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Wage effects from changes in local human capital in Britain

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Wage effects from changes in local human capital in Britain

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ABSTRACT: This paper examines the impact of local human capital on individuals' wages through external effects. Employing wage regressions, it is found that changes in individuals' wages are positively associated with changes in the shares of high-paid occupation workers in the British travel-to-work-areas for the late 1990s. I examine this positive association for different occupational groups (defined by pay) in order to disentangle between production function and consumer demand driven theoretical explanations. The wage effect is found to be stronger and significant for the bottom-paid occupational quintile compared to the middle-paid ones, and using also sectoral controls the paper argues to provide evidence for the existence of consumer demand effects.

Keywords: local labour markets; wages; consumer demand; human capital externalities

JEL Classifications: J21; J24; J31; R23; R12

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1. Introduction

Following stable wage structures for most of the 20th Century, earnings inequality in many Western economies started to rise from the mid-1970s onwards and drew the attention of researchers and policy makers. Most economists favoured an explanation along the lines of 'skill-biased technological change' (SBTC) in order to account for the rise in inequality. According to this, technological growth has favoured skilled workers, increasing their productivity and earnings (for reviews see Katz and Autor, 1999; Machin, 2008, Van Reenen, 2011).

Although SBTC might be able to explain the processes at the upper-tail of the wage distribution, recently economists started to challenge its capacity to adequately account for the processes at the lower tail of the wage distribution. In particular, they document trends of rising job polarisation in UK and US that the SBTC explanation would fail to predict (Goos and Manning, 2007; Autor et al. 2006, 2008). Instead, they point to the uneven impact of technological change that can substitute for human labour in routine tasks but not in non-routine tasks that are increasingly found in the upper and lower tail of the skill distribution (following Autor et al. 2003 routinisation hypothesis).

However, most of these accounts on polarisation do not have a specific spatial element[1], as they lie on a solely technological explanation. Recently it has been argued that polarisation can get a spatially differentiated pattern and empirical evidence for the British regions has shown London to be unique in terms of the

[1] The exception is the study of Autor and Dorn (2010) on polarisation in the US commuting zones.

magnitude of its employment polarisation (Kaplanis, 2007). Therefore this paper examines a relatively less researched explanation that is based on a consumer demand mechanism and has spatial considerations.

In brief, the suggested consumer demand mechanism is the following. There is a growing high-skill workforce residing in the cities that takes advantage both of the high-rewarded and specialised employment opportunities in the new growth sectors and the urban amenities offered in the cities. The rise of this high-skill workforce employed mainly in financial and business services induces further growth of consumption amenities and services through increased spending. A significant proportion of these services refer to the low-pay sector and notable examples are cleaning, security, restaurant and bar services as well as the retail sector. As they are also non-traded, they have to be produced and consumed locally and this implies physical proximity of the high-income workforce and the low-paid service workers.

This mechanism has the potential to generate spatially differentiated patterns of polarisation when there is a spatial sorting of high-skilled workers. Given an upward sloping supply curve, the increased demand for these local low-skill service jobs should be reflected in wage growth for the respective low-skill service workers in the local areas with growing shares of high-skill workforce[2]. Therefore the empirical analysis attempts to shed some light on this hypothesis for Britain by examining the wage effects from changes in the local human capital (measured by occupational

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[2] The positive shift of the labour demand for low-skilled workers should also have employment effects. Kaplanis (2010) applies a probit model to LFS microdata in order to examine how the employment probability of otherwise similar individuals is associated with changes in the share of degree holders in the local area.

composition) and particularly the differential effect on the wages of low-skill service jobs.

Besides consumer demand, these wage effects can arise alternatively from production side mechanisms like production complementarities and wider productivity spillovers. The former refer to productivity increases due to imperfect substitutability between low and high-skilled workers; the latter to human capital externalities through face-to-face interaction with high-skilled workers and knowledge spillovers. There is a well established literature on human capital externalities and agglomeration economies that is relevant to this analysis (Marshall, 1890; Lucas, 1988; Glaeser, 1999; Acemoglu and Angrist, 2000; Rosenthal and Strange, 2004; Moretti, 2004).

Using British data for the period 1997-2001, a scatter plot shows a strong positive association between the share of high-skilled workers in a travel-to-work-area and the average real hourly wage (excluding the high-skilled) (Figure 1). This is not surprising and the positive relationship can be attributed to various roots including worker characteristics (i.e. more productive workers) and area specific characteristics (like industrial mix, urban status and historical reasons), as well as reverse causality. Controlling for observed personal characteristics of the area’s population but also for some unobserved individual and area heterogeneity, this paper uses wage regressions in order to examine if there still remains a positive relationship between wages and shares of high-skilled workers in an area.

Specifically, employing wage regressions for the period 1997-2001, I examine how individual’s wages are affected by changes in the employment share of high-paid occupation groups in the British travel-to-work-areas (TTWAs). Splitting the sample to different occupational quintiles defined by pay, the differential wage impact found for each of these quintiles is used to shed light on the possible underlying causes: consumer demand and production side related ones. Different econometric specifications are employed to try to aid identification. Amongst others, I control for within-industry effects and also apply the analysis for a subset of low-pay occupations that can be closely associated with consumer demand effects.

The following section 2 provides a brief overview of the literature and the theoretical framework. Section 3 explains the data, the spatial level of the analysis and the empirical strategy that is employed. Section 4 presents the samples used and the empirical results. The last section 5 sums up the findings and concludes.

2. Theoretical Framework and Literature Review [3]

2.1. Consumer demand explanation

Let's first see the working hypothesis for the consumer demand mechanism. According to this hypothesis, cities have complementarities with high-skilled workers and increasing returns to human capital or local urban amenities might lure growing numbers of high-skilled workers to cities. The growing numbers of high-skilled workers in cities can induce further growth of consumption amenities and services through their spending. High-income, high educated workers spend more (in absolute

[3] A more extended discussion of the theoretical framework and the relevant literature is available in Kaplanis (2009).

and relative terms), compared to the other income and education groups, for services that are income and education elastic, like some leisure activities and personal services (as in Clark, 1957; Leonardi, 2008). Examples can be spending on restaurants and bars as well as care, cleaning and security.

Most of these services refer to the low-pay sector of the economy. As these services are labour intensive and technology cannot easily substitute for human labour in their performance, there will be increased demand for the relevant low-skill service occupations[4]. Furthermore, as they are non-traded, they need to be produced and consumed locally and this requires physical proximity of the high-income workforce and the low-paid service workers. Therefore, this consumer demand mechanism has the potential to create polarisation outcomes that differ across urban areas depending on the growth of the high-skilled individuals. It may be expected that urban areas or city regions with faster growing shares of high-skilled individuals will experience greater polarisation.

Albeit within different contexts, accounts relevant to the consumer demand story have been extensively analysed in the urban economics literature (Glaeser et al. 2001; Glaeser and Saiz, 2004; Shapiro, 2006). In their discussion of ‘consumer city’, Glaeser et al. (2001) argue that cities offer urban amenities and consumption opportunities that enabled them to sustain and increase their population and workforce giving rise to the recent urban resurgence. Urban amenities are vital to attracting high skill labour that in turn fosters the economic success of cities and thus may benefit the poorer city residents as well. At the same time, empirical evidence from the US shows

[4] See relevantly Baumol’s (1967) discussion of the “technologically non-progressive” sectors. More recently, Autor et al. (2003) and Goos and Manning (2007) have examined technology’s inability to perform non-routine tasks, that are not only found in high-skill jobs but also in low-skill manual jobs.

that high skill individuals are more likely to make use of the urban amenities and go to a performance or dine outside at a restaurant (Glaeser and Gottlieb, 2006). Consequently, restaurants, theatres and other consumption amenities tend to proliferate in cities with higher shares of educated residents. Shapiro (2006) showed that cities with higher human capital experienced higher growth of restaurants per capita in US in the nineties.

Important contributions to this direction have been offered by researchers in the urban sociology and geography disciplines that have theorised the transformation of cities by the growth of financial services and the new economy in the recent era of increased capital mobility and intensified competition (Friedman and Wolf, 1982; Mollenkopf and Castells, 1991; Sassen, 2001; Perrons, 2004). According to Sassen's original contribution, these new growth sectors with their soared profits concentrate in global cities which are the strategic sites for the location of global command functions because of the available infrastructure and facilities. The consequent expansion of high-income workforce in the cities has led to "high income residential and commercial gentrification [that] is labor intensive and raises the demand for maintenance, cleaning, delivery, and other types of low-wage workers" (2001, p.286).

There have also been recently contributions by economists along similar lines that offer empirical evidence for US. Manning (2004) and Mazzolari and Ragusa (2007) theoretical accounts lie on the outsourcing of non-traded housework activities by the high-skilled that generates increased demand for low-skilled workers in the home services sector. Specifically, Manning (2004) presents empirical evidence for US that cities with higher shares of college graduates have increased employment rate of low-skill workers. This effect declines for the medium-skill groups and disappears for the high-skilled ones. Higher shares of college graduates in a city increase employment of the low-skilled in the non-traded sector while decrease low-skill employment in the traded sector. This pattern is not documented for the other skill groups.

Mazzolari and Ragusa (2007) use US consumer expenditure data to demonstrate that richer or more educated households spend a larger part of their budget share on home services. Employing a panel of US cities they find evidence of a positive association between growth of relative wages at the bottom and the top of the distribution. This association increases with larger shares of low-wage workers employed in home services but not affected by larger shares of low-wage workers in the broader non-traded sector. As it also not affected by larger shares of college graduates in the city, they interpret this as evidence against the existence of human capital externalities or production complementarities as alternative accounts.

2.2. Production function explanations

Let's now consider the alternative explanations to the consumer demand story that are production related and can give rise to wage effects. These can be distinguished to human capital externalities and production complementarities between low skill and high skill workers.

There is an extensive literature on human capital externalities and therefore the discussion here will be brief. Lucas (1988) was arguing that some form of formal or informal interactions between workers generate external effects of human capital and enhance productivity of fellow workers. Subsequently, a strand of mainly empirical research has emerged trying to estimate these external effects of human capital (Rauch, 1993; Acemoglu and Angrist, 2000; Moretti, 2003, 2004; Ciccone and Peri, 2006). Researchers in this strand have often employed wage regressions that control for individual characteristics and human capital and include the level of human capital at the city or state level as an additional variable, in order to capture its external effects.

The source of the externalities that this exercise estimates might come from the kind of interactions that the agglomeration literature examines (see Duranton, 2006 for such an argument). This important literature, which stems out of Marshall's work (1890), attempts to examine the interactions between firms/workers in the workplace or the city level and their impact on productivity (Ciccone and Hall, 1996; Glaeser and Mare, 2001; Duranton and Puga, 2004; Rosenthal and Strange, 2004; Combes et al., 2008). As it is argued, firms agglomerate in space as they can gain productivity benefits from economies of scale due to local input sharing, labour market pooling and knowledge spillovers. In the agglomeration literature productivity benefits come from sectoral and/or urban agglomeration rather than higher human capital in a spatial unit (as the human capital externalities literature examines). However, it is reasonable to expect that locations with high human capital would offer increased provision of specialised inputs and reduced labour matching frictions due to the availability of appropriately skilled labour (Duranton, 2006). Furthermore, there is empirical evidence that cities with higher human capital favour communication interactions, which foster productivity (Charlot and Duranton, 2004).

Productivity spillovers should be expected to arise for all educational groups to one extent or another (Moretti, 2004). On the other hand, if we make the reasonable assumption of imperfect substitutability between different skill groups, then productivity increases could arise without the need for a greater productivity spillover effect. In a standard neoclassical model of perfect competition with two types of labour, skilled and unskilled, an increase in the numbers of skilled labour would raise the productivity of the unskilled labour just because of production complementarities (for relevant research see Moretti, 2004; Ciccone and Peri, 2006).

In order to disentangle between these two production mechanisms, Moretti (2004) looks on wage effects from higher human capital in US cities for different skill groups. For the low-skill groups, the productivity spillovers and the production complementarities mechanisms have both positive wage effects as they increase the productivity of the workers. For the high-skill groups, while knowledge spillovers tend to increase the productivity of the workers, the increased supply of high-skill workers has a negative wage effect as predicted by a downward sloping demand curve, leaving the direction of the final wage effect indecisive. The empirical pattern that arises for US is very consistent with the simultaneous effect of these two mechanisms. The wage premium is found to decrease as we move up the educational ladder.

3. Empirical Strategy and Data Used

3.1. The Data

The main empirical exercise conducted for this paper involves wage regressions and the data come from the historic series of Annual Survey of Hours and Earnings (ASHE) for Britain, that applies ASHE methodology to the earlier New Earnings Survey data (NES). ASHE is the survey that succeeded the New Earnings Survey (NES) in 2004 offering an improved version of it. As NES, it is an employer-based survey and covers all individuals whose national insurance number ends in a specific pair of digits- approximately 160,000 individuals a year. Statistical imputation for item non-response, weighting to be consistent with Labour Force Survey (LFS) population estimates and better coverage of low-earners and people who recently changed or started new jobs have been the main improvements compared to NES. The NES does not cover people who earn less than the threshold for paying national insurance contributions and therefore ASHE includes a supplement survey to improve their coverage. For the years before 2004, the NES data have been re-constructed using the ASHE methodology in order to give historic data for the period 1997-2003. Therefore for the period 1997-2003, historic data for ASHE exist that do not include though the supplementary sample of low-earners. These are essentially NES data with imputation and weighting that is applied to ASHE and henceforth referred as ‘ASHE’ for simplicity reasons (rather than ‘historic ASHE’). As the occupational coding changes in 2002 and in order to have a consistent coding for a sufficient time span, this paper examines the five year period 1997-2001. Detailed geographical information on the workplace of each employee at the postcode level enables analysis at different spatial levels (NES did not offer information at the postcode level). One of the limitations of the ASHE dataset is its lack of information on education. Therefore, an empirical strategy that does not use educational information but focuses on occupations has been developed and presented in the subsequent section.

3.2. The empirical strategy

The main task of the empirical strategy is to discern between the consumption demand hypothesis outlined earlier and alternative production function related approaches. The latter, as discussed, refer to the productivity spillovers and production complementarities mechanisms. Wage equations are applied to ASHE microdata to examine to what extent individuals accrue a wage growth premium in localities with growing shares of high-skilled individuals. Since ASHE does not have any information on education, I use a measure of skill based on pay and the explanatory variable of interest is defined as the share of individuals in the locality who are employed in the top-paid occupations.

Applying wage regressions to the whole sample of individuals is not particularly useful since all three accounts could generate a positive shift of the labour demand curve and contribute to the wage premium found. According to the consumer demand hypothesis, abundant high income high skilled individuals stimulate the local demand for low-paid low-skilled consumer services and inflate the wages for the relevant low paid occupations. Alternatively, the existence of human capital externalities would imply that abundant high-skilled labour force raises the productivity of the local workers through physical interaction and knowledge spillovers. However, it is possible to expect positive productivity spillovers even without the presence of wider human capital externalities if low and high skilled workers are considered to be imperfect substitutes. Then the productivity of low-skilled workers increases with the presence of larger numbers of high-skilled workers due to production complementarities as in a standard neoclassical model.

It should be noted here that the exact impact on wages from the outward shift of the labour demand would also depend on the elasticity of the labour supply. Assuming a non-elastic labour supply curve at least in the short run, larger shares of high-skilled individuals would exert an upward force on the wages.

Since these three mechanisms discussed above do not have a similar impact across the skill distribution, it is more informative to split the sample in different skill groups and apply separate regressions for each of them. The consumer demand and the production complementarities accounts would affect predominantly the wages of the low skilled groups while we expect productivity spillovers to have a similar effect across different skill groups. I compose these skill groups from occupation cells characterised by different median wages. These broader occupational groupings that denote different skill groups might serve better the purposes of capturing the consumer demand hypothesis than skill groups defined by qualifications would do. We will see in a following section that the low-paid occupational groups refer mainly to consumer and personal service occupations that are non-traded and according to the theoretical framework described earlier they are increasingly dependent on consumer demand arising from the presence of high-income workforce in the locality.

Before seeing in more detail how the differential impact of the share of high-skilled individuals on different occupational categories can inform on the three different accounts, let's first consider the main model that is used.

3.3. Model specification

Equation (1) presents the basic econometric specification employed in my empirical model.

$$log(w_{iat}) = X'_{it}\beta + \lambda * SHARE10_{at} + d_o + d_{rt} + u_{iat} \qquad (1)$$

where:

$$u_{iat} = \varphi_i + \theta_a + \xi_{at} + \varepsilon_{iat} \qquad (2)$$

It shows the log hourly wage of individual *i* who resides in area *a* in year *t*. Region-year fixed effects d_{rt} are included in the model to control for economic cycles at the broader regional level[5]. X_{it} is a vector of individual characteristics (a proxy of experience based on age and its quadratic form, dummies for gender, part-time employment, trainee/junior rate employment) and d_o is a set of occupational fixed effects (3-digit Standard Occupational Classification SOC90). *SHARE10* is our variable of interest that stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*. *u* is the error term that can be decomposed to φ_i: time invariant unobservable characteristics of the individual (e.g. ability); θ_a: permanent unobservable characteristics of the city (e.g. physical amenities); ξ_{at}: time-varying shocks at the area level and ε_{iat}: an idiosyncratic

[5] I have also produced results using a less restricted specification with just yearly fixed effects that control for national cycles.

individual part which is assumed to be independently and identically distributed across individuals, areas and years.

3.4. Classifying individuals in occupation groups according to pay

The 3-digit SOC90 occupational coding is used in order to classify occupations according to pay with 1997 as the base year. Each of the 367 available occupational cells is ranked from worst (1) to best (367) according to its median hourly pay in Britain in 1997 and then grouped into broader occupation categories so that each category contains the 10% of the employees nationally for 1997. This way ten 'occupational deciles' are created. The explanatory variable of interest *SHARE10* denotes the percentage of employees who are employed in occupations that form the highest paid occupational decile (i.e. the 10^{th}). Although *SHARE10* is 10% nationally for 1997 by construction, it varies across areas and years. The variable of interest was constructed using the highest decile since it aims to capture only the occupations that are very highly remunerated and serve as a proxy for the high-skilled.

As discussed in the 'Emprical Strategy' subsection, the main empirical exercise is to examine how *SHARE10* impacts on wages of different skill groups. I construct these different skill groups from occupational cells as before, but now 'occupational quintiles' rather than 'deciles' are used since I am interested in a broader definition of skill. There are now five 'occupational quintiles' (*Q1*-*Q5*) created according to pay data for Britain in 1997 (in a similar way with the creation of the 'occupational deciles'). Occupation quintile 1 (*Q1*) contains workers who are employed in the lowest paid occupations so that they form nationally the 20% of the employees in

1997, while *Q5* is the highest-paid occupation quintile. The main regression (1) is repeated separately for these five occupational quintiles, in order to examine how the share of the high-skilled jobs in an area (*SHARE10*) affects the wages of different skill groups (‘occupational quintiles *Q1-Q5*’).

A detailed list of occupations that form the top occupational decile *SHARE10* and their employment share in 1997 is shown in the Appendix A (Table A1). As most of them are in business and finance as well as the new economy sectors, they match the notion of the high-income workforce that is put forward in the consumer demand driven approach. For example, occupation cells of substantial size are the marketing and sales managers, that take up 1.9% of the total employment share in 1997, and brokers (0.7%). In Appendix A (Table A2), the bottom paid occupations that form occupational quintile *Q1* are also presented. The most sizable occupation cells are care assistants (1.9% of total employment), cleaners (3.3%) and sales assistants (5.2%), which is also the largest of all 367 cells.

3.5. The spatial level of the analysis

An important issue for consideration is the spatial units of the analysis, denoted as *a* in Equation (1). For the years 1997-2001 ASHE has information only on the workplace and not on the residence of an individual. Since workplace information would be more informative for production related human capital externalities, while residence information for the consumer demand hypothesis, this limits the potential for such dual analysis. Then although ASHE allows analysis to very fine geographies like postcode area or local authorities (LAs), I opt for larger geographical entities like travel-to-work-areas, that are based in non-administrative boundaries and is the best definition we can get to self-contained labour markets. TTWAs are constructed such that the bulk of their population lives and works within the same area (see Appendix B for more detail).

3.6. Dealing with Potential Sources of Bias

In estimating the basic regression (1), an issue of concern is potential sources of biases arising from omitted variables. Firstly, there may be area-specific unobserved characteristics that are correlated both with the share of high-paid occupation workers *SHARE10* but also with wages (that feed in the error term as θ_a in Eq.(2)). For example, areas with better urban amenities will attract a larger number of high-paid occupation workers (see Glaeser et al. 2001 for such an argument) and also pay higher wages to compensate for the higher urban rents. Similarly, dynamic areas that due to their industrial mix or historic reasons are booming generate more managerial and new economy sector jobs while at the same time pay higher wages. A way to control for variations in the wages that are caused from the time invariant part of area differences (industrial structure, historic reasons, physical and cultural amenities) is to use area fixed effects (d_a) (Equation (3)). The area fixed effects absorb the permanent unobserved area component θ_a in Equation (2).

Another potential source of bias can arise from unobserved individual characteristics, that can be correlated both with the SHARE10 and with wages (denoted as φ_i in the error term in Eq.(2)). Education and ability are both unobserved in our empirical model as data are not available in the ASHE dataset to control for them. Employees who are better educated and/or more able (e.g. a sale assistant with a bachelor degree) would possibly be more productive and a non-random sorting of them across areas would bias the results. If areas with more abundant high-paid workforce offer better returns to education/ability, then they would attract better educated/able employees. As these employees might be more productive compared to other areas' employees with similar observed characteristics doing similar jobs, a correlation of the share of high-paid occupation workers and high wages arises.

To control for time-invariant unobserved education/ability, I use individual fixed effects (d_i) (that absorb the component φ_i of the error term in Eq.(2)). Now, I essentially estimate how changes in the wage of a specific individual are associated with changes in the percentage of the top-paid jobs in the area. I drop atemporal personal characteristics like gender and keep experience and its quadratic form, full/part time status, adult/trainee rate and occupational dummies as my controls. The point of keeping the occupational dummies is to control for variation in the wages of individuals who move to jobs that have a higher remuneration.

$$log(w_{iat}) = d_i + d_a + X'_{it}\beta + \lambda * SHARE10_{at} + d_o + d_{rt} + u_{iat} \qquad (3)$$

Therefore using both individual and area fixed effects (Equation (3)), the identification for the coefficient *SHARE10* comes from two sources: people who stay in the same area and how changes in the shares of top-paid jobs in the area affect their wages, as well as from people who move to other areas. In the latter case, identification comes from a change in the wage of the mover by more (less) than is the level effect associated with that area and taken away with the area fixed effect.

However, this econometric specification (individual; area fixed effects) might still generate a positive coefficient for the share of top-paid jobs for the wrong reasons. For example it might be the case that workers move between areas for job purposes only if they are to get a higher wage (adjusting for the area level effect) and at the same time they self-select themselves to areas with better urban amenities, that are also the ones with abundant high-paid workforce. To control for that and estimate how changes in the percentage of top paid jobs affect the wage growth premium of people who stay in the same area over time, an econometric specification with individual interacted with area fixed effects ('individual-area', d_{ia}) is used (Equation (4)). Therefore a person will get a different dummy if she moves to another area and the identification in the econometric specification comes from the effect of the share of top-paid jobs on her wage for the years that stay in an area.

Furthermore, I add time-varying area controls Q_{at} (like population, unemployment, number of establishments) to account partly for any shocks at the area-year level. Then, the remaining unobservable part which feeds in the error term ξ_{at} (Eq.2) is assumed to be a random effect common to individuals within the same area-year. Clustering at the area-year level I adjust the standard errors allowing for correlation within area-years due to the remaining ξ_{at} component.

$$log(w_{iat}) = d_{ia} + X'_{it}\beta + \lambda * SHARE10_{at} + \gamma * Q_{at} + d_o + d_{rt} + u_{iat} \qquad (4)$$

This is my preferred econometric specification which is applied both for the full sample and for different subsamples representing different skill groups. Subsection 3.4 explained the construction of five 'occupation quintiles' (*Q1-Q5*) based on pay, that correspond to different skill groups. The next section examines how the differential performance of the preferred econometric specification for the different occupational quintiles might aid my identification strategy.

3.7. Distinguishing between the three different accounts

As said, the purpose of the empirical strategy is to shed light on the effect of the consumer demand mechanism and discern it from the two alternative production related mechanisms. The way to do so is to examine the differential impact of the share of top-paid occupation workers on the wages of the various occupational quintiles, that represent different skill groups. Regarding the productivity spillovers account, it is not expected to find a differential impact amongst the various occupational groups. Rather, human capital externalities arising from larger shares of high-killed workers would raise the productivity of the average worker in each of the occupational quintiles causing a shift of the corresponding labour demand. The induced wage impact should be roughly similar for the different occupational quintiles.

In contrast, if having more managers, bankers and generally top-paid occupation workers in an area boosts the labour demand for local low paid occupations such as cleaners, care workers and bartenders through consumption, the wage impact would affect the bottom occupational quintile (*Q1*). Also, if managers and bankers demand more receptionists and security staff in their workplace, then a wage premium at the bottom occupation quintile could be generated from production complementarities rather than consumer demand. Therefore, it could be informative to compare the coefficient of the share of top-paid occupation workers found for the bottom (*Q1*) and that found for the other occupational quintiles (*Q2-Q5*). A higher positive coefficient for bottom occupational quintile compared to the other quintiles can be considered a product of the simultaneous effect of consumer demand and production complementarities. However, it can prove more difficult to separate between the consumer demand and production complementarities effects.

Looking at the industrial composition of the area could be informative. Firstly, using occupation-industry fixed effects in the analysis can abstract from the coefficient of the variable of interest capturing changes in the industrial composition rather than genuine consumer demand effects. For example, it is possible that production complementarities could generate a move of cleaners and security staff to corporate sectors where remuneration might be higher and this could be picked up at the corresponding wage premium found. Occupation-industry fixed effects control for this possibility.

Furthermore, I would expect that production complementarities take place predominantly within the same industrial sector rather than across sectors, since larger shares of top-paid occupation workers would tend to generate demand for low-paid occupation workers of the same sector. Therefore I add a variable that captures the share of top-paid occupation workers in the same sector and area with the individual. At the same time I amend the variable of interest so that it captures the share of top-paid occupation workers in the local area excluding the sector that the individual observation belongs to. The relevant econometric specification is shown below.

$$log(w_{iats}) = d_{ia} + X'_{it}\beta + \lambda * SHARE10_{at,-s} + \mu * SHARE10_{sat} + \gamma * Q_{at} + d_o + d_{rt} + u_{iat} \quad (4)$$

where s stands for the sector of the individual i in year t and area a.

$SHARE10_{at,-s}$ is similar to (3) but now excludes the own sector, while $SHARE10_{sat}$ is the share of top-paid occupation workers that changes across sectors s, areas a and years t.

In that respect I interpret the coefficient of $SHARE10_{sat}$ as capturing production complementarities and productivity spillover effects within sectors, while the coefficient $SHARE10_{at,-s}$ capturing mainly the consumer demand effect at the area level. The coefficient of $SHARE10_{at,-s}$ is possibly an underestimate of the true consumer demand effect if there are consumer demand effects within sectors and an overestimate if there are production complementarities and productivity spillovers between sectors. To the extent that these opposing biases are small or cancel out, a coefficient close to an unbiased one would be expected.

Since in the case of $SHARE10_{sat}$ the economies are generated within the same sector, these productivity gains can be thought as ‘localisation economies’ that are internal to the industry but external to the firm (using the terminology of the agglomeration literature). In a similar vein, $SHARE10_{at,-s}$ can be thought as capturing ‘urbanisation economies’ that are external to the sector but internal to the area. However, caution is needed as these are economies not in the standard usage of the term referring to industrial agglomeration or urban agglomeration economies and therefore it might be more useful and accurate to simply think of $SHARE10_{sat}$ and $SHARE10_{at,-s}$ as capturing ‘within’ or ‘between sectors’ effects respectively (coming from any of the three accounts).

Finally, I select a subset of occupations out of the bottom occupational quintile that refer to consumer and personal service occupations but are not affected by production complementarities or spillovers in a straightforward way. Then I apply wage regressions to just this subset of occupations. To the extent that my selection criterion is satisfied, the variable of interest ($SHARE10_{at}$) may capture a wage impact that mainly feeds through the consumer demand mechanism rather than production related ones. The selected occupations combined make up 8.6% of the total national employment in 1997 and are presented in Appendix A (Table A3). The most sizeable of them are cleaners (3.3%), care assistants (1.9%), bar staff (0.8%), childcare workers (0.8%), cooks (0.7%) and waiters/waitresses (0.5%). On the other hand, I am dropping occupations like sales assistants, packers and receptionists.

4. Empirical Results

4.1. Samples used and Descriptive Statistics

The sample is restricted to men and women of age 16-64. Only individuals who appear in the sample for more than one year in the period 1997-2001 are included so that variation comes from multiple observations of the same individual in the individual-area fixed effects specifications. I drop observations whose pay was affected by absence and also those with unrealistically low or high real hourly wages (below £1 or above £200 in 2001 prices). Finally, observations with missing information on the location of workplace are excluded. The final sample I get is

610,016 observations in total for 1997-2001, that correspond to 169,842 individuals. The employees stay on the sample on average for 3.6 years. Summary statistics for this sample are shown in Table 1. This is the sample that is going to be used in most of the analysis that follows. It is slightly reduced for the analysis that includes sectoral controls since observations with missing information on industry were dropped.

The share of top-paid occupation employees *SHARE10* varies across 195 TTWAs and 5 years. Considering its distribution over the 975 area-years, the median TTWA had 7.4% of employees working at the top occupational decile (Table 2). The average is 7.7% with standard deviation 2.7%, which can be decomposed to 2.5% for the between areas and 1.2% for the within area component. The bottom 1% of the TTWAs have a share below 1.8% and the top 1% of TTWAs a share above 16.7%. Looking at the standard deviation of SHARE10 within TTWAs, it varies from 0.2% for the 1st percentile of TTWAs to 3.4% for the 99th percentile. Table 2 shows also distributions for the median real hourly wage and the share of university degree holders in the TTWAs of the sample[6].

4.2. Regressions

Table 3 presents a first set of results showing the positive association between share of high-paid occupation workers and wages. Column 1 shows pooled regression results for all workers of the sample, without linking individuals that appear in the sample more than once (Equation (1)). Log hourly wages are regressed on the share of the top-paid occupational decile workers *SHARE10* in the TTWA along with other

[6] The median sample size for the TTWAs is 299 with standard deviation 1488 (mean 626).

controls. Other controls include occupational fixed effects and personal characteristics with information available in the ASHE dataset. The specification uses region-year dummies to account for region specific shocks. In all econometric specifications that follow, the standard errors are corrected for the grouped nature of the data (area-year clusters). It is found that a 1 percentage point increase in the share of top-paid occupational workers in the area is associated with a 1.15% rise in wages. It should be noted that although the sample size is 610,016, identification of the variable of interest *SHARE10* comes from an effective sample of 975, since *SHARE10* varies over 195 TTWAs and 5 years.

As suggested earlier, it would be more informative for my research purposes to repeat this exercise for different occupational groups. Firstly, I restrict the sample to only workers employed in the bottom paid occupational quintile (Columns 2-5). The observations are now 113,499, roughly a fifth of the full sample. The results for the basic model specification are presented in Column 2. The wage premium arising to the bottom occupational quintile workers (*Q1*) from a higher share of top-paid occupational decile workers in the local area is now 0.84%. The magnitude and the significance of the coefficient are still quite high, although they declined compared to those of the full sample.

In order to control for some unobserved area heterogeneity that is time invariant (e.g. industrial structure, historic reasons, physical amenities), area fixed effects are included in the regression. The results are shown in column 3 of Table 3 for the pooled sample of bottom-paid occupational quintile workers. The coefficient of *SHARE10* now drops significantly to 0.238 but still remains marginally significant at the 1% significance level. The controls used have coefficients quite similar to the basic model specification. The identification comes from within area variation of wages and SHARE10 over time.

In column 4 of the same table, the results of the specification with area and individual fixed effects are shown. In this specification (Equation (3)), I am also controlling for the time-invariant part of unobserved characteristics of individuals, like education and ability (of course, both education and ability could possibly change). I now get identification in the model from two sources: the effect on the wage of an individual from changes in the share of high paid occupation workers in her area; wage gains (losses) from people who move between areas. The coefficient of *SHARE10* now takes a value of 0.217 and is significant at the 1% level. Only individual control variables that might change over time are included in the regression and their coefficients change substantially due to the inclusion of the individuals' fixed effects[7].

In order to abstract from variation arising from individuals moving between areas, a specification with individual interacted with area fixed effects ('individual-area') is used (Col.5/Table 3). This is the preferred specification for this analysis and a full set of controls is used as in Equation (4). The coefficient now of *SHARE10* stands to 0.225 and the t-statistic has risen to 3.00. This can be interpreted as a 0.23% rise in the hourly wage of an individual when the surrounding share of top-paid occupation workers in the TTWA increases by 1 percentage point. It corresponds to a wage rise of 0.62% for one standard deviation increase in *SHARE10* (2.7 percentage points).

[7] The results for the coefficient of SHARE10 are not affected by the inclusion of the part-time and trainee dummies in the model.

Table 4 presents comparative results from separate regressions on the 5 different occupational quintiles of workers. The specification used is the preferred one with a full set of individual-area fixed effects (Equation (4)). It is found that the share of high-paid occupation workers at the local area *SHARE10* has differential impact for different occupational quintile workers. Its coefficient is higher and strongly significant for the bottom occupational quintile, positive but weakly significant for the top occupational quintile, while insignificant for all other quintiles (though positive).

According to the discussion in subsection 3.2, a comparison of the coefficient for the different occupational quintiles can possibly inform on the three different accounts, consumer demand, production complementarities and productivity spillovers. The strongest coefficient found for the bottom occupational quintile can be interpreted as the product of the simultaneous effect of the consumer demand and production complementarities on top of productivity spillovers that are expected to have a roughly similar effect across occupational quintiles. The second occupational quintile has also a relatively high coefficient although insignificant and this might also be due to the effect of production complementarities, to the extent that the relevant low-skill employees are imperfect substitutes with the high-skilled employees captured by the variable of interest. Examining the list of occupations that compose the second occupational quintile, effects from a consumer demand root are less likely. The third and fourth occupational quintiles have low positive coefficients which are also insignificant, failing to show any strong impact arising from productivity spillovers.

The relatively high and weakly significant coefficient for the top occupational quintile (*Q5*) poses some caution in its analysis and possible interpretation. Since this quintile includes workers of the 9^{th} and the 10^{th} occupational decile, when trying to extract meaningful results on the relationship between the employment share of the 10^{th} occupational decile (*SHARE10*) and the wages of workers of the same decile, the direction of the causation is not clear. For example, it may be the case that migrant high skilled workers are attracted to the local area due to the higher growth of wages (or the rising productivity) of the high-skilled workers that reside in the area. In that respect, there is an important relevant literature examining human capital flows through domestic migration for the UK regions (Fielding, 1993; Faggian and McCann, 2006; Champion and Coombes, 2007).

Table 5 has similar regressions with Table 4 but now the employment share of the individual's own quintile is added as an additional control. The share of employment of the own quintile might account for supply changes in the same skill group as the individual belongs to. The coefficient of *SHARE10* is not affected much by the inclusion of this control variable for the quintiles one to four (Columns 1-4). For the top quintile (*Q5*), the results are not meaningful as there is overlap of variable *SHARE10* that refers to the share of the highest decile (*D10*) and the own quintile's share which consists of deciles 9 and 10 (*D9-D10*).

Taking a more agnostic approach, Table 6 presents similar regressions with Table 4 where now shares from all other occupational deciles are included as explanatory variables as well (where the reference base is decile 5). The purpose is to investigate if *SHARE10* was picking up earlier the effect on wages from high shares of other ‘occupational deciles’[8]. As shown in column 1 which refers to the bottom quintile sample, the coefficient of *SHARE10* remains strong and highly significant while all other coefficients are insignificant with the exception of the coefficient of the share of the third decile *SHARE3* which is weakly significant. Therefore, it can be seen that the top-paid occupational decile is the variable that drives the effect on the wages of the bottom-paid occupational quintile workers. For the middle occupational quintiles (*Q2*-*Q4*), all coefficients are insignificant. For the top occupational quintile (*Q5*), it appears that the shares of deciles 9 and 10 have the strongest positive association with wages, although their interpretation is suspect to issues of causation as briefly discussed earlier.

Although similar criticism for reverse causation can also apply to the regressions of the other occupational quintiles, for the top occupational quintile is clearly more relevant since it refers to the same sample from both sides of the equation. However, it is less clear why this reverse causation should matter for the bottom occupational quintile but not for the middle-occupational quintile ones. This can give some reassurance over my estimates for the bottom occupational quintile and the interpretation put forward in this paper. Of course, a formal treatment of concerns about reverse causality would require an empirical specification using instrumental variables. It has been difficult to find adequate variables to instrument for the share of top-paid occupation workers in the travel-to-work-area over time. Experimenting with plausible time-varying IVs like the number of first degree qualifications that were awarded in the previous year in the TTWA gave weak first stage results. An

[8] As seen in 3.4, these ‘occupational deciles’ were constructed so that each makes up 10% of the workforce in Britain in 1997. They vary over areas and years and their share is higher (lower) than 10% in an area-year if the respective occupations are over-represented (under-represented) in that area-year relative to the share for Britain in 1997.

alternative approach I tried was to use the initial age composition of each area as an instrument for the change in the share of top-paid occupation workers of the area in a first-differenced model for the beginning and the end of the period. Following Moretti (2004), I used an area-specific weighted average of national changes in SHARE10 by age-gender group between 1997 and 1991 in order to instrument the actual change in SHARE10 of each area. Areas with younger populations in 1997 would predict a larger increase in the share of top-paid occupation workers over the period. The validity of the instrument lies in the assumption that the age structure in the beginning of the period is orthogonal to time-varying shocks in the labour market over the period. The first stage gave an F-statistic of the excluded instrument of 8.5 and thus results are presented here with caution. In the second stage, the coefficient of SHARE10 was 1.52 and significant only at the 10% level.

4.3. Further examination of the bottom occupational quintile

With these caveats in mind, let's try now to shed more light on the strong positive significant coefficient found for the bottom occupational quintile in Table 4 (Column 1). Since there was not much evidence in favour of productivity spillovers from the analysis at the middle-paid occupational quintiles, this coefficient can be considered to be the outcome both of consumer demand mechanism and production complementarities. Before trying to discern between these two accounts, I present some more robustness checks for that quintile.

Firstly, I add the share of university degree holders in the TTWA as an additional control to my preferred econometric specification (Table 7). Its coefficient is about one third of *SHARE10* and its inclusion does not affect the coefficient of the latter (Columns 2-3). Using log average hourly wage of the top-decile (*D10*) as a additional control, its coefficient shows a small elasticity of 0.014%, which is weakly significant at the 10% level, while the coefficient of *SHARE10* does not change much (Column 4). In that respect, this result suggests that the main wage effect comes largely from greater shares of workers in top-paid occupations in the area and to a much less extent by higher levels of their wages. Finally, time-varying area controls like population, unemployment rate and house prices have the expected signs but insignificant coefficients and do not alter the results of *SHARE10* (Col.5-6). The house prices control can capture time-varying living costs for each TTWA and therefore addresses potential criticism that any wage impact found simply reflects compensating wage differentials for rising housing costs.

Furthermore, I control for effects arising from unaccounted changes in the industrial composition by using occupation-industry dummies. The 367 occupations are now interacted with 13 industries (1-digit SIC03) to compose the occupation-industry dummies[9]. In that respect, a cleaner in the 'Hotels and Restaurant' sector is distinguished from a cleaner in the 'Financial Intermediation' Sector. The regression results are shown in Column 2 of Table 8 and are very similar to the specification with just occupational dummies (Column 1; reproduced from Col.1/Table 4). Therefore this gives me reassurance on the results presented so far and for computational simplicity reasons I am going to continue with the occupational dummies specification (Equation (4)).

[9] Information on very detailed industries referring to the Standard Industrial Classification (SIC03) is available for each observation in ASHE. Using the one digit classification there are 17 sectors and aggregating further I end up with 13 industrial sectors.

In order to capture production complementarities within sectors, I include the variable $SHARE10_{sat}$ that denotes the employment share of top-paid occupation workers in the same industrial sector and area with the individual observation. The variable of interest $SHARE10_{at,-s}$ is amended to refer to the share of top-paid occupation workers employed in the area when excluding the sector the individual observation belongs to. The results are shown in Column 3 of Table 8. The coefficient of interest now captures consumer demand effects as well as production complementarities (and productivity spillovers) between sectors. As discussed in subsection 3.7, if the latter are minimal or cancel out with an opposing downward bias from within-sector consumer demand effects, $SHARE10_{at,-s}$ can be argued to capture the consumer demand impact generated from rising shares of high-paid occupation workers in the area. Both coefficients in the regression result are positive and significant. The wage effect arising from higher-shares of top-paid occupation workers within the sector is 0.119% and very strongly significant (as the share now changes across sectors, areas and years). Its inclusion reduces the coefficient of the variable of interest which now takes a value of 0.139 (down from 0.225 in Column 1) while it is still significant at the 5% level.

Additional time-varying area variables, constructed from IDBR (Inter-Departmental Business Register)[10], have been included as controls in column 4. I use the log of the employment in the area to capture any size effects, and also the log of the number of the establishments. The use of these variables is quite common in the agglomeration literature (e.g. Combes et al., 2008) in order to capture any urbanisation type effects[11].

[10] Inter-Departmental Business Register is a census of the UK businesses.
[11] Although the use of the log of the density of employment in the area might have been preferable to capture these urbanisation type effects.

Both coefficients for these variables are found positive but insignificant and do not alter my results.

The regression results for the selected subset of consumer and personal service occupations are presented in Columns 1 and 2 of Table 9. As discussed in 3.7, these occupations were selected out of the list of bottom quintile occupations so that they largely match the notion of consumer demand hypothesis rather than production related accounts. Applying the preferred econometric specification, the coefficient of interest now increases to 0.319 compared to 0.225 for the full set off occupations, possibly reflecting stronger wage effects through a consumer demand root for this selected set of occupations. Due to the nature of these occupations, it is expected that a larger part of this wage effect can be attributed to consumer demand explanations rather than production side ones.

The result from the regression that controls for within-sectors wage effects is consistent with such an argument (Column 2/ Table 9). The coefficient of interest rises to 0.230 compared to a value of 0.139 obtained for the full set of occupations (Column 3/ Table 8). The assertion that $SHARE10_{at,-s}$ might capture largely consumer demand effects is reinforced when looking at its performance in the regressions for the remaining bottom quintile occupations (i.e. the ones that do not belong to my 'selected subset' of occupations) (Columns 3 and 4/ Table 9). There, $SHARE10_{at,-s}$ has its coefficient falling close to zero, while the coefficient of $SHARE10_{sat}$ that captures the share of top-paid occupations workers in the sector-area remains significant. It appears that for the 'selected subset' of occupations there are both between and within-sector wage effects from higher human capital; while for the remaining occupations of the same bottom quintile, there are only within-sector wage effects. Having in mind the caveats of this analysis, a tentative concluding result is the following: cleaners, carers and personal service workers accrue a wage rise of 0.23% when the share of top-paid occupation jobs in their travel-to-work area rises by 1 percentage point.

4.4. Examining urban effects

It is of interest to examine if there is any urban specific story that might affect my variables. Therefore I add as an additional control *U_SHARE10*, the interaction of the *SHARE10* variable and an urban dummy for the 79 TTWAs that are classified as 'primary urban'[12]. I construct similar urban interacted variables for the between and within-sectors share variables (noted by the prefix *U*). The results of the wage regressions are presented in Table 10. Column 1 shows the baseline regression for the bottom quintile. The coefficient for *U_SHARE10* is 0.145 which should be added to the reference coefficient of 0.160 for *SHARE10* in order to get the full effect for the urban areas. However, this difference is not statistically significant. When controlling for within-sector effects, it is found that the coefficient for the urban interacted variable $U\_SHARE10_{at,-s}$ (that captures the between sector effects) is even stronger, as can be seen in column 2. Again, the difference with the baseline coefficient $SHARE10_{at,-s}$ is not statistically significant. The stronger effect for the urban areas is not present when looking at the coefficient of the urban interacted variable that captures mainly within-sector effects ($U\_SHARE10_{sat}$). Therefore, an urban specific

[12] These are the TTWAs that contain a Primary Urban Area (PUAs). Primary Urban Areas are defined using their physical extent and have a minimum population of 125,000. Similar notions were used in order to come up with meaningful definitions of PUAs for Wales and Scotland.

case appears to have some validity when looking for between sector effects and not when looking for within sector effects. Considering the former, it is consistent with the consumer demand story as I would expect that consumer demand effects that are captured at the area level (between sectors) to be more prominent in urban areas. It is also consistent with stronger wage effects of an ‘urbanisation economies’ type in urban areas than rural areas, which is what we would expect. On the other hand, ‘localisation economies’ type wage effects (as captured by the within-sector share variable) do not show any urban specific differentiation.

5. Concluding Remarks

The paper examined how high local human capital in a local area affects the wages of the individuals in the area. A positive association between the two is well documented in the literature and mainly attributed to production related accounts like production complementarities and wider productivity spillovers. The paper examines also an account through consumer demand that has not been discussed extensively so far. According to this account, a larger share of a high-skilled workforce in the local area boosts the demand for consumer services that are not necessities like personal and leisure services. These services are labour intensive and to a large extent involve low-pay sector occupations. Furthermore, as they are non-traded, they need to be produced and consumed locally and this requires physical proximity of the high-skilled high-income workforce and the low-paid service workers. The paper presents an empirical strategy that attempts to discern the effect of the consumer demand account from that of the production related accounts. Wage regressions are applied to ASHE microdata for the period 1997-2001 adding an additional variable that captures local human capital, the share of top-paid occupation workers in the travel-to-work-area. In order to shed light on the three different accounts, I examine the differential wage impact of the share of top-paid occupation workers on employees of different occupation quintiles defined by pay. The wage impact is stronger and significant for the bottom occupational quintile compared to the middle-occupational quintiles. This is argued to be the simultaneous product of production complementarities and consumer demand effects on top of productivity spillovers. Specifically, it is found that 1 percentage point rise in the share of high-paid occupation workers in the travel-to-work-area, is associated with an increase in the hourly wages of least-paid quintile occupation workers by roughly 0.23%. Accounting for within-sectors effects, the wage impact remains positive that is argued to come from consumer demand or production complementarities between sectors. If the latter are minimal, then my specification can be argued to capture a positive wage impact that comes mainly through the consumer demand mechanism.

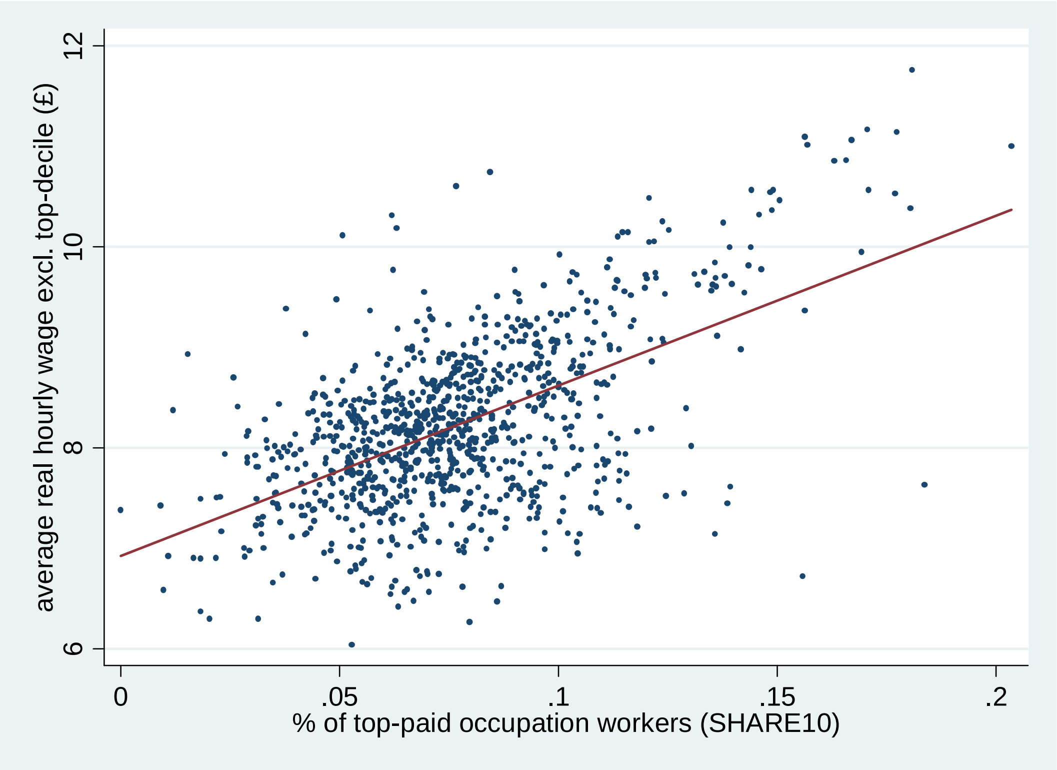
Applying the analysis to a subset of the bottom occupational quintile that consists of personal and consumer service occupations (like cleaners, carers and waiters/waitresses) gives even stronger results in consistence with a consumer demand explanation. A final result of the paper is the following: cleaners, carers and personal service workers accrue a wage growth premium of 0.62% when the share of top-paid occupation jobs in their travel-to-work area rises by one standard deviation[13]. When using urban interacted effects, it appears that between-sector wage effects are stronger in the urban areas compared to the rural ones, while within-sector wage effects are similar in urban and rural areas. However, the results are tentative subject

[13] which corresponds to £66 pay rise a year for an hourly wage of £5 and a 40 hour week.

to the limitations of the analysis and the paper has pointed to a number of caveats regarding the successful separation of the three different accounts and possible concerns with endogeneity of the variable of interest. Future research and better data would be needed in order to deal with these issues.

FIGURES

Figure 1. Share of top-paid occupation workers *SHARE10* of a TTWA and average real hourly wage excluding top-decile; 1997-2001



Source: ASHE

[a] The x-axis variable is the employment share of the top-paid occupation category in the travel-to-work-area (this 'top-decile' is defined in subsection 3.4 and shown in Table A2).

[b] Average real hourly wages have been calculated for the subsample that excludes top-paid occupation workers (deflated using the Retail Price Index (RPI) for 2001 prices).

TABLES

Table 1. Summary Statistics for 1997-2001

Observations (pooled sample)	N	Age	Real hourly wage (£) (2001prices)	Male	Full-time	Trainee/ Junior
All that stay in sample (>1 year)	610,016	39.4 (11.5)	£10.16 (7.46)	52.1%	77.9%	1.7%

Source: ASHE
[a] Standard deviations in brackets.
[b] Average hourly real wages are shown, deflated with the RPI for 2001.

Table 2. Distributions of time-varying area characteristics for 1997-2001

Variable/ Spatial level	**Mean**	**Standard deviation**	**1%**	**50%**	**99%**
Travel-to-work-areas 195 TTWAs x 5 years=975					
Real hourly wage (£ in 2001)	7.35	0.89	5.57	7.25	10.51
SHARE10 % (share of top-paid occ.workers)	7.66	2.74	1.83	7.37	16.70
Highly educated (University) % 194 TTWAs x 5 years=970	11.66	4.07	3.43	11.19	23.39

Source: ASHE, LFS
[a] Real hourly wages have been deflated for 2001 prices using RPI.
[b] *SHARE10* in a TTWA stands for the share of employment that belongs to the highest paid occupational decile.
[c] The third variable is the share of university degree holders out of all individuals in the TTWA.

Table 3. Wage effects from the share of top-paid occupation workers

	All	Bottom Occupational Quintile (*Q1*)			
Explanatory Variables	**Basic Model**	**Basic Model**	**area effects**	**area, individ. effects**	**areaXindiv. Effects**
	1	2	3	4	5
SHARE10	1.139	0.835	0.238	0.217	0.225
	(24.64)	(17.03)	(2.58)	(2.90)	(3.00)
Experience	0.024	0.012	0.012	0.031	0.033
	(74.42)	(47.31)	(47.15)	(5.79)	(6.09)
Experience sq.	-0.042	-0.022	-0.022	-0.045	-0.046
(coeff.x100)	(-68.40)	(-43.81)	(-43.69)	(-25.29)	(-25.33)
Trainee rate	-0.365	-0.217	-0.216	-0.147	-0.147
	(-58.62)	(-24.57)	(-24.49)	(-19.36)	(-19.42)
Part-time	-0.080	-0.059	-0.059	0.046	0.047
	(-45.69)	(-16.11)	(-16.05)	(11.78)	(12.11)
Female	-0.153	-0.101	-0.101		
	(-75.82)	(-31.45)	(-31.37)		
Occup.dummies	Yes	Yes	Yes	Yes	Yes
Region-Year dummies	Yes	Yes	Yes	Yes	Yes
Area dummies			Yes	Yes	
Individ. dumm.				Yes	
areaXindividual dummies					Yes
R^2	0.66	0.25	0.26	0.78	0.78
N	610,016	113,499	113,499	113,499	113,499

Source: ASHE

[a] The dependent variable is log hourly wage of the individual.

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] Additional controls include a proxy of experience based on age and its quadratic form, dummies for gender, part-time employment, trainee/junior rate employment) and occupational dummies (SOC90).

[d] T-statistics shown in parenthesis are corrected for area-year clusters.

Table 4. Wage effect of share of top-paid occupation workers on the various occupational quintiles (*Q1-Q5*)

Explanatory Variables	Bottom Quintile	2nd Quintile	3rd Quintile	4th Quintile	Top Quintile
SHARE10	0.225	0.091	0.035	0.019	0.170
	(3.00)	(1.55)	(0.52)	(0.26)	(1.93)
Experience	0.033	0.027	0.040	0.031	0.056
	(6.09)	(6.21)	(8.56)	(6.19)	(9.63)
Experience sq. (coeff.x100)	-0.046	-0.059	-0.067	-0.077	-0.114
	(-25.33)	(-35.36)	(-36.14)	(-39.52)	(-20.64)
Trainee rate	-0.147	-0.210	-0.241	-0.235	-0.242
	(-19.42)	(-22.19)	(-23.03)	(-19.14)	(-17.26)
Part-time	0.047	0.050	0.094	0.106	0.179
	(12.11)	(11.30)	(15.62)	(14.40)	(19.09)
Occ.dumm.	Yes	Yes	Yes	Yes	Yes
Region-Year dummies	Yes	Yes	Yes	Yes	Yes
areaXindiv dum.	Yes	Yes	Yes	Yes	Yes
R2	0.78	0.85	0.88	0.89	0.89
N	113,499	119,830	108,034	119,296	117,575

Source: ASHE

[a] The dependent variable is log hourly wage of the individual (Equation 4).

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] Additional controls include a proxy of experience based on age and its quadratic form, dummies for gender, part-time employment, trainee/junior rate employment) and occupational dummies (SOC90).

[d] T-statistics shown in parenthesis are corrected for area-year clusters.

Table 5. Wage effects including a supply control ('own quintile share')

Explanatory Variables	Bottom Quintile	2nd Quintile	3rd Quintile	4th Quintile	Top Quintile
SHARE10	0.242	0.088	0.033	0.017	-0.089
	(3.10)	(1.50)	(0.49)	(0.23)	(-0.69)
Own quintile share	0.030	-0.023	-0.040	-0.009	0.251
	(0.77)	(-0.58)	(-0.83)	(-0.19)	(3.05)
Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.78	0.85	0.88	0.89	0.89
N	113,499	119,830	108,034	119,296	117,575

Source: ASHE

[a] The dependent variable is log hourly wage of the individual.

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] The share of the quintile that each observation belongs to is added as a regressor in order to control for supply effects ('*Own quintile share*').

[d] All models control for region-year and individual-area fixed effects. Additional controls as in the previous table.

[e] T-statistics shown in parenthesis are corrected for area-year clusters.

Table 6. Wage effect of the various occupational deciles (*SHARE1-SHARE10*)

Explanatory Variables	Bottom Quintile	2nd Quintile	3rd Quintile	4th Quintile	Top Quintile
SHARE10	0.308***	0.110	0.061	0.026	0.331**
	(2.86)	(1.28)	(0.62)	(0.22)	(2.38)
SHARE9	0.044	0.022	0.054	0.003	0.377***
	(0.44)	(0.25)	(0.52)	(0.03)	(2.86)
SHARE8	0.120	0.098	0.047	-0.175	0.185
	(1.15)	(1.10)	(0.48)	(-1.56)	(1.38)
SHARE7	0.012	0.030	0.010	0.094	0.225*
	(0.13)	(0.39)	(0.11)	(0.86)	(1.91)
SHARE6	0.053	-0.061	0.004	-0.024	0.104
	(0.54)	(-0.72)	(0.04)	(-0.21)	(0.80)
SHARE5	-	-	-	-	-
SHARE4	0.002	-0.012	0.094	0.079	-0.003
	(0.02)	(-0.15)	(1.03)	(0.75)	(-0.03)
SHARE3	0.179*	-0.006	0.091	-0.042	0.016
	(1.78)	(-0.07)	(1.02)	(-0.38)	(0.13)
SHARE2	0.050	0.000	0.028	-0.013	0.202*
	(0.54)	(-0.01)	(0.34)	(-0.13)	(1.66)
SHARE1	0.125	0.026	0.021	0.006	0.165
	(1.45)	(0.37)	(0.27)	(0.06)	(1.53)
Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.78	0.85	0.88	0.89	0.89
N	113,499	119,830	108,034	119,296	117,575

Source: ASHE

[a] The dependent variable is log hourly wage of the individual.

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] All models control for region-year and individual-area fixed effects. Additional controls as in the previous table.

[d] T-statistics shown in parenthesis corrected for area-year clusters (* 10%, ** 5%, *** 1%).

[e] *SHARE5* is dropped to avoid multicollinearity.

Table 7. Results for Bottom Quintile (*Q1*): controlling for time-varying area characteristics

Explanatory Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)** England & Wales
$SHARE10_{at}$	0.225 (3.00)		0.227 (3.02)	0.235 (3.11)	0.224 (2.98)	0.265 (3.16)
High-skilled share (university level)		0.075 (2.03)	0.072 (1.94)			
High-wage control				0.014 (1.91)		
Log(Population)					0.136 (1.12)	0.161 (1.22)
Unemployment (claimant count rate)					-0.004 (-1.16)	-0.003 (-0.94)
House prices						$1.64*10^{-7}$ (0.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.78	0.78	0.78	0.78	0.78	0.78
N	113,499	113,419	113,419	113,473	113,499	102,717

Source: ASHE, LFS, NOMIS, Land Registry

[a] The dependent variable is log hourly wage of the individual.

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] All models control for region-year and individual-area fixed effects. Additional controls as in the previous table.

[d] T-statistics shown in parenthesis are corrected for area-year clusters.

[e] 'High-wage control' stands for the log of the average hourly wage of the workers who make up the highest occupational decile (*D10*).

[f] House prices are available only for England and Wales (Column 6).

Table 8. Regression results using sectoral and firm controls (Bottom Quintile)

Explanatory Variables	**Eq.(4)**	**Occupation-Industry dummies**	**Area-sector control Eq.(5)**	**Additional area controls**
	1	2	3	4
$SHARE10_{at}$	0.225	0.221		
	(3.00)	(2.95)		
$SHARE10_{at,-s}$			0.139	0.138
			(2.07)	(2.04)
$SHARE10_{sat}$			0.119	0.118
			(5.19)	(5.17)
$SHARE10_{fat}$				
Ln(employment)$_{at}$				0.020
				(1.26)
Ln(establishments)$_{at}$				0.045
				(0.80)
Occ.dumm.	Yes		Yes	Yes
Occ.-insustry dummies		Yes		
R2	0.78	0.82	0.82	0.78
N	113,499	113,000	113,000	113,000

Source: ASHE, IDBR

[a] The dependent variable is log hourly wage of the individual.

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] $SHARE10_{at,-s}$ is similar to $SHARE10_{at}$ but now excludes the own sector *s*

[d] $SHARE10_{sat}$ is the share of top-paid occupation workers in sector *s*, area *a* and year *t*.

[e] All models control for region-year and individual-area fixed effects. Additional controls as in the previous table.

[f] T-statistics shown in parenthesis are corrected for area-year clusters.

[g] Additional controls include the log of total employment and the log of the number of establishments in the area (constructed from IDBR).

Table 9. Regression results for 'Selected occupations' out of the Bottom Occupational Quintile

Explanatory Variables	Selected occupations Eq.(4) 1	Selected Occupations Eq.(5) 2	Rest occupations Eq.(4) 3	Rest occupations Eq.(5) 4
$SHARE10_{at}$	0.319		0.090	
	(2.29)		(1.01)	
$SHARE10_{at,-s}$		0.230		-0.008
		(1.91)		(-0.10)
$SHARE10_{sat}$		0.137		0.087
		(3.71)		(2.89)
Controls	Yes	Yes	Yes	Yes
R2	0.78	0.78	0.81	0.81
N	42,233	41,800	71,266	71,200

Source: ASHE

[a] The dependent variable is log hourly wage of the individual.

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] $SHARE10_{at,-s}$ is similar to $SHARE10_{at}$ but now excludes the own sector *s*

[d] $SHARE10_{sat}$ is the share of top-paid occupation workers in sector *s*, area *a* and year *t*.

[e] All models control for region-year and individual-area fixed effects. Additional controls as in the previous table.

[f] 'Selected occupations' were selected out of the bottom quintile occupations so that they match the notion of consumer demand hypothesis (e.g. cleaners, care assistants, bar staff). 'Rest' refers to the remaining occupations of the bottom occupational quintile.

[g] T-statistics shown in parenthesis are corrected for area-year clusters.

Table 10. Urban specific effects on the wage growth premium

Explanatory Variables	Bottom quintile Eq.(4) 1	Bottom quintile Eq.(5) 2
$SHARE10_{at}$	0.160	
	(1.69)	
$U\_SHARE10_{at}$	0.145	
	(1.00)	
$SHARE10_{at,-s}$		0.060
		(0.68)
$U\_SHARE10_{at,-s}$		0.173
		(1.35)
$SHARE10_{sat}$		0.119
		(3.19)
$U\_SHARE10_{sat}$		0.005
		(0.10)
Controls	Yes	Yes
R^2	0.78	0.78
N	113,499	113,000

Source: ASHE

[a] The dependent variable is log hourly wage of the individual.

[b] *SHARE10* stands for the employment share of individuals who do the highest-paid occupations in the area *a* at a given year *t*.

[c] $SHARE10_{at,-s}$ is similar to $SHARE10_{at}$ but now excludes the own sector *s*

[d] $SHARE10_{sat}$ is the share of top-paid occupation workers in sector *s*, area *a* and year *t*.

[e] All models control for region-year and individual-area fixed effects. Additional controls as in the previous table.

[f] The prefix *U* stands for an interaction of the regressor with an urban dummy that gets the value 1 for the TTWAs that are classified as “urban”.

[g] T-statistics shown in parenthesis are corrected for area-year clusters.

Appendix A. Composition of occupational categories

Table A1. Top occupational decile (*SHARE10*); Britain 1997

Pay rank	SOC	Label of Occupation Cell	Empl.Share %	Median wage £
367	101	General managers; large companies and organisations	0.07	49.99
366	100	General administrators; national government	0.02	31.41
365	331	Aircraft flight deck officers	0.04	28.32
364	703	Air, commodity and ship brokers	0.02	23.09
363	120	Treasurers and company financial managers	0.49	22.15
362	113	Managers in mining and energy industries	0.03	21.36
361	152	Police officers (inspector and above)	0.06	20.36
360	241	Barristers and advocates	0.01	20.17
359	232	Education officers, school inspectors	0.04	19.75
358	220	Medical practitioners	0.42	19.00
357	126	Computer systems and data processing managers	0.38	17.88
356	125	Organisation and methods and work study managers	0.08	17.84
355	222	Ophthalmic opticians	0.02	17.69
354	223	Dental practitioners	0.03	17.34
353	215	Chemical engineers	0.03	17.27
352	253	Management consultants, business analysts	0.16	17.20
351	242	Solicitors	0.23	16.81
350	131	Bank, Building Society and Post Office managers	0.46	16.77
349	330	Air traffic planners and controllers	0.02	16.65
348	361	Underwriters, claims assessors, brokers, investment analysts	0.67	16.41
347	290	Psychologists	0.05	16.27
346	230	University and polytechnic teaching professionals	0.43	16.27
345	235	Special education teaching professionals	0.17	16.10
344	212	Electrical engineers	0.11	16.07
343	240	Judges and officers of the Court	0.01	16.02
342	384	Actors, entertainers, stage managers, producers & directors	0.11	15.84
341	252	Actuaries, economists and statisticians	0.06	15.82
340	233	Secondary education teaching professionals	1.70	15.81
339	123	Advertising and public relations managers	0.20	15.69
338	121	Marketing and sales managers	1.87	15.69
337	214	Software engineers	0.30	15.29
336	124	Personnel, training and industrial relations managers	0.30	15.10

Source: ASHE

[a] Shading indicates the largest five occupations in terms of employment share.

[b] Wages are median real hourly wages deflated for 2001 prices using the RPI.

Table A2. Bottom occupational quintile (*Q1*); Britain 1997

Pay rank	SOC	Label of Occupation Cell	Occup. Decile	Empl.Share %	Median wage £
1	732	Market and street traders and assistants	1	0.01	2.34
2	621	Waiters, waitresses	1	0.52	3.67
3	622	Bar staff	1	0.81	3.67
4	660	Hairdressers, barbers	1	0.17	3.74
5	952	Kitchen porters, hands	1	0.67	3.89
6	556	Tailors and dressmakers	1	0.01	3.94
7	722	Petrol pump forecourt attendants	1	0.08	4.04
8	953	Counterhands, catering assistants	1	0.96	4.14
9	956	Window cleaners	1	0.01	4.15
10	958	Cleaners, domestics	1	3.30	4.20
11	673	Launderers, dry cleaners, pressers	1	0.18	4.24
12	659	Other childcare and related occupations	1	0.76	4.33
13	670	Domestic housekeepers and related occupations	1	0.02	4.36
14	791	Window dressers, floral arrangers	1	0.04	4.40
15	720	Sales assistants	1	5.16	4.41
16	951	Hotel porters	2	0.05	4.43
17	553	Sewing machinists, menders, darners, embroiderers	2	0.51	4.45
18	959	Other occupations in sales and services	2	0.04	4.48
19	955	Lift and car park attendants	2	0.05	4.48
20	721	Retail cash desk and check-out operators	2	0.84	4.54
21	593	Musical instrument makers, piano tuners	2	-	
22	619	Other security and protective service occupations	2	0.11	4.68
23	644	Care assistants and attendants	2	1.91	4.73
24	902	All other occupations in farming and related	2	0.10	4.75
25	934	Driver's mates	2	0.02	4.79
26	699	Other personal and protective service occupations	2	0.45	4.80
27	651	Playgroup leaders	2	0.03	4.81
28	999	All others in miscellaneous occupations	2	0.03	4.85
29	620	Chefs, cooks	2	0.70	4.90
30	954	Shelf fillers	2	0.25	4.97
31	813	Winders, reelers	2	0.02	5.02
32	661	Beauticians and related occupations	2	0.04	5.07
33	812	Spinners, doublers, twisters	2	0.03	5.11
34	643	Dental nurses	2	0.15	5.11
35	595	Horticultural trades	2	0.08	5.12
36	863	Weighers, graders, sorters	2	0.07	5.15
37	920	Mates to woodworking trades workers	2	0.02	5.15
38	862	Packers, bottlers, canners, fillers	2	1.07	5.17
39	800	Bakery and confectionery process operatives	2	0.17	5.18
40	671	Housekeepers (non-domestic)	2	0.03	5.21
41	581	Butchers, meat cutters	2	0.15	5.24
42	950	Hospital porters	2	0.08	5.24
43	591	Glass product & ceramics finishers & decorators	2	0.07	5.25
44	641	Hospital ward assistants	2	0.11	5.28
45	652	Educational assistants	2	0.52	5.28
46	615	Security guards and related occupations	2	0.62	5.30
47	460	Receptionists	2	0.85	5.32
48	874	Taxi, cab drivers and chauffeurs	2	0.12	5.36
49	544	Tyre and exhaust fitters	2	0.05	5.39
50	990	All other labourers and related workers	2	0.46	5.40

Table A3. Selected occupations out of the bottom occupational quintile (1997)

Pay rank	SOC	Label of Occupation Cell	Occup. Decile	Empl.Share %	Median wage £
1	732	Market and street traders and assistants	1	0.01	2.34
2	621	Waiters, waitresses	1	0.52	3.67
3	622	Bar staff	1	0.81	3.67
4	660	Hairdressers, barbers	1	0.17	3.74
6	556	Tailors and dressmakers	1	0.01	3.94
10	958	Cleaners, domestics	1	3.30	4.20
11	673	Launderers, dry cleaners, pressers	1	0.18	4.24
12	659	Other childcare and related occupations	1	0.76	4.33
23	644	Care assistants and attendants	2	1.91	4.73
27	651	Playgroup leaders	2	0.03	4.81
29	620	Chefs, cooks	2	0.70	4.90
32	661	Beauticians and related occupations	2	0.04	5.07
48	874	Taxi, cab drivers and chauffeurs	2	0.12	5.36

Source: ASHE

[a] Wages are median real hourly wages deflated for 2001 prices using the RPI.

Appendix B. Details on the spatial level of the analysis

Travel-to-Work-Areas (TTWAs)

Office for National Statistics (ONS) constructed TTWAs for UK according to a logarithm that ensures that the majority of the workers of an area live in the same area and also the majority of residents of an area work in the same area (75%). The population can vary widely but the lowest threshold by construction is 3,500 individuals. The London TTWA is the largest one and includes both London Government Office Region and few adjacent localities. ONS defined 243 TTWAs for UK utilising the 2001 Census information on home and work addresses of the population. Excluding Northern Ireland, there are 232 TTWAs for Britain which is the focus of study. After the cleaning of the sample, TTWAs that were left with few observations (less than 50) were dropped so that each TTWA has large enough sample size for reliable analysis. The final working set consists of 195 TTWAs for Britain. Experimenting with a different spatial level, like the Local Authorities (LAs) that are based on administrative boundaries, has produced qualitatively similar results to those presented in the paper with weaker coefficients.

Regions

When controlling for cycles in the regional economy, region-year fixed effects are included. The working definition of 'region' refers to standard administrative spatial entities used for regional analysis in Britain. These are the 9 Government Office Regions of England (North East, North West, Yorkshire & Humber, East Midlands, West Midlands, South West, East, London, South East) together with the devolved administrations of Wales and Scotland (11 in total).

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