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Local monopsony power

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Abstract

This paper studies monopsony power in a low pay labour market and explores its determinants. I emphasise the role of the spatial distribution of activity and workers' distaste for commuting in generating imperfect substitutability between jobs, and heterogeneity in monopsony power. To formalise the role of commutes in generating monopsony power I develop a job search model where utility depends on wages, commutes and an idiosyncratic component. The model endogenously defines probabilistic spatial labour markets which are point specific and overlapping, and generates labour supply to the firm elasticities which vary across space. Distaste for commuting is shown to increase monopsony power, but does so heterogeneously, increasing monopsony power in rural areas more than in denser urban ones. Using detailed applicant data for a firm with hundreds of establishments across the UK, coupled with two sources of job-establishment level exogenous wage variation I estimate the model parameters and show that commutes generate considerable spatial heterogeneity in monopsony power and are responsible for approximately 1/3 of the total wage markdown. A decomposition exploiting the granularity of the model demonstrates that 40% of spatial variation in monopsony power is within Travel To Work Areas. Calculating employer concentration based on highly-granular 1km² grids and probability of applying across grids based on pair-wise grid travel times shows how coarsely discretised labour markets such as Commuting Zones can cause sizeable mismeasurement in concentration measures.

Key words: monopsony

JEL: J31; J42

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1 Introduction

The labour supply elasticity to the firm is a key measure of wage-setting power. An infinite elasticity corresponds to the canonical perfect competition outcome, where workers are paid their marginal product; however, as it becomes more inelastic, wage markdowns increase. The past decade has seen an explosion in the number of papers attempting to estimate this elasticity,¹ focusing primarily on measurement and probing the crucial question: how much monopsony power do firms wield? Yet, the sources of monopsony power remain obscure but are vitally important for understanding what drives inefficiencies in labour markets, the heterogeneity in markdowns, and how to design optimal labour market policies. This paper instead asks the question: why do firms have wage-setting power, and does that vary across firms? Specifically, it estimates and explores the spatial heterogeneity of monopsony power and examines a source of monopsony power: workers’ distaste for commuting, coupled with the spatial distribution of economic activity.

The role of commutes in generating monopsony power is straightforward. The length of commute to a place of work is a non-wage factor that can affect the utility from a job, and thus generate imperfect substitutability between differently located jobs. The importance of commutes is determined by the size of the commuting-wage elasticity. If there is evidence of a strong distaste for commuting (a low elasticity), this can create geographical heterogeneity in monopsony power, as jobs and workers are not evenly distributed across the spatial economy. To formalise this mechanism I develop a job search model of “local monopsony power”, where utility depends on the wage, commuting, and an idiosyncratic component. The model endogenously defines spatial labour markets which are continuous and overlapping such that they generate firm labour supply elasticities that vary across space. The model suggests that as distaste for commuting increases, monopsony power also increases, but does so heterogeneously across space. Rural areas, where job options are more limited, are shown to be less competitive than denser more urban areas, as a result of commutes. The model is flexible such that this key result holds under a wide array of preference distributions.

The model has two sets of parameters: the commuting-wage elasticity and those associated with the worker-firm idiosyncratic preference distribution. Given these parameters and the spatial distribution of economic activity, the model provides the labour supply elasticity to the firm measured by the application-wage elasticity, for any spatially located firm at any wage rate. To estimate the model, I utilise a novel dataset for a large UK-based services firm with hundreds of establishments across the UK, coupled with two sources of exogenous wage variation. The dataset includes rich human resources (HR) data with vacancy and applicant information, where the former contains the precise address of the job and the latter includes data on applicant home location. I also use administrative social security data for the UK on a large sample of existing worker-firm matches, which has precise location information on workers’ home addresses, work addresses and their incumbent wages. Combined, the data allows me to estimate

¹See [Manning \(2021\)](#) and [Sokolova and Sorensen \(2021\)](#) for recent review papers.

the application-wage elasticity for establishments in the firm’s sample and the commuting-wage elasticity, using a reduced form approach. I then match model predicted application elasticities to those estimated in the reduced form to back out the remaining model parameters.

Identification of the various parameters is non-trivial using observational data. Wage changes for firms are likely to be correlated with outside options, which will induce a downward bias in both labour supply and willingness to commute responses. To elicit causal estimates for the application-wage elasticities and the commuting-wage elasticity, I use two instruments. The first is a location-specific Living Wage floor that only affects firms in my sample and not other outside options, due to the fact that my firm has local government contracts. The second is an advertising irregularity within the firm, whereby some job adverts include a pro-rata hourly wage top up from annual-leave in the advertised wage, and others do not. The first instrument provides establishment-job-time variation in the advertised wage, while the second provides variation at the advert level. Given these two instruments, the reduced form estimation elicits the necessary elasticities, and the structural estimation can match these elasticities using the model counterparts, estimating the remaining parameters.

The results suggest that workers have a strong distaste for commuting. The firm’s local labour market size is relatively unresponsive to increases in wage offers. I find a commuting-wage elasticity of approximately 1-1.2, which implies that a minimum wage worker would require an extra £0.37 (\$0.46) per hour for an extra five minute commute. To validate the model, I show that the model predictions regarding heterogeneity in monopsony power across space are consistent with heterogeneity found in my causal estimates. Furthermore, the model predictions for monopsony power across 7,250 Built Up Areas (cities, towns and villages) in the UK are strongly negatively correlated with wages and worker density for the low-pay retail market. Structurally estimating the model and performing a partial-equilibrium counterfactual, which shrinks commutes to zero, suggests that commutes are responsible for approximately one-third of the wage markdown. Put another way, the mean application-wage elasticity in my sample is approximately 3, and in the absence of commutes this would increase to 5. The results also show a striking heterogeneity across space, with denser areas being more competitive. A decomposition shows that 40% of the variation in monopsony power is within Travel To Work Areas (TTWAs) implying that large discretised geographies will likely induce large mismeasurement.

Arguably, the most restrictive assumption in the model is that both worker and firm locations are fixed, and therefore the spatial heterogeneity in monopsony power depends on the existing spatial distribution of activity. The mobility of workers and firms will then determine to what extent one should view this spatial heterogeneity in market power as being short-run or long-run. I document evidence showing low mobility rates in both the UK and US, and present causal evidence that firm counts, worker and firm migration and employment are all unresponsive to exogenous geographical wage changes, exploiting the bite of the UK’s minimum wage. I show this using data over a 10-year panel. The results imply low mobility of both workers and capital and slow response times to spatial shocks, consistent with other recent evidence using both

structural and empirical approaches (Kleinman et al., 2023; Dix-Carneiro and Kovak, 2017).

This paper makes three contributions. Firstly, it contributes theoretically to the sources of monopsony power. There are two strands of literature on this front: one that attributes monopsony power to search frictions (Burdett and Mortensen, 1998; Manning, 2003) in a dynamic setting, and a newer strand borrowing from Industrial Organization, where firms are imperfect substitutes for workers due to idiosyncratic preferences over non-wage aspects of a job (Card et al., 2018).² This study aligns with the latter, but develops it further by separating the roles of location and commutes from the single idiosyncratic parameter, which recent research suggests is the most important non-wage aspect of a job for workers (Caldwell and Oehlsen, 2018; Blundell, 2020), and formally modeling them. In a job search model of labor supply where utility is partly dependent on the commuting distance between the worker’s location and the firm’s location, I demonstrate that spatial labor markets become point-specific and weaken over distances. Monopsony power is increasing in the variance of the idiosyncratic component of utility, and the influence of the spatial distribution of activity on generating monopsony power depends on the commuting-wage elasticity. As distaste for commuting increases, so does monopsony power, albeit heterogeneously across locations. Areas with few local job opportunities, where workers must commute for work, exhibit greater monopsony power than more congested city areas. Even in congested city areas, firms can still exercise some local monopsony power, as even short commutes within a city generate disutility. Despite originating from a different approach, the results of this model exhibit features similar to those in Monte et al. (2018), where their general equilibrium model generates endogenous employment elasticities dependent on spatial linkages across goods and factor markets.

The above result contributes to the literature on the spatial determinants of wages in urban economics. The seminal paper by Glaeser and Mare (2001) noted that urban workers earn on average 33% more than their non-urban counterparts, a phenomenon partly due to level differences in wages (Heuermann et al., 2010; de la Roca and Puga, 2017). Much of the literature attributes this urban wage premium to productivity gains from agglomeration (Ciccone and Hall, 1996; Glaeser, 1998; Puga, 2010; Enrico, 2011) in a competitive labor market setting. This study adds to new evidence from Hirsch et al. (2020) that part of the premium may also be driven by differences in monopsony power, as urban areas with densely packed job markets offer more jobs in close proximity, making them closer substitutes and increasing competition. This means that, *ceteris paribus* in terms of productivity, workers in cities would get paid higher wages. I also provide a micro-foundation for this phenomenon.

Secondly, this study contributes by empirically assessing the sources of monopsony power, placing a strong focus on the role of commutes. It therefore joins a number of papers looking at the role of distance affecting economic outcomes, including the gender wage gap (Le Barbanchon et al., 2021), spatial mismatch (Marinescu and Rathelot, 2018), and commuting-wage trade-offs

²For evidence of heterogeneity in preferences over non-pecuniary job attributes see Eriksson and Kristensen (2014); Mas and Pallais (2017); Wiswall and Zafar (2018); Datta (2019). For studies using this imperfect substitute framework see Azar et al. (2022); Berger et al. (2022); Lamadon et al. (2022).

([Van Ommeren and Fosgerau, 2009](#); [Mulalic et al., 2014](#)). The IV estimates of the commuting-wage elasticity, the first I am aware of using exogenous wage variation, indicate a strong distaste for commuting and show that a firm’s geographic labor market size responds only mildly to wage increases. These estimates reveal that even identical jobs, when located differently within the same city, are imperfect substitutes, as workers exhibit strong travel preferences.

Lastly, it contributes to the literature on spatial labour markets and concentration. There has been a recent surge of interest in the role of market structure and concentration on wages, and its role in the wage setting power for the firm³ leading to increased calls for a stronger regulatory response to market concentration ([Krueger and Posner, 2018](#); [Naidu et al., 2018](#); [Marinescu and Hovenkamp, 2019](#); [Marinescu and Posner, 2019](#)). Studies typically calculate a concentration ratio using the Herfindahl-Hirschman Index (HHI) based on some market local labour market definition. Aside from a few papers unrelated to the market power literature (e.g [Monte et al. \(2018\)](#); [Amior and Manning \(2018\)](#); [Manning and Petrongolo \(2017\)](#)) local labour markets are typically discretised geographic areas (interacted with either industry or occupation) such as Commuting Zones (CZs) in the US and TTWAs in the UK, which implicitly assume that travel within them is costless and that borders create infinite costs. This has recently come under criticism ([Berry et al., 2019](#); [Rose, 2019](#)), partly due to the very local nature of labour markets ([Manning and Petrongolo, 2017](#)). Moreover, they do not take into account the fact that lower skilled (and thus lower wage) occupations commute fundamentally different distances than their higher-skilled counterparts. For example, the median commuting distance for a retail worker in the UK is 15 minutes, while the TTWA for Greater London, which encompasses one-sixth of the UK working population, spans an area where commuting times can exceed 90 minutes.

By modelling spatial labour markets continuously, in the spirit of [Manning and Petrongolo \(2017\)](#), this paper documents the degree of mismeasurement which can arise from treating local labour markets as discretised. The last section of the paper compares retail labour market HHIs for TTWA labour markets against a (relatively) continuous version which splits the UK into 1 km² grids and calculates grid-specific HHIs using data on all grid pair-wise commute distances and the structure of the model to generate probabilities of applying for jobs across grids. The results shows that existing measures of HHIs using coarsely discretised labour markets considerably underestimate concentration. The median HHI at the TTWA level is 0.10 while at the 1 km² it is 0.32. The Antitrust Division of the DoJ consider HHIs above 0.18 to be “highly concentrated”. The results reveal there is considerable heterogeneity of HHIs within a TTWA, and that areas along major road networks exhibit considerably lower HHIs. More generally, the results highlight some of the issues with using HHI as a proxy for market power. Specifically, they demonstrate that HHIs are unable to capture aspects of market power not generated by spatial substitution. Furthermore, HHIs do not take into account the spatial distribution of workers, only firms, while the model in this paper shows that both are important.

³Examples include [Schubert et al. \(2021\)](#); [Naidu and Posner \(2021\)](#); [Azar et al. \(2020b\)](#); [Azkarate-Askasua and Zerecero \(2024\)](#); [Arnold \(2020\)](#); [Azar et al. \(2020a\)](#); [Benmelech et al. \(2020\)](#); [Nimczik \(2020\)](#); [Berger et al. \(2022\)](#); [Jarosch et al. \(2024\)](#); [Qiu and Sojourner \(2023\)](#); [Rinz \(2022\)](#); [Abel et al. \(2018\)](#); [Lipsius \(2018\)](#); [Hershbein et al. \(2018\)](#).

The results of this paper are relevant for policy across several dimensions. Improved infrastructure and travel links, such as new railway lines, are likely to increase competition by expanding the size of local labour markets and thus exert upward pressure on wages. However, the area affected may be limited (e.g., small radii around railway stations) due to the strong distaste for commuting. Additionally, the low commuting-wage elasticity suggests that reduced travel times would be highly valued by workers. Similarly, changes to work patterns, such as an increased ability to work from home, would similarly enhance worker utility and have a strong positive effect on reducing monopsony power. This effect is driven by a drastic increase in outside options for workers when all commutes are essentially reduced to zero.

The remainder of this paper is organised as follows. In section 2 I formally develop the model of local monopsony power and discuss its implications. In section 3 I discuss the data, variation and estimation of the model parameters. Section 4 presents the results and provides evidence on the validity of the model. Section 5 quantifies the role of commutes in generating monopsony power and discusses the implications for measures of concentration and section 6 concludes.

2 The Role of Commutes in Generating Monopsony Power

The following section formalises the mechanism outlined in the introduction. I utilise a job search model in a similar spirit to Manning and Petrongolo (2017) where firms gain profits from hiring (or maintaining) workers and worker utility depends on the wage, commuting and an idiosyncratic component. The model endogenously defines spatial labour markets which are continuous and overlapping, generates endogenous labour supply to the firm elasticities which vary across space, and shows the importance of the distribution of spatial activity, and preferences over commuting in generating monopsony power. Sources of monopsony power in the model are generated by idiosyncratic preferences over jobs, preferences over commuting, and the spatial distribution of activity. An extension studying the role of search costs is explored in the appendix in section C.

2.1 Model Setup

There are many firms j and workers i , spatially located across the economy, l_i , l_j . Firm and worker locations are treated as given and fixed.⁴ Firms consider themselves as small and therefore I abstract away from strategic interaction. Furthermore, it's assumed that firms can not wage discriminate workers. In the following subsection I concentrate on the applying (recruitment) worker problem, however results for the maintaining (separation) problem are very similar and can be found in section B in the appendix. Additionally, while the model can flexibly include search costs, I shall predominantly focus on a version where search costs are assumed to be zero. Derivations including search costs can be found in the appendix in section C.

⁴This is a strong assumption and is given careful treatment in demonstrating its validity in section 4.3.

2.2 The Firm Problem

Firm gain profits from job j according to:

$$\Pi_j = (p_j - w_j)n_j(w_j) \quad (1)$$

where p_j is productivity of job j , w_j is the wage and n_j is the employment. The subscript j on the employment function demonstrates the fact that this will vary across firms.

Therefore the first order condition for the firm can be written as

$$w_j = p_j \frac{\varepsilon_{nw_j}}{1 + \varepsilon_{nw_j}} \quad (2)$$

where ε_{nw_j} is the elasticity of labour supply to the firm. The above is a form of the traditional monopsonistic “rate of exploitation” (Pigou, 1924) where the gap between wages and productivity grows as the labour supply to firm - wage elasticity shrinks. The limiting case where ε_{nw_j} tends to infinite is akin to a perfectly competitive market.

In the steady-state, employment is such that

$$n_j = \frac{r_j(w_j)}{s_j(w_j)} \quad (3)$$

where r_j is recruitment for firm j which is a function of wages, and similarly s_j is separations for firm j which is additionally a function of wages. Therefore taking logs and differentiating by w_j yields the relationship between the labour supply elasticity and the recruitment and separation elasticity.

$$\varepsilon_{nw_j} = \varepsilon_{rw_j} - \varepsilon_{sw_j} \quad (4)$$

Recruits can be further described such that when a firm posts a job advert for job j the number of recruits are

$$r_j(w_j) = \Phi(A_j(w_j)) \quad (5)$$

where Φ describes the relationship between recruitment and the number of job applications A_j , which in turn is a function of wages. Unlike the application-wage function and the separation-wage function, Φ is assumed to be constant across firms. Therefore the recruitment elasticity can be represented by

$$\varepsilon_{rw_j} = \varepsilon_{\Phi A} \varepsilon_{Aw_j} \quad (6)$$

Equation 6 shows that if the firm hired a constant ratio of job applicants then $\varepsilon_{\Phi A} = 1$ and $\varepsilon_{rw_j} = \varepsilon_{Aw_j}$. However, assuming there is only one vacancy to fill as per The Company, then

$\varepsilon_{\Phi A} < 1$. I shall assume going forward the latter of these is the case.⁵

Workers are homogenous in productivity, however some worker-firm matches are determined “unsuitable”. Therefore there is a non-zero probability of a vacancy being unfilled despite $A_j \geq 1$, as is a feature of the data described in section 3.1. In particular I assume the probability of some worker being suitable to be q , which is independent of any other characteristics of the workers and unknown to the worker before applying. Thus

$$\Phi(A_j) = 1 - (1 - q)^{A_j} \quad 6 \quad (7)$$

Which implies $\Phi(A)$ is concave and bounded between 0 and 1.

2.3 The Worker Problem

Firms post jobs j , which are advertised with a wage w_j and a location l_j .

Worker i located at l_i , employed in job j gets utility from the job according to:

$$u_{ij} = w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \nu_{ij} \quad (8)$$

where $d_{ij} = |l_i - l_j|$ is a measure of distance between the worker and the job. ν_{ij} is an idiosyncratic utility component known only to the worker⁷ and is distributed iid following some distribution $F(\nu_{ij})$, defined over the support $[0, \infty]$. ν_{ij} could be thought of as j specific characteristics and i 's preferences over them, for example, management style, flexibility and firm ethics. The parameter ε_{cw} is the commuting-wage elasticity and reflects the importance of commutes in determining worker utility. The utility function in equation (8) reflects how workers will see jobs as imperfect substitutes as a result of idiosyncratic preferences and the commuting distance and the importance of these two factors will be determined by the size ε_{cw} and the variance of $F(\nu_{ij})$.

A worker i , who is currently in job j ⁸ will choose to apply to posted job j' if the expected utility of doing so is greater than not applying:

$$P(A_{j'})u_{ij'} + (1 - P(A_{j'}))u_{ij} \geq u_{ij} \quad (9)$$

where $P(A_{j'})$ is the probability of getting the job, which is a function of the total number of applicants to job j' , $A_{j'}^9$

Rearranged worker i will apply to j' if

⁵Datta (2023) uses data for the same firm and shows this is predominantly the case.

⁶At low values of q one can approximate using $\Phi(A_j) = 1 - e^{-qA}$. This would imply $\frac{\partial \Phi}{\partial A} = qe^{-qA} > 0$ and $\frac{\partial^2 \Phi}{\partial A^2} = -q^2 e^{-qA}$

⁷Firms never observe worker locations and ν_{ij} , only the distributions to avoid wage discrimination.

⁸The model is flexible enough to allow job j to be unemployment. In such a case w_j would be their unemployment benefit and d_{ij} could be considered the average distance they have to travel to attend job interviews and meetings at their local job centre.

⁹This drops out in this setting but is important when search costs are introduced as explored in section C.

$$\nu_{ij'} \geq \underbrace{\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}}}_{\equiv x_{ijj'}} \quad (10)$$

Therefore the probability of worker i in job j applying to job j' is given by:

$$Pr(Apply_{ij}^{j'}) = 1 - F(x_{ijj'}) \quad (11)$$

Note that $x_{ijj'}$ here is a measure of relative utility between the incumbent job j , and the potential job j' . The idiosyncratic component related to the incumbent job in in equation 10 is normalised to $\bar{\nu}$, which in practice will be treated as the median draw.¹⁰

2.4 The Individual's Elasticity

The first key observation here relates to the elasticity of applying for the individual. Under the assumption the distribution $F(x)$ is such that $\frac{\partial h(x)x}{\partial X} \geq 0$, where $h(x)$ is the hazard function related to $F(x)$ ¹¹ the individual specific application elasticity is given by

$$\varepsilon_{Aw_{ij}^{j'}} = h(x_{ijj'})x_{ijj'} \quad (12)$$

and is decreasing in potential relative utility. The above assumption on the distribution of ν_{ij} is not a restrictive one and is fulfilled by commonly used distributions including Weibull, exponential, lognormal, loglogistic and Frechet.¹²

The above formulation of the individual's responsiveness of applying with respect to wages has a number of interesting and important features. Firstly, it can be seen that as the posted wage increases, $x_{ijj'}$ decreases and therefore the elasticity of applying to wages decreases. Given that the probability of applying is bounded between 0 and 1, this result is intuitive.¹³ Secondly, the smaller the standard deviation of idiosyncratic preferences, the closer the behaviour of the individual to the perfectly competitive benchmark, and vice versa.¹⁴ Both of these points are demonstrated graphically in figure (1).

¹⁰This normalisation is required for tractability reasons, as distributions under study do not have a neat closed form for the ratio of two random variables. The key patterns from the simulation exercises in sections 2.4 and 2.5 are however unchanged when allowing the incumbent idiosyncratic component to be a random variable.

¹¹I.e. $h(x) = \frac{f(x)}{1-F(x)}$

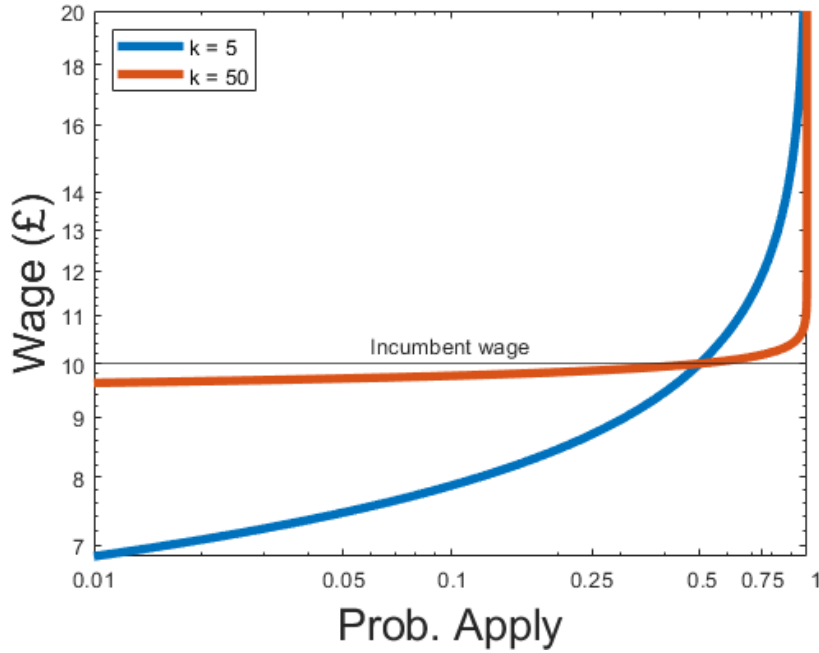
¹²Manning and Petrongolo (2017) utilise a pareto distribution which has the feature that $h(x)x$ is equal to a constant parameter of the distribution, and therefore $\varepsilon_{Aw_{ij}^{j'}}$ is constant for all worker-firm combinations.

¹³A worker who is being paid £10 an hour in their incumbent job would see a much greater percentage change in their probability of applying if the wage was increased from £8 to £8.80 than from £12 to £13.20 ceteris paribus, as in the former example their initial probability of applying would be closer to 0, and in the latter closer to 1.

¹⁴It can in fact be shown that in the absence of commuting costs, the shape parameter related to the weibull distribution will equate to the labour supply elasticity facing the firm, which is outlined in greater detail in section 2.5

Thirdly, the lower the elasticity of commuting to wages¹⁵, ε_{cw} , the more important commutes are in determining the elasticity of applying to wages for the individual. For example, assuming $\varepsilon_{cw} < \infty$, the inelastic part of the curve occurs when a firm offers higher wages, or is located relatively nearer to workers than their current job. This would suggest that workers which currently have to commute far, but a job opening comes up close by to them, would have a more inelastic labour supply curve to the posted job. The lower the commuting elasticity, the greater the impact of space on the application elasticity. This is exemplified in figures 2 and 3 which present a simulated distribution of two workers and their respective labour supply curves.

Figure 1: Individual Labour Supply To the Firm



Note: The figure plots the probability of applying for the worker as per equation (11), against the advertised wage on log scales. Parameterisation is such that $\varepsilon_{cw} = \infty$ and $\nu_{ij} = \text{median}(\nu_{ij})$. F is assumed to follow a weibull distribution with scale parameter $\lambda = 1$ and the figure plots for both shape parameter values of $k = 5$ and $k = 50$.

2.5 The Elasticity of Labour Supply To The Firm

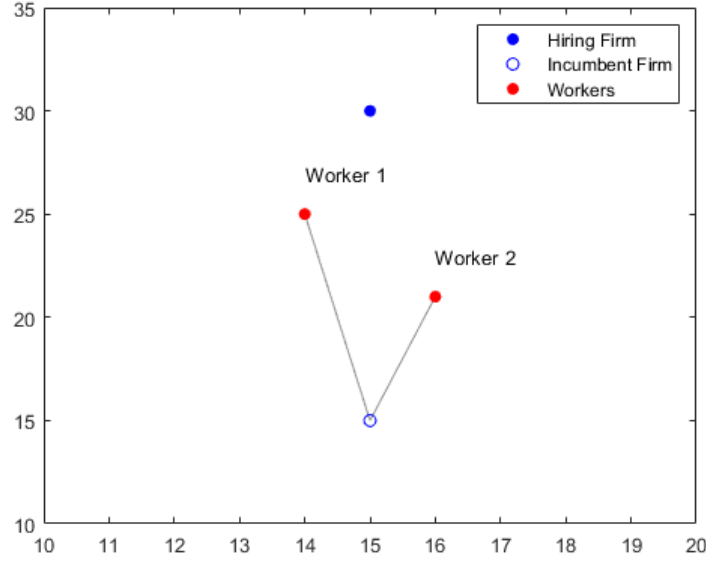
The labour supply to the firm can be calculated by summing equation (11) over all relevant workers in the economy, which gives

$$A_{j'} = \sum_{i,j} [1 - F(x_{ijj'})] \quad (13)$$

Equation (13) reflects the lack of need to discretise the economy into geographical labour markets. Labour markets are endogenously constructed, point specific, become continuous, and weaken over distances. Ceteris paribus workers close by to the advertised job are more likely

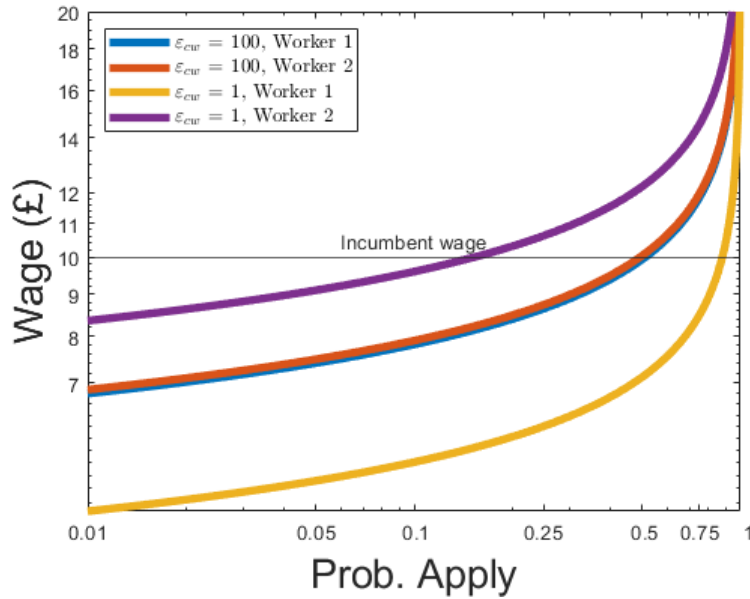
¹⁵I.e. The greater the preference for a smaller commute.

Figure 2: Spatial Heterogeneity in Individual Labour Supply To the Firm I



Note: The figure presents a simulated spatial distribution of two workers with current wage of £10, their incumbent firm and a hiring firm.

Figure 3: Spatial Heterogeneity in Individual Labour Supply To the Firm II



Note: The figure plots the probability of applying to the hiring firm for the two workers spatially located as per figure 2 under different parameterisations of ε_{cw} , calculated according to equation (11), against the advertised wage on log scales. Parameterisation is such that $c = 0$ and $\nu_{ij} = \text{median}(\nu_{ij})$. F is assumed to follow a weibull distribution with shape parameter $k = 5$ and scale parameter $\lambda = 1$. When $\varepsilon_{cw} = 100$, where distance plays little role in determining utility, the supply curves are close to identical. When $\varepsilon_{cw} = 1$ where worker 2 experiences a lower elasticity of labour supply to the firm for any given wage than worker 1.

to apply and workers farther away from the job are less likely to apply, and the extent of this factor is dependent on their disutility for commuting. Furthermore, it also accounts for workers' incumbent options. For example, if a firm is located far from workers, but those workers are currently commuting a similar distance, the size of the labour market would be larger than a situation where a firm is close to workers and those workers only currently commute a small distance.

It can be shown that the application elasticity to the firm is

$$\varepsilon_{Awj'} = \frac{\sum_{(i,j)} \varepsilon_{Aw_{ij}^{j'}} [1 - F(x_{ijj'})]}{\sum_{(i,j)} [1 - F(x_{ijj'})]} \quad (14)$$

which is simply a weighted average of the individual level elasticity from equation (12), where the weights are the probability of applying to the job. Therefore workers who are more likely to apply to the job (and therefore have a lower individual elasticity) will receive higher weights than those relatively less likely to apply.

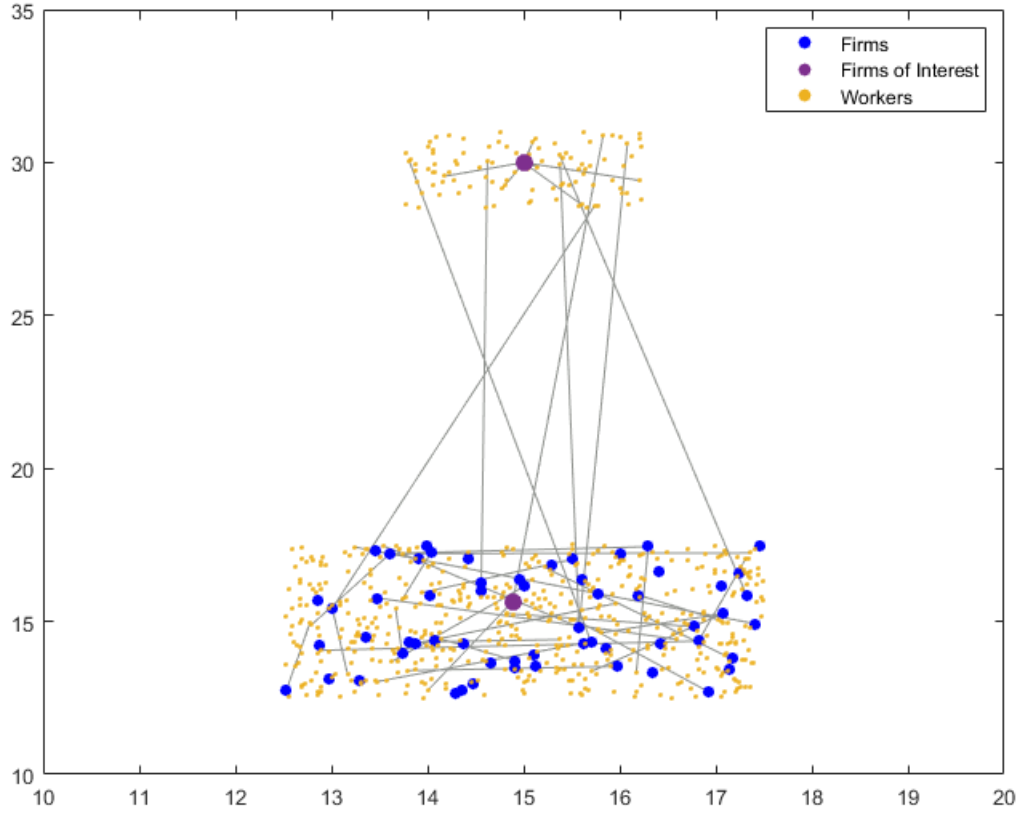
As the application elasticity to the firm is a weighted average of the individual level elasticities, many of the features of the individual level elasticities outlined in section 2.4 aggregate up to the firm level. Thus, the larger the spread of idiosyncratic preferences over jobs, the lower the elasticity of labour supply to the firm, and the greater the monopsony power. Additionally, the lower the commuting-wage elasticity, the greater the monopsony power and the more important the spatial distribution of activity in generating heterogeneities in monopsony power. Both of these last two points can be demonstrated in a similar simulation exercise as seen in figures 2 and 3.

Figure 4 presents a simulated spatial distribution of 600 workers and 60 firms, where 500 of the workers and 59 firms are located in a “city” while 100 workers and 1 firm is located in a “satellite town”. Each firm has a labour force of 10 workers, lines demonstrate existing commutes for some workers and as can be seen some workers living in the satellite town commute into the city for work. As before it's assumed that all workers are currently in jobs with a wage of £10¹⁶. To explore the impact of commuting on monopsony power I examine the labour supply curve to two firms, one city firm and the satellite town firm, when posting a new vacancy.

As seen in figure 5 in the setting where a worker's commuting elasticity is extremely large ($\varepsilon_{cw} = 100$) there is virtually no difference between the labour supply to the two firms. This is generated by the fact that worker's incumbent utilities would be almost identical across space, as would their potential utility from the advertised job. Put another way, when the commuting elasticity is large, the location differences do not generate any heterogeneity in utility. The advertising firms would still have considerable monopsony power under this parameterisation which is generated by the idiosyncratic term.

¹⁶The above analysis is very much a partial analysis. For such an equilibrium to exist this would require variation in firm level productivity, p_j , such that each maintaining firm's optimal wage offer was £10.

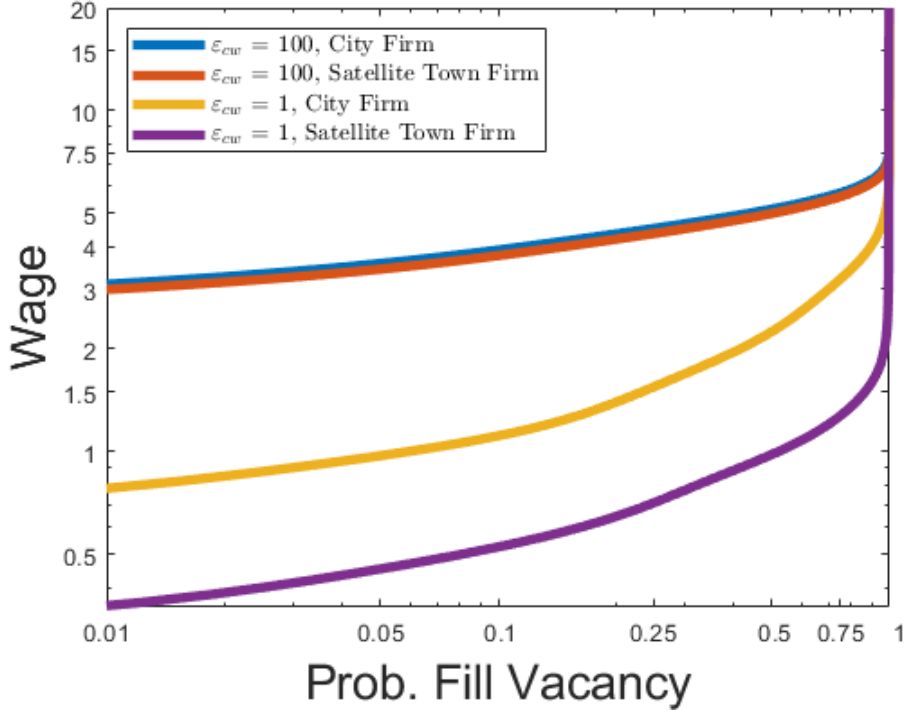
Figure 4: Spatial Heterogeneity in Labour Supply To the Firm I



Note: The figure presents a simulated spatial distribution of 600 workers, and 60 firms. 500 workers and 59 firms are located in the “city” while 100 workers and 1 firm is located in the “satellite town”. Lines are drawn to demonstrate some of the existing commutes.

The parameterisation where $\varepsilon_{cw} = 1$ represents a scenario where workers have a strong distaste for commuting. This scenario has two effects, it increases monopsony power for both firms, but does so heterogeneously. At any given wage rate the satellite town firm experiences a more inelastic labour supply curve than the city firm. As many workers living in the satellite town have to commute into the city due to lack of local options, when a job opening appears locally, that job exercises considerable local monopsony power. While the satellite town firm experiences more, both firms experience greater monopsony power (a more inelastic slope) at any given wage rate in comparison to the $\varepsilon_{cw} = 100$ scenario and would therefore be able to markdown wages more than in the high commuting elasticity scenario. This is driven by the fact that distance plays an important role in determining utility from a job, so even the city firm would still enjoy some local monopsony power, as even small commutes within the city generate disutility.

Figure 5: Spatial Heterogeneity in Labour Supply To the Firm II



Note: The figure plots the labour supply to the firm curves as per figure 4 under different parameterisations of ε_{cw} , calculated according to equation (13) and (7), against the advertised wage on log scales. Parameterisation is such that $c = 0$ and $v_{ij} = \text{median}(v_{ij})$. F is assumed to follow a weibull distribution with shape parameter $k = 5$ and scale parameter $\lambda = 1$, and the exogenous suitability parameter $q = 0.075$.

2.6 Model Implications

A key result of this model is that all firms¹⁷ would likely experience some local monopsony power, and therefore some of the monopsony power observed in empirical studies is likely driven by distaste for commuting coupled with the spatial locations of firms and workers. Models which coarsely discretise the spatial economy and treat commuting within areas as costless, and across boundaries as (infinitely) costly are likely to be misspecified. For example, many recent models rely on idiosyncratic preferences (typically assumed extreme value distributed) to generate monopsony power and lump distance to work within those idiosyncratic preferences (e.g. Lamadon et al. (2022); Berger et al. (2022); Card et al. (2018); Azar et al. (2022)). However, there is a strong reason to believe that these preferences are not idiosyncratic but rather systematic with clear spatial patterns as outlined above.

The model additionally gives rise to heterogeneity in monopsony power across space, and denser urban areas are likely to see less monopsony power than rural areas with fewer outside options. The model therefore offers a new micro-founded explanation for the urban wage premium. Specifically that markdowns in cities are likely to be smaller in size due to the more competitive

¹⁷Except in the extreme case where a firm is relatively located far from all workers.

nature of the markets. That said, each firm located at a specific point would have its own specific level of monopsony power, and this would likely vary even within a city. Typically labour market analysis has been done at the TTWA level in the UK and the mean area for TTWAs is 1,064 km², and the above model suggests there is likely to be considerable heterogeneity within that area.

Figure 14 in the appendix shows the map for the TTWA for London¹⁸, and its surrounding TTWAs, and exemplifies the issue. A study of monopsony power in the UK labour market with discretised areas into TTWAs would suggest the travel time between Rickmansworth (in the North West of London) and Gravesend (in the South East) is costless whereas google-maps estimates a travel time of 90 minutes utilising either car or public transport. Additionally, using a model where distance to work is lumped into the idiosyncratic component, though allowed to vary by area, would result in a firm located on the edge of the TTWA (e.g. Potters Bar) as having the same degree of competitiveness as a firm operating in central London (e.g. Holborn), which seems unlikely.

Another result of this model is that the labour supply elasticity is endogenous.¹⁹ While the labour supply elasticities are still a function of the idiosyncratic component (which could now be assumed to be constant across areas), they are also determined by the spatial distribution of activity, and the wage-commuting elasticity. This result bares a striking resemblance to that in Monte et al. (2018) which finds that local employment elasticities with respect to labour demand shocks are endogenous and spatially heterogenous depending on the local market's openness. It's worth noting that if workers did not care about commuting, and $\varepsilon_{cw} = \infty$ then the model would collapse to the typical logit model utilised in other studies, and this is shown in section D.

A final observation from this model is that it suggests that general reductions in travel times should in turn increase market competitiveness, and generate upward pressure on wages. Therefore, one way in which infrastructure investments or changes to working patterns (i.e. increased working from home) could affect wages is through increased competition between firms.

The sources of monopsony explored in the above exposition focus entirely on imperfect substitution between jobs, unlike some of the original literature which focused on dynamic search frictions (see Manning (2003)). The model however can flexibly introduce search frictions and is done so in section C of the appendix. Monopsony power is shown to be weakly increasing in search costs, but more interestingly it is shown that the individual level elasticity can actually be negative in some instances.

¹⁸This TTWA represents almost a sixth of the Great Britain working population.

¹⁹In models utilising a logit structure where all monopsony power is generated by the idiosyncratic component as those mentioned above, the elasticity of labour supply to the firm is $1/\beta_{\text{area}}$ where β_{area} is the scale parameter related to the extreme value distribution and the subscript reflects that it can vary by area. Thus, in these models the labour supply elasticity to the firm, and therefore the extent of monopsony power, is entirely determined by the area specific scale parameter.

3 Estimating The Model Parameters

The model has two key sets of parameters, the commuting wage elasticity (ε_{cw}) and those associated with the idiosyncratic preference distribution of ν_{ij} , F . Given these two sets of parameters and the spatial distribution of activity, the model generates labour supply elasticities to the firm which vary across space, and thus differences in spatial monopsony power. Section 2 showed key results of the model would hold under a variety of distributions but for tractability reasons going forward I impose F to follow a Weibull distribution. This comes with two key benefits. First, it reduces the number of parameters related to the idiosyncratic preferences to one (k) plus a scale parameter (α), while also having a neat parallel with logit models of monopsony (see section D in the appendix for more details).

To estimate the above parameters I use a combination of a well identified reduced-form approach combined with exploiting the structure of the model laid out in the previous section. In the following section I discuss the data, exogenous variation and methods for estimating the parameters. In brief, the commuting-wage elasticity estimate will exploit the detailed information on job applicant home address, to ascertain how commutes of applicants responds to exogenous wage changes, while the idiosyncratic preference parameter will be estimated via matching model predicted application-wage elasticities of job adverts across space, with those causally estimated from the natural experiment.

3.1 Data & Variation

I utilise a rich bespoke dataset for a large UK based services firm (The Company) with operations in over 300 establishments spatially distributed across the UK. Establishments are centrally operated by the same company using the same structure of operations and management, but there is establishment level autonomy over employment and workforce composition decisions. While The Company’s main competitors are firms operating in the private sector, a large part of the firm’s business is government procurement contracts. Due to disclosure limitations within the data sharing agreement I am unable to name The Company nor disclose the precise industry in which they operate. Datta (2023) discusses in detail the external validity and representativeness of The Company, but in short, they face a similar degree of local competition as hairdressers, mechanics’ garages, pubs and restaurants, and the sets of occupations utilised by the firms have similar job and industry substitutability as to those for the entire economy. Moreover, the kind of services supplied in The Company’s establishments are common across the world and the industry is worth 10s of billions of dollars in the United States.

The dataset includes vacancy and applicant data for the period 2016-2019. The vacancy data includes all information that is contained in a job advert including, job role, wage, location and all text within the advert. The applicant data includes the number of applicants for each vacancy, and details on the applicants including home location, gender, ethnicity and whether the applicant was internal or external. The combination of these datasets allows me to explore labour supply and commutes, and how they respond to wages.

Table 1 presents summary statistics for The Company in March 2019 and paints a picture of a typical firm operating in a low wage labour market, where younger and female workers are overrepresented. 60% of the firm’s workforce are female, and the median worker 33 years old. Almost half of the firm’s workers are classified as “Entry-Level”. These jobs are typically minimum-wage jobs in the UK, and would be considered unskilled. The Company has a very large number of workers on non-salaried, hourly wage contracts²⁰ which is more usual for the low-pay sector. The average wage in the firm is £12.88.

Table 1: Summary Statistics, March 2019

Variable	Mean	S.D.	Median
Female	0.60		
Age	35.9	14.3	33.0
Entry-Level	0.49		
Salaried	0.28		
Hourly Rate (£)	12.88	5.87	10.20
N			
Workers	18,773		
Establishments	362		

Note: *The table presents worker-level summary statistics for The Company as of March 2019.*

Estimating the application-wage and commuting-wage elasticities relies on being able to isolate exogenous variation in wages at a minimum at the establishment-level while the rest of the market remains unchanged. I exploit two instruments to achieve this. Firstly, I utilise a location specific wage floor that affects a very small number of workers in an area, but is binding for The Company in that location for jobs which are paid less than the Living Wage. The Living Wage Foundation (LWF) is a charitable organisation in the UK that was established in 2011, that campaigns for employers to pay workers a living wage. Organisations can voluntarily sign up to become Living Wage employers and following appropriate audits by the LWF can achieve accredited status. As of July 2020, the LWF lists 6,562 accredited employers and included in this list are 107 local government units. When public bodies achieve accreditation, they are required to enforce the living wage in their procurement contracts. The Company operates in the service sector and a significant portion of their business is through procurement contracts with local councils. As the firm operates hundreds of establishments across the UK, different establishments become contractually obliged to pay the LLW and UKLW at different times. This is dependent on whether, and when, the local government unit has voluntarily signed up to the LWF’s Living Wage, as well as idiosyncratic timings of contractual renewal or renegotiation. When an establishment is exposed to the Living Wage, it effects only those workers within the establishment whose pay point is below the mandated Living Wage (i.e. entry-level workers), and the remainder of wages in the local labour market remain unchanged.

²⁰For a complete description of what these types of contracts entail see [Datta et al. \(2019\)](#).

Between 2012 and 2019 107 local government units gained accreditation. For example, of the 32 London Boroughs, 17 have received accreditation, the earliest (Islington) receiving accreditation in May 2012, and the most recent (Redbridge) receiving accreditation in November 2018²¹. As figure 6 shows, this setting gives a large amount of variation in Living Wage treatment for establishments run by The Company. The living wage rates for London (LLW) and the rest of the UK (UKLW) are calculated each year by the LWF and the Resolution Foundation and have typically been considerably higher than the mandatory National Minimum Wage (NMW) and National Living Wage (NLW). The LLW rate has typically been approximately 30-35% higher than the mandatory minimums, while the UKLW has been about 15-20% higher as can be seen by figure 13 in the appendix .

Figure 6: Living Wage Roll-out



Note: The figure shows the cumulative establishment-level Living Wage treatment for The Company, 2011 - 2019.

To ensure that this instrument can causally identify the application and labour market size responsiveness to wages, it's necessary to ensure that the Living Wage adoption within an area only affects a very few number of jobs. If for example, it affected all low pay jobs in the area the relative wage offered by the establishment would remain unchanged, and therefore it would be reasonable to assume this would have little affect. It's important to highlight therefore that when a council signs up to the LWF's living wage it only affects council employees and those who are subcontracted to do work for the council. Council employment makes up approximately 3% of employment and is usually made up of workers more skilled than would be affected by the wage floor. As an example table 11 in the appendix gives estimates of the employment

²¹Correct as of July 2019.

counts and shares for the London Borough of Hackney, and shows council employment accounts only for 3.3% of total employment in the borough. Furthermore, examination of the pay scale documentation for the borough show that the lowest paid point is 8% above the binding LLW for 2019. This is suggestive that the council adoptions of the Living Wage affects only a fraction of a percentage of workers in the area. Datta (2023) provides causal evidence to show that this is indeed the case. Specifically, he shows using UK social security data that when a Local Authority governmental unit signs up to the Living Wage the proportion of workers being paid the Living Wage in the area remains unchanged.

Secondly, I utilise an instrument related to saliency of the wage posted. In the UK, whether a job has a permanent or zero-hours contract, the firm is required by law to give the worker 28 days paid annual leave. Due to the nature of non-permanent work, many firms opt to give the statutory annual leave as a top up to the wage, which calculates to a wage supplement of 12.07%. Within the vacancy data, some non-permanent jobs (approximately 20%) are advertised with the annual leave top-up included in the advertised wage, while the text of the adverts stay constant. Discussions with the HR team at The Company concluded that this occurred due to idiosyncrasies in whomever happened to be posting the job that day onto the HR system.²² This lends itself for use as a seemingly random instrument.

3.2 Estimating ε_{cw} in reduced form

To estimate the commuting-wage elasticity I regress

$$\log(Comm_{iajem_y}) = \beta_1 \log(Wage_{ajem_y}) + \kappa' X_{imy} + \gamma_{je} + \lambda_{ey} + \nu_{ym} + \theta_{jy} + \epsilon_{iajem_y} \quad (15)$$

where $Comm_{iajem_y}$ is the commuting time measured in minutes between applicant i 's home and address of the establishment applying to a job advert a , advertising for job-role j in establishment e in month-year my , $Wage_{ajem_y}$ refers to the advertised hourly wage (in £), γ_{je} are job-role establishment fixed effects, λ_{ey} and θ_{jy} are time-varying establishment and job-role fixed effects,²³ ν_{ym} are year-month fixed effects.

Commutes are measured using the Google Maps API and are calculated for an arrival time of 9am so as to account for traffic. Commuting times utilised in this exercise are therefore considerably more accurate than typical “as the crow flies” distances calculated via GIS software. Given the popularity of google maps for routing²⁴ it is also a reasonable approximate of expected commuting times by job searchers. Commuting time was calculated for both car and public transport, and it is assumed that workers choose the fastest method of the two options.²⁵

²²This phenomenon was observed consistently over the entire time period, and there is considerable variation within establishments and across jobs.

²³The time varying job-role fixed effects are only used in some specifications due to saturation concerns.

²⁴The app is ranked top for navigation on the apple and android app stores, and has over one billion active monthly users.

²⁵In practice this means that many people working in London are assumed to utilise public transport.

Equation (15) utilises variation within the same job role-establishment combination while controlling for establishment-level time shocks, and job-level time shocks. It is akin to a triple-difference specification. Though this specification is very flexible, concerns relating to endogeneity still exist. Job-location specific time shocks are still conceivable, which in turn could be correlated with wages and commuting patterns (see Belot et al. (2022); Marinescu and Wolthoff (2020) for evidence of this with regards to application responses). As a result I instrument $\log(Wage)$ with the two instruments outlined in section 3.1. The first LW_{jewm} , the Living Wage instrument which is defined at the establishment-job-time level, and the second, AL_{ajemy} , the annual leave wage saliency instrument which is defined at the advert level.

$$LW_{jewm} = \begin{cases} 1 & \text{if establishment is subject to LW \& LW was binding for job} \\ 0 & \text{otherwise} \end{cases} \quad (16)$$

$$AL_{ajemy} = \begin{cases} 1 & \text{if advert included annual leave in hourly rate} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

The estimate $\hat{\beta}_1$ is a naive estimate of ε_{cw} . The approach used in 15 is estimated at the advert level, and commutes are only observed conditional on applying for the job. Thus, the truer interpretation of β_1 is the responsiveness of labour market size (averaged out over appliers) for a job posting, in response to an exogenous change in wages. As such this will only directly map to ε_{cw} under certain circumstances, which relates to the degree of continuity in the spatial distribution of activity (and existing commutes). As an extreme example, if one imagined a small, single firm, town in the middle of a large desert with no other towns nearby for hundreds of miles, then even a large change in wages would likely result in no change to the average commuting distance of appliers. This however, does not imply that the structural preference of workers is such that they do not value short commuting distances. As Great Britain is a relatively small, dense, island, such an example is unlikely to pose a threat. As a first approximation I will treat the estimate $\hat{\beta}_1$ as ε_{cw} in the model when estimating the remaining parameters. I will however carry out two robustness checks.

First, I will compare the OLS estimates version of equation 15 with a comparison from the Annual Survey of Hours and Earnings (ASHE, social security) data, which contains information on realised worker-firm matches. While both are likely to suffer from endogeneity issues, one would expect the bias to be in the same direction, while the realised matches will be informative of the slope of the indifference curve between wages and commutes similar in spirit to the approach in Le Barbanchon et al. (2021)²⁶. If both are of a similar size, this will be reassuring that the approach using commutes of realised applicants will be informative of the trade-off between wages and commutes. Secondly, I will use the structure of the model to generate the model

²⁶There are however key differences. Importantly Le Barbanchon et al. (2021) utilise data on stated preferences regarding reservation wages and reservation commutes.

equivalent of β_1 and use that as an additional moment restriction in the structural estimation.

3.3 Structural Estimation

3.3.1 Baseline

The model gives rise to application elasticities which vary by job advert, as per equation 14. I assume F follows a Weibull distribution, which implies 14 has a closed form solution given by

$$\varepsilon_{Awajemy} = \frac{\sum_{i,j} k \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}} \bar{\nu}}}{\lambda w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \exp \left(- \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}} \bar{\nu}}}{\lambda w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \right)}{\sum_{i,j} \exp \left(- \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}} \bar{\nu}}}{\lambda w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \right)} \quad (18)$$

Given values of ε_{cw} and k (related to the variance of the Weibull distribution), this can be calculated for each job advert in my sample from The Company, using information on incumbent wages, incumbent commutes and potential commutes for potential appliers in the wider population. I use data from the ASHE for 2016-2019 for Great Britain ([Office for National Statistics, 2020](#)) for information on w_j , d_{ij} and $d_{ij'}$. d_{ij} and $d_{ij'}$ are calculated at the 6-digit postcode level.²⁷ I additionally utilise the Open Street map dataset for Great Britain and ArcGIS's networking tool for commute calculation. This allows for a very accurate time of commute between home and work postcodes.²⁸ For each job advert j' , workers with the same occupation code²⁹ that job j' related to was included in the calculation of (18). For the incumbent value of ν_{ij} , I assume it is equal to the median value of the distribution $\ln(2)^{\frac{1}{k}}$ ³⁰.

I use the estimate of β_1 as ε_{cw} , and then to elicit the parameter k I use a minimum distance estimator, that minimises the difference between the model predicted applications elasticities and the empirically estimated elasticities using the data and exogenous variation outlined in section 3.1. I additionally introduce a log-scaling parameter α . In practice this parameter ensures that the elasticities match in absolute-value, rather than in just relative value. The parameter, therefore allows for a clearer interpretation of the following results.

The labour supply function (in logs) then becomes

²⁷A 6-digit postcode typically relates to either a building (in the case of flats) or a few houses on a street, therefore it is almost the exact location of the individual's residence to their place of (potential) work.

²⁸The Open Street map data contains the full road network for Great Britain, speed limits for each road, as well as locations of speed obstructions (roundabouts, traffic lights, crossings etc). The networking tool in ArcGIS allows time obstructions to reflect a delay (measured in seconds) and also allows for delays when crossing or joining new roads.

²⁹Typically these are to the 4 digit SOC level, however in some cases multiple 4 digit SOC codes were included.

³⁰I use the median rather than the mean ($\lambda \Gamma(1 + \frac{1}{k})$) to avoid the need to utilise the gamma function. Additionally, in practice this makes no difference to simulated results when drawing a value of incumbent utility from F .

$$\log(A_{j'}) = \alpha \log\left(\sum_{ij} [1 - F(x_{ijj'})]\right) \quad (19)$$

and for each job advert the empirical counterpart becomes

$$\tilde{\varepsilon}_{Aw_{ajemy}} = \alpha * \varepsilon_{Aw_{ajemy}} \quad (20)$$

where $\varepsilon_{Aw_{ajemy}}$ is defined in equation 18.

The algorithm used to estimate k and α is as follows:

1. Guess parameters k and α .
2. Calculate equation (20) for each job advert using the guessed parameters and the estimate of ε_{cw} from estimate $\hat{\beta}_1$ from section 3.2.
3. Split the sample in half at the median based on the model calculated $\tilde{\varepsilon}_{Aw_{ajemy}}$, labelling the top half “high”.

$$HighElast = \begin{cases} 1 & \text{if } \tilde{\varepsilon}_{Aw_{ajemy}} \geq med(\tilde{\varepsilon}_{Aw_{ajemy}}) \\ 0 & \text{otherwise} \end{cases} \quad (21)$$

4. Estimate regression equation

$$\begin{aligned} \log(Apps_{ajemy}) = & \beta_2 \log(Wage_{ajemy}) + \beta_3 \log(Wage_{ajemy}) X HighElast_{ajemy} \\ & + \beta_4 HighElast_{ajemy} + \gamma_{je} + \lambda_{ey} + \theta_{my} + \epsilon_{ajemy} \end{aligned} \quad (22)$$

with the high group as calculated from step 3 and with $\log(Wage_{ajemy})$ instrumented with the two instruments discussed in section 3.1.

5. Calculate the euclidean distance between the empirical elasticities from step 4 and the means of the model elasticity groups from step 3:

$$Euclidean\ distance = \sqrt{(\hat{\beta}_2 - \bar{\varepsilon}_{Aw,low})^2 + (\hat{\beta}_2 + \hat{\beta}_3 - \bar{\varepsilon}_{Aw,high})^2}. \quad (23)$$

6. Repeat steps 1-5 until equation (23) in step 5 is minimised.

The regression equation 22 is of a similar triple difference style form as that in section 3.2, and relies on the same identification strategy. Identification of k comes through the variation the parameter induces in the relative difference between the model predicted elasticities of the high and low group. This is exemplified in table 2 below which documents the relative difference between the high and low group elasticities for the sample of adverts for The Company, using data from ASHE for incumbent wages, commutes and potential commutes. The higher the value of k , the larger the relative difference between the high and low group elasticities. This is consistent with intuition. The lower the value of k the larger the variance of the idiosyncratic term ν_{ij} , and

the more important the idiosyncratic term is in determining monopsony power in comparison to location and commutes. Thus, the more similar the levels of monopsony power between the high and low group. Identification of α comes through matching the absolute levels of the elasticities.

Table 2: Model Elasticity Estimates

k	Pooled Mean	High Elast. Mean	Low Elast. Mean	High/Low Elast. Mean
1	0.97	1.21	0.73	1.66
3	1.21	1.58	0.84	1.88
5	1.21	1.64	0.79	2.08
7	1.23	1.73	0.75	2.31
9	1.24	1.76	0.72	2.44

Note: The table presents descriptive statistics for the pooled, high group and low group for estimates of $\varepsilon_{AWj'}$ based on equation 18 where $\varepsilon_{cw} = 1$, under different values of k , for a sample of 2,239 job adverts from The Company, using additional data from ASHE.

3.3.2 Advert Level Commuting as Moment

As already discussed in section 3.2, using $\hat{\beta}_1$ as ε_{cw} may pose some misspecification issues. Thus, as an additional robustness check I calculate the model equivalent of β_1 (signified with the superscript M) and use that as an additional moment restriction in the structural estimation. Specifically, it can be shown that the model equivalent of average commuting response of job appliers, to a change in the wage is given by

$$\beta_1^M = \frac{1}{N_{j'}} \sum_{j'} \left[\frac{\sum_{i,j} d_{ij'} \frac{k}{\alpha} \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{\alpha w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \exp \left(- \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{\alpha w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \right)}{\sum_{i,j} d_{ij'} \exp \left(- \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{\alpha w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \right)} - \varepsilon_{Awj'} \right] \quad (24)$$

where $N_{j'}$ is the number of job adverts. The interpretation of 24 is relatively straightforward. The left hand side term within the bracket represents the expected increase in total commutes to an exogenous wage change in elasticity terms while the right hand term is simply the exogenous wage change to applicants in elasticity terms.³¹ This is then averaged over all job adverts.

The algorithm using this moment condition then becomes:

1. Guess parameters ε_{cw} , k and α .
2. Calculate equations (20) and (24) for each job advert using the guessed parameters.
3. Split the sample in half at the median based on the model calculated $\tilde{\varepsilon}_{Aw_{ajemy}}$, labelling

³¹If we let $\text{Average commute}(w_j) = \frac{\text{Total Commute}(w_j)}{\text{Applicants}(w_j)}$, then $\varepsilon_{ACw} = \varepsilon_{TCw} - \varepsilon_{Aw}$

the top half “high”.

$$HighElast = \begin{cases} 1 & \text{if } \tilde{\varepsilon}_{Aw_{ajemy}} \geq med(\tilde{\varepsilon}_{Aw_{ajemy}}) \\ 0 & \text{otherwise} \end{cases} \quad (25)$$

4. Estimate regression equation

$$\begin{aligned} \log(Apps_{ajemy}) = & \beta_2 \log(Wage_{ajemy}) + \beta_3 \log(Wage_{ajemy}) X HighElast_{ajemy} \\ & + \beta_4 HighElast_{ajemy} + \gamma_{je} + \lambda_{ey} + \theta_{my} + \epsilon_{ajemy} \end{aligned} \quad (26)$$

with the high group as calculated from step 3 and with $\log(Wage_{ajemy})$ instrumented with the two instruments discussed in section 3.1.

5. Calculate the euclidean distance between the empirical elasticities from step 4 and the means of the model elasticity groups from step 3 as well as between β_1^M and $\hat{\beta}_1$, the model predicted and empirical commuting response. :

$$Euclidean\ distance = \sqrt{(\hat{\beta}_2 - \bar{\varepsilon}_{Aw,low})^2 + (\hat{\beta}_2 + \hat{\beta}_3 - \bar{\varepsilon}_{Aw,high})^2 + (\hat{\beta}_1 - \beta_1^M)^2}. \quad (27)$$

6. Repeat steps 1-5 until equation (27) in step 5 is minimised.

4 Results & Model Validation

4.1 Results

Table 3 presents results from estimating equation (15). Aside from column (1) which reports the OLS estimate (which is underestimated), point estimates across all specifications are consistent and imply a commuting-wage elasticity $\varepsilon_{cw} \approx 1$. Specifications containing the annual leave instrument are more precisely estimated, and the specification with both instruments is statistically significant to a 5% level. All specifications have a sizeable first stage F-stat, and the over-identified specifications in column (4) indicates that the validity of the instruments cannot be rejected.

The estimated commuting-wage elasticity suggests a strong distaste for commuting, and that a firm’s geographic labour market size is only mildly responsive to wage increases. For an hourly wage of £7.50 (\$9.38) (the NMW for the midpoint of the sample period) and average commute of 25 minutes, a commuting-wage elasticity ≈ 1 implies an extra 5 minutes of total commute would require an extra £3.00 (\$3.75) per day³², or £0.37 (\$0.46) per hour assuming an 8 hour work day. The results are suggestive that commuting distances are likely to be a strong factor in generating imperfect substitutability between jobs.

³²The average worker at The Company works 4 hours a day, as noted previously there are many non-permanent and part time staff employed.

The results imply a willingness-to-pay (WTP) considerably larger than recent estimates from [Le Barbanchon et al. \(2021\)](#) but similar in size to higher end values of the Value of Travel Time used by the British Department of Transport ([Batley et al., 2019](#)) and earlier estimates from the literature ([Timothy and Wheaton, 2001](#); [Van Ommeren and Fosgerau, 2009](#)). It is unsurprising that estimates in a UK context imply a stronger distaste for commuting than those in France (i.e. compared to [Le Barbanchon et al. \(2021\)](#)). Public transport costs in the UK are considerably higher than other European countries. As of 2017, which makes up part of the sample timing, a monthly pass for the 35 mile trip from Luton to London Kings Cross represents 14% of average monthly wages in the UK, for a similar price in Germany one could purchase a Bahncard 100 which would allow unlimited travel across the entire Deutsch Bahn network, while the Mantes-la-Jolie to Paris equivalent would take up only 2.4% of average wages ([Duncan and Swann, 2017](#)).

Table 3: Commuting - Wage Estimates

	(1)	(2)	(3)	(4)	(5)
	log(Comm)	log(Comm)	log(Comm)	log(Comm)	log(Comm)
log(Wage)	0.362***	1.081	0.922*	0.955	0.931**
	0.105	(1.208)	(0.494)	(0.774)	(0.417)
Job-Centre FE	Yes	Yes	Yes	Yes	Yes
Centre-Year FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Job-Year FE	Yes	Yes	No	No	No
N	47313	47313	19585	19585	19585
First Stage F-Stat.	-	673.3	3440.7	1220.7	2562.1
Hansen J Stat.	-	-	-	-	0.00141
Instrumented With AL	No	No	Yes	No	Yes
Instrumented With LW	No	Yes	No	Yes	Yes
Sample	All	All	Non-Perm	Non-Perm	Non-Perm

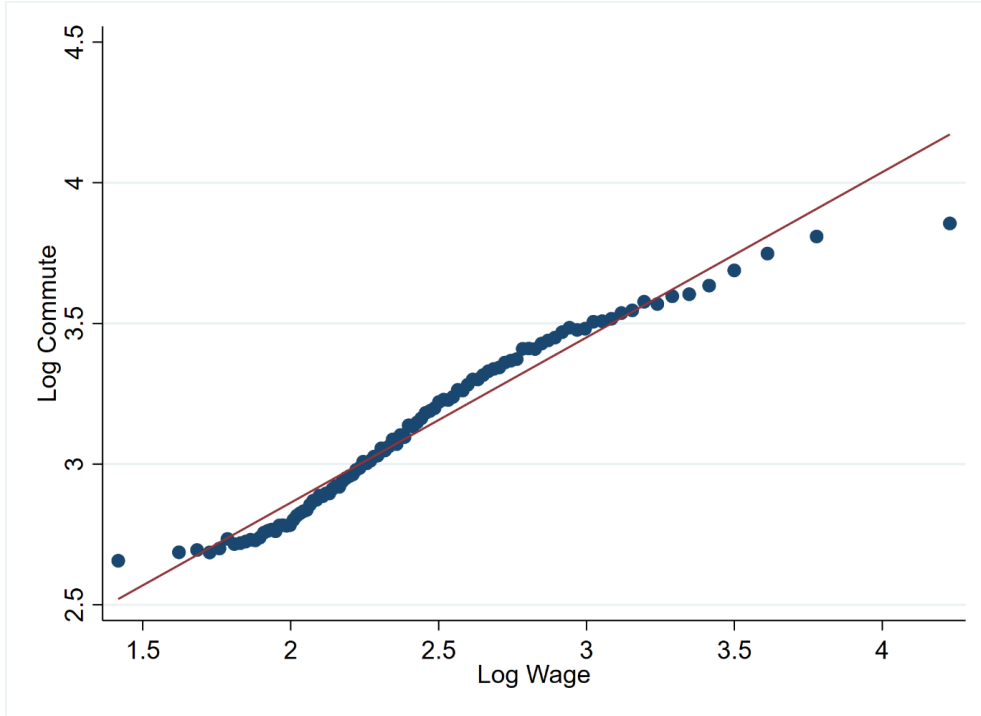
Note: *The table presents estimates of $\hat{\beta}_4$ from equation (15) where $\log(\text{Wage})$ is instrumented with either $LW_{j\text{emy}}$, $AL_{aj\text{emy}}$ or both instruments. If both instruments are used the table reports the over identifying test statistic. All columns report the first stage F statistic. Standard errors are reported in parentheses and are clustered at the advert. Regressions are weighted by the inverse number of applicants for each job. Controls include gender, ethnicity, whether applicants were internal and whether the advert was for a permanent job. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

While the OLS understandably suffers from an endogeneity issue, it is reassuring the OLS regression from this approach gives an estimate within a similar ballpark for the estimate that would arise from an estimation using the matched employer-employee ASHE data. Figure 7 presents a bin-scatter plot of log commutes against log wages, controlling for occupation, industry and year fixed effects, age, gender and employment contract status (part time, full time, temporary). The results suggest a relatively constant relationship between the two, with a slope

of approximately 0.5, about 14 log points higher than the OLS estimation in table 3.

Table 4 presents estimates of the structural parameters using the algorithm outlined in section 3.3.1. k is estimated to be 5.49, which is reasonable as it would suggest in the absence of commutes the application elasticity would be equal to approximately 5.5 using a transformation to a logit model (see section D). Table 5 presents the model implied elasticities along with the empirically estimated counterparts, while table 6 presents the interaction estimates of equation 22 from step 4 in the algorithm.

Figure 7: Log Commutes vs Log Wage



Note: The figure presents a binned scatter plot of log commutes against log wages, with commutes and wages orthogonalised against year and industry fixed effects, age, gender, part time and temporary contract. The sample is based on 2,152,513 observations from the Annual Survey of Hours and Earnings between 2002 and 2019.

Table 4: Structural Parameter Estimates

k	α
5.49	2.44

Note: The table presents the structural estimates for the remaining model parameters, based off the algorithm outlined in section 3.3.1. The sample includes 2,239 non-permanent job adverts for The Company, and 1,062,022 worker-advert pairs from ASHE.

The model does a good job of matching the respective empirical elasticities, while the interaction estimates from the IV estimation suggest a statistically significant difference in the elasticities between the “high” and “low” group areas. The model predicted high group has an elasticity

Table 5: Model vs Empirical Elasticities

	Elasticity		
	Mean	High	Low
<i>Model</i>	2.93	3.95	1.91
<i>Empirical</i>	3.03	3.71	2.34

Note: The table presents the model predicted and estimated mean elasticities for the high group, low group and all pooled with the parameter estimates of $k = 5.49$ and $\alpha = 2.44$. The sample includes 2,239 non-permanent job adverts for The Company, and 1,062,022 worker-advert pairs from ASHE.

Table 6: Interaction estimates

	(1)	(2)
	log(Apps)	log(Apps)
log(Wage)	2.34*** (0.71)	3.03*** (0.62)
log(Wage)X HighElast	1.37** (0.69)	
N	2239	2239
First Stage F-Stat.	48.2	318.3
Hansen J Stat.	1.43	0.48
Instrumented With ALL	Yes	Yes
Instrumented With LW	Yes	Yes

Note: The table presents estimates of $\hat{\beta}_2$ and $\hat{\beta}_3$ from regression equation (22) utilising both the LW and AL instrument. High and low groups are defined according to the model predicted elasticities $\varepsilon_{AW_{ajemy}}$ from equation 18 where the value of $k = 5.49$ and $\varepsilon_{cw} = 1$. Standard errors are reported in parentheses and are clustered at the job-establishment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

approximately 60% higher than the low group, suggesting the model does a good job of predicting more and less competitive job adverts.

Tables 7 and 8 present the counter part estimates from the method outlined in section 3.3.2 using the additional commuting-response moment restriction. The results are qualitatively unchanged from the method treating $\hat{\beta}_1$ as ε_{cw} . The estimate of k reduces from 5.49 to 5.25, while the estimate of the commuting-wage elasticity, ε_{cw} , increases from 1 to 1.2. The model and empirical elasticities are again very close in value, though notably the model and empirically estimated values of β_1 are not as well matched as the application elasticities, and β_1^M is closer in fact to the OLS estimate of $\hat{\beta}_1$.

Table 7: Structural Parameter Estimates II

k	α	ε_{cw}
5.25	2	1.20

Note: The table presents the structural estimates for the remaining model parameters, based off the algorithm outlined in section 3.3.2. The sample includes 2,239 non-permanent job adverts for The Company, and 1,062,022 worker-advert pairs from ASHE.

Table 8: Model vs Empirical Elasticities II

	Application Elasticity			
	Mean	High	Low	β_1
Model	3.00	4.13	1.88	0.35
Empirical	3.03	4.03	1.97	0.931

Note: The table presents the model predicted and estimated mean applications elasticities for the high group, low group, all pooled and β_1 with the parameter estimates of $k = 5.25$, $\alpha = 2$ and $\varepsilon_{cw} = 1.2$. The sample includes 2,239 non-permanent job adverts for The Company, and 1,062,022 worker-advert pairs from ASHE.

4.2 Descriptive Evidence

As a test of validation I look at the relationship between the degree of competitiveness as predicted by the model for different geographic locations across England and Wales, and measures of wages, density and population.

Choice of geographic locations for this exercise is non-trivial. Typically for the UK one would use centroids of TTWAs or Local Authorities (LA), however, the model is particularly granular and treats space continuously. Therefore, using such large areas carries a high risk of measurement error.³³ On the other hand the choice of specific points to calculate competitiveness for any country is effectively infinite, and some structure would be beneficial. I therefore utilise the

³³By using the centroid of a TTWA or LA it's not clear that specific point would be representative of the rest of the geographic area. For example the centroid of a LA could be agricultural land located between two major towns.

ONS’s geography of Built-Up Areas and their subdivisions (BUAs). BUAs are defined as land which is “irreversibly urban in character” (Harding et al., 2013) and comprise of villages, towns or cities. Approximately 95% of the population of England and Wales live in BUAs and the land area of BUAs only makes up 9.6% of the total land. The smallest BUA has a population of just over 100, while the largest is Greater London with almost 10 million, though for the following analysis however London is split into many subdivisions to improve granularity. Figure 15 in the appendix presents a map of the BUAs and where appropriate, their subdivisions for England and Wales. In total there are 7,625 areas.

For each BUA I take the centroid point and calculate equation 18 using estimated parameter values from the previous section, for the market of retail shop workers present in ASHE for the year 2019. I choose this occupation as it represents the largest occupation group of minimum wage jobs for the UK, in total there are 10,138 workers located across England and Wales in the dataset. As before distances are measured in minutes utilising the Open Street map data and ArcGIS, incumbent wages are taken from ASHE and the elasticities are calculated at the point of the LWF’s Living Wages for 2019.³⁴

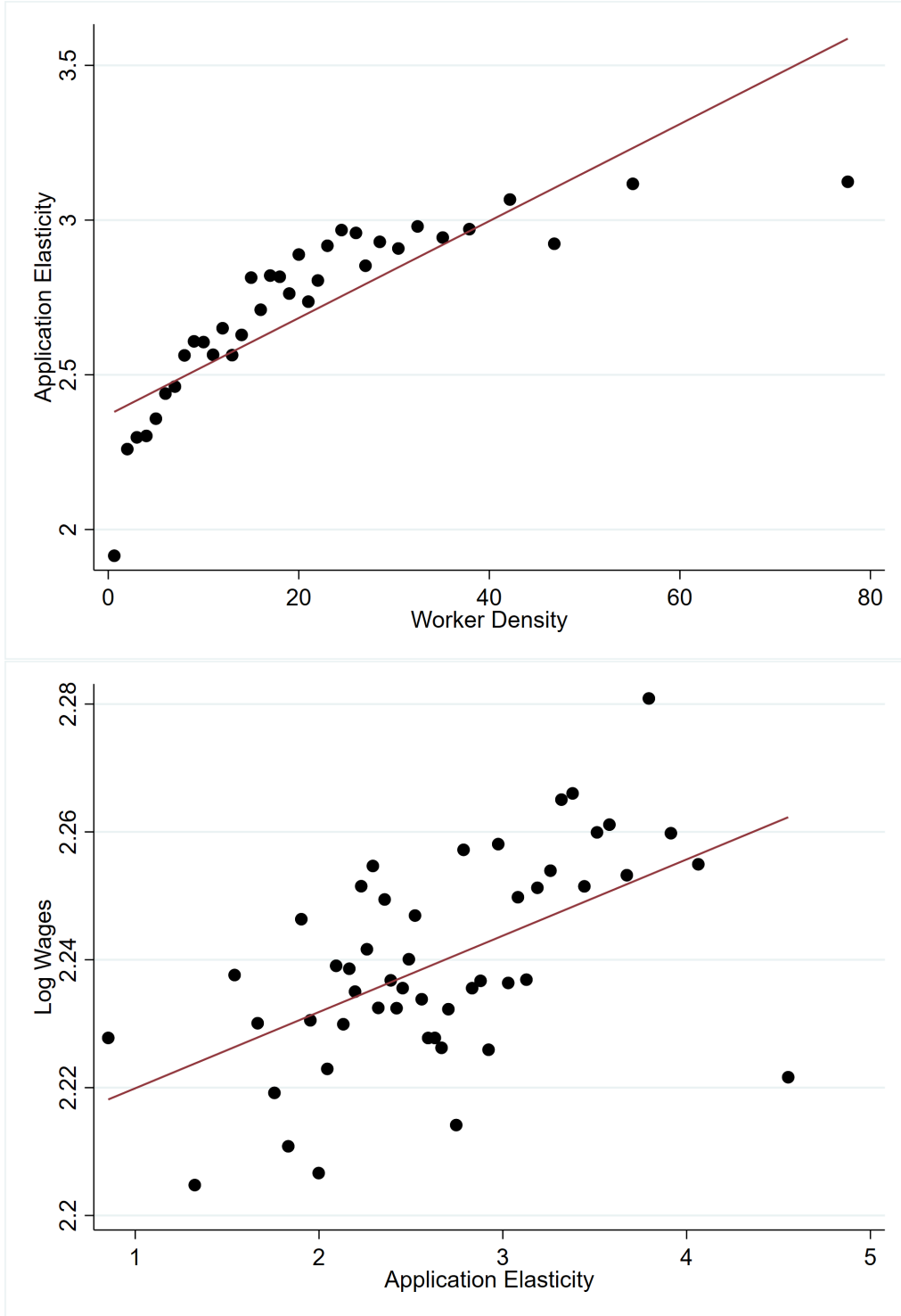
Figure 8 presents binned scatter plots of the worker density and wages against the model predicted application elasticity, using parameter estimates from the previous results section. Worker density is measured by the number of retail workers within a 25 minute drive of the centroid in the sample, while wages is the mean of those workers’ wages. Both plots show a strong positive correlation. Denser areas are expected to be more competitive due to the close proximity of outside options, and similarly areas that are more competitive should have higher wages. The slope relating the application elasticity to wages is likely to be slightly muted due to the existence of a national minimum wage policy, however it still shows a strong relationship. The positive relationship between the application elasticity also holds when using measures at the BUA level, such as residential density and population as shown in figures 16 in the appendix. These results are suggestive that denser more populated areas are likely to experience more competitive labour markets, and thus higher wages, and may go some way in explaining the urban wage premium. They additionally give credence to the mechanism suggested by the model, that distaste for commuting is a key factor in generating monopsony power.

4.3 Fixed Location Assumption

Arguably the strongest assumption in the model laid out in section 2 is that locations are fixed for both workers and firms. Early spatial models were partial to such assumptions (e.g. Krugman (1991) had fixed locations for agricultural workers) but typically spatial general equilibrium models endogenise location choices for both workers and firms (e.g Monte et al. (2018)). However, there is increasing evidence that adjustment times to spatial shocks are slow. Kleinman et al. (2023) show that the average half life to steady-state convergence in response to productivity and amenity shocks is around 20 years in the context of the US in the half century

³⁴ £9.30 for non-London areas and £10.75 for London.

Figure 8: Model Predicted Elasticities vs Density and Wages



Note: The figure presents binned scatter plots of the application elasticity as calculated by equation 18 using values of $k = 5.49$, $\varepsilon_{cw} = 1$ and $\alpha = 2.44$ for centroids of 7,625 BUAs and BUASDs for the market of retail workers against worker density and average log wages. Worker density is measured by those workers within a 25 minute drive of the centroid and wages are calculated by the mean hourly wage of those individuals.

between 1965 and 2015, and argue that initial conditions are the main driving force in explaining declines in income convergence. Similarly, [Dix-Carneiro and Kovak \(2017\)](#) show that imperfect spatial mobility of labour and capital can result in decades long adjustments to earnings in response to trade liberalisation. An interpretation of the framework employed here therefore could be: given a particular distribution of economic activity, how does that inform market power in the medium run. In the following subsection I first document existing evidence on low mobility rates in the UK and US, and then follow by presenting causal evidence for my particular context showing unresponsive firm and worker migration rates and firm births across TTWAs to average wage changes as a result of heterogeneous binding of the National Minimum Wage over a 10 year period. The results suggest highly strong persistence in location choice consistent with the recent literature ([Porcher, 2020](#); [Kulka and McWeeny, 2019](#)) while complementing descriptive evidence on the intergenerational persistence of location choice. Research from the [U.S. Census Bureau \(2022\)](#) in particular shows that 60% of young adults live within 10 miles of where they grew up. It therefore also goes some way in assuaging concerns regarding potential spatial sorting dependent on commuting preferences, which would likely introduce some bias into the results in the previous section.

There is now a fair amount of evidence that geographic mobility is low in many developed economies, and that moves are generally not related to employment. In the UK people move on average once every 14 years, only 7% of moves are for employment ([Pelikh et al., 2020](#)), and the median moving distance is only 3.2 miles ([Lomax, 2021](#)). Mobility in the US is higher, but still relatively low (especially by historical standards, e.g. see [Molloy et al. \(2011\)](#)). People in the US move on average once every 7 years ([Frost, 2020](#)), 65% of those moves are within the same county and only 21% are for job related reasons. In both the US and UK the main reason for moving is for housing and family reasons. Furthermore, [Marinescu and Rathelot \(2018\)](#) show that 81% of job applications are within the same CZ, and the relative probability of a job application falls to 30% at 25 miles and 3.4% at 50 miles. This paper additionally focuses more so on the low wage labour market, and mobility has been shown to be even lower for less-educated lower skilled workers ([Notowidigdo, 2020](#); [Amior, 2024](#); [Amior and Manning, 2018](#); [Wozniak, 2010](#)). Related specifically to the time and location of this paper, based on the sample the panel of workers within ASHE for the years 2011-2019, 0.028 workers move Travel To Work Area every year, this implies workers mover TTWA on average every 35.7 years.

Similarly firms are shown to be highly location stable. Using data from the Business Register and Employment Survey for years 2009-2021, which covers 500,000 local units, only 5.4% of firms move in a year. A large proportion of these moves tend to be dominated by small firms. Weighting by jobs shows that only 3.3% of jobs move in a year, implying a move once every 30 years on average. Conditioning on movers, the median distance moved is 3.4 miles. Larger firms tend to move much smaller distances. For example, the median move for firms with between 0 and 9 workers is 3.2 miles while the median move for firms with more than 100 employees is less than one mile. The median distance moved, weighted by firm size is 1.6 miles.

To test whether there are firm location or worker migratory responses as a result of area specific wage growth I estimate the following equation:

$$\Delta Y_{it} = \beta_5 \Delta \ln(Wage)_{it} + \epsilon_{it} \quad (28)$$

where i is the TTWA and t is the year. Outcome variables for Y include firm migration, firm counts, total employment and worker migration. Firm and worker migration is normalised against the incumbent TTWA population such that $Inward\ Migration_{it} = \frac{No.\ Movers\ to\ TTWA_{it}}{No.\ in\ TTWA_{it}}$.

To deal with endogeneity concerns I instrument $\Delta \ln(Wage)_{it}$ with the TTWA exposure to the National Minimum Wage. Specifically the first stage is given by:

$$\Delta \ln(Wage)_{it} = \beta_6 Wage\ Gap_{it-1} + \epsilon_{it} \quad (29)$$

where

$$Wage\ Gap_{it-1} = \frac{1}{N_{it-1}} \sum_j \min\{NLW_t - wage_{jit-1}, 0\}$$

and j is a worker located in TTWA i .

Table 1 reports the results of the instrumented version of equation (1) along with the first stage coefficient from equation (2) for the four variables. The first column reports the results for firm migration, the second for $\ln(firm\ counts)$ (so would also capture changes in initial location decisions for firms), the third $\ln(employment)$ and the fourth worker migration. Columns 1-3 use data for 2010-2019, and column 4 for 2002-2019, the difference stems from differences in data availability. Columns (1) and (4) imply a precisely estimated zero effect for worker and firm migration responses to wage changes. Specifically column 1 implies a doubling of TTWA wages induces an increase in firm migration of approximately 1.7% of the incumbent firms, and column 4 implies worker migration reduces by 1.7%. Columns (2) and (3) imply a firm count - wage elasticity and employment - wage elasticity of 0.3 but are not statistically different from 0, both inconsistent with low mobility frictions. The implied effect sizes for all columns are very small and not statistically significant from zero indicating that an assumption of fixed location in the structural model is not unreasonable.

5 Counterfactuals & Implications for Concentration

5.1 Shrinking Commutes to Zero

The model lends itself to an exercise where all commutes are assumed to shrink to zero.³⁵ That is, the model can look at the effect on incumbent and potential utilities, and therefore job

³⁵Or all workers and firms were to be located at the exact same point.

Table 9: Fixed Location Tests

	(1)	(2)	(3)	(4)
	ΔF Migration	$\Delta \ln(\text{Firm Count})$	$\Delta \ln(\text{Employment})$	ΔW Migration
$\Delta \ln(\text{Wage})$	0.0170 (0.0210)	0.280 (0.297)	0.279 (0.377)	-0.0183 (0.0576)
First Stage	0.165*** (.038)	0.165*** (.038)	0.165*** (.038)	0.215*** (.039)
N	2117	2117	2117	3706
First Stage F-Stat.	18.9	18.9	18.9	30.3
Sample	2010-2019	2010-2019	2010-2019	2002-2019

Note: The table presents IV estimates of $\hat{\beta}_6$ from equation (28) and the corresponding first stage $\hat{\beta}_5$ from (29) based on data from BRES for columns (1)-(3) and worker data from ASHE in column (4). Standard errors are clustered at the TTWA level.

specific elasticities when commutes are assumed away (or $\varepsilon_{cw} = \infty$), but incumbent wages are held constant. The following analysis does not therefore take into account general equilibrium effects; i.e. the fact that firms would also change wages for their incumbent workers, as their optimal wage would also change. One interpretation of the following exercise is, what would happen to the labour supply elasticity to the firm and therefore markdowns, if all workers were immediately assumed to work from home, and incumbent wages were unchanged in the short run. Another interpretation is that the resulting elasticities will go some way in explaining how much of monopsony power is generated by commutes and the spatial distribution of activity.

Methodologically, the exercise is straightforward and is based off equation 20. Using the parameter estimates of $k = 5.49$, $\alpha = 2.44$, and $\varepsilon_{cw} = 1$, I compare the model predicted elasticities with the predicted elasticities where $\varepsilon_{cw} = \infty$. This is equivalent to assuming both d_{ij} and $d_{ij'}$ equal 1.³⁶

Table 10 presents the mean advert-level application-elasticities under the true parametrisation of $\varepsilon_{cw} = 1$ and the alternative of $\varepsilon_{cw} = \infty$, where the alternative is equivalent to assuming away all commutes. The average application elasticity is approximately two thirds higher in the counterfactual scenario and suggests that commutes are a key source of monopsony power. Interestingly, under the no-commute counterfactual, the mean application elasticity is close in size to the estimated parameter k , which as discussed previously would be the application elasticity in the absence of commutes in an EV logit model. This gives additional reassurance to the credibility of the exercise.

Benchmarking the recruitment-wage elasticity and separation-wage elasticity against the application-wage elasticity estimated in Datta (2023)³⁷ it would suggest in the absence of commutes the labour supply elasticity to the firm would be approximately 7 and the markdown 12.5%, around

³⁶As utility is multiplicative assuming they become 0 would not be practical.

³⁷It finds a recruitment elasticity of 3, application elasticity of 3.5 and separation elasticity of -1.6

Table 10: True vs Work form Home Elasticities

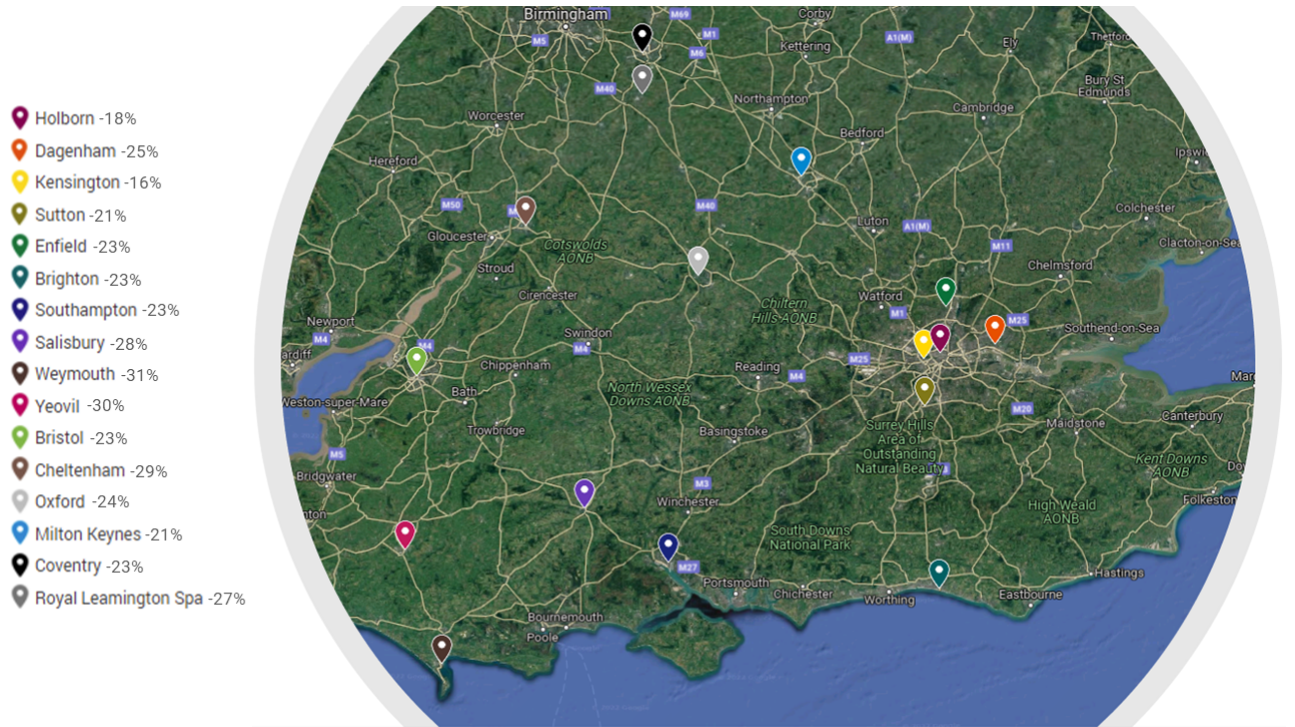
	Application Elasticity	
	$\varepsilon_{cw} = 1$	$\varepsilon_{cw} = \infty$
Mean	2.93	4.95

Note: The table presents the mean of the advert-level elasticities calculated via equation 18 under the true parametrisation of $\varepsilon_{cw} = 1$ and counterfactual of $\varepsilon_{cw} = \infty$ utilising the sample of 2,239 non-permanent job adverts for The Company, 1,062,022 worker-advert pairs from ASHE and the structurally estimated parameter values of $k = 5.49$ and $\alpha = 2.44$.

6 percentage points lower than its actual value.

These results indicate the spatial distribution of activity and distaste for commuting are a key contributor to monopsony power. The results imply that commutes are responsible for about one third of the markdown of wages. It is reasonable to assume however, that this is a lower bound, as incumbent wages would be expected to rise which would in turn lower markdowns further for the advertising firms, if incumbent wage responses were considered.

Figure 9: Markdown Map for UK Retail Sector



Note: The figure presents estimated markdowns for retail occupations based off estimates of the application elasticity from equation (18) using values of $k = 5.49$, $\varepsilon_{cw} = 1$ and $\alpha = 2.44$, for point specific areas marked on the map, and benchmarks of the recruitment-wage elasticity and separation-wage elasticity against the application-wage elasticity estimated in Datta (2023). The estimates use incumbent wage, commute and potential commute data for retail workers from ASHE.

5.2 Spatial Heterogeneity in Monopsony Power

Figure 9 presents estimated markdowns based on the structural equation (18), the estimated parameters, and the UK social security data for a number of specific points in the south and midlands area of the UK for the retail sector which has the largest number of low pay workers. The first five of these points (Holborn, Dagenham, Kensington, Sutton and Enfield) all fall within the London TTWA and the estimated markdowns range from 16% up to 25%. A within-between decomposition for BUAs suggests that 40% of the variance in elasticities is within TTWAs.³⁸ By using a continuous framework with overlapping labour markets a much more accurate and granular measure of labour market power is possible, and the results are indicative of some of the issues that arise from splitting labour markets up into relatively large areas.

More generally the model suggests there is a huge variation in monopsony power across the UK with markdowns in Yeovil (a relatively rural town in the south west of England with 50,000 inhabitants) as high as 30%, dropping to as low as 16% in central London. In wealthy areas in and around London the role of commutes may likely be *increasing* wages beyond what they would be in the absence of them, as rich areas have less low paid workers living there, and thus firms have to pay higher wages for workers to commute in.

5.3 Concentration

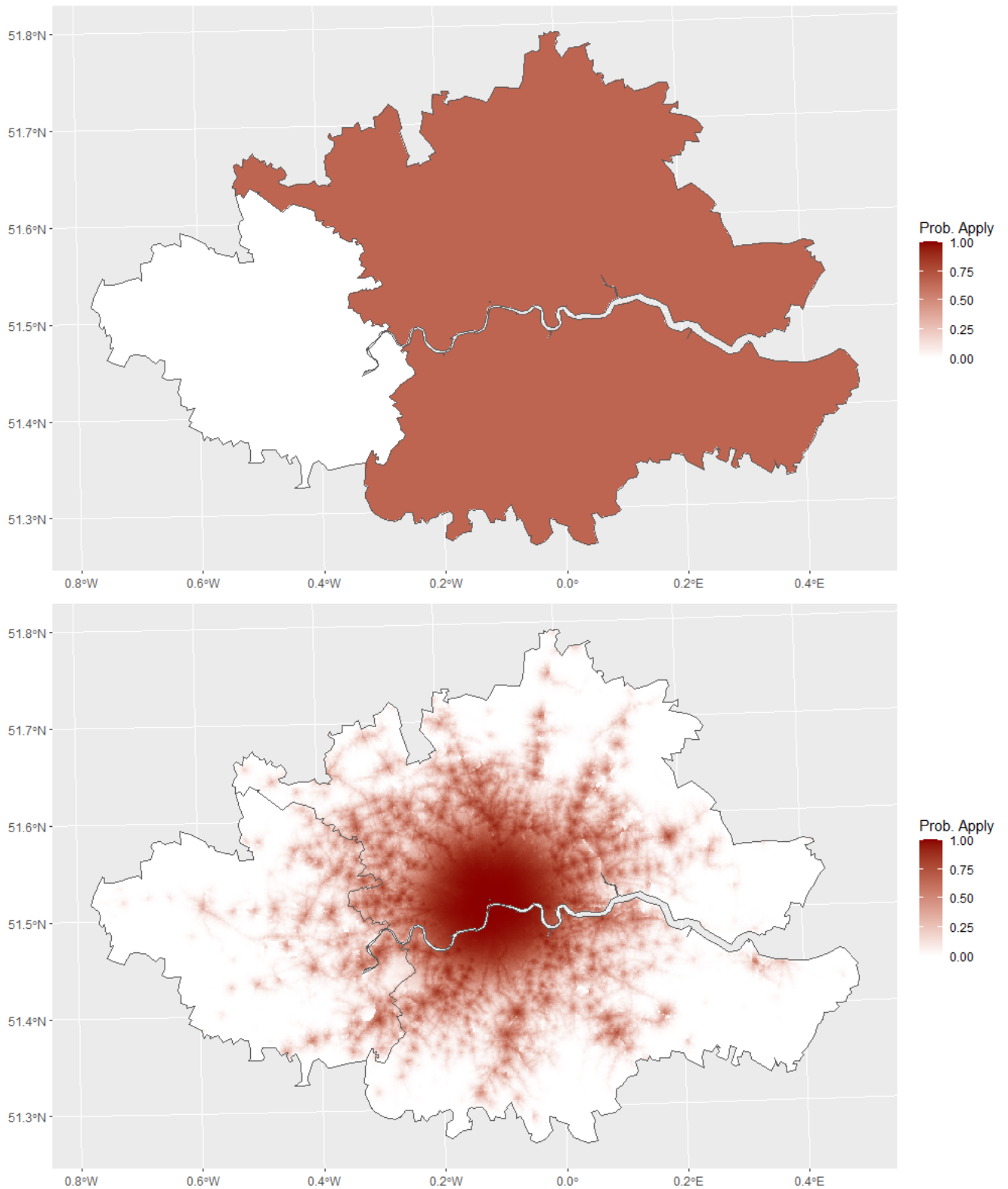
There has been a recent surge in literature and policy debates concerning employer concentration and market power in the labour market.³⁹ Until now studies have generally relied on the discretisation of labour markets into non-overlapping, relatively large areas with travel assumed to be costless within this area and infinitely costly at the border. This has recently come under criticism (Berry et al., 2019; Rose, 2019), partly due to the very local nature of labour markets (Manning and Petrongolo, 2017). In the UK this is generally done at the TTWA and in the US at the CZ level. The mean area for TTWAs is 1,064 km² and travel distances within TTWAs can exceed 90 minutes. The results for the commuting-wage elasticity suggest that by using the aforementioned definitions of a spatial labour market, employer concentrations are likely to be underestimated.

Figure 10 exemplifies this issue presenting the probability of applying for a job when local labour markets are discretised into TTWAs, against a continuous one consistent with the model in section 10, for the Greater London area. The TTWA version shows workers to have equal probability of applying for a job across the entire TTWA and stopping hard at the border, while the continuous version shows the decreasing nature continuously over space. What's more the

³⁸Specifically a regression of BUA calculated elasticities as per equation 13 of those calculated in section 4.2 against a TTWA fixed effect elicits a R^2 of 0.62.

³⁹Examples of work in this vein includes CMA (2024); Schubert et al. (2021); Naidu and Posner (2021); Azar et al. (2020b); Azkarate-Askasua and Zerecero (2024); Arnold (2020); Azar et al. (2020a); Benmelech et al. (2020); Nimczik (2020); Berger et al. (2022); Jarosch et al. (2024); Qiu and Sojourner (2023); Rinz (2022); Abel et al. (2018); Lipsius (2018); Hershbein et al. (2018).

Figure 10: Spatial Probability of Applying to a Posted Job - TTWAS vs Continuous



Note: The figure presents the probability of applying to a job located in Holborn, London, conditional on home location. The top panel assumes distances within a TTWA are all equal, and infinite at the border. The bottom panel calculates travel times for $100m^2$ grids using the Travel Time API optimising over public transport, driving, walking and cycling. Probabilities are calculated according to $1 - F(x_{ijj'})$ from the model in section 2, where the posting job is paying a wage 10% higher than the incumbent job, and the incumbent travel time for the bottom panel is assumed to be 40 minutes, which is the average commute time in London.

continuous version shows how infrastructure can have a major impact on local labour market construction. Areas more than double the straight line distance away from the job may have a higher probability of applying to their closer counterparts if there is a suitable road or train line. This is an important development which should be modelled given the increased calls for a stronger regulatory response to market concentration (Krueger and Posner, 2018; Naidu et al., 2018; Marinescu and Hovenkamp, 2019; Marinescu and Posner, 2019). Furthermore, within sizeable discretised areas firms' labour market power are likely to be highly heterogeneous.

The Herfindahl-Hirschman Index (HHI) is the key measure used in the aforementioned studies, and is generally considered to be a marker for where there be monopoly or monopsony power. The benefit of HHI measures is that they are descriptive in nature and do not require well identified causal settings to elicit estimate. Unlike product demand or labour supply to the firm elasticities however, HHIs are not structural objects and thus may not be definitive of market power.⁴⁰

The HHI for area l is measured by:

$$HHI_l = \sum_i s_{il}^2 \quad (30)$$

where s_{il} is the market share of employment firm i in location l .

Typically HHIs have been measured at the industry-TTWA (CZ) or occupation-TTWA (CZ) level as spatial labour markets. This measure comes with obvious issues as mentioned above.

In this exercise I use the estimated spatial monopsony model to predict the probability that a worker would be interested in a job across $1km^2$ grids in the UK and using that estimate construct measures of market shares at the $1km^2$ level. Specifically, the probability of a worker living in grid a , willing to work in grid b is calculated according to

$$Prob(apply_j^i) = 1 - F \left(\frac{\bar{d}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{d_{ab}^{\frac{-1}{\varepsilon_{cw}}}} \right) \quad (31)$$

where ε_{cw} is the commuting wage elasticity and is set to 1, $\bar{d}$ is the median commuting time for incumbent worker-firm matches for the low paying industries under study (15 minutes), d_{ab} is the commuting time between grid a and b , and the function F is the Weibull CDF. Commuting distances between all pair-wise grids in the UK was calculated using the Travel Time API. This is an incredibly powerful tool that allows batch calculations for a huge number of pairwise distances for both public transport and driving.

The market share of firm j for grid l who is located in grid b , and have employment N_{jb} is given by:

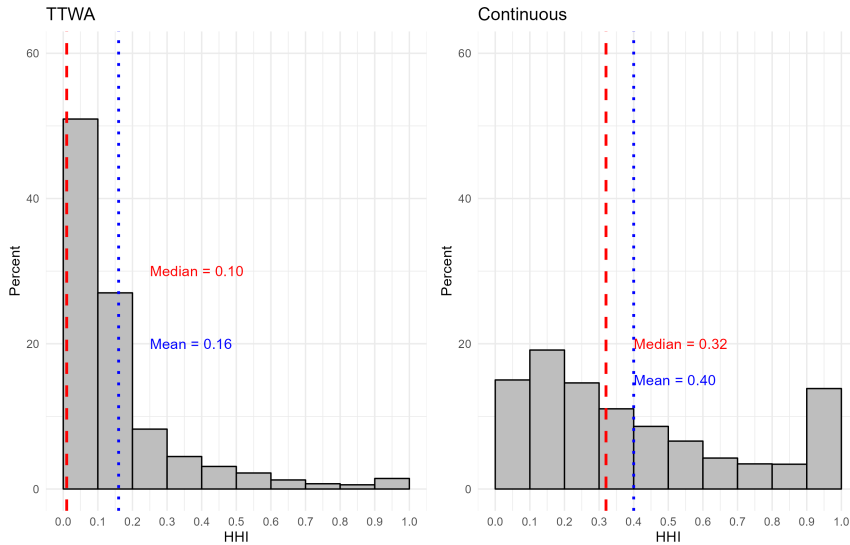
⁴⁰As an example, a highly productive firm would potentially have a higher marginal productivity, and may have a higher employment share as they are able to pay higher wages.

$$S_{jlb} = \frac{\sum_b \left[1 - F \left(\frac{\frac{-1}{d_{lb}^{\varepsilon_{cw}} \bar{\nu}}}{\frac{-1}{d_{lb}^{\varepsilon_{cw}}}} \right) \right] N_{jb}}{\sum_j \sum_b \left[1 - F \left(\frac{\frac{-1}{d_{lb}^{\varepsilon_{cw}} \bar{\nu}}}{\frac{-1}{d_{lb}^{\varepsilon_{cw}}}} \right) \right] N_{jb}} \quad (32)$$

Put simply this tells us a firms market share for some grid l is the sum across all their employment across all grids (in the case of multiple location establishments), multiplied by the probability of applying to the grid(s) they operate in from the origin grid l , all divided by the same of the above summed over all firms. The model equivalent in the discretised world at the TTWA level would be equivalent to equation 31 equal to $1 - F(\bar{\nu})$ if the worker and job are in the same TTWA, and equal to 0 otherwise, this would collapse in equation 32 to the typical HHI measure.

The following results are performed for the top 20 employment industries as highlighted by the UK's Low Pay Commission (an independent public body that advises the British government on the minimum wage) as “Low-paying industries” for the year 2019⁴¹. Firm employment and location information are taken from the Business Register and Employment Survey (BRES) dataset (Office for National Statistics, 2023).

Figure 11: Geographic Concentration by TTWA & 1km grids



Note: The figure presents histograms for HHIs as calculated by discretised TTWA-Industry markets (left panel) and continuous 1km^2 grid-Industry markets (right panel), where the shares in the latter are calculated according to equation (32).

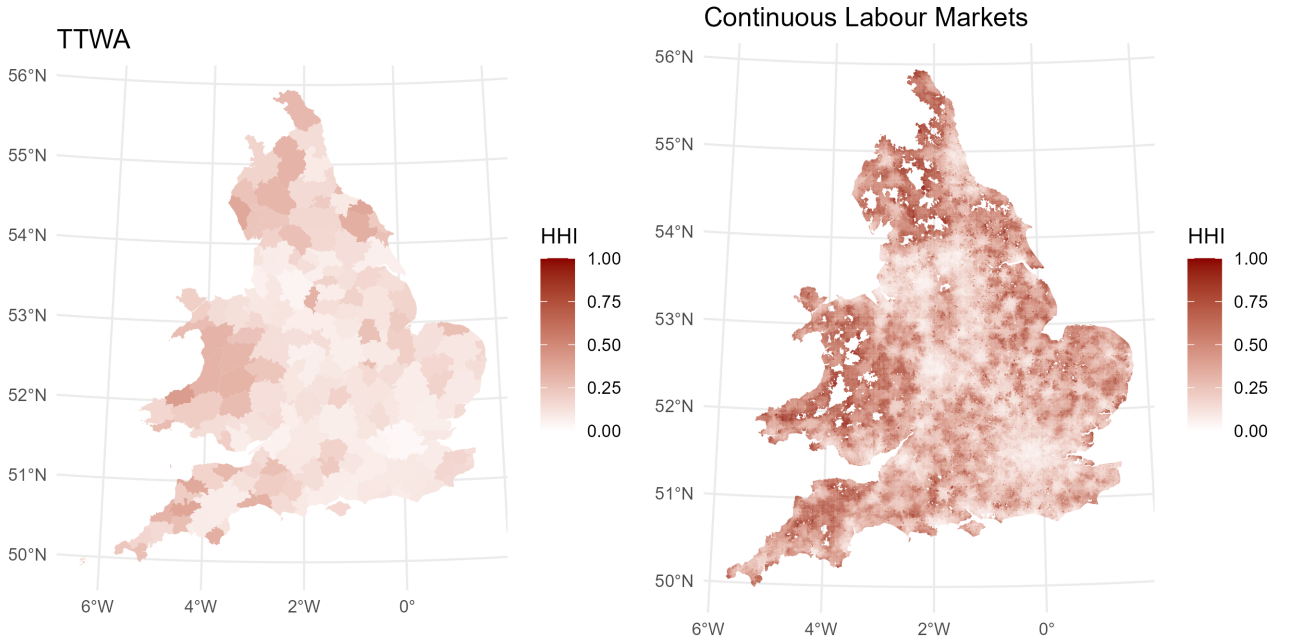
Figure 11 presents a side by side histogram comparison of HHIs calculated at the TTWA-Industry and 1km^2 Grid-Industry level, using the 20 industries mentioned above. As can be seen the estimates of the HHI using the continuous model are considerably higher and place

⁴¹The SIC codes are: 47100, 78200, 56101, 56302, 52103, 81210, 56102, 55100, 88100, 47710, 87900, 87300, 47190, 56103, 45200, 81100, 78109, 88910, 87100, 80100

both the mean and median figure to numbers that would be considered “highly concentrated” as defined by the Antitrust Division of the DOJ in the US.

Figure 12 presents geographic representations for each TTWA and each 1km grid, with the mean HHI for each geography over the 20 industries and figure 17 in the appendix presents the same but honed in on the Greater London area. A number of interesting features emerge from these maps. Firstly, as shown by the above histogram, on average labour market measures are considerably more concentrated than previously. Secondly, even within TTWAs there is considerable heterogeneity and major road infrastructure is correlated with reduced areas of concentration as exemplified by figure 18 in the appendix, which overlays the major road network with the right panel from figure 12. Unsurprisingly, urban areas are found to have lower levels of concentration in comparison to more rural areas, and this result is consistent with the broad findings in the model and estimation in this paper - denser urban areas will have thicker labour markets and thus less market power from the firm perspective. More generally the results suggest use of the typical discretised spatial labour markets will likely highly underestimate spatial labour markets, especially for lower pay workers who typically commute far shorter distances.

Figure 12: Geographic Concentration by TTWA & 1km grids - UK



Note: The figure presents maps for HHIs as calculated by discretised TTWA-Industry markets (left panel) and continuous 1km² grid-Industry markets (right panel), where the shares in the latter are calculated according to equation (32).

The comparison of the share measure in equation 32 to the elasticity equation in 18 highlights

some of the more general pitfalls associated with using HHIs as marker for monopsony power. In particular, if workers do not care about commuting and $\varepsilon_{CW} = \infty$, equation 32 collapses to the firms total share of employment across the entire economy, and concentration would not vary across the spatial economy. This implies that variation in employment HHIs across space is generated only by some distance function (whether discontinuous in the case of discretised space, or continuous as outlined in the methodology here). HHIs are unable to capture aspects of market power which are not generated by spatial substitution, such as what the idiosyncratic k parameter captures in the model. Furthermore, HHIs do not take into consideration the spatial distribution of workers, only firms. A firm located in a rural area where there is only one potential worker may have a market share of 1 in that area, resulting in a HHI equal to 1. However, if they want to draw in more workers they would find themselves on the elastic part of the labour supply curve in figure 5 and needing to increase wages considerably to induce workers to commute to them to increase employment. It is therefore not obvious that wage markdowns would be the largest in the darker parts of 12. They may also be the areas with the fewest workers, resulting in higher HHIs by construction.

6 Conclusion

This paper provides new evidence and theory on the sources of market power in the labour market and how that can generate spatial heterogeneity in monopsony power. In order to formalise the mechanism of commutes generating monopsony power I develop a search model where a worker’s utility from a job is dependent on the wage, an idiosyncratic component and the commute from their home to work. The model avoids discretising labour markets and instead endogenously defines continuous labour markets which are decreasing in distance, and the size depends on worker’s preferences over commuting, the commuting-wage elasticity. The model additionally generates endogenous labour supply to the firm elasticities which vary across space. The model suggests that the spatial distribution of activity coupled with a distaste for commuting can play a key role in generating imperfect substitution between jobs. As a result firms in areas with fewer local job opportunities exercise greater monopsony power than firms in urban areas.

I estimate the model parameters, the commuting-wage elasticity and parameters associated with the idiosyncratic preference distribution using a bespoke dataset containing information on job applicants for a UK services firm with hundreds of establishments across the UK, coupled with two instruments to generate exogenous wage variation. Estimates of the commuting-wage elasticity suggest workers have a strong distaste for commuting. A structural estimation exercise matching the model predicted application-wage elasticities to those empirically estimated suggest that commutes are responsible for approximately 1/3 of the wage markdown. I validate the model by showing how the model predictions of heterogeneity in monopsony across space are consistent with heterogeneity found in causal estimates of the application-wage elasticity and additionally show model consistent measures of competitiveness for Built Up Areas in England and Wales are shown to be strongly correlated with worker and residential density, residential

population, and wages. I further present evidence backing up one of the models more restrictive assumptions - that locations are relatively fixed for workers and firms.

The results from this paper go some way in furthering our understanding of the sources of monopsony power, while also contributing to our understanding on the causes of the urban wage premium. By directly modelling in commutes and taking a more granular approach to the spatial economy, discussions concerning market concentration can adopt a much more precise measure. The results from this study suggest that TTWAs and CZs are likely to be overestimating geographic labour market size. Furthermore, the results also speak to the role that transportation infrastructure spending can have on reducing monopsony power. Finally, there is hope that if there are structural shifts in the way we work in response to the COVID-19 pandemic such as a greater shift to working from home, as seems to be the case ([Barrero et al., 2023](#)), there is scope for increased competition in the labour market as the implied length of commutes would drop.

This paper has placed a strong focus on the definition of a spatial labour market, and its role in generating imperfect substitution between jobs. A next step would be to combine this flexibility in spatial labour markets with the flexibility developed in [Schubert et al. \(2021\)](#) concerning occupational labour market definition in order to construct an even finer measure of market definition for the individual.

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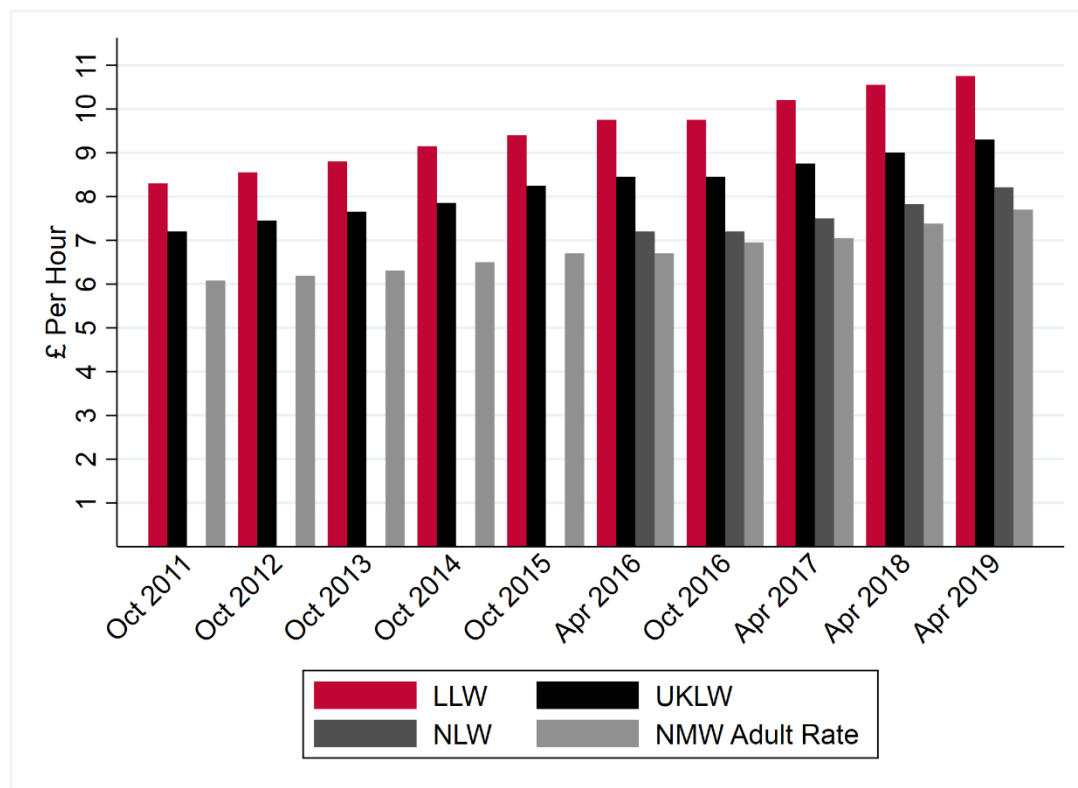
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A Additional Tables & Figures

Figure 13: Living Wage and Minimum Wage Rates



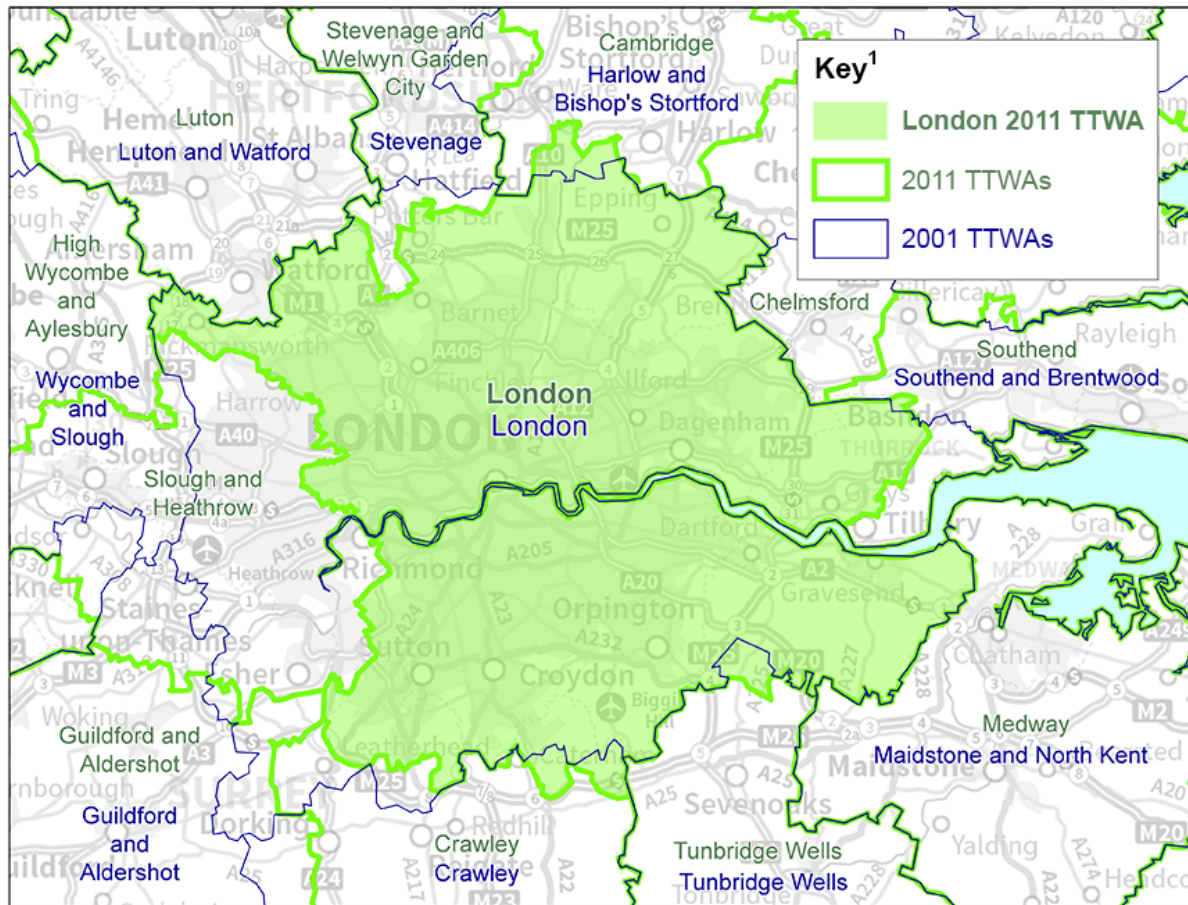
Note: The figure shows the Living Wage Foundations' London and UK wide rates, as well as the statutory National Living Wage and National Minimum Wage adult rate for 2011 - 2019.

Table 11: London Borough of Hackney, Employment

London Borough of Hackney (estim)		
Sector	Employment	%
All	133,000	100
Private	115,100	86
Public		
NHS	5,549	4.3
Council	4,390	3.3
Civil Service	1,790	1.4
Education (LEA)	2,148	1.6
Education (Acad.)	2,864	2.1
Other	1159	1.3

Note: The table presents employment shares by sector for the London Borough of Hackney for the year 2019.

Figure 14: London TTWA

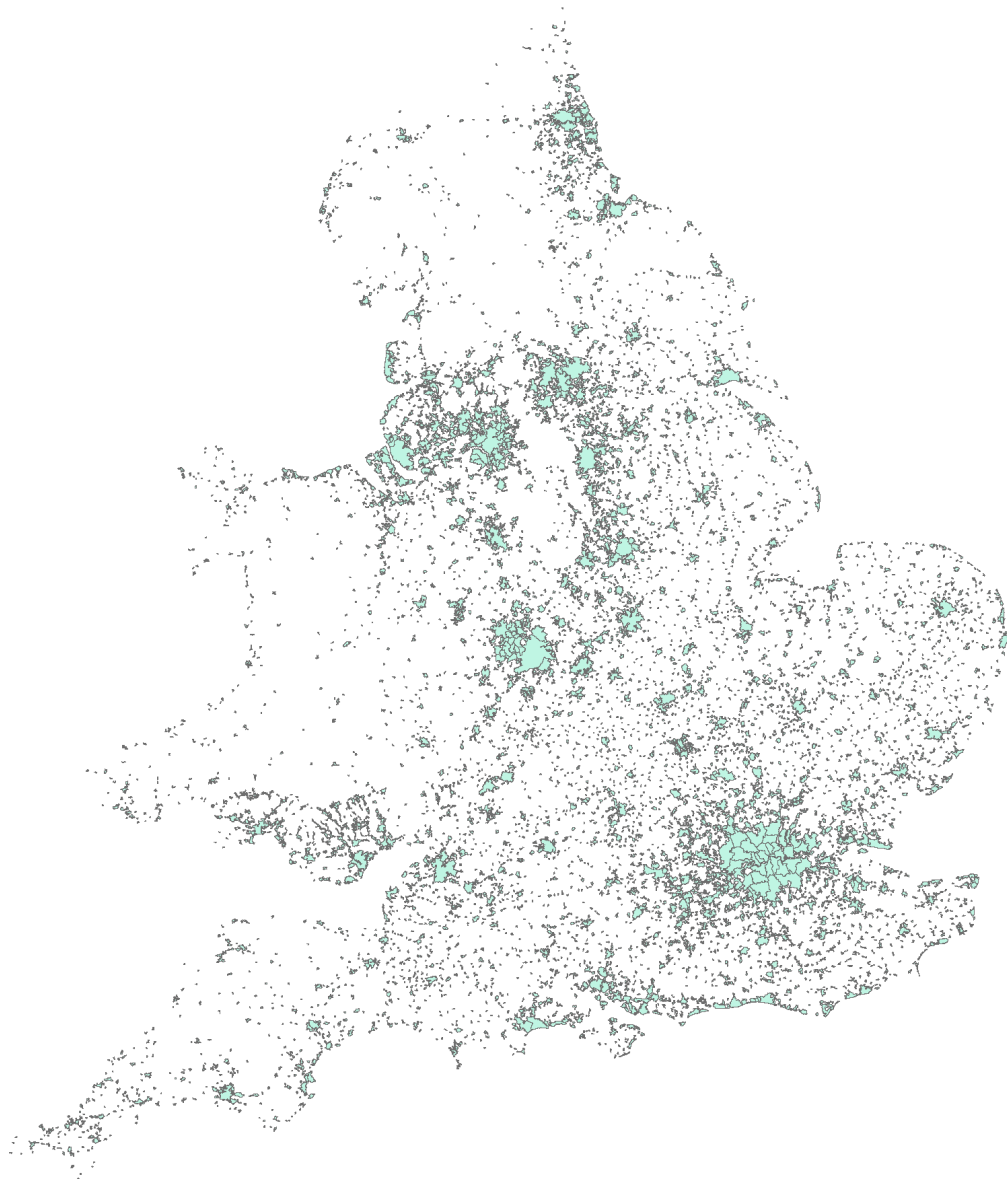


¹ Travel to Work Area (TTWA).

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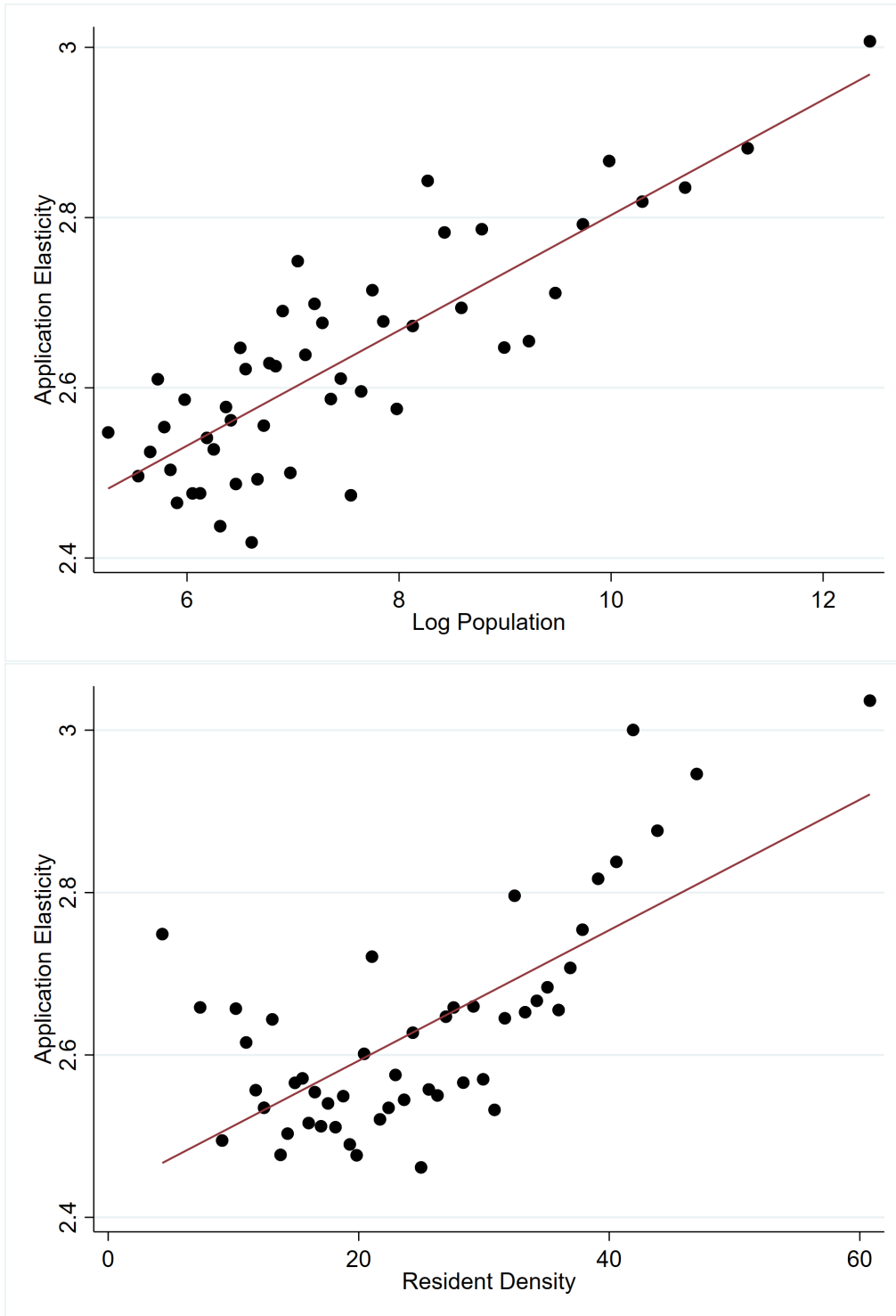
Note: The figure presents the map of the London TTWA for the years 2001 and 2011.

Figure 15: Built Up Area Sub Divisions for England and Wales



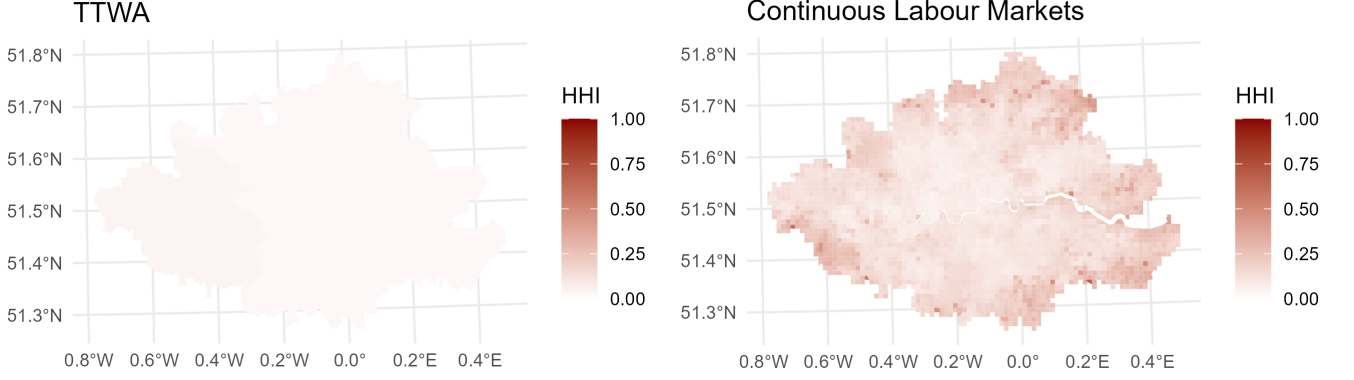
Note: *The figure presents a map of the Built Up Area and Built Up Area Sub Divisions for England and Wales.*

Figure 16: Model Predicted Elasticities vs Density and Wages



Note: The figure presents binned scatter plots of the application elasticity as calculated by equation 18 using values of $k = 5.49$, ε_{cw} and $\alpha = 2.44$ for centroids of 7,625 BUAs and BUASDs for the market of retail workers against population and residential density.

Figure 17: Geographic Concentration by TTWA & 1km grids - Greater London



Note: The figure presents maps for HHIs as calculated by discretised TTWA-Industry markets (left panel) and continuous 1km^2 grid-Industry markets (right panel), where the shares in the latter are calculated according to equation (32).

B The Maintaining Worker Problem

For simplicity assume $c = 0$. Worker i , in job j , when job j' is advertised will stay with probability:

$$\varphi_{ijj'}(w_j) = 1 - P(A_{j'})(1 - F(x_{ijj'})) \quad (33)$$

This implies

$$\varepsilon_{\varphi w_{ijj'}} = \frac{P(A_{j'})f(x_{ijj'})}{1 - P(A_{j'})(1 - F(x_{ijj'}))} \tilde{x}_{ijj'} \quad (34)$$

Note that

$$\varepsilon_{sw} = -\frac{\varphi}{1 - \varphi} \varepsilon_{\varphi w} \quad (35)$$

$$\varepsilon_{sw_{ijj'}} = -h(x_{ijj'})x_{ijj'} \quad (36)$$

It is straight forward to see how the above is the inverse of the hiring problem and particularly obvious when looking at equation 34. As incumbent utility increases, $x_{ijj'}$ increases .

If $h(\cdot)$ is increasing in argument, it follows that $\frac{f(\cdot)}{F(\cdot)}$ is decreasing in argument. Thus

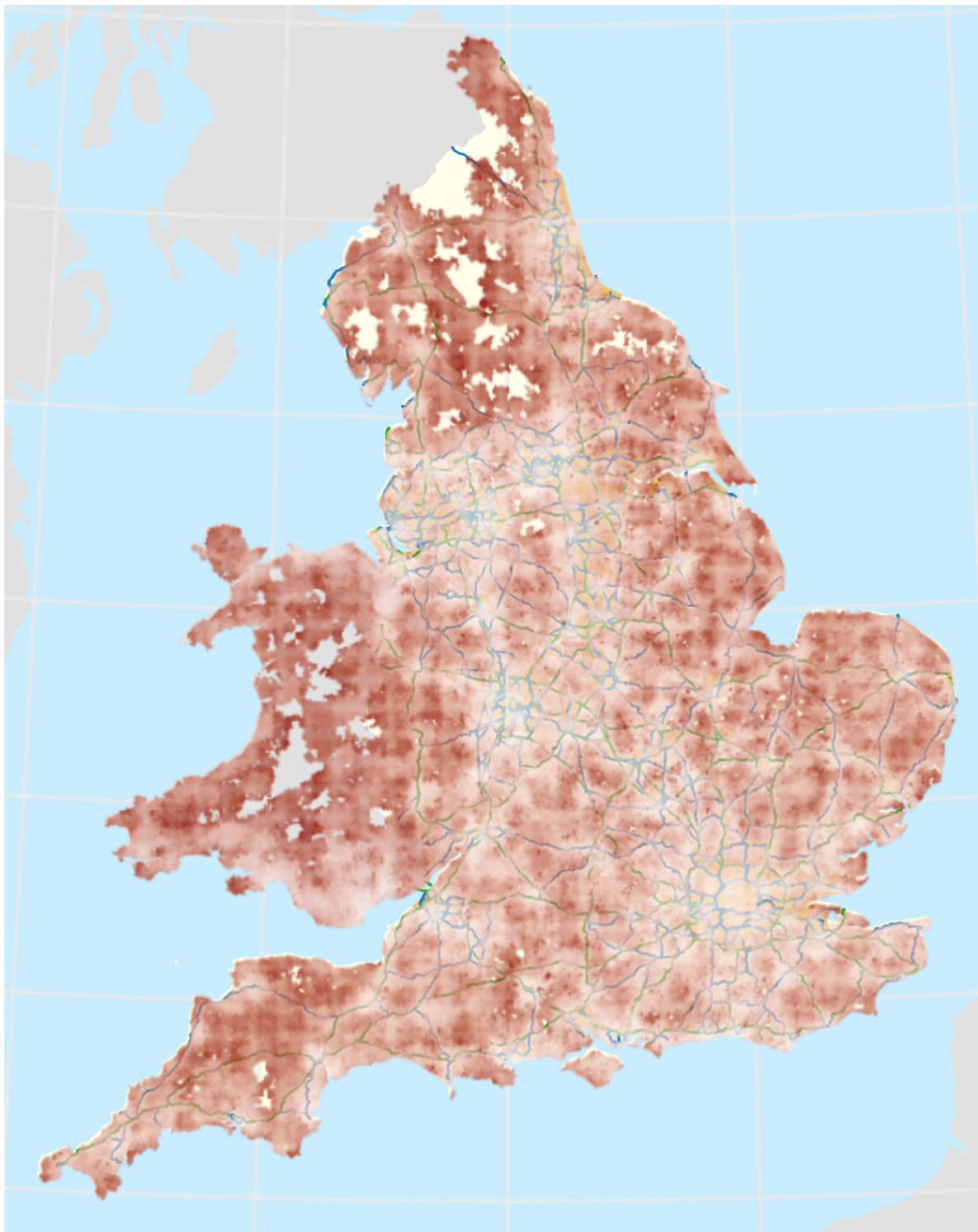
- As w_j increases, $x_{ijj'}$ increases and therefore $\varepsilon_{\varphi w_{ijj'}}$ decreases.
- It is easy to see that the behaviour of $\varepsilon_{\varphi w_{ijj'}}$ follows a similar pattern as $\varepsilon_{Aw_{ijj'}^j}$.

Assuming many firms were posting vacancies, aggregation would then follow such that

$$\varphi_{(ij)}(w_j) = \sum_{j'} \varphi_{(ij),j'}(w_j) \quad (37)$$

where as before there is an assumption that the probability of receiving more than one job offer is infinitesimal.

Figure 18: Geographic Concentration by 1km grids Overlayed with England's Major Road Network



Note: The figure presents maps for HHIs as calculated by continuous 1km^2 grid-Industry markets calculated according to equation (32) overlayed with English Major Road Network.

C Introducing Search Costs

The simplest way to introduce search costs into the model is by introducing an application cost into the application decision for the worker. A worker will choose to apply to posted job j' according to:

$$P(A_{j'})u_{ij'} + (1 - P(A_{j'}))u_{ij} - c \geq u_{ij} \quad (38)$$

where c is some fixed application cost. This implies the worker will apply if

$$\nu_{ij'} \geq \underbrace{\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \nu_{ij} + \frac{c}{P(A_{j'})}}{w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}}}_{\equiv \tilde{x}_{ijj'}} \quad (39)$$

where $\tilde{x}_{ijj'}$ is akin to $x_{ijj'}$ in the model without search costs.

C.1 The Individual's Elasticity

The individual's elasticity of applying with respect to posted wage becomes

$$\tilde{\varepsilon}_{AW_{ij}^{j'}} = h(\tilde{x}_{ijj'}) \left(\tilde{x}_{ijj'} + \frac{c}{P(A_{j'}) w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \varepsilon_{PA} \tilde{\varepsilon}_{AW_{j'}} \right) \quad (40)$$

where $\varepsilon_{PA} \leq 0$ is the elasticity of the probability of getting the job with respect to the number of applicants, and $\varepsilon_{AW_{j'}}$ is as before the aggregate elasticity of applications to wages for the firm, but now in the presence of search costs included.

One can see a key change with the addition of search costs that as more workers apply for a job, they have an externality on other worker's choice decision, and this in turn can have a negative impact on the size of the responsiveness of an individual worker applying for a job. Intuitively, if a wage is posted much higher than the going market rate, some workers may not apply as they believe that the probability of getting the job goes down, and this matters when applications are costly. The size of this externality depends on two factors c and ε_{PA} . The role of the first of these is trivial while the latter depends somewhat on the production function of the firm. For example, if firms hire all workers that apply for a vacancy (such as on some online task markets) then $\varepsilon_{PA} = 0$ and the problem collapses to a similar framework as in section 2. In the situation where a firm only has one job vacancy on the other hand, $\varepsilon_{PA} > 0$ and any increase in applicants would reduce the probability of getting an offer. Additionally, without imposing any additional restrictions it is not clear that $\varepsilon_{AW_{ij}^{j'}}$ is positive for all individuals, nor that the elasticity is decreasing in the posted wage.

C.2 The Elasticity of Labour Supply To The Firm

Aggregating to the firm level the application elasticity is the application elasticity absent of search costs divided by one plus a "search wedge", $S^{j'}$. $S^{j'} \geq 0$, and this wedge is increasing in c and ε_{PA} . Furthermore this search wedge is a weighted average of the individual specific search wedges, $S_{i,j}^{j'}$.

$$\tilde{\varepsilon}_{AW^{j'}} = \frac{\varepsilon_{AW^{j'}}}{1 + S^{j'}} \quad (41)$$

such that

$$S^{j'} = |\varepsilon_{PA}| \frac{\sum_{(i,j)} S_{i,j}^{j'} (1 - F(x_{ijj'}))}{\sum_{(i,j)} (1 - F(x_{ijj'}))} \quad (42)$$

and

$$S_{i,j}^{j'} = h(x_{ijj'}) \frac{c}{P(A_{j'}) w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \quad (43)$$

As a result the introduction of search costs reduces the application elasticity to the firm, and the extent of this depends on the size of c and ε_{PA} .

D Relationship with Logit Models of Monopsony

A number of recent studies have used logit models of search (Card et al., 2018; Azar et al., 2022; Lamadon et al., 2022) to illustrate monopsony power in the labour market. The utility function set up in this setting with a Weibull distribution speaks directly to these models due to the relationship between the Extreme Value Type 1 distribution and the Weibull distribution.

Given utility is such that $u_{ij} = w_j d_{ij} \nu_{ij}$ where ν_{ij} is Weibull distributed with shape parameter k and scale parameter λ utility can be log transformed such that

$$\hat{u}_{ij}^* = \log w_j - \frac{1}{\varepsilon_{cw}} \log d_{ij} + \xi_{ij}^*. \quad (44)$$

Where ξ_{ij}^* is distributed Extreme Value type 1 (i.e. Gumbel) with scale parameter $\beta = \frac{1}{k}$ and location parameter $\mu = \log(\lambda)$.

Assuming $\varepsilon_{cw} = \infty$, that is, commuting does not matter, the utility function can be rewritten

$$\hat{u}_{ij} = \frac{1}{\beta} \log w_j + \xi_{ij} \quad (45)$$

where ξ_{ij} now has variance $\frac{\pi^2}{6}$.

The choice decision facing the searching worker implies the probability they will apply to some job j within choice set $j \in \mathcal{J}$ if

$$P_{ij} = Pr(\xi_{ij'} - \xi_{ij} < w_j - w_{j'}) \forall j' \neq j \in \mathcal{J} \quad (46)$$

Which gives the logit formulation

$$P_{ij} = \frac{\exp(\frac{1}{\beta}w_j)}{\sum_{j'} \exp(\frac{1}{\beta}w_{j'})} \quad (47)$$

Therefore, if there are L workers in the market the number of applications to the firm is given by

$$A_j = L * \frac{\exp(\frac{1}{\beta}w_j)}{\sum_{j'} \exp(\frac{1}{\beta}w_{j'})} \quad (48)$$

Taking logs, equation (48) can be re written as

$$a_j = \log(L) + \frac{1}{\beta}w_j - \log\left(\sum_{j'} \exp(\frac{1}{\beta}w_{j'})\right). \quad (49)$$

And therefore the elasticity of applications to the firm is given by

$$\varepsilon_{AW} = \frac{1}{\beta}(1 - s_j) \quad (50)$$

where s_j is akin to the share of firm j in the labour market.

Assuming there is a large number of firms, $s_j \approx 0$ and therefore $\varepsilon_{AW} = \frac{1}{\beta} = k$. This therefore demonstrates that in the absence of commuting costs, the elasticity of applications to the firm is equal to the shape parameter of the Weibull model.

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