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Abstract
This paper investigates wage disparities across sub-national labour markets in Britain using a newly available microdata set. The findings show that wage disparity across areas is very persistent over time. While area effects play a role in this wage disparity, most of it is due to individual characteristics (sorting). Area effects contribute a very small percentage to the overall variation of wages and so are not very important for understanding overall levels of wage disparity. Specifically, in our preferred specification area effects explain less than 1% of overall wage variation. This share has remained roughly constant over the period 1998-2008.

Keywords: wage, disparities, labour
JEL Classifications: R11, J31

1 Introduction

Places throughout the UK - regions, cities and neighbourhoods - appear very unequal. This is true if we look at average earnings, employment, and many other socio-economic outcomes. Take Gross-Value-Added per person, potentially a good indicator of income.[2] In 2005, the highest ranked (NUTS 3) regions in the UK were West Inner London and Berkshire with GVAs of £44050 and £39850 respectively. The lowest ranked were Liverpool and Blackpool, with GVAs of £19800 and £21050. These examples are representative of a broader trend – the top ranked 10% of UK (NUTS 3) regions have GVA at least 50% higher than the bottom ranked 10%.

Spatial policy at all scales is largely based around concerns about such disparities. But these figures are simply aggregates of the outcomes for people who live and work in these places. Without further analysis, we do not know whether outcomes for people working in London would be any different if they worked in Liverpool. We do not know if the productivity of London and Liverpool would change if these movements of people happened. Similarly, we do not know whether replicating the economic, policy, and institutional regime of London in Liverpool would change anything without moving people. In short, while it is (relatively) easy to measure aggregate differences between places, it is much harder to work out what these differences mean in terms of the advantages and disadvantages a place offers to people who live and work there.

Looking at these aggregated figures for areas, it is tempting to conclude that disparities between places are big drivers of individual disparities. But this need not be the case. The differences between people living and working within the same local area could far exceed the differences between areas. Knowing whether 'between-area' or 'within-area' disparities dominate is thus important in understanding the role policy might play in helping address individual disparities.

In this paper we present evidence on the nature, scale and evolution of economic disparities in Britain, keeping these considerations of the relative contribution of people and place to the fore. We focus on wages because wages are linked to productivity and variation in wages is an important cause of variation in income. We also have good individual level (micro) data on wages. Using this

[2] We estimate GVA per employee for NUTS 3 areas by dividing GVA by workplace-based employment. We then multiply GVA per employee by the working-age employment rate amongst residents in each NUTS 3 area. Employment-adjusted GVA per employee is thus indicative of expected GVA for a working age resident in a NUTS 3 area, assuming they could work in the same jobs as existing employees and have the same employment probability as existing residents. The employment numbers come from the Annual Business Inquiry via nomis (nomisweb.co.uk). GVA come from the ONS Sub-regional GVA release (ONS 2008). We present GVA figures rounded to the nearest £50.

micro data on workers' wages, linked to their place of work, we examine wage disparities across labour market areas. We assess to what extent these disparities arise because of differences in the types of workers in different areas (sorting) versus different outcomes for the same types of workers in different areas (area effects). We then examine the extent to which these area differences contribute to overall wage disparities. Our evidence provides a first step in answering questions about the likely effectiveness of ‘people’-based policy directed at similar people in different places as against ‘place-based’ policy directed at specific places in addressing overall disparities.

Our findings show that wage disparity across areas is very persistent. While most of this wage disparity across areas is due to individual characteristics (sorting), area effects also play a role. Specifically, in our preferred specification, sorting accounts for around 90% of the disparity between places, while area effects account for around 10%. Area effects play an even smaller role in understanding overall levels of individual wage disparity. In our preferred specification area effects explain less than 1% of overall wage variation. The share accounted for by area effects has remained fairly constant over the period 1998-2008.

Our paper is related to several literatures. Labour economists have long been concerned with the role sorting on individual characteristics might play in explaining differences in wages between groups of workers (particularly wage differences across industries). See, for example, Krueger and Summers (1988), Gibbons and Katz (1992) and Abowd, Kramarz and Margolis. (1999). Sorting as an explanation of spatial disparities has received less attention. Duranton and Monastiriotis (2002), Taylor (2006) and Dickey (2007) use individual data to consider regional earnings inequalities in the UK. Bell et al (2007) look at sub-regional wage differentials with a specific focus on the public versus private sector.[3] Relative to these papers we work with functional labour market areas (rather than administrative boundaries) at a smaller spatial scale and, most importantly, we use panel data to control for unobserved individual characteristics. A number of studies also use individual data to study spatial sorting and agglomeration economies. See, for example, Mion and Natticchioni (2009), Dalmazzo and Blasio (2007) and Combes, Duranton and Gobillon (2008). This paper is most closely related to the last of these in terms of its overall approach and use of individual data. However, whereas that paper is predominantly interested in the importance of skills, endowments or

[3] There is also a large literature using data for areas, rather than individuals, which controls for structural characteristics of the regions when considering, for example, spatial disparities in earnings or productivity. See, for example, Rice, Venables and Pattachini (2006).

interactions based explanations of area effects, we focus on the contribution of area effects to overall wage disparity.

The rest of this paper is structured as follows. Section 2 describes the data. Section 3 describes the evolution of area disparities in Britain. Section 4 outlines our methodology for separating out the role of area effects and composition and considering the contribution of these two components to overall wage disparities. Section 5 presents results, while section 6 offers some conclusions.

2 Data

Our analysis is based on the Annual Survey of Hours and Earnings (ASHE) and its predecessor the New Earnings Survey (NES) and covers 1998-2008. ASHE/NES is constructed by the Office of National Statistics (ONS) based on a 1% sample of employees on the Inland Revenue PAYE register for February and April. ASHE provides information on individuals including their home and work postcodes, while the NES provides similar data but only reports work postcodes. We mainly focus on area differences with workers allocated according to their work postcode allowing us to use the whole sample. The National Statistics Postcode Directory (NSPD) provides a map from every postcode to higher-level geographic units (e.g. local authority, region, etc). We assign individuals to Travel to Work Areas using each individual's work postcode. Given the way TTWA are constructed (so that 75% of the resident population also work within the same area) the work TTWA will also be the home TTWA for the majority of workers.

NES/ASHE include information on occupation, industry, whether the job is private or public sector, the workers age and gender and detailed information on earnings including base pay, overtime pay, basic and overtime hours worked. We use basic hourly earnings as our measure of wages. NES/ASHE do not provide data on education but information on occupation works as a fairly good proxy for our purposes. NES/ASHE provide national sample weights but as we are focused on sub-national (TTWA) data we do not use them in the results we report below.[4]

Our analysis divides Britain into 157 "labour market areas" of which 79 are single "urban" TTWA and 78 are "rural areas" created by combining TTWA. We reached this classification in three steps: a) we identified the primary urban TTWAs as TTWA centred around, or intersecting urban-footprints with populations of 100,000 plus; b) we identified TTWA with an annual average

[4] Using these weights makes little difference to our results and no difference to our broad conclusions.

NES/ASHE sample size greater than 200 as stand-alone non-primary-urban TTWA (e.g. Inverness); and c) we grouped remaining TTWA (with sample sizes below 200) into contiguous units (e.g. North Scotland). A full list of the resulting labour market areas along with their average wage is provided in Table A5 in the appendix. The geographical area boundaries are shown in Appendix 3.

3 The evolution of labour market wage disparities

We start by considering the evolution of wage disparities over the period 1998-2008 for our 157 labour market areas. Table 1 provides summary statistics by year. We report the mean area wage (Mean), the standard deviation across areas (SD), the minimum and maximum area wage (Min and Max), the coefficient of variation (CV) and the variance of log wage (var(lnw)). Unsurprisingly, the mean, minimum and maximum of nominal wages all rise monotonically across time. The standard deviation also rises which is not surprising given the increase in mean wage. The coefficient of variation controls for rising overall wages by dividing the standard deviation by the mean. The variance of log wages provides an alternative measure of variation which is invariant with respect to common growth rates across areas. The coefficient of variation shows that, during the period, wage disparity between areas rose slightly before falling back to roughly its initial level. The variance of log wages (which will forms the focus of our analysis) shows an identical pattern. That is, the overall level of between area wage disparity has remained roughly constant during our study period.

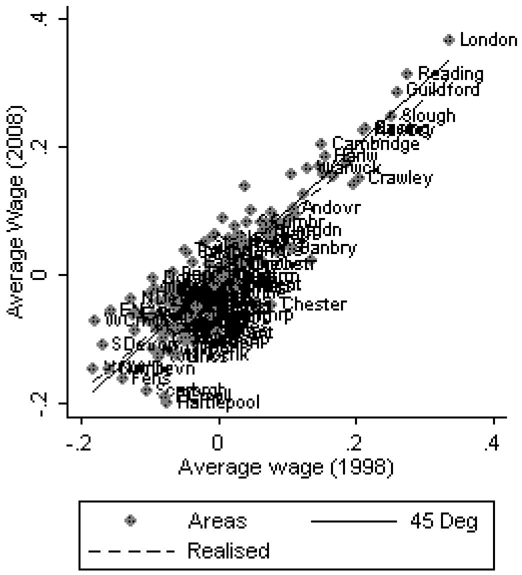
Table 1: Summary statistics: mean hourly wages, 157 labour market areas, 1998-2008

Year	Obs	Mean	SD	Min	Mean	CV	var (lnw)
1998	157	7.60	0.74	6.30	10.58	0.10	0.0087
1999	157	8.00	0.80	6.31	11.10	0.10	0.0093
2000	157	8.35	0.86	6.91	11.57	0.10	0.0098
2001	157	8.83	0.96	7.46	12.39	0.11	0.0105
2002	157	9.16	1.01	7.43	12.98	0.11	0.0109
2003	157	9.53	1.04	7.86	13.57	0.11	0.0107
2004	157	9.77	1.07	7.86	13.90	0.11	0.0108
2005	157	10.06	0.99	7.97	14.36	0.10	0.0087
2006	157	10.46	1.03	8.88	14.76	0.10	0.0088
2007	157	10.77	1.11	9.04	15.44	0.10	0.0095
2008	157	11.12	1.14	9.06	15.92	0.10	0.0095

Notes: Authors own calculations using NES/ASHE.

Of course, these measures of disparity cannot tell us anything about the degree of persistence in any given area's average wages across time. It is possible that the overall stability in between area wage disparity masks large changes in the fortunes of particular areas. Perhaps unsurprisingly, Figure 1 shows this is not the case. For each of our 157 areas, the figure plots hourly wages in 1998 against hourly wages in 2008 (data for all areas are provided in Table A5 of the appendix, while Table A6 reports the top and bottom 10 areas in each year). Wages are normalised by dividing by the average wage in the respective year so that areas with values less than 1 have below average wages in that year (and vice-versa). If relative average area wages were completely persistent across time the dots would sit on the 45 degree line drawn in the figure. The dashed line (which shows the results from regressing 2008 normalised wages on 1998 normalised wages) shows this is not quite the case. On average, the lowest wages areas have caught up slightly, while the highest wages areas have fallen back although the effect is not very pronounced.[5] Further, it appears that this 'churning' tendency amongst the rankings is not being driven by the highest wage areas which tend, if anything, to have seen their position improve (as they mainly sit above the 45 degree line). Overall, our findings suggest that wage disparity across areas is persistent over time. The aim of the rest of this paper is to look closely at the role of people and place in explaining these patterns.

Figure 1: Normalised hourly wage in 1998 and 2008 across 157 areas



Notes: Plots average area wage in 1998 against average area wage in 2008 (expressed as ratio to UK average)

4 Methodology

We have established that there is marked wage disparity across areas and that these disparities are persistent across time both in terms of the overall level and areas' individual rankings. In this

[5] In the economic growth literature, this tendency is referred to as 'beta' convergence but should not be confused with the idea that areas are converging in the sense that the variance in wages is decreasing and area disparities are reduced.

section, we outline our methods to consider the extent to which these area differences are driven by area effects and the extent to which these, in turn, matter for individual outcomes. Our main focus is: a) on the magnitude of these area effects and their contribution to overall wage disparities across individuals, and b) the extent to which observed area differences arise because of differences in the characteristics of workers who work in these areas (sorting of people) versus different outcomes for the same workers living in different areas (area effects).

4.1 Wage regressions

Our empirical strategy is based on regression analysis of individual wages, which allows us to estimate the magnitude of area effects, after allowing for differences in the characteristics of workers in different areas. Imagine, for the moment, that all workers are identical and live in one of J areas.[6] Then allowing for area effects we can assume that wages are determined as:

$$\ln w_i = \alpha + d_i^{'}\delta + \varepsilon_i \qquad (1)$$

where $\ln w_i$ is the (natural logarithm of) wage of individual i, δ is a Jx1 vector of area effects, d_i is a J x 1 vector or dummy variables that indicates in which of the J areas individual i works and ε_i is an error term that represents unobserved wage factors that are uncorrelated with the area effects. Estimating (1) by regressing individual (log) wages on a set of area dummy variables (using data from 1998 and 2008) and plotting δ would give us a picture like Figure 1. Putting log wages on the left hand side of (1) means that the component δ represents (approximately) the percentage difference between the mean wage in a given area and the mean wage in some baseline area.

Of course, all workers are not identical. For example, those in higher-skill occupations, will get paid more than those in low-skill occupations. We can capture the effect of *both* area and individual characteristics by assuming that wages are determined as:

$$\ln w_i = \alpha + x_i^{'}\beta + d_i^{'}\delta + \varepsilon_i \qquad (2)$$

where x_i is a vector of individual variables measuring skills, gender, age and other characteristics, β is a vector of coefficients that capture the "returns" to different individual characteristics and everything else is as before. Now δ captures the impact of area controlling for the observed

[6] Alternatively, assume workers differ but are randomly assigned to different places.

characteristics of individuals. That is they capture area effects once we control for the fact that people with different characteristics get paid different wages and may work in different areas. Likewise β captures the impact of individual characteristics controlling for area.

These regressions identify area effects allowing for the possibility that workers with different characteristics sort across areas providing that we have data available on all individual characteristics that affect wage.[7] Unless we have very rich data on individuals there is always the possibility that sorting on some unobserved characteristic of individuals might drive the differences in wages across areas and that the area dummies capture the effect of this sorting rather than the causal effect of working in a particular area. Unfortunately, even with detailed data, we cannot be certain that we are observing everything that might affect wages. For example, in our data we have no information on education, cognitive abilities or motivation. So when we compare people with identical observed characteristics it may be that those with higher education or ability live in a particular area. Assuming workers with higher education or ability get paid more, it is the unobserved individual characteristics (education and ability) that explain the higher wage of the individuals living in the area but we mistakenly attribute it to an effect of the area.

One solution is to follow the same individual as they move across areas. Providing that unobserved characteristics are fixed over time, if the same individual earns more in some areas than others we can be more confident in attributing this to an area effect rather than a composition (sorting) effect. Even then, we cannot rule out the possibility that something changed for the individual that both affected their wage and their place to work. In the absence of random allocation (or a policy change that as good as randomly assigns people) tracking individuals and observing the change in wages experienced when they move between areas is the best we can do to identify true area effects.

Formally, we use the panel dimension of NES/ASHE to include fixed effects for each individual *i*:

$$\ln w_i = \alpha_i + \lambda_t + x_i^{'}\beta + d_i^{'}\delta + \varepsilon_i \qquad (3)$$

where the α_i are individual fixed effects (that capture the effect of unobserved time invariant characteristics such as ability) and the λ_t are time dummies that pick up the fact that average wages

[7] More precisely we need data on all individual characteristics that are correlated with the area effects.

change over time.[8] The need to pool data across time to control for unobserved individual characteristics comes at a cost – sample size restrictions mean we can no longer consider year on year changes in the area specific effects.[9] As we shall see, however, these area specific effects appear to be quite stable over time, while individual unobserved characteristics are, unsurprisingly, important for explaining wage. So there are good reasons to think that the panel regression which assumes area effects are fixed but allow us to include individual fixed effects may give the most accurate picture of the relative roles of composition versus area effects.

Once we have estimated these area effects we can use the distribution across areas to describe the impact on an individual of moving from a "bad place" (in terms of wages) to a "good place". We can also describe how this distribution of area effects changes as we include observed individual characteristics and individual fixed effects in the wage regressions. This provides a first indication of the extent to which observed area disparities are due to sorting versus area effects. To provide a more formal assessment we use several related variance decompositions to assess the contribution of area effects to area disparities and to overall wage disparities. These decompositions allow for the fact that the contribution to overall wage disparities depends not only on the size of specific effects but also on the overall distribution of good and bad places *and* on the distribution of individuals across those places. Variance decompositions summarise this interaction, while also providing a more rigorous assessment of the extent to which sorting contributes to observed area wage disparities.

4.2 Analysis of Variance

For simplicity, consider the wage regressions for one year where we are only worried about controlling for observed individual characteristics such as age, gender and skills (vector x_i):

$$\ln w_i = \alpha + x_i^{'}\beta + d_i^{'}\delta + \varepsilon_i \qquad (4)$$

where everything is defined as above. We want to find the contribution of area effects to area disparities and to the total variance of (log) wages. We focus on deriving the contribution of area

[8] Note that we did not need to include these time dummies before because, when we do not include fixed effects, we can run the regressions year by year.

[9] Theoretically, we could still allow for such year on year changes in place specific effects, but identifying them requires movers in and out of all areas in every year which turns out to be too demanding given our sample sizes.

effects to overall wage disparities and use this to back out the contribution of area effects to area disparities. There are, however, two ways to conceptualise and measure the contribution to overall wage disparities. The first is to estimate the ratio $Var(d_i^{'}\delta)/Var(\ln w_i)$ whilst allowing δ to be correlated with individual characteristics x_i.[10] The second is to estimate the ratio $Var(u)/Var(\ln w_i)$ where we consider only u the components of δ that are uncorrelated with x_i. We now explain this in more detail.

Suppose we ignore the differences between individuals and run the regression of log wage on a set of area dummy variables to estimate the area effects $d_i^{'}\delta$. The R-squared from this regression, $R^2(\ln w_i; d_i^{'}\hat{\delta})$, captures the proportion of total variance in wages explained by area including both the effects of sorting and area effects. This is because the R-squared is $Var(d_i^{'}\hat{\delta})/Var(\ln w_i)$ where $\hat{\delta}$ are the estimated area effects (i.e. the coefficients on the area dummy variables). Assuming that sorting is 'positive' or (so individuals with high wage characteristics tend to move to high wage places) then this provides an upper bound for the contribution of area effects (because some of the difference between areas is due to sorting but we attribute it all to area effects).

To include individual characteristics, regress log wage on x_i and area dummies d_i. Next, predict the components of wages due to characteristics ($x_i'\hat{\beta}$) and area effects ($d_i^{'}\hat{\delta}$) and note that:

$$\begin{aligned} Var\left(\ln w_i\right) &= Var\left(x_i'\hat{\beta} + d_i'\hat{\delta} + \hat{\varepsilon}_i\right) \\ &= Var\left(x_i'\hat{\beta}\right) + Var\left(d_i'\hat{\delta}\right) + 2Cov\left(x_i'\hat{\beta}, d_i'\hat{\delta}\right) + Var\left(\hat{\varepsilon}_i\right) \end{aligned} \tag{5}$$

where we ignore the covariance terms between the residual ($\hat{\varepsilon}$) and x_i and $d_i^{'}\hat{\delta}$ because they are uncorrelated by construction.[11] As before, we can obtain a measure of the contribution of area effects as $Var(d_i^{'}\hat{\delta})/Var(\ln w_i)$. This measure is smaller than the R-squared without any covariates x_i, because that measure attributed *all* of the covariance between x_i and $d_i^{'}\hat{\delta}$ to area effects. Notice that there is no reason why the estimated area effects $\hat{\delta}$ should be uncorrelated with the individual

[10] Note the variance $Var(\delta)$ is the variance over the sample of individual workers, not areas

[11] This statement holds for the *estimated* residuals even if these components are correlated with the true error term.

characteristics x_i, but that the initial regression does control for the fact that individuals with different x_i earn different wages and may live in different areas when estimating $\hat{\delta}$. This means that $Var(d_i'\hat{\delta})/Var(\ln w_i)$ excludes the direct contribution of sorting (i.e. the covariance term in equation (5)), but captures any indirect effect that sorting may have on the variance of the area effects. That is, it captures the contribution of area effects *including* those induced by composition (e.g. spillovers and interactions) but not the effects, if any, that area has in determining individual characteristics. We refer to this as the *correlated area variance-share*, because the estimated area effects are potentially correlated with individual characteristics. Because the correlated variance-share excludes the direct contribution of sorting it can also be used to calculate the contribution of area effects to area disparities. To do this we simply take the ratio of the correlated area variance share (which excludes sorting) to the proportion of total variance in wages explained by area including both the effects of sorting and area effects. That is, we take the ratio of the correlated variance share to $R^2(\ln w_i; d_i'\hat{\delta})$ that we get by estimating area effects from a regression of log wages on only a set of area dummy variables.

We can also estimate the contribution of the components of area effects that are uncorrelated with individual characteristics. There are a number of equivalent methods for doing this that give a statistic that is usually called the semi-partial R-squared. One way is to first regress log wage on observed individual characteristics x_i and area dummies and obtain the R-squared based on the estimated coefficients, $R^2(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta})$. This measures the proportion of the overall variance explained by both individual characteristics and area effects. Next, regress log wage on *just* the observed individual characteristics and take the R-squared $R^2(\ln w_i; x_i'\hat{\beta})$. This gives the proportion of the overall variance explained by just the individual characteristics. The semi-partial R-squared is the difference between the two $R^2(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}) - R^2(\ln w_i; x_i'\hat{\beta})$. Note, that if we do not include x_i in the regression, we just have the simple R-squared, $R^2(\ln w_i; d_i'\hat{\delta})$, which is the same as that produced by the variance-share method without any individual control variables. Another approach is based on partitioned regression and starts by regressing log wage on x_i and area dummies, and obtaining the predicted values $x_i'\hat{\beta}$ and $d_i'\hat{\delta}$. Next regress $d_i'\hat{\delta}$ on $x_i'\hat{\beta}$ and get the uncorrelated residual area components $\hat{u}_i$. Finally, regress log wage on the residual $\hat{u}_i$ and look at the R-squared (or square the partial correlation between log wage and the residual). Appendix 5 shows that these methods are equivalent. In practise, the semi-partial R-squared can also be obtained using Analysis of Variance (ANOVA), by dividing the partial sum of squares for the area effects $d_i^{'}\hat{\delta}$ by the total sum of squares.

The semi-partial R-squared can be estimated by all these methods, and in this context we refer to it as the *uncorrelated area variance-share*. This is because it shows the amount of variation in log wage that is explained by the part of the area effect that is uncorrelated with individual characteristics (those that are included in x_i). That is, it captures the contribution of the components of area effects that are uncorrelated with individual characteristics. This variance share will be smaller than the *correlated area variance-share* described above (see Appendix 5) and may understate the contribution of area effects if sorting has indirect effect on area effects or if areas induce changes in the observed individual characteristics. Again, because the uncorrelated variance share excludes both the direct *and* indirect contribution of sorting it can be used to calculate another measure of the contribution of area effects to area disparities. As with the correlated variance share, to do this we simply take the ratio of the uncorrelated area variance share (which excludes the direct and indirect contribution of sorting) to the proportion of total variance in wages explained by area including both the effects of sorting and area effects.

To recap, the *correlated area variance-share* (when controlling for x_i) shows the contribution of the area effects after controlling for sorting. However, it includes the contribution of area effects that arise *because* of that sorting, for example as a result of interactions between area effects and individual characteristics, or because of spillovers to an individual from the average worker characteristics in an area. The *uncorrelated area variance-share* (when controlling for x_i) captures only the contribution of area effects that are uncorrelated with individual characteristics. It thus nets out any benefits an individual gets from an area because of the composition of the labour force in that area, for example any benefits from being located in an area with more high-skill workers.

To summarise, it is useful to consider an example. Suppose some areas have a better climate than others, but are otherwise identical, and that a better climate makes people more productive. Imagine that a) a better climate also attracts more high-skill workers such that places with a good climate also have higher than average skills or b) a better climate encourages workers to acquire more skills. In these cases the places with the better climate also have a high skilled workforce, but the area effect on individual productivity that we are interested in is caused only by the climate. In this case the 'upper bound' estimate of the contribution of area effects is obtained by $R^2(\ln w_i; d_i^{'}\hat{\delta})$,where $\hat{\delta}$ is estimated from a regression without any controls for worker skills, and captures the effect of climate and the impact on area disparities from the sorting of high skill workers. If instead, $\hat{\delta}$ is estimated from a regression with controls for skills, then both the correlated variance share $Var(d_i'\hat{\delta})/Var(\ln w_i)$ and the uncorrelated variance share $R^2(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}) - R^2(\ln w_i; x_i'\hat{\beta})$ yield an upper bound estimate of the contribution of area differences in climate to individual disparities, purged of any additional area disparities caused by sorting.

Suppose in addition, that working in an area amongst high skill workers makes individuals more productive. In this case the correlated variance share will pick up this area effect in addition to the direct effect from the climate. The uncorrelated variance share on the other hand will be an area contribution to individual wage disparity that is purged of this contribution to individual wages that acts from climate, via the average skill level in the area, and purged of any other components of climate that are correlated with skills (e.g. through sorting). The uncorrelated variance share is thus a lower bound to the contribution of area effects.

5 Results

5.1 All areas

We start by estimating equations 1, 2 and 3 to show how allowing for sorting across areas affects the magnitude of estimated area effects. To summarise the distribution of effects we report the percentage change in wages when we move between different parts of the distribution: the minimum to maximum and to mean, mean to maximum, the 10^{th} to the 90^{th} percentile and the 25^{th} to the 75^{th} percentile. Table 2 reports results based on several different specifications. The first row reports results from equation (1) when only including time dummies giving the upper bound estimates of area effects as discussed above. The second row reports results from equation (2) when the observable variables are a set of age dummies, a gender dummy and a set of 1 digit occupation dummies. The third row uses a set of age dummies, a gender dummy, two digit occupations dummies, industrial dummies (three digit SIC) and dummies for public sector workers, part time workers and whether the worker is part of a collective agreement. Results from equation (3) using individual fixed effects are reported in rows four and five. In row four, we simply include year dummies and individual effects. Row five uses individual effects, year dummies, age dummies and one digit occupation dummies. The coefficients from one of these specifications (set of age dummies, a gender dummy and a set of 1 digit occupation dummies) are reported in Appendix 4.[12]

Table 2: Distribution of area effects

	min-max	Min-mean	mean-max	p90-p10	p75-p25
Year dummies	61.6%	18.2%	36.8%	22.0%	10.6%
+ age, gender, occ (1)	37.2%	9.3%	25.5%	12.6%	6.6%
+ age, gender, occ (2), sic(3), public, union, pt	29.4%	6.7%	21.3%	10.0%	4.2%
Individual fixed effects and year dummies	20.3%	7.6%	11.8%	8.8%	4.3%
+ age, occ (1)	17.4%	6.0%	10.8%	7.4%	3.8%

Notes: Results for 157 areas. Row 1 based on 1,510,872 observations (305,717 individuals). Rows 2-5 based on 1,457,426 observations (252,571 individuals) of which movers across areas account for 552,196 observations (90,483 individuals).

If we ignore the role of sorting then the differences in area average wages look quite large. Moving from the worst to the best area, average wages increase by just over 60%, from the minimum to the mean by a little under 20% and from the mean to the maximum by just over 35%. Of course the minimum and maximum represent extremes of the distribution. The move from the 10th to the 90th percentile sees average wages increase by 22%, from the 25th to 75th percentile by just over 10%. Introducing a limited set of observable characteristics (row 2) to control for sorting substantially reduces estimated area differences. A larger set of individual characteristics (row 3) reduces the estimated differences further as does allowing for individual fixed effects, with or without additional observable characteristics (rows 4 and 5). As should be clear from these results, interpreting observed area differences as area effects considerably overstates the impact on wages that occurs as individuals move from bad to good areas. Specifically, across the comparisons we report, ignoring the role of sorting overstates area effects by a factor of three. In fact, as we shall see, these comparisons overstate the role that area effects play in explaining area disparities.

As discussed above, the contribution of area effects to area and overall wage disparities depends not only on the size of specific effects but also on the overall distribution of good and bad places *and* on the distribution of individuals across those places. We suggested two different ways of capturing

[12] The coefficients in Appendix 4 show, approximately, the difference in wages between a given gender, age and occupational group, and the baseline group (in proportional terms). The baseline group is a hypothetical group of professional men age 16-20. For example, women earn around 15% less than men in the same age and skill group. The analysis of area effects in this section is therefore based on the components of area mean wages that are *not* due to differences in the characteristics shown in the regressions in Appendix 4

these contributions by considering the correlated and uncorrelated area variance-shares of estimated area effects, controlling for individual characteristics.

Table 3 reports results for the contribution of area differences to area and overall wage disparities using these two different measures. We calculate them from regression specifications using the same individual characteristics as in Table 2. To recap, the first specification includes only time dummies, the second dummies for gender, age and 1 digit occupation, the third additional job characteristics and a fuller set of occupation and industry dummies, the fourth individual fixed effects and the fourth individual fixed effects, age and one digit occupation dummies. For comparison, the second part of the table reports the contribution of the individual characteristics using the two different measures. The third part reports the contribution of area effects to area disparities calculated by taking the ratio of the correlated and uncorrelated variance shares to the variance share with area and year effects only (i.e. that reported in the first column).

Table 3: Variance decomposition

	Year dummies only	+ age, gender, occ (1)	+ age, gender, occ (2), sic(3), public, union, pt	Individual fixed effects and year dummies	+ age, occ (1)
Area variance share					
Correlated with X	5.96%	2.88%	2.08%	0.75%	0.62%
Uncorrelated with X	5.96%	2.73%	1.51%	0.08%	0.06%
Individual variance share					
Correlated with area	-	58.2%	76.0%	86.4%	87.9%
Uncorrelated with area	-	55.0%	71.6%	83.7%	84.9%
Area share of area disparities					
Correlated with X		48.4%	35.1%	12.6%	10.4%
Uncorrelated with X		46.8%	25.4%	1.3%	1.0%

Notes: Column 1 based on 1,510,872 observations (305,717 individuals). Columns 2-5 based on 1,457,426 observations (252,571 individuals) of which movers across areas account for 552,196 observations (90,483 individuals).

Even if we ignore the effects of sorting, and simply consider raw area differences in mean log wages, the first column of Table 3 shows that these only explain 6% of the overall variation in wages (remember that if we don't control for any Xs then the variance share of area effects is the same whichever we calculate it). The contribution of area effects is less than 3% once we control for basic observable characteristics (columns 1 and 2) and less than 1% once we control for unobservable individual characteristics. In short, area effects only play a small role in explaining overall wage disparities. The final part of the table shows that they play a somewhat more important role in explaining area disparities. When we only account for basic characteristics, sorting accounts for a little over half of the observed area disparities leaving area effects to account for around 48%.

Once we control for individual fixed effects the upper bound estimate of the contribution of area effects to area disparities is considerably smaller at a little over 10% with the lower bound estimate around 1%.

As discussed in Section 4.2, the correlated variance share provides an upper bound to the combined contribution of exogenous area effects plus interactions-based spillovers. The uncorrelated variance share provides a lower bound to the contribution of exogenous area effects alone. Looking at the gap between these lower and upper bounds reveals that area effects arising from interactions-based spillovers cannot account for much of the individual disparity in wages - between 0.56 and 1.2%. This is however, quite substantial part of the overall contribution of area effects, accounting for nearly all of it in the last column.

In contrast to these results on area effects, the contribution of individual characteristics is large. Age, gender and occupation variables alone account for 55-58% of the individual disparity in wages. Adding in individual fixed effects drives this share up to between 85% and 88% in the last column, implying that the contribution of individual characteristics is over 140 times bigger than that of area effects.

Table 4 shows that this contribution has been stable over time. For each year, the table reports the contribution of raw area disparities (column 1) and the correlated (column 2) and uncorrelated (column 3) area variance shares controlling for the fullest possible set of individual characteristics. For comparison, the first row reports results when pooling across years (taken from table 3). Repeating other results from table 3 by year (or by three year pools for the individual fixed effects specifications) give figures that are similarly stable across years. Given this stability over time, we tend to focus on the results for data pooled across years in the remainder of the paper.

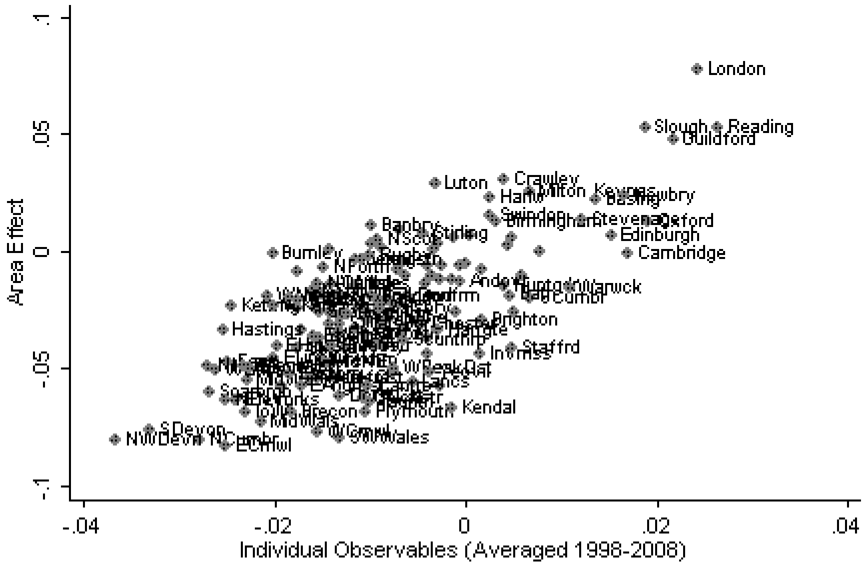
Table 4: Area effects: Results by year

	Year dummies only	+ age, gender, occ (2), sic(3), public, union, pt correlated x	+ age, gender, occ (2), sic(3), public, union, pt uncorrelated x
Pooled	5.96%	2.08%	1.51%
1998	6.15%	2.05%	1.08%
1999	6.03%	1.95%	1.04%
2000	6.00%	1.99%	1.06%
2001	6.34%	2.07%	1.11%
2002	6.56%	2.32%	1.24%
2003	6.60%	2.35%	1.27%
2004	6.65%	2.32%	1.26%
2005	6.53%	2.11%	1.17%
2006	6.23%	2.07%	1.15%
2007	6.78%	2.06%	1.12%
2008	6.67%	2.10%	1.14%

Notes: Column 1 based on 1,510,872 observations (305,717 individuals). Columns 2 and 3 based on 1,457,426 observations (252,571 individuals) of which movers across areas account for 552,196 observations (90,483 individuals). Contribution for pooled lower than average of years because pooled regressions impose time invariant area effects and coefficients on individual characteristics.

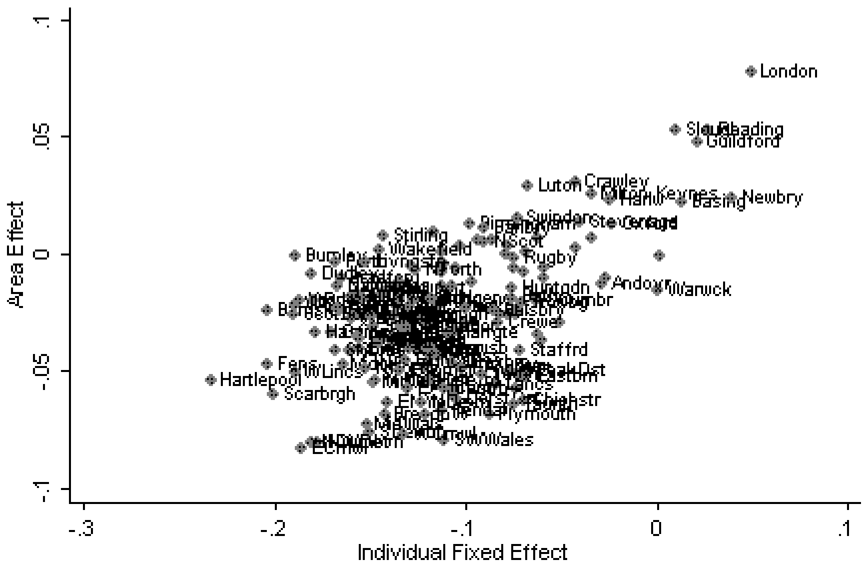
We have suggested that observed area differences overstate the contribution of area effects because they conflate the effect of place with sorting across place on the basis of individual characteristics. Figures 2-4 demonstrate this sorting process. Each figure graphs normalised area effects against normalised area averages for predicted wages on the basis of observable individual characteristics (figure 2), unobservable individual characteristics (figure 3) and both the sum of observable and unobservable individual characteristics (figure 4). That is, in the notation of equations (3) and (4), the figures plot normalised $\hat{\delta}$ against normalised $\overline{x\hat{\beta}}$ (figure 2), $\overline{\hat{\alpha}}$ (figure 3) and $\overline{\hat{\alpha}+x\hat{\beta}}$ (figure 4) where hats designate estimated coefficients and means are taken for all individuals in each area.

Figure 2: Area effects against observed individual characteristics



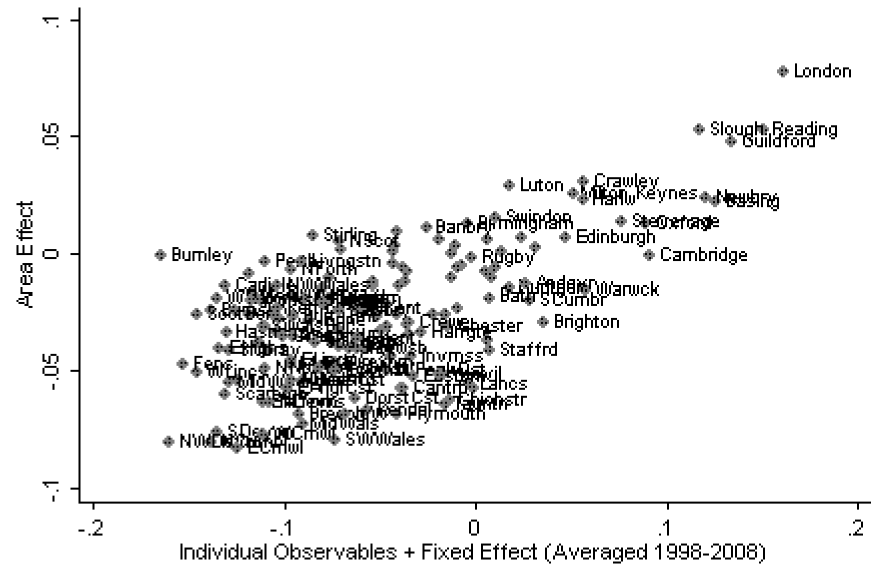
Notes: Plots area effects against average area predicted wage based on observed individual characteristics from a regression that includes individual fixed effects *and* observed individual characteristics (set of age dummies and a set of 1 digit occupation dummies)

Figure 3: Area effects against unobserved individual characteristics



Notes: Plots area effects against average area individual effects from a regression which includes individual fixed effects *and* observed individual characteristics (set of age dummies, and a set of 1 digit occupation dummies)

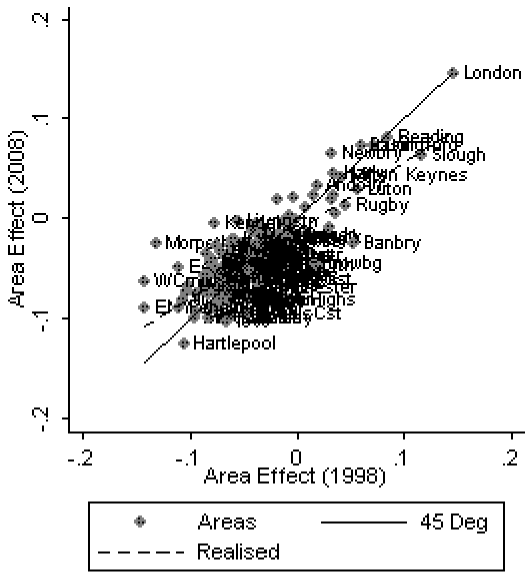
Figure 4: Area effects against observed and unobserved individual characteristics



Notes: Plots area effects against average area predicted wage based on both individual fixed effects and observed individual characteristics (set of age dummies, a gender dummy and a set of 1 digit occupation dummies)

We have shown in figure 1 that observed spatial disparities are highly stable over time in the sense that places at the top have tended to stay at the top, and places at the bottom have tended to stay at the bottom. Figure 5 shows that this stability is not quite as pronounced for area effects.

Figure 5: Normalised area effects in 1998 and 2008 across 157 areas



Notes: Plots area effects from 1998 against area effects in 2008, based on regressions of wage on area dummies and observed individual characteristics (set of age dummies, a gender dummy, a set of 3 digit occupation dummies, 2 digit sector dummies and dummies for whether worker is part-time, public sector and subject to collective wage bargaining)

Once again, the 45 degree line shows what would have happened if there were no changes in the distribution of area effects, while the dashed line reports a regression line showing what actually happened. We see that, as for the overall area means, there is some churning, but the patterns are quite stable. Once again, this stability is particularly pronounced for those areas at the upper end of the area effects distribution. Further detail is provided in Table A7 in the appendix which reports the figures for the top and bottom 10 area effects in 1998 and 2008.

Before moving on, note that Figure 5 is quite reassuring for our specifications where we control for individual fixed effects. To do this, we need to assume that area based effects are fixed over time. Of course, checking this in an internally consistent manner is impossible given that we have to *impose* the assumption of stability to allow for the introduction of fixed effects to control for unobserved individual effects. Still, it is reassuring that area based effects identified by controlling only for observable individual characteristics were quite stable over time.

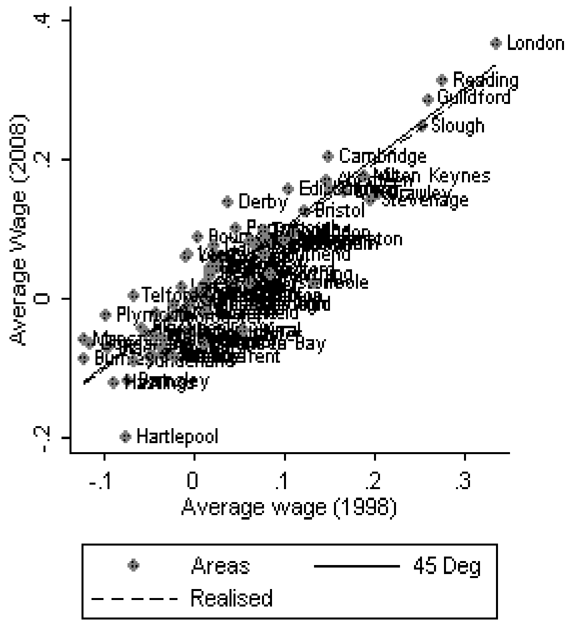
Overall, our findings so far suggest that area effects do not play a very important role in explaining the difference in wages across areas but that positive correlation between area effects and individual effects reinforce the effect that each has individually on overall wage inequality.

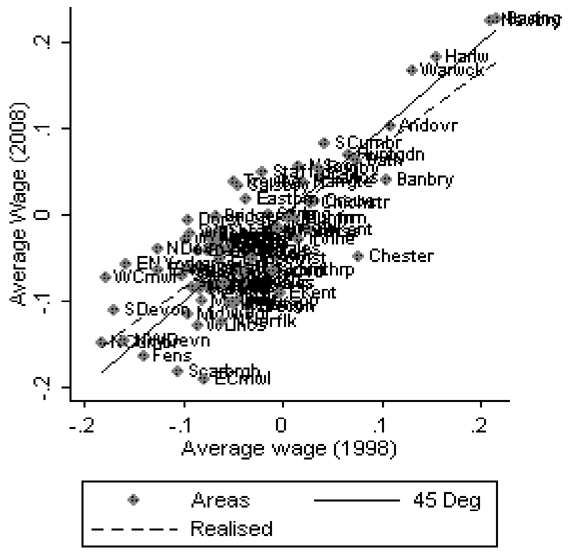
5.2 Urban versus Rural Areas

Our analysis so far has been based on 157 areas which represent both urban TTWA and aggregations of rural TTWA. This section examines the differences between those urban and rural areas as well as considering whether there are rural-urban differences within each of the TTWAs. We start in figure 6, by replicating figure 1 showing the relationship between observed area average wages in 1998 and 2008 but with the samples now split in to urban and rural areas.

Several things are apparent from the figures. First, unsurprisingly, the places with the highest average wages are urban areas, while the places with the lowest average areas are rural (to see this take a look at the minimum and maximums of the axis). Second, the distribution of rural averages is slightly narrower than the distribution of the urban averages and there is substantial overlap between the two sets of areas in terms of average wages. Third, there has been more change in the rankings of rural areas (the regression line is below the 45 degree line) and almost no change on the rankings in urban areas (which lies on the 45 degree line).

Figure 6: Normalised area wages in 1998 and 2008 for urban (top) and rural (bottom) areas





Notes: Plots average area wage in 1998 against average area wage in 2008 (expressed as ratio to UK average) for 79 urban areas (top panel) and 78 rural areas (bottom panel)

Not only has there been slightly more movement in the rankings of areas within the rural group, but rural areas have also slightly improved their average position with respect to urban areas. The summary statistics make this clearer. Table 5 reports observed area averages over time for the urban and rural group as well as the average percentage urban-premium. In 1998 average area wages for the urban group where £7.87 per hour, 7.4% above average wages for the rural group of £7.33 per hour. By 2008 the percentage difference in area averages had fallen to 6.5%.

Table 5: Mean area wages for rural and urban areas

	Urban	Rural	urban premium
1998	7.87	7.33	7.4%
1999	8.29	7.70	7.7%
2000	8.65	8.04	7.6%
2001	9.16	8.49	7.8%
2002	9.54	8.78	8.6%
2003	9.91	9.15	8.3%
2004	10.11	9.43	7.2%
2005	10.40	9.72	7.0%
2006	10.79	10.13	6.5%
2007	11.13	10.41	6.9%
2008	11.46	10.77	6.5%

Notes: Column 1 reports average wage for 79 urban areas, column 2 average wage for 78 rural areas. Column 3 reports average percentage urban-premium

As with our earlier analysis we would like to distinguish between the role of area effects and that of composition or sorting on individual characteristics. To do this we again run regressions based on equations (1)-(3) above. We do this separately for the rural and urban samples to allow the effects of individual characteristics x_i on log wages to be different in the rural and urban areas (the regression coefficients are shown in Appendix 4). Table 6 replicates results in table 2 on the distribution of area effects for the two different samples of rural and urban areas

Table 6: Distribution of area effects for rural and urban areas

	Min-max	Min-mean	mean-max	p90-p10	p75-p25	Urban-rural[1]
Urban						
Year dummies	51.3%	14.2%	32.6%	26.1%	10.9%	6.5%
+ age, gender, occ (1)	33.1%	8.4%	22.8%	13.6%	6.4%	4.2%
+ age, gender, occ (2), sic(3), public, union, pt	28.3%	7.5%	19.3%	11.6%	5.3%	2.9%
Individual fixed effects and year dummies	18.0%	7.4%	9.9%	6.3%	3.3%	2.8%
+ age, occ (1)	14.8%	5.3%	9.0%	5.8%	3.1%	2.4%
Rural						
Year dummies	47.6%	14.5%	28.9%	20.0%	8.0%	
+ age, gender, occ (1)	27.9%	7.4%	19.1%	12.6%	5.2%	
+ age, gender, occ (2), sic(3), public, union, pt	20.1%	5.2%	14.2%	7.6%	3.6%	
Individual fixed effects and year dummies	20.3%	6.8%	12.7%	10.0%	5.6%	
+ age, occ (1)	18.1%	6.6%	10.7%	8.4%	5.4%	

Notes: Results for 79 urban and 78 rural areas. Urban results based on 1,208,698 observations (260,240 individuals). Rural results based on 302174 observations (75,717 individuals). Last columns reports the difference between the mean urban area effect and the mean rural area effect.

The effect of sorting between urban and rural areas is immediately apparent from the final column. Starting from a raw urban-rural area premium of 6.5% the premium reduces markedly to 2.4% once we control for observed and unobserved individual characteristics. With the exception of min to mean, the table shows greater spread in the raw observable differences between urban areas relative to rural areas. The picture is mixed once we control for individual characteristics. The extremes of the urban distribution are more pronounced, but the rural distribution shows slightly more dispersion across the 90-10 and the 75-25 percentiles.

Once again, we use variance decompositions for the two different samples to make more precise statements about the relative importance of area effects. Results are reported in table 7 and should be compared to those in table 3. When we ignore the role of sorting, area effects explain 5.7% of the variance of wages for individuals working in urban areas, almost twice as much as for those working in rural areas. Initially, this difference (i.e. that areas account for more of the variance of urban wages) persists when controlling for individual characteristics. Area effects explain less than 1% of rural wage disparities when we control for basic individual characteristics (second column), while continuing to explain about 2.5% of urban disparities. Interestingly, this difference disappears once we control for unobserved individual characteristics. Turning to the contribution of area effects to area disparities we see that when we control for basic observable characteristics the importance of sorting is roughly similar across the two types of areas leaving area effects to explain slightly less than half of observed area disparities. Controlling for individual fixed effects the share of area effects in area disparities decreases more for urban than for rural areas. Overall, these differences suggest two things. First, sorting is more pronounced across urban than rural areas (which explains why, for urban areas, there is a greater difference between the role of observed area effects and that of area effects once we control for sorting). Second, the fact that individual unobservables play a larger role in reducing the contribution of area effects for urban areas, suggests that sorting on unobservables must be more important for urban than for rural areas. Figures 7-9 show that this is indeed the case.

Table 7: Variance decomposition in urban and rural areas

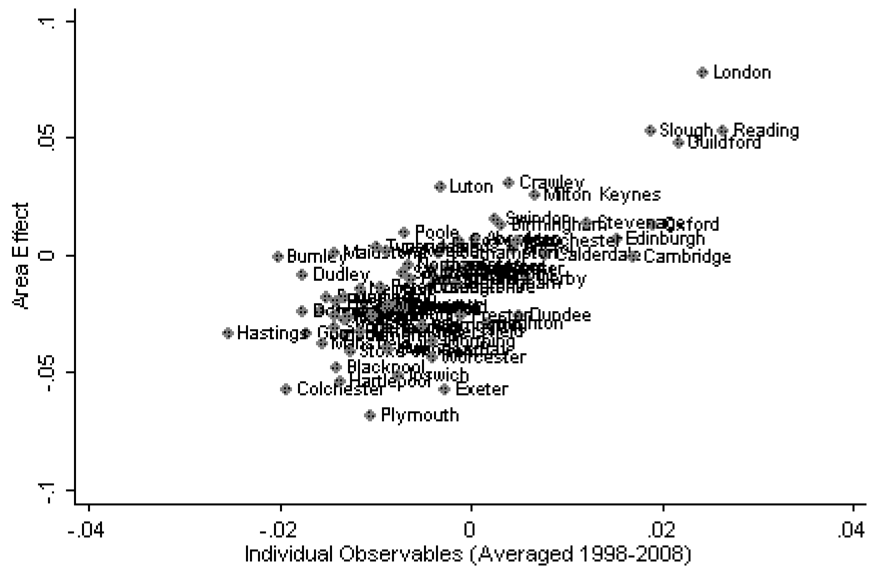
	Year dummies only	+ age, gender, occ (1)	+ age, gender, occ (2), sic(3), public, union, pt	Individual fixed effects and year dummies	+ age, occ (1)
Urban					
Area variance share					
Correlated with X	5.71%	2.70%	2.07%	0.63%	0.52%
Uncorrelated with X	5.71%	2.78%	1.47%	0.06%	0.06%
Area share of area disparities					
Correlated with X		47.3%	36.3%	11.0%	9.1%
Uncorrelated with X		48.7%	25.7%	1.1%	1.1%
Rural					
Correlated with X	2.39%	0.99%	0.54%	0.61%	0.51%
Uncorrelated with X	2.39%	0.97%	0.29%	0.02%	0.02%

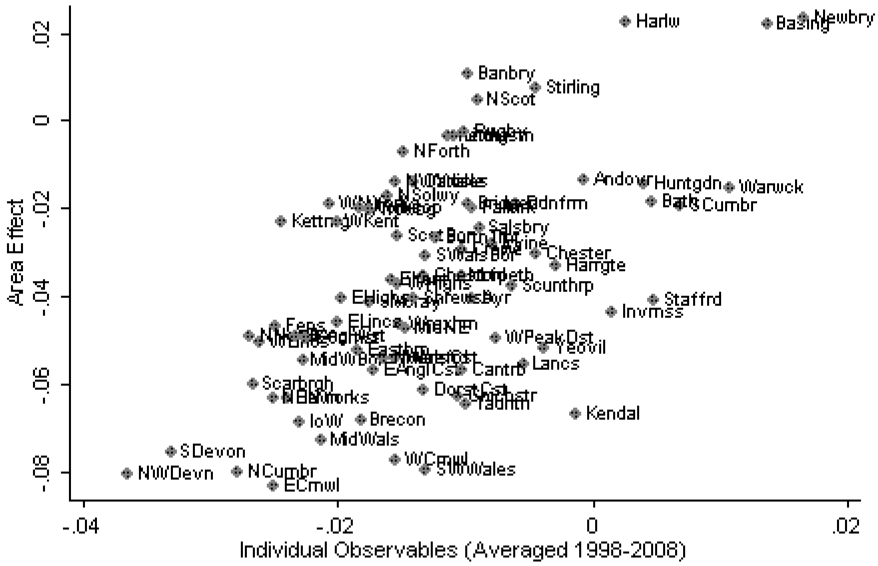
Area share of area disparities				
Correlated with X	41.4%	22.6%	25.5%	21.3%
Uncorrelated with X	40.6%	12.1%	0.8%	0.8%

Notes: Results for 79 urban and 78 rural areas. Urban results based on 1,208,698 observations (260,240 individuals). Rural results based on 302174 observations (75,717 individuals).

Figure 7 shows that sorting on observables occurs for both urban and rural areas (the positive slope) but that positive association is less strong for the rural areas. Figure 8 shows that sorting on unobservables is much more pronounced for urban than for rural areas. Indeed, for rural areas there is almost no relationship between area effect and the (unobserved) individual effects while for urban areas it is clearly positive. Finally Figure 9 shows the overall effect of sorting on both observable and unobservable individual characteristics. As discussed above, sorting is stronger for urban than for rural areas. This is consistent with the fact that areas account for more of the variance of urban wages than of rural wages *before* we control for sorting (5.71% versus 2.39%) but that there is no difference in the contribution of area effects to overall wage disparities once we control for sorting (see the final column of Table 7).

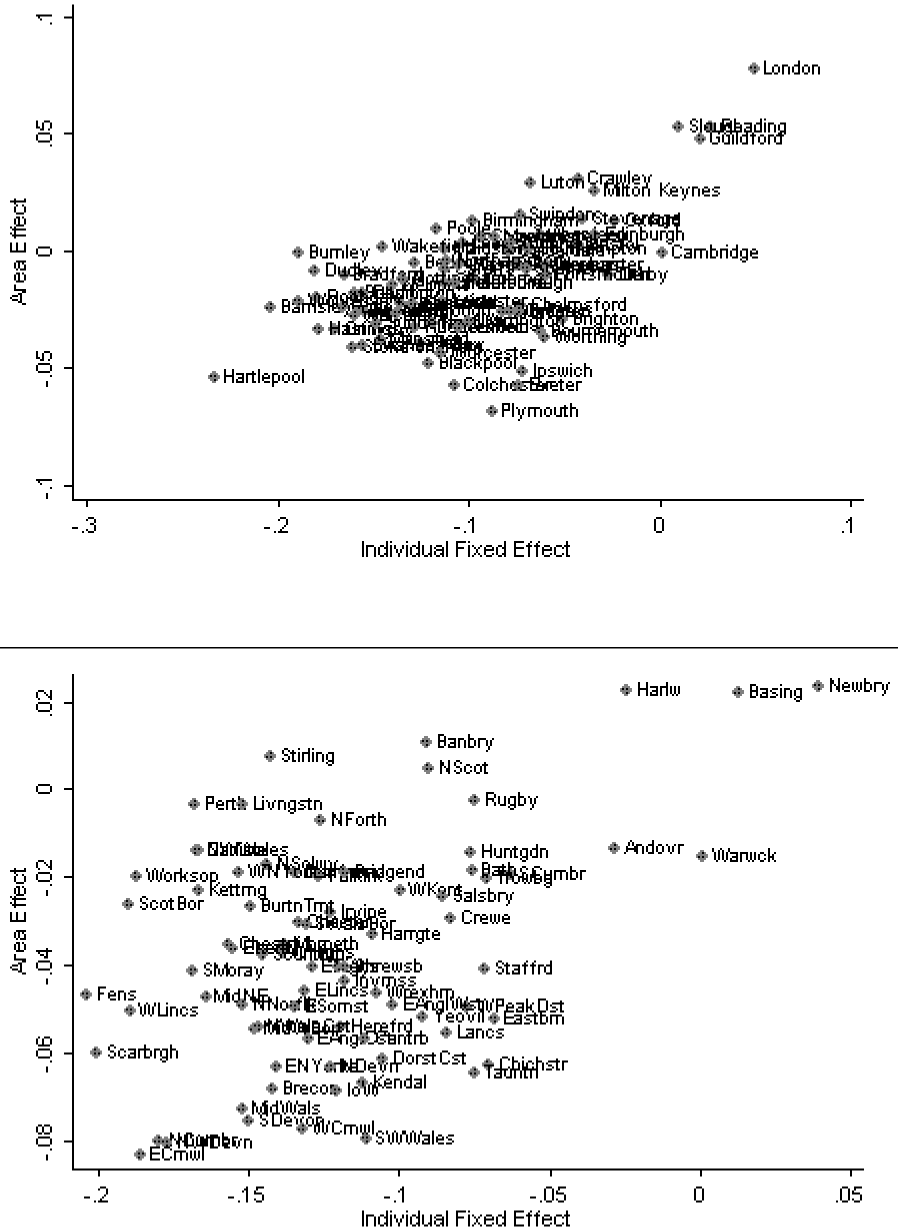
Figure 7: Area effects against observed individual characteristics for urban (top panel) and rural (bottom panel) areas





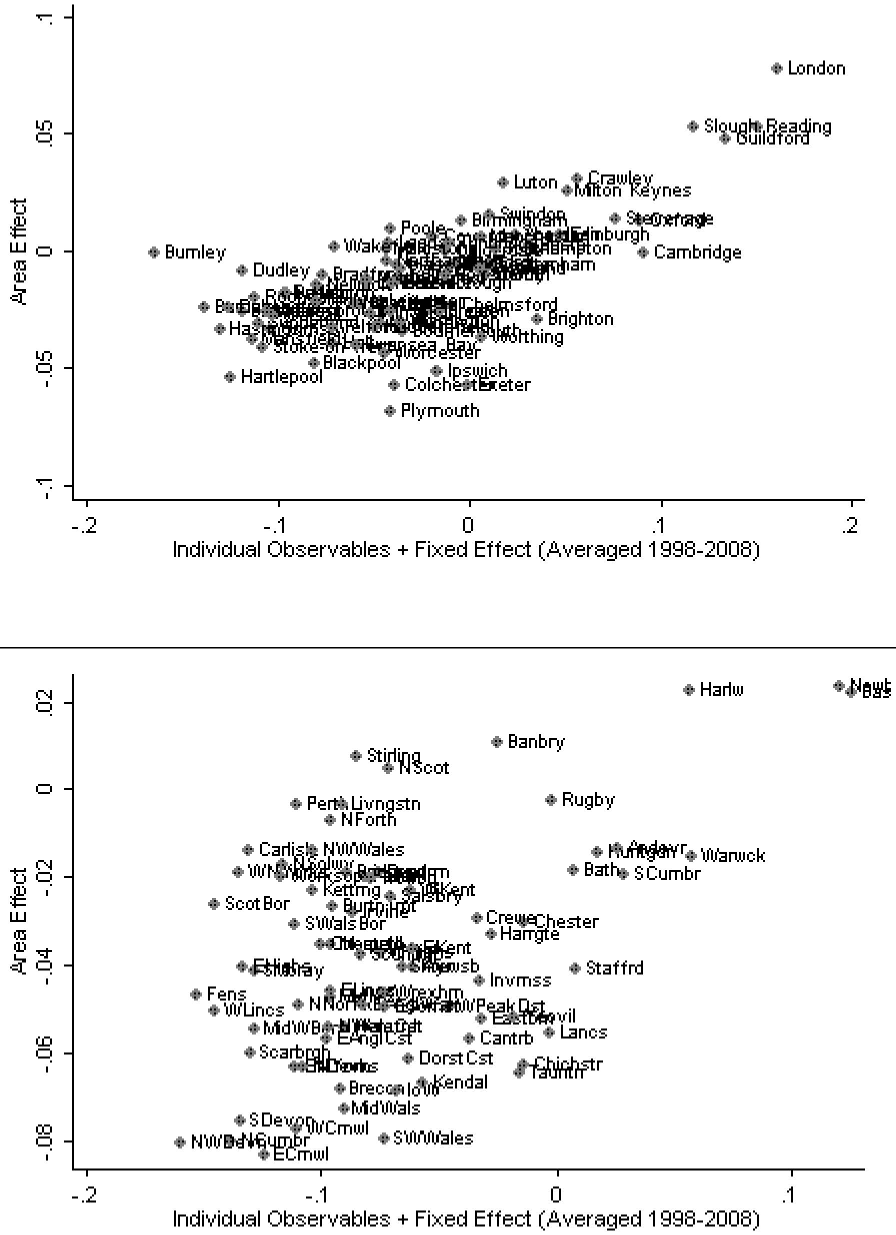
Notes: Plots area effects against average area predicted wage based on observed individual characteristics from a regression that includes individual fixed effects *and* observed individual characteristics(of age dummies and a set of 1 digit occupation dummies) for 79 urban areas (top panel) and 78 rural areas (bottom panel)

Figure 8: Area effects against unobserved individual characteristics for urban (top panel) and rural (bottom panel) areas



Notes: Plots area effects against average area individual effects from a regression which includes individual fixed effects *and* observed individual characteristics (set of age dummies and a set of 1 digit occupation dummies) for 79 urban areas (top panel) and 78 rural areas (bottom panel).

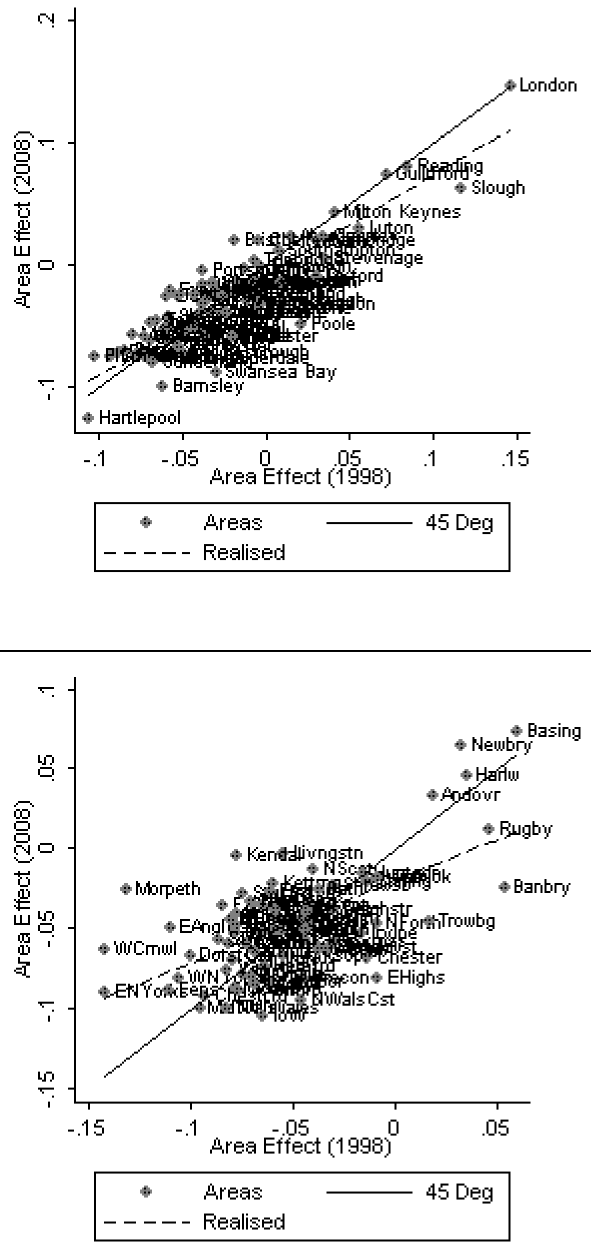
Figure 9: Area effects against observed and unobserved individual characteristics for urban (top panel) and rural (bottom panel) areas



Notes: Plots area effects against average area predicted wage based on both individual fixed effects and observed individual characteristics (set of age dummies and a set of 1 digit occupation dummies) for 79 urban areas (top panel) and 78 rural areas (bottom panel).

Finally, as for the overall sample, we can ask whether area effects are as stable as observed area differences once we separate between rural and urban areas. Figure 10 shows that, as with observed disparities, we have seen greater churn in area effects for rural than for urban areas.

Figure 10: Normalised area effects in 1998 and 2008 for urban (top panel) and rural (bottom panel) areas



Notes: Plots area effects from 1998 against area effects in 2008 for 79 urban areas (top panel) and 78 rural areas (bottom panel). Based on regressions of wage on area dummies and observed individual characteristics (set of age dummies, a gender dummy, a set of 3 digit occupation dummies, 2 digit sector dummies and dummies for whether worker is part-time, public sector and subject to collective wage bargaining)

5.3 Other issues

One obvious concern is that, for the specifications that include individual effects, identification comes from movers, but the variance analysis is based on all individuals. Results reported in table 8 show what happens when the sample is restricted to movers only. Comparing to table 3 we see that the upper bound estimate of area differences attributes less of the variation in wages (about 4% compared to 6%) to area, but once we start controlling for individual differences we see similar results with area effects explaining a small percentage of variation in wages. Two offsetting effects could be at work here. First, the variance of log wages may be higher for movers than for the whole sample so if estimated area effects were unchanged their contribution would necessarily be lower. Offsetting this, we expect movers to either (i) be more affected by area differences (because they move in response to those differences) or (ii) to be people who have experienced a shock to wages that make them more likely to move. Both these effects would tend to increase the magnitude of estimated area effects. In practise, these offsetting effects appear to be in play, but neither is large.

Table 8: Movers

Area variance share	Year dummies only	+ age, gender, occ (1)	+ age, gender, occ (2), sic(3), public, union, pt	Individual fixed effects and year dummies	+ age, occ (1)
Correlated with X	4.23%	2.01%	1.43%	0.67%	0.52%
Uncorrelated with X	4.23%	1.96%	0.98%	0.22%	0.17%

Results based on 552859 observations (91146 individuals).

Another issue of possible concern is that our analysis is based on where individuals work, rather than where they live. If areas were closed so that people did not commute across borders then this would make no difference. But in a world where people do commute it is possible that home based area effects play a more important role than work based area effects in explaining wage disparities. In fact, a comparison of work and home-based areas (results not tabulated here) shows that these differences are small. Aarea disparities are marginally bigger for work-based than home-based areas, but the general patterns are the same as we observed in Table 3 above.

6 Conclusions

This paper assesses the extent and evolution of wage disparities across sub-national labour markets in Britain using a newly available microdata set. The findings show that wage differences across areas are very persistent. While some of this is due to individual characteristics (sorting), area effects also play a role. However, area effects contribute a small percentage to area disparities and a very small percentage to total variation in wages. That is, they are not very important for understanding either area or overall wage disparity. Specifically, in our preferred specification area effects contribute around 10% to area disparities and less than 1% of total wage variation. This share remained roughly constant over the period 1998-2008.

These results need to be interpreted with caution. We note three main caveats. First, our estimates remain an upper bound if unobserved time varying individual effects are correlated with area effects because of their impact on moving decisions. Second, we do not study differences in the probability of earning a wage (e.g. due to employment rate differences) or in other components of income. Third, we do not control for differences in costs of living and in access to amenities across places. In other words, we are studying nominal *not* real wages. These issues are important and we consider them in a companion paper (Gibbons, Overman, Resende, 2010)

These caveats aside, we identify several important policy messages. First, area effects do not make a large direct contribution to area disparities. Second, area affects are even less important in understanding total wage disparities. Third, there is a positive correlation between area effects and individual characteristics associated with higher wages. This means that these effects may play an important role in shaping the economic geography of the UK because they (partly) drive sorting which does play an important role in driving area disparities. Fourth, if we view spatial policy as a means of addressing individual wage inequalities then identifying places with bad area effects may help with targeting (due to the correlation between individual characteristics and area effects). However, trying to address area effects directly will not have a large impact on total wage disparities. If addressing total wage disparities is the primary policy objective (and we would argue that it should be), then policy objectives expressed in terms of aggregate area outcomes may lead policy to focus too strongly on area effects and on the spatial sorting of workers with different characteristics. As a result policy may focus too little on addressing much more significant within-area inequalities.

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Appendices

1 The NES/ASHE databases

We have checked the ASHE and NES databases for consistency. A few observations with inconsistencies (such as miscodings in age or gender) have been either corrected (e.g. by using the annual nature of the survey to correct age and by using modal gender to correct year-on-year changes in classification) or dropped. To reduce the impact of outliers, we drop 0.5% of observations from both the top and the bottom of the wage distribution each year 1998-2008. If an individual has multiple jobs, only the main job is included in the analysis.

Table A1 reports descriptive statistics for the number of individual observations for our 157 labour market areas. The minimum number of observations is 136 and the maximum is 22503. The mean number of observations drops between 1998 and 2008 due to reduced sampling frequencies in ASHE relative to NES.

Table A1. Number of ASHE individual observations across 157 areas in 1998 and 2008

	1998	2008
Mean	892	799
S.D.	1854	1668
min	159	136
10%	272	237
25%	321	291
50%	465	437
75%	960	907
90%	1635	1573
max	22258	20058

Notes: Authors own calculations using NES/ASHE.

The left panel of Table A2 reports summary statistics for the variables used in the regressions in section 5 (pooled sample), while the right panel reports the same statistics for the sub-sample of movers that provide identification in the fixed effects specification. Compared to the full sample movers have higher wages are younger, less likely to work for public sector, or have their wages set by collective agreement.

Table A2: Summary statistics all observations and movers

	All		Movers	
Variable	Mean	S.D.	Mean	S.D.
Hourly Wage	10.29	6.57	10.89	6.76
Female	0.48	0.50	0.44	0.50
Part-time	0.24	0.42	0.19	0.39
Collective Ag.	0.57	0.49	0.55	0.50
Public Sector	0.26	0.44	0.23	0.42

2 Detailed area level results

Table A3 provides a list of the 79 urban areas together with the average wages in 1998 and 2008, our estimated area effects, predicated average wages based on observed characteristics and unobserved characteristics. Table A4 provides the same statistics for the 78 rural areas. These are the data used for figure 1. Table A5 picks out the ten areas with highest and lowest average wages and area effects.

Table A3: Urban area names, mean area wages, area effects and predicted wages

Area name	Wage 1998	Wage 2008	Area average	Area effect	Predicted (observables)	Predicted (unobservables)
Aberdeen	8.77	13.10	0.0311	0.0070	0.0004	0.0227
Barnsley	7.06	9.82	-0.1611	-0.0240	-0.0160	-0.1218
Bedford	8.13	10.95	-0.0128	-0.0051	-0.0002	-0.0086
Birmingham	8.26	11.94	0.0095	0.0126	0.0032	-0.0053
Blackburn	6.88	10.29	-0.1437	-0.0254	-0.0142	-0.1027
Blackpool	7.16	10.58	-0.1288	-0.0480	-0.0140	-0.0674
Bolton	7.71	10.38	-0.1132	-0.0184	-0.0148	-0.0784
Bournemouth	7.61	12.05	-0.0672	-0.0339	-0.0130	-0.0231
Bradford	7.53	10.50	-0.0860	-0.0107	-0.0033	-0.0703
Brighton	8.14	11.95	0.0068	-0.0295	0.0015	0.0362
Bristol	8.55	12.52	0.0343	0.0023	0.0044	0.0273
Burnley, Nelson & Colne	6.70	10.11	-0.1645	-0.0010	-0.0192	-0.1408
Calderdale	7.74	11.92	-0.0052	-0.0006	0.0096	-0.0143
Cambridge	8.80	13.53	0.0905	-0.0014	0.0170	0.0745
Cardiff	7.66	11.28	-0.0436	-0.0082	0.0018	-0.0376
Chelmsford & Braintree	7.89	11.51	-0.0317	-0.0233	-0.0112	0.0011
Cheltenham & Evesham	8.10	11.96	0.0045	-0.0060	-0.0041	0.0148
Colchester	7.64	10.47	-0.0950	-0.0573	-0.0192	-0.0176
Coventry	7.76	11.74	-0.0132	0.0055	-0.0013	-0.0155
Crawley	9.27	12.86	0.0879	0.0303	0.0040	0.0552
Darlington	7.54	10.39	-0.1149	-0.0177	-0.0135	-0.0851
Derby	7.86	12.68	-0.0003	-0.0108	0.0060	0.0034
Doncaster	6.75	10.36	-0.1494	-0.0242	-0.0177	-0.1080
Dudley & Sandwell	7.30	10.27	-0.1259	-0.0089	-0.0172	-0.0988
Dundee	7.80	11.64	-0.0480	-0.0260	0.0051	-0.0266
Edinburgh	8.41	12.92	0.0545	0.0068	0.0153	0.0311
Exeter & Newton Abbot	7.92	11.25	-0.0574	-0.0571	-0.0027	0.0010
Glasgow	7.80	11.74	-0.0435	-0.0061	-0.0025	-0.0357
Gloucester	8.05	11.98	-0.0156	-0.0059	-0.0008	-0.0100
Grimsby	7.31	10.20	-0.1352	-0.0334	-0.0170	-0.0837
Guildford & Aldershot	9.83	14.71	0.1821	0.0480	0.0216	0.1119
Hartlepool	7.02	9.06	-0.1750	-0.0540	-0.0129	-0.1058
Hastings	6.94	9.78	-0.1621	-0.0331	-0.0252	-0.1037
Huddersfield	7.67	11.01	-0.0812	-0.0325	-0.0063	-0.0423
Hull	7.26	10.80	-0.1101	-0.0395	-0.0088	-0.0608
Ipswich	7.72	11.48	-0.0681	-0.0516	-0.0076	-0.0104
Lanarkshire	7.47	11.22	-0.0672	-0.0142	-0.0042	-0.0497
Leeds	7.53	11.75	-0.0393	0.0028	-0.0033	-0.0375
Leicester	7.61	11.12	-0.0677	-0.0216	-0.0077	-0.0379
Liverpool	7.78	11.53	-0.0488	-0.0124	-0.0027	-0.0351
London	10.59	15.93	0.2393	0.0776	0.0241	0.1380
Luton & Watford	8.96	12.86	0.0470	0.0290	-0.0033	0.0196
Maidstone & North Kent	8.06	11.31	-0.0422	0.0008	-0.0143	-0.0286
Manchester	8.19	12.02	0.0124	0.0054	0.0048	0.0012
Mansfield	6.71	10.41	-0.1500	-0.0375	-0.0154	-0.0982

Middlesbrough & Stockton	7.18	10.50	-0.1312	-0.0254	-0.0143	-0.0909
Milton Keynes & Aylesbury	9.14	13.16	0.0776	0.0257	0.0068	0.0434
Newcastle & Durham	7.47	10.81	-0.0818	-0.0224	-0.0087	-0.0501
Newport & Cwmbran	7.31	10.44	-0.0921	-0.0143	-0.0112	-0.0657
Northampton & Wellingborough	7.67	11.10	-0.0470	-0.0043	-0.0066	-0.0359
Norwich	7.41	10.94	-0.0766	-0.0311	-0.0088	-0.0370
Nottingham	7.57	11.11	-0.0649	-0.0124	-0.0014	-0.0508
Oxford	8.80	12.91	0.1030	0.0129	0.0191	0.0697
Peterborough	7.69	10.93	-0.0523	-0.0135	-0.0094	-0.0301
Plymouth	6.88	10.77	-0.1082	-0.0687	-0.0105	-0.0299
Poole	8.66	11.29	-0.0297	0.0096	-0.0067	-0.0315
Portsmouth	7.94	12.21	-0.0234	-0.0107	-0.0063	-0.0061
Preston	7.73	11.56	-0.0415	-0.0259	-0.0011	-0.0159
Reading & Bracknell	9.98	15.09	0.2038	0.0527	0.0263	0.1253
Rochdale & Oldham	7.25	10.15	-0.1290	-0.0195	-0.0135	-0.0917
Sheffield & Rotherham	7.53	10.94	-0.0791	-0.0227	-0.0070	-0.0493
Southampton	8.37	12.04	0.0137	0.0004	-0.0035	0.0155
Southend & Brentwood	8.18	11.76	-0.0017	-0.0079	-0.0071	0.0135
Stevenage	9.22	12.72	0.0903	0.0131	0.0122	0.0633
Stoke-on-Trent	7.22	10.16	-0.1479	-0.0407	-0.0125	-0.0934
Sunderland	7.09	10.08	-0.1406	-0.0310	-0.0143	-0.0959
Swansea Bay	7.66	10.35	-0.0985	-0.0401	-0.0085	-0.0499
Swindon	8.47	12.12	0.0257	0.0148	0.0025	0.0090
Telford & Bridgnorth	7.08	11.08	-0.1033	-0.0322	-0.0116	-0.0599
Tunbridge Wells	8.17	12.19	-0.0065	0.0035	-0.0097	0.0010
Wakefield & Castleford	7.68	10.83	-0.0684	0.0011	-0.0085	-0.0599
Walsall & Cannock	7.26	10.44	-0.1288	-0.0278	-0.0129	-0.0862
Warrington & Wigan	7.71	11.41	-0.0655	-0.0300	-0.0050	-0.0300
Wirral & Ellesmere Port	8.00	10.54	-0.0764	-0.0267	-0.0124	-0.0361
Wolverhampton	7.40	10.15	-0.0999	-0.0215	-0.0082	-0.0686
Worcester & Malvern	7.36	10.75	-0.0871	-0.0440	-0.0041	-0.0400
Worthing	8.23	11.45	-0.0296	-0.0367	-0.0038	0.0113
Wycombe & Slough	9.74	14.15	0.1709	0.0527	0.0187	0.1002
York	7.51	11.74	-0.0668	-0.0259	-0.0104	-0.0304

Notes: Area effects, average area predicted wage based on observables and unobservable from regression of log wages on fixed effects and observables (set of age dummies and a set of 1 digit occupation dummies)

Table A4: Rural area names, mean area wages, area effects and predicted wages

Area name	Wage 1998	Wage 2008	Area average	Area effect	Predicted (observables)	Predicted (unobservables)
Andover	8.42	12.24	0.0129	-0.0133	-0.0007	0.0277
Ayr & Kilmarnock	7.49	10.53	-0.1010	-0.0403	-0.0092	-0.0506
Banbury	8.44	11.52	-0.0153	0.0107	-0.0098	-0.0152
Basingstoke	9.39	13.89	0.1484	0.0222	0.0136	0.1130
Bath	8.16	11.77	-0.0090	-0.0185	0.0047	0.0048
Brecon and South Mid Wales	7.31	9.94	-0.1592	-0.0680	-0.0181	-0.0729
Bridgend	7.07	11.04	-0.1073	-0.0187	-0.0101	-0.0792
Burton upon Trent	7.02	10.79	-0.1207	-0.0266	-0.0123	-0.0837
Canterbury	7.11	10.67	-0.0926	-0.0569	-0.0101	-0.0271
Carlisle	6.96	10.40	-0.1440	-0.0137	-0.0142	-0.1160
Chester & Flint	8.16	10.54	-0.0444	-0.0305	-0.0044	-0.0102
Chesterfield	7.25	10.34	-0.1345	-0.0351	-0.0130	-0.0836
Chichester & Bognor Regis	7.77	11.21	-0.0748	-0.0626	-0.0099	-0.0061
Crewe & Northwich	7.81	11.23	-0.0640	-0.0293	-0.0109	-0.0266
Dorset-Devon Coast	6.88	10.99	-0.1238	-0.0615	-0.0135	-0.0521
Dunfermline	7.66	11.01	-0.0941	-0.0188	-0.0060	-0.0691
East Anglia Coast - Gt Yarmouth and Lowestoft	6.69	10.38	-0.1550	-0.0569	-0.0172	-0.0806
East Anglia West - Bury and Thetford	6.94	10.60	-0.1320	-0.0492	-0.0237	-0.0602
East Cornwall	6.99	9.12	-0.2074	-0.0832	-0.0254	-0.1005
East Highlands	6.97	10.20	-0.1740	-0.0404	-0.0193	-0.1139
East Kent - Dover and Margate	7.54	10.10	-0.0947	-0.0360	-0.0153	-0.0423
East Lincolnshire	7.10	10.51	-0.1408	-0.0456	-0.0200	-0.0749
East North Yorkshire	6.46	10.43	-0.1749	-0.0631	-0.0244	-0.0884
East Somerset - Bridgwater and Wells	7.36	10.51	-0.1218	-0.0495	-0.0223	-0.0500
Eastbourne	7.29	11.25	-0.0840	-0.0523	-0.0187	-0.0134
Falkirk	7.30	10.56	-0.1011	-0.0197	-0.0095	-0.0719
Greenock, Arran and and Irvine	7.69	10.75	-0.1142	-0.0282	-0.0079	-0.0769
Harlow & Bishop's Stortford	8.84	13.28	0.0791	0.0226	0.0027	0.0530
Harrogate	7.73	11.48	-0.0611	-0.0330	-0.0031	-0.0266
Hereford & Leominster	6.95	10.14	-0.1435	-0.0541	-0.0153	-0.0744
Huntingdon	8.07	11.85	0.0039	-0.0144	0.0038	0.0149
Inverness	7.60	10.83	-0.0751	-0.0437	0.0019	-0.0375
Isle of Wight	7.18	9.99	-0.1355	-0.0687	-0.0228	-0.0428
Kendal	7.01	10.60	-0.1230	-0.0668	-0.0012	-0.0545
Kettering & Corby	7.20	9.97	-0.1262	-0.0232	-0.0244	-0.0782
Lancaster & Morecambe	7.88	11.53	-0.0581	-0.0555	-0.0053	0.0031
Livingston & Bathgate	7.04	10.78	-0.0944	-0.0033	-0.0113	-0.0834
Mid North East England	7.29	10.24	-0.1413	-0.0470	-0.0141	-0.0764
Mid Wales	6.97	10.02	-0.1627	-0.0727	-0.0215	-0.0680
Mid Wales Border	6.88	9.86	-0.1824	-0.0544	-0.0225	-0.1042
Moray Firth	7.03	10.14	-0.1696	-0.0412	-0.0176	-0.1113
Morpeth, Ashington & Alnwick	7.06	10.69	-0.1310	-0.0354	-0.0101	-0.0841
Newbury	9.36	13.84	0.1463	0.0237	0.0171	0.1079
Norfolk, Linolnshire Fens	6.57	9.38	-0.1991	-0.0469	-0.0250	-0.1278
North Cumbria	6.30	9.53	-0.2177	-0.0802	-0.0281	-0.1097
North Devon	6.67	10.63	-0.1707	-0.0632	-0.0253	-0.0829
North Firth of Forth	7.48	10.84	-0.1025	-0.0069	-0.0148	-0.0819
North Norfolk	7.12	9.76	-0.1585	-0.0491	-0.0268	-0.0815
North Scotland	7.70	11.71	-0.0676	0.0049	-0.0092	-0.0633
North Solway Firth	6.72	10.69	-0.1326	-0.0170	-0.0158	-0.1023

North Wales Coast	6.89	10.39	-0.1494	-0.0538	-0.0164	-0.0806
North West Devon	6.45	9.55	-0.2410	-0.0805	-0.0371	-0.1244
North West Wales	7.12	10.20	-0.1164	-0.0141	-0.0150	-0.0898
Perth & Blairgowrie	7.20	10.71	-0.1124	-0.0035	-0.0116	-0.1005
Rugby	7.87	11.67	-0.0042	-0.0023	-0.0099	0.0059
Salisbury, Shaftesbury and Blandford	7.23	11.44	-0.0938	-0.0243	-0.0088	-0.0632
Scarborough, Bridlington and Driffield	6.81	9.22	-0.1899	-0.0598	-0.0267	-0.1030
Scottish Borders	7.04	10.19	-0.1721	-0.0261	-0.0154	-0.1304
Scunthorpe	7.49	10.38	-0.1207	-0.0377	-0.0059	-0.0748
Shrewsbury	7.09	10.83	-0.1049	-0.0403	-0.0141	-0.0517
South Cumbria	7.88	12.00	0.0094	-0.0194	0.0069	0.0231
South Devon	6.38	9.90	-0.2093	-0.0757	-0.0331	-0.1021
South Wales Border	6.84	10.30	-0.1433	-0.0307	-0.0129	-0.0959
South West Wales	7.17	10.63	-0.1535	-0.0797	-0.0133	-0.0626
Stafford	7.42	11.62	-0.0323	-0.0410	0.0048	0.0035
Stirling & Alloa	7.45	11.06	-0.0767	0.0077	-0.0041	-0.0805
Taunton	7.62	11.02	-0.0800	-0.0644	-0.0101	-0.0082
Trowbridge & Warminster	7.21	11.48	-0.1004	-0.0204	-0.0178	-0.0611
Warwick & Stratford-upon-Avon	8.62	13.05	0.0425	-0.0152	0.0107	0.0456
West Cornwall	6.33	10.27	-0.1869	-0.0771	-0.0154	-0.0950
West Kent - Ashford and Folkestone	7.78	10.87	-0.0841	-0.0230	-0.0200	-0.0403
West Lincolnshire	6.94	9.72	-0.1945	-0.0504	-0.0260	-0.1163
West North Yorkshire	6.91	10.17	-0.1546	-0.0191	-0.0206	-0.1138
West Peak District - Matlock and Buxton	6.89	10.82	-0.0955	-0.0496	-0.0077	-0.0384
Western Highlands	6.86	10.74	-0.1114	-0.0371	-0.0152	-0.0588
Worksop & Retford	7.23	10.00	-0.1359	-0.0197	-0.0176	-0.0956
Wrexham & Whitchurch	7.30	10.36	-0.1193	-0.0464	-0.0149	-0.0573
Yeovil & Chard	7.53	10.89	-0.0693	-0.0517	-0.0037	-0.0131

Notes: Area effects, average area predicted wage based on observables and unobservable from regression of log wages on fixed effects and observables (set of age dummies and a set of 1 digit occupation dummies)

Table A5. Areas with highest and lowest wages and area effects

Top 10 area averages (with 2008 wages)		Top 10 area effects	
London	22.6%	London	7.8%
Reading & Bracknell	19.1%	Wycombe & Slough	5.3%
Guildford & Aldershot	17.0%	Reading & Bracknell	5.3%
Wycombe & Slough	16.1%	Guildford & Aldershot	4.8%
Basingstoke	13.9%	Crawley	3.0%
Newbury	14.0%	Luton & Watford	2.9%
Oxford	9.9%	Milton Keynes & Aylesbury	2.6%
Cambridge	8.7%	Newbury	2.4%
Stevenage	9.1%	Harlow & Bishop's Stortford	2.3%
Crawley	9.0%	Basingstoke	2.2%
Bottom 10, 1998			
Hartlepool	-17.5%	Brecon and South Mid Wales	-6.8%
Mid Wales Border	-18.2%	Isle of Wight	-6.9%
West Cornwall	-18.7%	Plymouth	-6.9%
Scarborough, Bridlington and Driffield	-19.0%	Mid Wales	-7.3%
West Lincolnshire	-19.5%	South Devon	-7.6%
Norfolk, Linolnshire Fens	-19.9%	West Cornwall	-7.7%
East Cornwall	-20.7%	South West Wales	-8.0%
South Devon	-20.9%	North Cumbria	-8.0%
North Cumbria	-21.8%	North West Devon	-8.1%
North West Devon	-24.1%	East Cornwall	-8.3%

Notes: Area averages for 1998-2008 and area effects from regression of log wages on area effects, individual effects and observables (set of age dummies and a set of 1 digit occupation dummies) reported as percentage above or below reference area (Southampton, ranked 19th for area averages and 28th)

3 Geographical units

The figures show the 157 geographical units (aggregations of TTWAs) that we use in our analysis

Rural TTWA aggregates

Primary urban TTWAs

4 Rural versus urban

Table A.6 shows results from regressions of wage on individual characteristics for the urban and rural areas separately, and for all areas pooled. Results are for a specification that includes a dummy for gender, a set of dummies for age, and for one digit occupation. The coefficients and standard errors suggest there are differences between the samples.

Table A.6: Wage regressions for urban, rural and all areas.

Variables	Urban		Rural		All	
Female	-0.1458	(0.0007)***	-0.1581	(0.0013)***	-0.1480	(0.0006)***
Age group 2	0.1465	(0.0018)***	0.1243	(0.0034)***	0.1419	(0.0016)***
Age group 3	0.2754	(0.0017)***	0.2317	(0.0033)***	0.2669	(0.0015)***
Age group 4	0.3487	(0.0017)***	0.2959	(0.0032)***	0.3385	(0.0015)***
Age group 5	0.3749	(0.0017)***	0.3239	(0.0032)***	0.3648	(0.0015)***
Age group 6	0.3800	(0.0017)***	0.3357	(0.0032)***	0.3712	(0.0015)***
Age group 7	0.3807	(0.0017)***	0.3387	(0.0032)***	0.3722	(0.0015)***
Age group 8	0.3615	(0.0017)***	0.3238	(0.0032)***	0.3539	(0.0015)***
Age group 9	0.3192	(0.0018)***	0.2848	(0.0034)***	0.3125	(0.0016)***
Age group 10	0.2530	(0.0023)***	0.2201	(0.0040)***	0.2466	(0.0020)***
Occupations (rev. 1990)						
Professional	0.1501	(0.0020)***	0.2309	(0.0041)***	0.1639	(0.0018)***
Technical	-0.1428	(0.0021)***	-0.1186	(0.0043)***	-0.1393	(0.0019)***
Administrative	-0.5256	(0.0018)***	-0.4871	(0.0036)***	-0.5198	(0.0016)***
Skilled trades	-0.5350	(0.0022)***	-0.5082	(0.0041)***	-0.5318	(0.0019)***
Personal Services	-0.6540	(0.0021)***	-0.5924	(0.0040)***	-0.6436	(0.0019)***
Sales	-0.7160	(0.0022)***	-0.6615	(0.0044)***	-0.7074	(0.0020)***
Manufacturing	-0.6744	(0.0021)***	-0.6119	(0.0039)***	-0.6630	(0.0019)***
Elementary	-0.8423	(0.0023)***	-0.7578	(0.0042)***	-0.8261	(0.0020)***
Occupations (rev. 2003)						
Professional	0.1074	(0.0015)***	0.2145	(0.0031)***	0.1257	(0.0014)***
Technical	-0.2187	(0.0015)***	-0.1472	(0.0030)***	-0.2068	(0.0013)***
Administrative	-0.5050	(0.0014)***	-0.4411	(0.0029)***	-0.4947	(0.0013)***
Skilled trades	-0.5586	(0.0018)***	-0.4946	(0.0033)***	-0.5483	(0.0016)***
Personal Services	-0.6924	(0.0019)***	-0.5941	(0.0033)***	-0.6745	(0.0016)***
Sales	-0.7928	(0.0017)***	-0.7091	(0.0033)***	-0.7788	(0.0015)***
Manufacturing	-0.7031	(0.0018)***	-0.6123	(0.0032)***	-0.6864	(0.0016)***
Elementary	-0.8358	(0.0015)***	-0.7155	(0.0029)***	-0.8129	(0.0014)***
Constant	2.1569	(0.0022)***	2.0702	(0.0043)***	2.1412	(0.0019)***
Observations	1208698		302174		1510872	
R-squared	0.595		0.587		0.596	

Notes: Results for urban, rural and pooled sample based on classification described in the text.

Looking at the results, we see that women are paid less than men in all areas, but that the effect is slightly more pronounced in urban areas. The coefficients on the age group dummies report the effect of age on wages relative to the omitted category (age 16-20). They show that in both urban and rural areas, wages rise with age until workers reach their 40s and then decline but that the effect of age is slightly more pronounced in urban than in rural areas. The coefficients on occupations also give the effect relative to the omitted category (managers and senior officials). As explained in the text, the classification in the data changes over time, although they are fairly comparable at the one digit level we use here. The pattern of coefficients show that in both rural and urban areas professional occupations pay a premium relative to managerial occupations (the positive coefficient on the professional dummy) but that managerial occupations pay a premium relative to the remaining categories (the negative coefficients on the other occupations). The professional occupation premium is more pronounced in rural areas (the coefficient on the professional dummy is larger) but managerial premium is lower (the negative coefficients on the other occupations are smaller). Explaining these differences is beyond the scope of this paper, but we do take them in to account by allowing the effect of individual observables to differ between the two different samples in the results reported in the text.

As described in the text, our classification of areas in to rural and urban was based on the urban footprint of primary urban areas and sample sizes in our data set (with any area with a large enough sample being classified as non-primary urban). With the data available, sample size restrictions prevent us from using smaller areas (we are already forced to aggregate up smaller TTWA as described in the text). We are, however, able to consider differences between rural and urban postcodes locations within our 157 labour market areas. To do this, we can run the same regression as above, but include a rural dummy. That is:

$$\ln(w_i) = \alpha + x_i^{'}\beta + d_i^{'}\delta + \gamma\theta_{rural} + \varepsilon_i$$

where theta is a dummy variable that takes value 1 when the worker works in a rural postcode (defined according to whether the postcode is part of a settlement with more or less than 10,000 people). This classification is based on the ONS rural/urban definition introduced in 2004. The definition is based on a settlement based approach and comprises four settlement types (urban; town and fringe; village; hamlet and isolated dwelling). To ensure sufficient sample sizes we aggregate the three rural settlement types and define rural locations as any location not classified as urban.

If we do not include area effects or any individual characteristics, the coefficient on theta (the rural dummy) tells us how much lower wages are for workers in rural postcodes. When we control for individual characteristics, we can see whether this effect is due to the sorting of workers between rural and urban postcodes. Including area dummies for our 157 areas tells us about the effect of working in a rural postcode compared to “nearby” urban postcodes (e.g. the effect of working in a rural location in North Cornwall, relative to working in an urban location in North Cornwall). Table

A.7 reports results for various specifications. The first column reports the raw effects without controlling for individual characteristics, the second and third column add individual characteristics (as in the text), while the fourth to sixth columns add individual fixed effects (again, as in the text). The final three columns drop individual fixed effects, but include area effects (for the 157 aggregations of TTWA).

Reading across the table we see that the raw urban-rural premium is 8.4%. This is slightly higher than the 6.5% urban-rural area premium reported in the first row of Table 6 in the main text. In terms of simple averages, urban-rural location matters slightly more for wages than the urban-rural area classification used in the text. Controlling for basic observable characteristics of individuals nearly halves the estimate to 4.5%, broadly in line with the 4.2% urban-rural area premium reported in the second column of Table 6 in the main text. This again demonstrates the importance of sorting on observable characteristics. Allowing for unobserved individual characteristics reduces the premium further with our lowest estimate on the basis of controlling for observed and unobserved individual characteristics suggesting an urban-rural postcode premium of 1.5%, now slightly lower than the 2.4% for the urban-rural area difference reported in the fifth row of Table 6. The fact that the premium for an urban postcode falls further than that for the urban area premium (from 8.4% to 1.5% compared to 6.5% to 2.4%) suggests that sorting plays slightly more of a role in explaining the lower wages paid in urban postcodes. The final three columns show that this effect is reduced further once we allow for the fact that urban areas pay a 2.4% premium over rural areas. Controlling for observed individual characteristics and area effects (but not individual unobserved characteristics) we estimate an urban location premium of 0.6 of a percentage point. That is, jobs in rural postcodes pay only 0.6% less than *nearby* urban postcodes within the same labour market area. We would expect these effects to be even smaller if we controlled for unobserved individual characteristics (which we cannot do due to computational limitations). We conclude that focusing on 157 labour market areas does not disguise large disparities between urban and rural locations within these labour market areas .

Table A.7: Coefficient on rural dummy (various specifications)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
rural10k	-0.0842***	-0.0620***	-0.0454***	-0.0198***	-0.0189***	-0.0154***	-0.0191***	-0.0190***	-0.0062***
	0.0012	0.0008	0.0007	0.0009	0.0009	0.0008	0.0012	0.0008	0.0008

Notes: Reports coefficient and standard error on rural dummy for 9 specifications. Specification (1) includes only year dummies; (2) adds age, gender, 1 digit occupation to (1); (3) adds age, gender, 2 digit occupation, 3 digit sic, and dummies for public sector, collective agreement and part time workers to (1); (4) includes only year dummies and individual fixed effects; (5) adds age and 1 digit occupation to (4); (6) adds dummies for public sector, collective agreement and part time workers to (5); (7) includes year dummies, individual fixed affects and area dummies; (8) adds age, gender, 1 digit occupation to (7); (9) adds dummies for public sector, collective agreement and part time workers to (8)

5 Notes on variance decomposition in the context of area effects

5.1 Introduction

Consider the linear regression model for log wages $\ln w_i$

$$\ln w_i = x_i'\beta + d_i'\delta + \varepsilon_i \qquad (1)$$

where x_i are individual characteristics and $d_i'\delta$ is an "area effect" in which d_i is a J x 1 column vector of J area dummies, and δ is a J x 1 vector of parameters. Our aim is to find the contribution of $d_i'\delta$ to the total variance of $\ln w_i$.

Note that

$$\begin{aligned} Var\left(\ln w_i\right) &= Var\left(x_i'\hat{\beta} + d_i'\hat{\delta} + \hat{\varepsilon}_i\right) \\ &= Var\left(x_i'\hat{\beta}\right) + Var\left(d_i'\hat{\delta}\right) + 2Cov\left(x_i'\hat{\beta}, d_i'\hat{\delta}\right) + Var\left(\hat{\varepsilon}_i\right) \end{aligned} \qquad (2)$$

where $Var(.)$ is taken to mean the sample variance and $\hat{\varepsilon}$ is the residual. Alternatively,

$$\frac{Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} + \frac{Var\left(d_i'\hat{\delta}\right)}{Var\left(\ln w_i\right)} + \frac{2Cov\left(x_i'\hat{\beta}, d_i'\hat{\delta}\right)}{Var\left(\ln w_i\right)} + \frac{Var\left(\hat{\varepsilon}_i\right)}{Var\left(\ln w_i\right)} = 1 \qquad (3)$$

and

$$\frac{Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} + \frac{Var\left(d_i'\hat{\delta}\right)}{Var\left(\ln w_i\right)} + \frac{2Cov\left(x_i'\hat{\beta}, d_i'\hat{\delta}\right)}{Var\left(\ln w_i\right)} = R^2\left(\ln w_i; x'\beta_i, d_i'\delta\right) \qquad (4)$$

Here the notation $R^2\left(\ln w_i; x'\hat{\beta}_i, d_i'\hat{\delta}\right)$ means the R-squared from a regression of y_i on x_i and d_i

Consider now some ways to decompose $Var\left(\ln w_i\right)$ into components attributable to x_i and d_i

5.2 Method A. Uncorrelated Variance Share

The following methods give the same result which we refer to in the main text as the *uncorrelated variance share*. This is sometimes referred to as the semi-partial R-squared and by Borcard (2002) as "Fraction a" partitioning:

a) R-squared method:

(i) Regress y_i on x_i and d_i to get $R^2\left(\ln w_i; x'\hat{\beta}_i, d_i'\hat{\delta}\right)$

(ii) Regress y_i on x_i and get $R^2\left(\ln w_i; x_i'\hat{\beta}\right)$

(iii) Calculate $R^2\left(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}\right) - R^2\left(\ln w_i; x_i'\hat{\beta}\right)$

b) Note that $R^2\left(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}\right) - R^2\left(\ln w_i; x_i'\hat{\beta}\right) = \dfrac{RSS\left(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}\right) - RSS\left(\ln w_i; x_i'\hat{\beta}\right)}{TSS\left(\ln w_i\right)}$ in which RSS is Regression Sum of Squares and TSS is the total sum of squares. The numerator in this expression is the Partial Sum of Squares of d. All these sums of squares are routinely computed by standard ANOVA software

c) Partitioned regression:

(i) Regress $\ln w_i$ on x_i and d_i and predict $d_i'\hat{\delta}$ and $x_i'\hat{\beta}$

(ii) Regress predicted $d_i'\hat{\delta}$ on $x_i'\hat{\beta}$ and obtain the residual $\hat{u}_i = d_i'\hat{\delta} - \hat{\theta}x_i'\hat{\beta}$

(iii) Regress y_i on the residual $\hat{u}_i$ from (ii) and look at the R-squared $R^2\left(\ln w_i; \hat{u}_i\right)$ or simply square the Pearson correlation coefficient of $\ln w_i$ and $\hat{u}_i$

Proof that a) and c) are equivalent (b, follows by definition of the Partial Sum of Squares):

Let sample regression of $d_i'\hat{\delta}$ on $x_i'\hat{\beta}$ be

$$d_i'\hat{\delta} = \hat{\theta}x_i'\hat{\beta} + \hat{u}_i \tag{5}$$

Which implies, from (1)

$$\ln w_i = x_i'\hat{\beta} + \hat{\theta}x_i'\hat{\beta} + \hat{u}_i + \hat{\varepsilon}_i \tag{6}$$

From (4) and (5)

$$\begin{aligned} R^2\left(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}\right) &= \frac{Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} + \frac{Var\left(d_i'\hat{\delta}\right)}{Var\left(\ln w_i\right)} + \frac{2Cov\left(x_i'\hat{\beta}, d_i'\hat{\delta}\right)}{Var\left(\ln w_i\right)} \\ &= \frac{Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} + \frac{Var\left(d_i'\hat{\delta}\right)}{Var\left(\ln w_i\right)} + \frac{2\hat{\theta}Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} \end{aligned} \tag{7}$$

Now, from equation (6),

$$R^2\left(\ln w_i; x_i'\hat{\beta}\right) = \frac{Var\left(\left(1+\hat{\theta}\right)x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} = \frac{\left(1+2\hat{\theta}+\hat{\theta}^2\right)Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} \tag{8}$$

So from (7) and (8) we have:

$$R^2\left(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}\right) - R^2\left(\ln w_i; x_i'\hat{\beta}\right) = \frac{Var\left(d_i'\hat{\delta}\right) - \hat{\theta}^2 Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} \tag{9}$$

Now in Method A c) (iii)

$$R^2\left(\ln w_i; \hat{u}_i\right) = \frac{Var\left(\hat{u}_i\right)}{Var\left(\ln w_i\right)} \tag{10}$$

Where the numerator is

$$\begin{aligned} Var\left(\hat{u}_i\right) &= Var\left(d_i'\hat{\delta}\right) + \hat{\theta}^2 Var\left(x_i'\hat{\beta}\right) - 2Cov\left(\hat{\theta}x_i'\hat{\beta}, d_i'\hat{\delta}\right) \\ &= Var\left(d_i'\hat{\delta}\right) + \hat{\theta}^2 Var\left(x_i'\hat{\beta}\right) - 2Var\left(\hat{\theta}x_i'\hat{\beta}\right) \\ &= Var\left(d_i'\hat{\delta}\right) - \hat{\theta}^2 Var\left(x_i'\hat{\beta}\right) \end{aligned} \tag{11}$$

Hence from (9)-(11) the uncorrelated variance share is:

$$R^2\left(\ln w_i; \hat{u}\right) = R^2\left(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}\right) - R^2\left(\ln w_i; x_i'\hat{\beta}\right) = \frac{Var\left(d_i'\hat{\delta}\right) - \hat{\theta}^2 Var\left(x_i'\hat{\beta}\right)}{Var\left(\ln w_i\right)} \tag{12}$$

And so the Method A c) and A a) are equivalent.

All of these methods consider only the component of the area effect $d_i'\delta$ that is orthogonal to (uncorrelated with) individual characteristics x_i (e.g. if London is has a high wage effect and high skills, then the correlation of the area effect with individual skills is partialled out).

Note, for comparison, another similar measure is the 'partial R-squared'. This measures the share of the components of area effects that are uncorrelated with x_i, in the components of $\ln w_i$ that are uncorrelated with x_i. The partial R-squared is:

$$\frac{R^2(\ln w;\hat{u})}{1-R^2\left(\ln w_i;x_i'\hat{\beta}\right)}=\frac{R^2\left(\ln w_i;x_i'\hat{\beta},d_i'\hat{\delta}\right)-R^2\left(\ln w_i;x_i'\hat{\beta}\right)}{1-R^2\left(\ln w_i;x_i'\hat{\beta}\right)}$$

Note too the following decomposition of $\ln w_i$ into orthogonal (uncorrelated) components applies:

Define

$$R^2(\ln w_i;\hat{u}_i)=R^2\left(\ln w_i;x_i'\hat{\beta},d_i'\hat{\delta}\right)-R^2\left(\ln w_i;x_i'\hat{\beta}\right)$$
$$R^2(\ln w_i;\hat{v}_i)=R^2\left(\ln w_i;x_i'\hat{\beta},d_i'\hat{\delta}\right)-R^2\left(\ln w_i;d_i'\hat{\delta}\right)$$
$$R^2\left(\ln w_i;\tilde{x}_i'\beta,\tilde{d}_i'\delta\right)=R^2\left(\ln w_i;x_i'\hat{\beta},d_i'\hat{\delta}\right)-R^2(\ln w_i;\hat{u}_i)-R^2(\ln w_i;\hat{v}_i)$$

Then

$$R^2\left(\ln w_i;x_i'\hat{\beta},d_i'\hat{\delta}\right)=R^2(\ln w_i;\hat{u}_i)+R^2(\ln w_i;\hat{v}_i)+R^2\left(\ln w_i;\tilde{x}_i'\beta,\tilde{d}_i'\delta\right)$$

and

$$R^2(\ln w_i;\hat{u}_i)+R^2(\ln w_i;\hat{v}_i)+R^2\left(\ln w_i;\tilde{x}_i'\beta,\tilde{d}_i'\delta\right)+\frac{Var(\hat{\varepsilon}_i)}{Var(\ln w_i)}=1$$

5.3 Method B: Correlated variance share

From the decomposition in (3) an alternative estimate of share of the variance attributable to $d_i'\delta$ is simply.

$$\frac{Var\left(d_i'\hat{\delta}\right)}{Var(\ln w_i)} \tag{13}$$

We refer to this ratio as the correlated variance share. Comparing the numerators in the uncorrelated variance share in (11) and correlated variance share in (13) we see

$$\begin{gathered}Var\left(d_i'\hat{\delta}\right)\geq Var\left(d_i'\hat{\delta}\right)-\hat{\theta}^2 Var\left(x_i'\hat{\beta}\right)\\ \Rightarrow\\ \frac{Var\left(d_i'\hat{\delta}\right)}{Var(\ln w_i)}\geq R^2(\ln w_i;\hat{u}_i)\end{gathered} \tag{14}$$

With equality if $d_i'\hat{\delta}$ is uncorrelated with $x_i'\hat{\beta}$.

Therefore the correlated variance share from Method B yields an answer for the contribution of $d_i'\delta$ that is bigger than that obtained by the uncorrelated variance share in Method A.

5.4 Method C: Standard deviations × correlation

Another method has been used in some previous studies e.g. Borcard (2002) Method 1 and Combes, Duranton Gobillon (2008).

Note that, if $s.d.(.)$ $r(.)$ are the sample standard deviation and Pearson correlation coefficient

$$\begin{aligned}
&\frac{s.d.\left(x_i'\hat{\beta}\right)}{s.d.(\ln w_i)} r\left(\ln w_i, x_i'\hat{\beta}\right) + \frac{s.d.\left(d_i'\hat{\delta}\right)}{s.d.(\ln w_i)} r\left(\ln w_i, d_i'\hat{\delta}\right) \\
&= \frac{Cov\left(\ln w_i, x_i'\hat{\beta}\right)}{Var(\ln w_i)} + \frac{Cov\left(\ln w_i, d_i'\hat{\delta}\right)}{Var(\ln w_i)} \\
&= \frac{Var\left(x_i'\hat{\beta}\right)}{Var(\ln w_i)} + \frac{Var\left(d_i'\hat{\delta}\right)}{Var(\ln w_i)} + \frac{2Cov\left(x_i'\hat{\beta}, d_i'\hat{\delta}\right)}{Var(\ln w_i)} \\
&= R^2\left(\ln w_i; x_i'\hat{\beta}, d_i'\hat{\delta}\right)
\end{aligned} \tag{13}$$

Hence

$$\frac{s.d.\left(d_i'\hat{\delta}\right)}{s.d.(\ln w_i)} r\left(\ln w_i, d_i'\hat{\delta}\right) = \frac{Cov\left(\ln w_i, x_i'\hat{\beta}\right)}{Var(\ln w_i)} = \frac{Var\left(d_i'\hat{\delta}\right) + Cov\left(x_i'\hat{\beta}, d_i'\hat{\delta}\right)}{Var(\ln w_i)} \tag{14}$$

Provides yet another possible measure of the share attributable to $d_i'\delta$

Inspection of the share in Method C (14) and Method B (11) shows that Method C simply adds $Cov\left(x_i'\beta, d_i'\delta\right)$ to the correlated variance share. Hence, with positive covariance between x_i and $d_i'\delta$, Method C must give you a bigger number than the correlated variance share for the partial contribution of $d_i'\delta$. All methods give the same result if x_i and $d_i'\delta$ are uncorrelated.

<u>Extension to individual and area fixed effects</u>

All the methods can be extended to allow for multiple groups of effects η_f.

$$\ln w_i = \sum_f \eta_{fi} + \varepsilon_i$$

Then the uncorrelated variance shares (semi-partial R^2) are $R^2\left(\ln w_i;\hat{\eta}_{\sim fi},\hat{\eta}_{fi}\right)-R^2\left(\ln w_i;\hat{\eta}_{\sim fi}\right)$ and

$$\left\{\sum_f\left[R^2\left(\ln w_i;\hat{\eta}_{\sim fi},\hat{\eta}_{fi}\right)-R^2\left(\ln w_i;\hat{\eta}_{\sim fi}\right)\right]\right\}+\left\{R^2\left(\ln w_i;\hat{\eta}_{\sim fi},\hat{\eta}_{fi}\right)-\sum_f R^2\left(\ln w_i;\hat{\eta}_{\sim fi}\right)\right\}+\frac{Var\left(\hat{\varepsilon}_i\right)}{Var\left(\ln w_i\right)}=1$$

Here, the notation $\hat{\eta}_{\sim fi}$ means all η effects not including η_{fi}.

For the correlated variance shares $\frac{Var\left(\hat{\eta}_{fi}\right)}{Var\left(\ln w_i\right)}$:

$$\sum_f\frac{Var\left(\hat{\eta}_{fi}\right)}{Var\left(\ln w_i\right)}+\sum_f\sum_g\frac{Cov\left(\hat{\eta}_{fi},\hat{\eta}_{gi}\right)}{Var\left(\ln w_i\right)}+\frac{Var\left(\hat{\varepsilon}_i\right)}{Var\left(\ln w_i\right)}=1$$

The stata routine a2reg for two way fixed effects (Ouazad 2008) is useful for practical implementation and is based on Abowd, Creecy and Kramarz (2002) http://courses.cit.cornell.edu/jma7/abowd-creecy-kramarz-computation.pdf)

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