that women should prioritize "home making" while men are expected to "provide." Indeed, despite advances in gender equality, women continue to perform a much higher share of unpaid domestic work compared to men. As a result of their domestic responsibilities, women are likely to face more stringent time constraints and greater difficulties in accommodating long commutes. Time spent on home production is negatively correlated with time spent commuting, with the relationship being stronger for women compared to men (Gimenez-Nadal and Molina 2016). Women also show higher well-being losses when commuting long distances, especially when they are partnered and have small children (Black, Kolesnikova, and Taylor 2014; Lorenz 2018; Roberts, Hodgson, and Dolan 2011; Wheateley 2014).

Social norms may affect women's choices not only by creating gendered expectations around the provision of domestic work but also by gendering expectations around labor market success. Women internalizing such expectations will downplay their own career ambitions in favor of their partner's. For example, women have been found to be less motivated by money when choosing a job (Bertrand 2018; Fortin 2008). Similarly, couples prioritize the male partner's career when making residential mobility decisions even when these choices do not maximize family income (Shauman 2010; Sorenson and Dahl 2016).

Women prioritizing their family responsibilities over career advancement, whether due to internalized preferences or social pressure, limits the range of job opportunities they are able to consider, a pattern referred to as "spatial entrapment" (Carlson and Persky 1999; England 1993). Women are more likely to work closer to home (Semyonov and Lewin-Epstein 1991), limit the spatial radius of their job search (Le Barbanchon, Rathelot, and Roulet 2021), and disregard job opportunities that conflict with their family needs (Mueller-Gastell and Pedulla 2023). They are also more likely to chain trip and to combine their commutes with household serving trips (Kwan 1999). These patterns are accentuated by parenthood but affect all partnered women, not just women with children (Gimenez-Nadal and Molina 2016; Rapino and Cooke 2011).

Commuting Costs, Job Matches, and Bargaining Power

As a result of their spatial entrapment, women may be forced to prioritize shorter commutes over other desirable job characteristics such as higher wages or better promotion prospects (Hirsch, Schank, and Schnabel 2010; Hirsch and Schnabel 2012; Nafilyan 2020; Ransom and Oaxaca 2010). In limiting the time and distance they are willing to commute, women also limit the pool of job opportunities they have available, potentially leading to worse job matches (Nisic 2017). Career enhancing job moves have been shown to be a crucial factor underpinning wage growth for both men and women, especially early in a worker's career (Kronberg 2013; Topel and Ward 1992). By limiting the range of alternative job opportunities they are willing to consider to those closer to home, women will be less able to benefit from this type of career advancing job mobility (Avram, Harkness, and Popova 2024). They will be more likely to be crowded in geographically dispersed jobs in the service sector that tend to be female dominated and lower paid (Nisic 2017; Smith and Glauber 2013). These outcomes can occur entirely through women and men sorting themselves into different jobs, in the absence of employer discrimination.

However, in addition to sorting, the increased costliness of commuting may also affect women's bargaining power. In perfectly competitive labor markets, employers cannot underpay their employees because these employees would immediately quit and hiring other workers at these lower wages would be impossible (Ashenfelter, Farber, and Ransom 2010; Manning 2003). However, if workers are unlikely to immediately quit, either because searching for alternative jobs is costly, or because they value particular job characteristics such as location, then employers can exploit this lack of mobility and pay below market wages (Ashenfelter, Farber, and Ransom 2010; Bhaskar and To 1999; Burdett and Mortensen 1998; Manning 2003). If employers can differentiate between workers who are more or less likely to quit in response to below market wages, they could maximize profits by paying the latter less. Thus, if employers are aware that women's alternative job opportunities are more constrained by their higher commuting costs, they can exploit these constraints by offering women lower wages when hiring and/or offering women lower pay rises. Note that this type of discrimination is not based on tastes, stereotypes, or prejudices, but purely on rational, profit maximizing behavior (Hirsch 2009).

The link between commuting costs (and how they vary with distance) and job opportunities depends on the spatial distribution of jobs. "Thicker" labor markets with an agglomeration of jobs and job opportunities will limit the disadvantage faced by less mobile workers, including women. Evidence that urban wage premia are larger for women compared to men in densely populated areas has been found in Germany (Hirsch, König, and Möller 2013; Nisic 2017), Israel (Semyonov and Lewin-Epstein 1991), the United States (Carlson and Persky 1999; Smith and Glauber 2013), and the UK (Phimister 2005). Although these studies provide suggestive evidence, they do not provide a direct test of the mechanism behind commuting costs and wages. For that a direct measure of job opportunities is needed. Furthermore, steeper spatial wage gradients for women compared to men are consistent with both sorting and bargaining. Understanding the relative importance of the two mechanisms requires a different approach that simultaneously examines wages, job mobility, and job opportunities.

Measuring Job Opportunities

Both sorting and bargaining models suggest that commuting costs will impact on wages via job opportunities, either through differential sorting into jobs or through reduced bargaining power. However, measuring job opportunities is not straightforward. The most common approach derives from studies of economic concentration. In the case of labor markets, concentration is generally measured using employment and/or vacancy data. A well-established measure is the HHI that is defined as the sum of the square of each employer's share of employment/vacancies in a well-defined geographical area. Formally, $HHI_k = \sum_{i=1}^{N_k} s_{ik}^2$, where HHI_k is the value of the concentration index in labor market k, N_k is the number of employers in labor market k, and s_{ik} is the share of employment/vacancies attributable to employer i in labor market k. The index is easy to compute and gives an indication of the range of alternative job opportunities a worker faces. Its values range between 0 and 10,000, with values above 2,500 suggesting strongly concentrated markets and values between 1,500 and 2,500 suggesting moderately concentrated markets. HHI has been used extensively to study the relationship between labor market concentration and wages (Abel et al. 2018; Azar et al. 2022; Benmelech et al. 2022; Qiu and Sojourner 2022). In addition, Azar et al. (2019) show that HHI does a good job of measuring employer wage-setting power.

The drawback of HHI is it requires geographically well-defined labor markets: All jobs/vacancies inside the boundary are considered equally desirable, whereas jobs outside the boundary are not considered at all. In practice, the spatial distribution of jobs and vacancies is not binary but a continuum: job opportunities further away are (all else equal) less desirable because of increased commuting costs, without there necessarily being a clear hard threshold beyond which no job is considered. In addition to the arbitrariness involved in selecting geographical units to define labor markets, the HHI is also problematic if one is interested in gender differences. Because men and women are spread relatively uniformly across areas, geographical differences in concentration do not normally give rise to gender differences. To address these shortcomings, we propose a new methodology that combines information on employment concentration and commuting costs and show how our methodology can be applied to study gender differences in concentration/job opportunities using data from the UK.

Data

We use the Business Structure Database (BSD)[1] to calculate employment concentration indices. BSD is an annual extract of the Inter-department Business Register (IDBR), an administrative data set, which includes information on all organizations that are either registered for VAT or pay at least one member of staff through the Pay As You Earn (PAYE) tax system. Starting with 1997, approximately 2 million organizations are included covering approximately 99 percent of economic activity in the UK (Office for National Statistics 2006). BSD represents a snapshot view of the IDBR and makes available basic information including geographical location at the postcode level, industry, and number of employees, which we use to construct employment concentration indices at various geographical levels.

Our second data source is represented by the UK Household Longitudinal Study (UKHLS)[2]. UKHLS is a household longitudinal survey that interviewed approximately 40,000 households in the first wave. It collects annual demographic, labor market, and other information, such as information about commuting patterns, commuting distances, and geographical location. We use the information on a small area geographical identifier (called lower layer super output area [LSOA]) of the respondent's residence contained in the Special Licence data[3].

Methodology

Constructing Herfindahl-Hirschman Employment Concentration Indices (HHI) at Different Geographical Levels

We use the BSD data set to construct employment concentration indices at various geographical levels. To measure employment concentration, we use the HHI, which is defined as $HHI_k = \sum_{i=1}^{N_k} s_{ik}^2$, where HHI_k is the value of the concentration index in labor market k, N_k is the number of employers in labor market k, and s_{ik} is the share of employment attributable to employer i in labor market k. The index varies between 0 and 10,000, with values higher than 2,500 indicating severe concentration and values between 1,500 and 2,500 indicating moderate concentration. We define labor markets by crossing industry (2-digit SIC 07 codes) with geographical identifiers.

We start with small geographical areas (called LSOAs) that have an average population of 1,500 individuals. For each LSOA, we define progressively larger areas with the reference LSOA at the center and containing all LSOAs found within a given radius. We use radii of 2 km, 5 km, 10 km, 15 km, 20 km, 30 km, and 50 km and thus obtain seven different geographical levels of progressively larger size with the reference LSOA at the center. We use data on the universe of private and public firms to compute HHIs by industry (2 digits) and year for each of these seven geographical levels. Thus, we obtain a set of seven concentration indices—one for each radius—for each LSOA–industry–year combination. We then merge this information into the UKHLS data set based on year, industry, and LSOA of residence. We are only able to map LSOAs in England and Wales, and our results exclude Scotland and Northern Ireland.

Calculating a Cost of Distance

In the next step, we use information about commuting times and commuting distance in UKHLS to calculate an individual cost of distance. UKHLS collects annual information about commuting time and biennial information on commuting distance. Following Jacob et al. (2019), we regress changes in subjective well-being measured using the 12-items General Health Questionnaire (GHQ-12)[4] on changes in commuting time in a subsample of individuals who did not switch jobs and did not move house since the last interview. Theory suggests that individuals will engage in longer commutes if they are compensated either in the labor market (through a higher wage, e.g., or better working conditions) or in the housing market (through better housing or amenities). By restricting estimation to a subsample of individuals who do not change jobs and do not move house, we ensure that observed changes in commuting time are not in response to labor market or housing opportunities. Instead, these changes in commuting time are likely to be the result of exogenous shocks such as changes in transport infrastructure. In addition, we also exclude individuals who report regularly working from home. We obtain an initial sample size of 34,521 observations for 10,436 men and 45,761 observations for 13,148 women.

Measurement error is potentially a concern when looking at changes in commuting time. To minimize the influence of outliers, we winsorize commuting travel time to the value of the 99th percentile. Because individuals are more likely to report commuting times that are multiples of 5 minutes, we exclude observations where the change in commuting time has been 5 minutes or less. Most observed changes in commuting time are small. Restricting the sample to changes larger than 5 minutes leaves us with a sample size of 8,604 observations for 4,972 men and 10,087 observations for 5831 women.

We estimate first difference equations separately for men and women and control for year fixed effects, changes in health, changes in household income, changes in partnership and parenthood status, changes in carer status, and changes in working hours. To allow for maximum flexibility, we include the change in commuting time as a third-degree polynomial and allow the effects to vary by parenthood status, couple status, carer status, number of hours worked (full time vs. part time), and education (low, medium, and high)[5]. Formally, we estimate

$$\begin{aligned}\Delta SWB_{i,t} = {} & \beta_0 + \beta_1 \Delta CT_{i,t} + \beta_2 \Delta CT_{i,t}^2 + \beta_3 \Delta CT_{i,t}^3 + \beta_4 \Delta CT_{i,t} CP_{i,t} + \beta_5 \Delta CT_{i,t} P_{i,t} \\ & + \beta_6 \Delta CT_{i,t} CR_{i,t} + \beta_7 \Delta CT_{i,t} PT_{i,t} + \beta_8 \Delta CT_{i,t} Educ_{i,t} + \beta_9 A_{i,t} + \beta_{10} A_{i,t}^2 \\ & + Y_t + R_t + \gamma \Delta X_{i,t} + \epsilon_{i,t},\end{aligned}$$

where $\Delta SWB_{i,t}$ is the change in subjective well-being experienced by individual i from $t-1$ to t, $\Delta CT_{i,t}$ is the change in commuting time for individual i from $t-1$ to t, $CP_{i,t}$ is an indicator for being partnered at time t, $P_{i,t}$ is an indicator for being a parent (of a child under 16) at time t, $CR_{i,t}$ is an indicator for being a carer at time t, $PT_{i,t}$ is an indicator for working part time at time t, $Educ_{i,t}$ measures the highest educational qualification at time t (low, medium, and high), $A_{i,t}$ is the age at time t, Y_t is the year fixed effects, R_t is the region fixed effects, and $\Delta X_{i,t}$ is a vector of individual changes from $t-1$ to t, including changes in self-estimated health status, changes in partnership status, changes in the number of children under 5, changes in parenthood status, changes in working hours (full time vs. part time), changes in carer status, and changes in household income. We estimate the equation separately for men and women and cluster errors at the individual level. To check the sensitivity of our results, we also restricted the analysis to a subsample of individuals who have not changed travel mode. Results are virtually identical (available from the author).

Next, we estimate the relationship between commuting time and commuting distance. We employ a flexible specification whereby we allow the effect of commuting distance on travel time to be nonlinear (quadratic) and to vary by transportation mode (eight categories) and rural–urban classification within each of nine English regions and Wales. We estimate models separately for men and women and thus allow all coefficients to vary by sex[6], and use cross-sectional weights provided by UKHLS. Formally, we estimate

$$\begin{aligned} CT_{i,t} = &\beta_0 + \beta_1 CD_{i,t} + \beta_2 CD_{i,t}^2 + \beta_3 CD_{i,t} P_{i,t} + \beta_5 CD_{i,t} TM_{i,t} + \beta_6 CD_{i,t} UR_{i,t} \\ &+ \beta_7 CD_{i,t} R_t + \beta_8 CD_{i,t}^2 R_t + \beta_9 CD_{i,t} \times TM_{i,t} R_t + \beta_{10} CD_{i,t} UR_{i,t} R_t + \epsilon_{i,t}, \end{aligned}$$

where $CT_{i,t}$ is the commuting time of individual i at time t, $CD_{i,t}$ is the commuting distance of individual i at time t, $P_{i,t}$ is an indicator for parenthood status, $TM_{i,t}$ is a variable measuring transport mode (eight categories), $UR_{i,t}$ is an indicator for rural/urban location, and R_t is the region fixed effects. Commuting distance is only measured every second wave. Thus, we have a sample size of 32,243 observations for 27,408 men and 40,080 observations for 32,831 women.

Having estimated the effect of commuting distance on commuting time, we then use this equation to calculate the predicted amount of time needed to travel 2 km, 5 km, 10 km, 15 km, 20 km, 30 km, and 50 km for each observation. To limit the influence of outliers, we cap the predicted travel times for each distance at the observed 1st and 99th percentiles of the distribution. Next, we input the predicted travel times into the first model and obtain the predicted loss of well-being associated with commuting 2 km, 5 km, 10 km, 15 km, 20 km, 30 km,and 50 km. Thus, we obtain a set of seven cost of distance variables that vary across both individuals and over time.

Combining HHI Using the Cost of Distance

In the final step, we combine the seven employment concentration indices using the cost of distance variable as a weight and obtain an indicator of labor market opportunities. Weights reflect individual variation in the rate at which commuting costs increase with distance. They are constructed such that they are inversely proportional to the speed with which the individual cost of distance increases. For example, if an individual experiences a loss of well-being associated with a 20 km journey is twice as large as that for a 10 km journey, then their corresponding weight for the 20 km radius HHI measure is half the weight corresponding to the 10 km radius HHI measure.

The resulting index is rescaled so that, as the original HHI, it varies between 0 and 10,000. Individual variation in this indicator is driven by two factors: (1) the spatial distribution of employment by industry and (2) the individual cost of distance. Thus, the index incorporates both the spatial distribution of employment around a respondent's home and the respondent's (subjective) commuting costs. Individuals facing a lower cost of distance will (all else equal) have access to more job opportunities. Having a high cost of distance places greater weight on job opportunities that are in proximity and discounts those that are further away. In this way, the index also overcomes the problem of arbitrary geographical boundaries for a labor market. All jobs within a 50 km radius are considered but jobs closer to home are given more weight, and this weighing varies with the individual cost of distance.

Because the index is constructed in several steps, standard errors cannot be computed using the usual formulae for descriptive statistics. Instead, we provide standard errors using bootstrapping with 200 replications. We resample individuals rather than observations due to the longitudinal nature of the data.

Results

Gender Differences in Commuting Costs

We first document gender differences in the cost of travel time and the cost of distance. Figure A1 in the online supplement shows the distribution of commuting times for men and women with and without children. Consistent with previous findings, women are more likely to have shorter commutes. On average, women commute 4 minutes less than men (24 minutes vs. 28 minutes). Similarly, Figure A2 shows that women commute on average significantly shorter distances (13 km vs. 20 km).

Next, we estimate a subjective well-being cost of commuting time from a regression of annual well-being changes on annual changes in commuting time. As discussed in the methodology section, we focus on exogenous changes in commuting time by restricting the estimation sample to individuals who have not changed job and have not changed address. Figure A1 shows that the distribution of commuting time is not completely smooth, with individuals being more likely to report multiples of 5 minutes. To ensure we focus on real changes in commuting times, rather than changes in reporting, we exclude cases where the reported change in commuting time is 5 minutes or less. Subjective well-being has been recoded so that higher values indicate a more positive outcome. Controls include age (and its square), changes in couple and parenthood status, changes in the number of preschool children, changes in health, changes in household income, changes in the number of dependent children, changes in carer status, and year and region fixed effects. We also allow the effect of travel time to vary by couple and parenthood status, education, carer status, and hours of work (full time vs. part time). A full set of coefficients can be found in Table A1 in the online supplement.

Figure 1 shows the predicted changes in well-being associated with different changes in commuting time. We find that both men and women experience a loss of well-being on account of their commutes. On average, men experience a drop of around 0.30 points in subjective well-being for a 10-minute increase in commuting time (the average change in well-being in our estimation sample is -0.22; well-being varies from 0 to 36). Further increases in commuting time result in small drops in well-being for men without children but relatively larger falls for fathers. For example, a one hour increase in commuting time is predicted to decrease well-being by 0.34 points for men without children and 0.42 for fathers. However, these differences are not statistically significant.

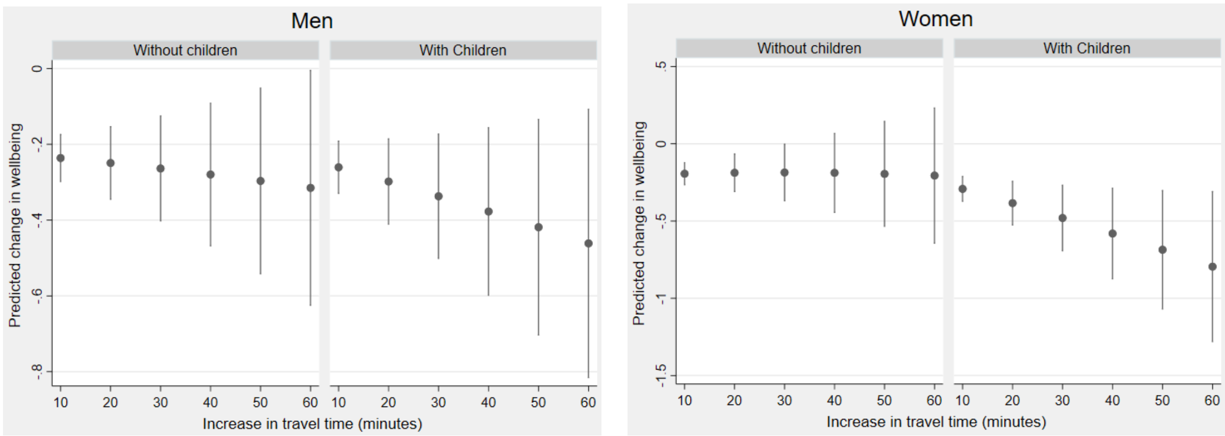

Figure 1: Predicted changes in well-being in response to changes in commuting time for men and women with and without children. *Note:* Bars represent 95 percent confidence intervals. *Source:* Own calculations based on UKHLS Waves 1–10.

For women, small increases in commuting time are associated with limited reductions in well-being, especially for women without children. For example, an increase in 10 minutes is predicted to reduce well-being 0.11 points for women without children and 0.23 for mothers. However, the cost of travel time accumulates much faster for women, especially among mothers. A one hour increase in commuting time reduces well-being by a full point among mothers and 0.31 points among women without children.

Overall, our results suggest that while men and women experience similar well-being losses in response to small increases in commuting time, gender differences increase substantially for longer times. This pattern has been repeatedly documented in the literature (Nafilyan 2020) and is consistent with women, especially those with children, having a higher opportunity cost of time.

To arrive at the individual cost of distance, we estimate the relationship between travel time and travel distance using a flexible specification that allows for region-specific effects of travel mode, population density (urban vs. rural), and non-linear effects. Because the previous literature (Kwan 1999; Olmo Sánchez and Maeso González 2016) has suggested that parents might combine commutes with other non-work related trips, we also allow for heterogeneous effects by parenthood status. We estimate separate models for men and women, meaning we allow all the effects to be gender specific.

A full set of our results can be found in Table A2 in the online supplement. As expected, there are important regional differences in the way distance translates into travel time. Individuals using a car (either as a driver or as a passenger) have the lowest distance to time “conversion” rates. Public transport, cycling, and walking all involve significantly longer commuting times for the same distance, but this varies significantly across regions. Consistent with traffic jams more likely to affect urban areas, we find that rural areas require shorter times for the same distance.

The marginal effect of distance on travel time is significantly higher for women compared to men. Figure 2 shows that, on average, women need 1.90 minutes for

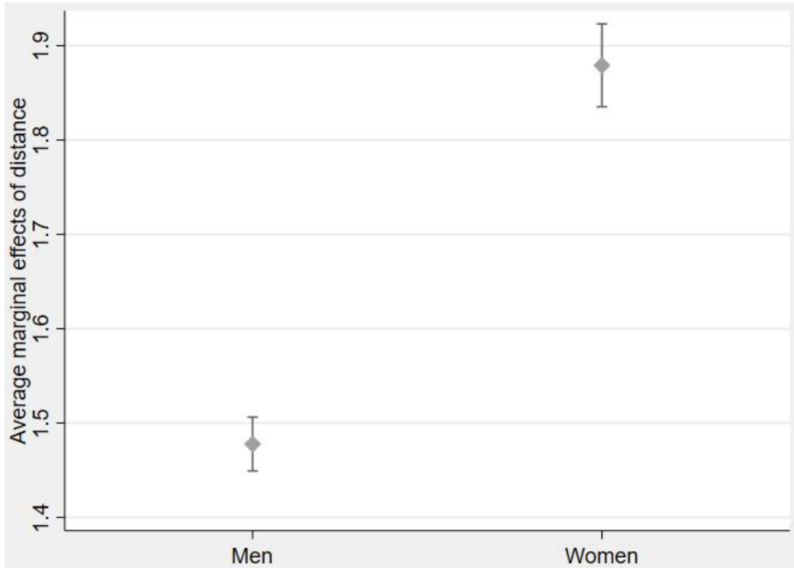

Figure 2: Average marginal effects of commuting distance on commuting time by sex. *Note:* Bars indicated 95 percent confidence intervals. *Source:* Own calculations based on UKHLS Waves 1–10.

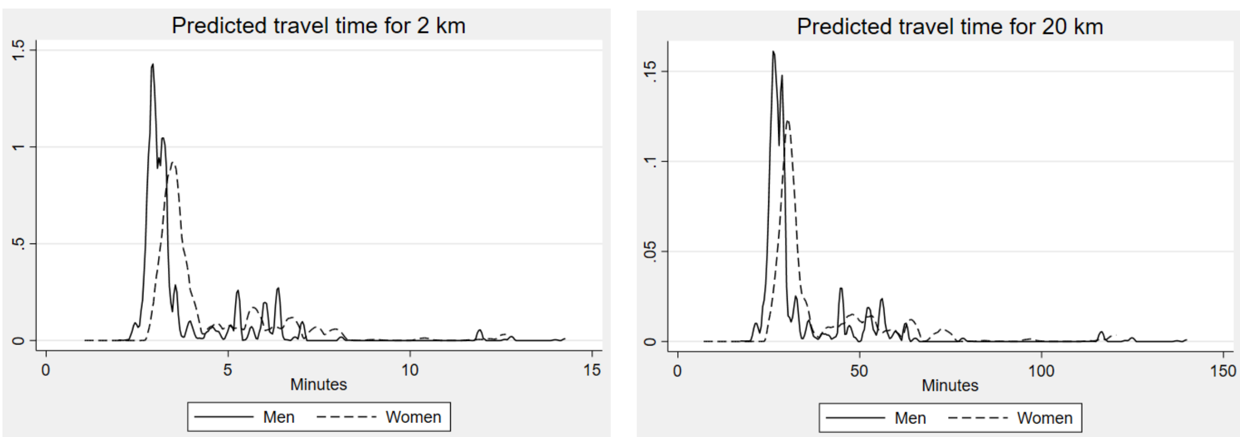

Figure 3: Distribution of predicted travel time of 2 km (left) and 20 km (right). *Source:* Own calculations based on UKHLS Waves 1–10.

each additional kilometer, whereas men need 1.49 minutes. These differences are highly significant and in line with previous research showing that women are more likely to use public transport or drive more slowly (Casado-Díaz, Simón-Albert, and Simón 2023; Dissanayake 2017). However, we do not find any evidence that parenthood status affects the relationship between commuting time and commuting distance, either for men or women.

In the next step, we use the above specification to predict the travel times associated with commuting 2 km, 5 km, 10 km, 15 km, 20 km, 30 km, and 50 km. Figure 3 shows the distribution of predicted times associated with 2 km (left panel) and 20 km (right panel), separately for men and women. The distribution

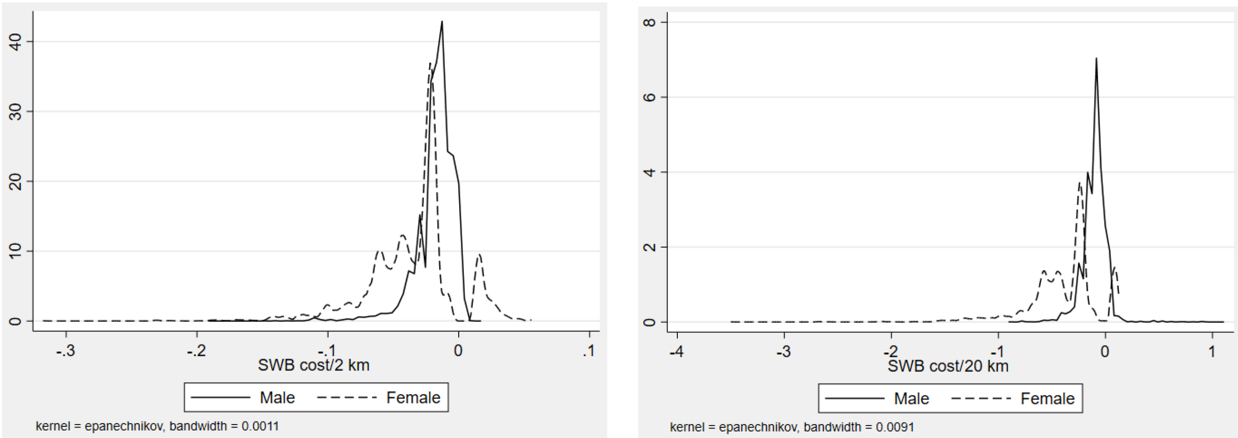

Figure 4: Distribution of SWB costs for a commuting distance of 2 km (left) and 20 km (right). *Source:* Own calculations based on UKHLS Waves 1–10.

of predicted times for all seven distances is shown in Figure A3 in the online supplement.

As expected, predicted travel times are always larger for women. Figure A3 in the online supplement shows that the distribution of predicted travel times for women is always to the right of that of men, but that the difference reduces as commuting distance increases. Thus, the gap in the predicted travel time is proportionately largest at shorter distances. For example, median predicted travel times are 18 percent larger for women compared to men when traveling 2 km (3.67 minutes vs. 3.11 minutes) but only 12 percent larger (31.48 minutes vs. 28.04 minutes) when traveling 20 km.

Finally, we combine our estimations of the effect of distance on travel time and travel time on subjective well being to derive the cost (in terms of lost well-being) of commuting 2 km, 5 km, 10 km, 15 km, 20 km, 30 km, and 50 km. Having predicted travel times associated with commuting a particular distance, we then plug in these values in the cost of commuting time specification to obtain a predicted loss of well-being associated with traveling that distance. To avoid results being driven by outliers, we cap the predicted travel times at the observed first and 99th percentiles of the distribution.

We obtain the predicted cost of distance values for 68,050 observations for men and 84,967 observations for women. Figure 4 shows the distribution of these costs for men and women, when the commuting distance is set to 2 km and 20 km respectively. Figure A4 in the online supplement shows the distribution of subjective well-being loss for remaining distances.

Commuting the same distance is likely to result in higher losses in well-being for women compared to men, as shown by the female distribution being to the left of the male distribution both for losses associated with 2 km and 20 km commutes. The female distributions also have longer and thicker left tails suggesting that women are more likely to experience disproportionately large well-being costs associated with both short and longer commutes. Figure A4 in the online supplement shows

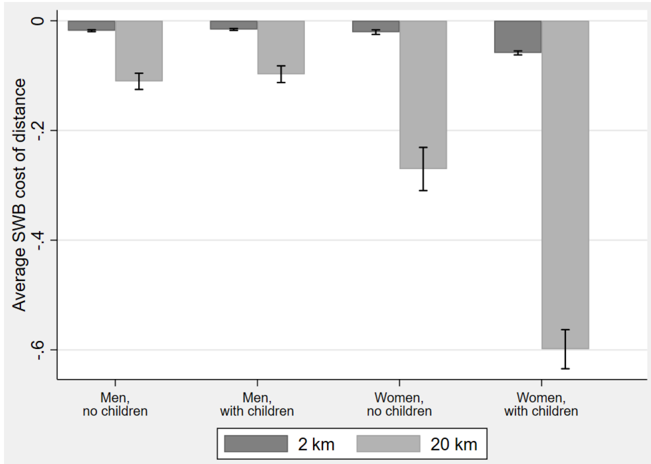

Figure 5: Average predicted losses in subjective well-being associated with commuting 2 km and 20 km. *Note:* Error bars represent 95 percent confidence intervals computed using bootstrapping with 200 replications. *Source:* Own calculations based on UKHLS Waves 1–10.

that this pattern is maintained for the other distances as well. Interestingly, we find that some women have positive predicted changes associated with shorter commutes (10 km or less) but not for longer ones.

A different way of examining differences in subjective well-being losses is to look at means. Figure 5 shows the average predicted well-being losses associated with commutes of 2 and 20 km, respectively, by sex and parenthood status. Error bars have been computed using bootstrapping with 200 replications. At shorter distances, differences are relatively small, although mothers clearly experience higher losses. However, it is at higher distances that differences become significantly larger. The average predicted well-being loss associated with a 20 km commute is almost four times larger for women compared to men (0.4 points vs. 0.1 points). There do not appear to be large differences in predicted well-being loss between fathers and men without children. In contrast, mothers experience significantly higher losses. On average, predicted well-being losses for women with children are almost six times larger than those of men (0.6 vs. 01) and twice as large as for women without children (0.6 vs. 0.3).

Gender Differences in Job Opportunities

We next turn to deriving a labor market concentration measure that takes into account commuting costs. We first calculate HHI values for progressively larger areas that include all LSOAs within a given radius of the reference LSOA. We calculate HHI for areas with a radius of 2 km, 5 km, 10 km, 15 km, 20 km, 30 km, and 50 km. Figure 6 shows the distribution of HHI measures calculated using a radius of 2 km and 20 km, separately for men and women. Figure A5 in the online supplement shows the same distribution for the remaining radii.

The first thing to note is that using a 2 km radius and even a 5 km radius results in a significant number of men and women finding themselves in concentrated

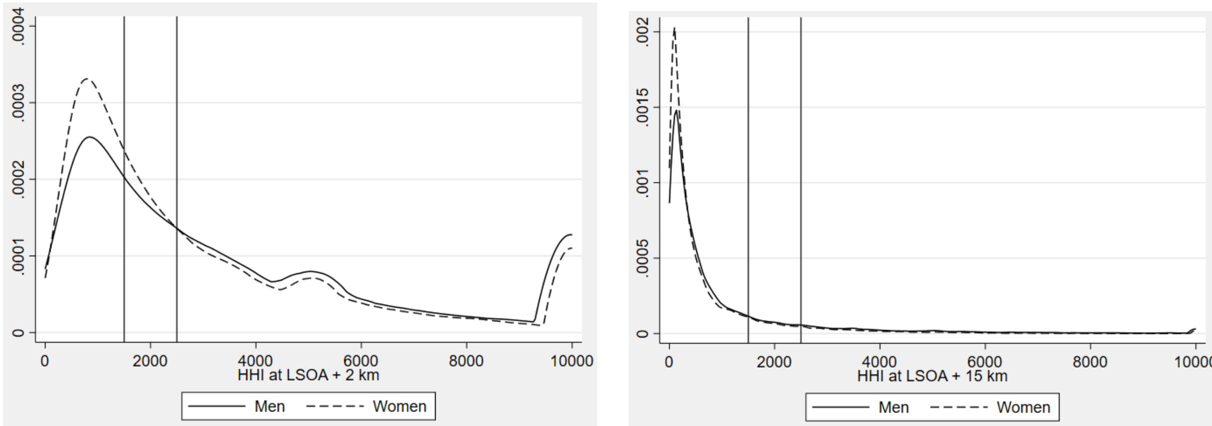

Figure 6: Distribution of employment concentration for men and women: LSOA + 2 km (left) and LSOA + 20 km (right). *Note:* The HHI index ranges from 0 to 10,000. The two vertical lines mark the threshold values for moderate (1,500) and severe (2,500) concentration. *Source:* Own calculations based on UKHLS, 2009–2020 and BSD, 1997–2021.

labor markets. For example, 46 percent of workers find themselves in severely concentrated labor markets when using the LSOA + 2 km specification and 26 percent when using the LSOA + 5 km specification. As distance increases, concentration levels fall. However, even at LSOA + 20 km, around 6 percent of workers are in severely concentrated markets and another 5 percent in moderately concentrated ones.

Generally, women are less likely to be found in concentrated markets, irrespective of the radius used to define the labor market. For example, if labor markets are defined at the LSOA + 2 km level, more than 50 percent of men face severe concentration, while only 43 percent of women do so. Using the 20 km radius, approximately 14 percent of men find themselves in severely or moderately concentrated markets, whereas the same figure for women is little more than 9 percent. Figure 7 plots the average concentration levels for men and women using all seven radii.

Lower concentration indices for women are due to sex segregation across industries. Women are generally more likely to work in services, which are more geographically spread out. Thus, not accounting for the cost of travel differences between men and women would suggest that women generally face less concentrated labor markets with more job opportunities and thus are less vulnerable to immobility-related employer discrimination.

Finally, we combine the seven HHI indices using the cost of distance as weights. Weights are inversely proportional to the cost of distance. On the one hand, women are more likely to have higher commuting costs, meaning that HHIs calculated at higher radii have a lower weight. On the other hand, women generally face less concentrated labor markets at a given radius, due to being more likely to work in services, which are spatially dispersed. The weighted HHI measure incorporates both these effects. Its distribution is shown in Figure 8.

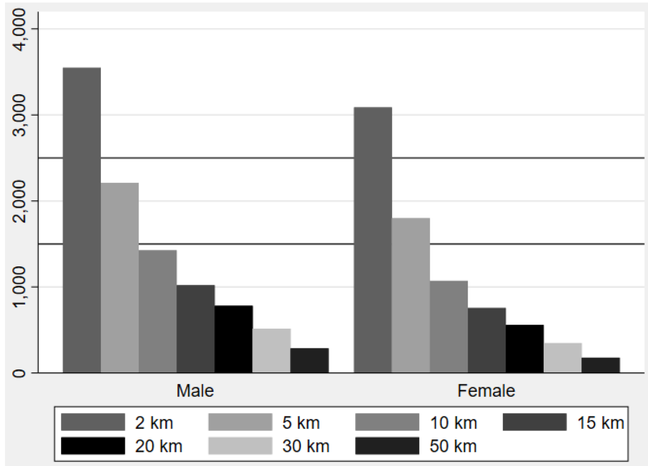

Figure 7: Average HHI values for areas with different radii by sex. *Note:* The HHI index ranges from 0 to 10,000. The two horizontal lines mark the threshold values for moderate (1,500) and severe (2,500) concentration. *Source:* Own calculations based on UKHLS, 2009–2020 and BSD, 1997–2021.

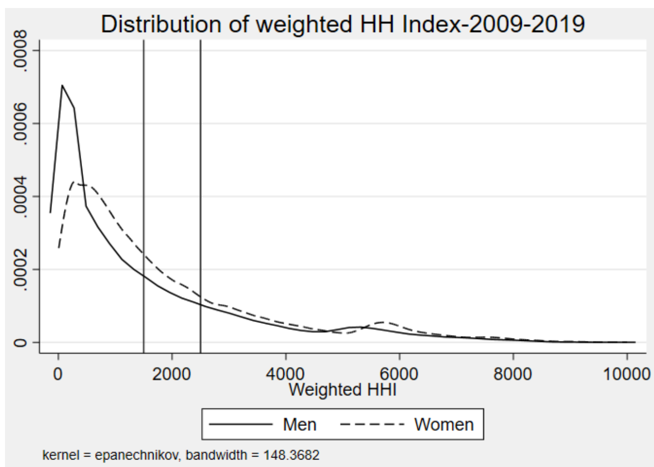

Figure 8: Distribution of weighted HHI by sex. *Note:* The HHI index ranges from 0 to 10,000. The two vertical lines mark the threshold values for moderate (1,500) and severe (2,500) concentration. *Source:* Own calculations based on UKHLS, 2009–2020 and BSD, 1997–2021.

Both men and women face substantial amounts of concentration. Approximately 25 percent of women and 20 percent of men face severely concentrated labor markets, whereas another 18 percent of women and 14 percent of men face moderate concentration. Women generally face higher concentration. Figure 9 shows that this is primarily driven by mothers. Average concentration for mothers is about 200 points larger than for women without children (1,958 vs. 1,762) and almost 600 points larger than average concentration among men without children (1,958 vs. 1,403). Fathers also face slightly higher concentration compared to men without children, but differences are much smaller (around 150 points on average, 1,552 vs. 1,403).

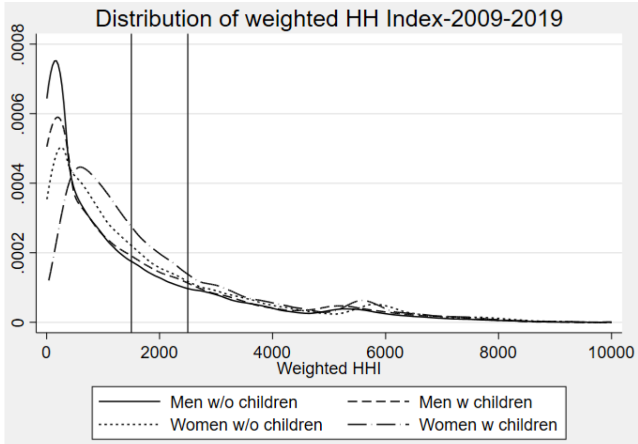

Figure 9: Distribution of weighted HHI by sex and parenthood status. *Note:* The HHI index ranges from 0 to 10,000. The two vertical lines mark the threshold values for moderate (1,500) and severe (2,500) concentration. *Source:* Own calculations based on UKHLS, 2009–2020 and BSD, 1997–2021.

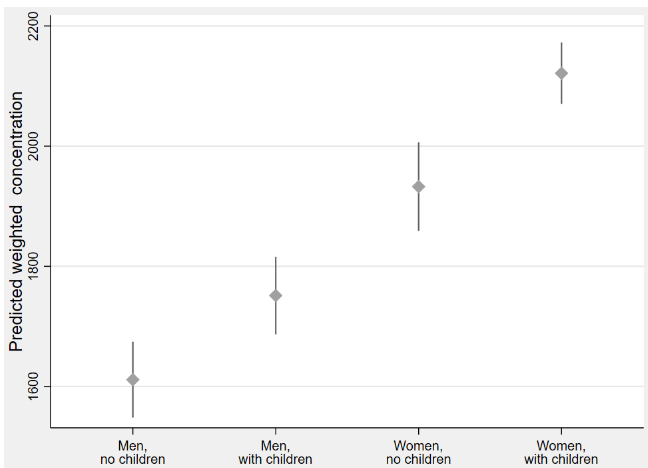

Figure 10: Predicted HHI by gender and parenthood status, controlling for year, region fixed effects, and demographic characteristics. *Note:* Error bars represent 95 percent confidence intervals computed using bootstrapping with 200 replications. *Source:* Own calculations based on UKHLS, 2009–2020 and BSD, 1997–2021.

Overall, women's higher commuting costs dominate their higher likelihood of working in geographically dispersed industries, resulting in significantly more concentrated labor markets. This pattern applies to both women with and without children, with mothers being most affected. To isolate the effect of sex and parenthood status on concentration, we estimated a simple regression equation that controls for differences in age, education, health status, and year and region fixed effects. Predicted average concentration levels are shown in Figure 10. Mothers face labor markets that have concentration levels on average 200 points higher than those of women without children and 400 and almost 600 points higher than those of men with and without children, respectively.

Finally, we examine how mothers' higher likelihood to face concentrated markets varies with education. Figure 11 shows the average predicted weighted HHI

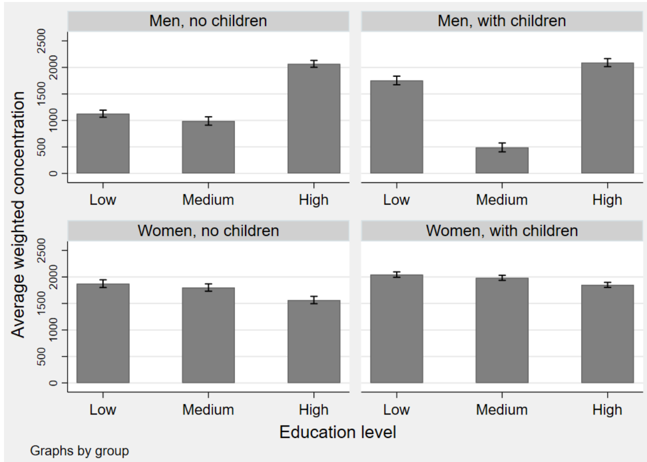

Figure 11: Predicted average HHI by gender, parenthood status, and education level. *Note:* Education is measured through three categories: high (higher education degree), medium (A-levels), and low (GCSE or less); error bars represent 95 percent confidence intervals computed using bootstrapping based on 200 replications. *Source:* Own calculations based on UKHLS, 2009–2020 and BSD, 1997–2021.

concentration indices for men and women with high (higher education degree), medium (A levels), and low (GSCSE or less) levels of education. Standard errors have been computed using bootstrapping with 200 replications. Among women, concentration varies less by education compared to men. Low educated women without children face the lowest concentration, whereas average concentration is highest among highly educated women with children. For both women with and without children, the education gradient is negative: more educated women find themselves in more concentrated markets. In contrast, there are large differences in average concentration by education level among men. This is because low educated men, both those with and without children, face disproportionately high concentration. Having children is associated with higher average concentration among highly educated men but not among medium educated men, perhaps because educated men are more involved with raising children (Flouri and Buchanan 2003).

To summarize, we find that women and especially mothers have much higher commuting costs, which effectively reduce the range of job opportunities they have available and leave them facing significantly more concentrated markets. This effect is found for both women with and without children but is especially strong for mothers. Mothers face labor markets that have concentration levels that are up to 600 points higher than other groups of workers. These are very significant differences. They represent up to 40 percent of the threshold for moderate concentration and 24 percent of the threshold for severe concentration.

Discussion and Conclusions

A long-established finding in the literature studying gender differences in labor market outcomes is that women commute on average shorter distances and in return, earn lower wages. The existing literature has attributed this result to women facing more stringent time constraints that restrict the pool of job opportunities they have available. Yet, in the absence of direct measures of job opportunities, previous studies have been unable to directly test this mechanism. In this study, we propose a novel methodology for deriving an indicator of job opportunities that incorporates commuting costs. The indicator is constructed by combining information about the spatial distribution of employment and commuting costs: HHIs at various geographical levels are weighted using a cost of distance measure.

The methodology that we propose allows us to map in detail how job opportunities vary with sex and parenthood status, something that is currently missing in the literature. Our results indicate that accounting for commuting costs is very important to accurately measure job opportunities. When disregarding differences in commuting costs, women find themselves in, on average, less concentrated labor markets due to their higher likelihood of working in services, which are more geographically dispersed. Once we account for differences in commuting costs, which are significantly higher for women, especially mothers, this result is reversed. Mothers on average face labor markets that have concentration levels between 200 and 600 points higher than other groups of workers. These differences are substantively important. For example, the average difference in concentration between women with children and men without children amounts to approximately 40 percent of the threshold for moderate concentration and 24 percent of the threshold for severe concentration. Interestingly, we find that low educated men also face highly concentrated markets.

Our results highlight a structural disadvantage that women, and especially mothers, face in the labor market. Higher commuting costs restrict the pool of job opportunities available to women with consequences for gender pay inequality. These results are consistent with previous findings that documented steeper gender pay gaps in sparsely populated areas where the link between commuting costs and job opportunities is likely to be strongest (Hirsch, König, and Möller 2013; Nisic 2017; Smith and Glauber 2013). They are also consistent with previous work that found women are more likely to choose jobs close to home with negative consequences for their pay (Le Barbanchon, Rathelot, and Roulet 2021; Nafilyan 2020).

Addressing women's structural disadvantage in the labor market will require policies that expand their job opportunities either by reducing commuting costs or by weakening the relationship between commuting costs and job opportunities. Enhanced transport infrastructure, better childcare provision, and policies that aim to re-balance work and family commitments such as teleworking or a four-day working week should all help reduce the structural disadvantages associated with unpaid domestic work.

Meanwhile, we find that women and mothers potentially anticipate some of the constraints they are likely to face and respond by sorting themselves into service industries, which are more geographically dispersed. Yet, it is not clear to what extent sorting accounts for the entirety of the patterns we observe. Reduced job opportunities are likely to impact wages both via sorting and depressed bargaining power. Future research should establish the importance of each of these two channels, as policy implications are likely to be very different. Future research should also investigate what other groups are more vulnerable to high commuting costs and restricted job opportunities and quantify the wage penalties associated with these restricted opportunities.

Notes

1 Office for National Statistics (2023). Business Structure Database, 1997–2022: Secure Access [data collection]. 15th Edition. UK Data Service. SN: 6697, DOI: 10.5255/UKDA-SN-6697-15.

2 University of Essex, Institute for Social and Economic Research. (2022) Understanding Society: Waves 1–11, 2009–2020 and Harmonised BHPS: Waves 1–18, 1991–2009. [data collection]. 15th Edition. UK Data Service. SN: 6614, DOI:10.5255/UKDA-SN-6614-16.

3 University of Essex, Institute for Social and Economic Research. (2021). Understanding Society: Waves 1–11, 2009–2020 and Harmonised BHPS: Waves 1–18, 1991–2009: Special Licence Access, Census 2001 Lower Layer Super Output Areas. [data collection]. 13th Edition. UK Data Service. SN: 6670, DOI: 10.5255/UKDA-SN-6670-13.

4 In a robustness test, we have also experimented with using the mental component of the Short Form 12 (SF-12) Health Survey, as well as with a general measure of life satisfaction. Results using SF-12 are very similar to those using GHQ-12. Variability in the life satisfaction variable is more limited and so this variable was rejected as unsuitable.

5 The categories of education are defined as follows: low: GSCE or less; medium: A levels; and high: higher education degree.

6 In both cases, we constrain the constant to be zero as it does not make sense to have a non-zero predicted travel time for zero distance.

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