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| Monopsony and minimum wage effects | |  |
| A report for the Low Pay Commission |  | |
| 22 October 2024 | | |

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# Executive Summary

1. The Low Pay Commission is an independent public body that advises the Government on the National Living Wage (NLW) and the National Minimum Wage (NMW). The Low Pay Commission has an ongoing remit to monitor the operation of the NLW and the NMW and evaluate the effects brought about by changes in these wage floors.
2. Previous research on the employment effect of the NLW has tended to show modest to negligible impacts. Different explanations have been offered for this, including that the level of the NLW was not binding, or that businesses use other channels to adjust to increases in the NLW. With the level of the NLW increasing substantially in recent years, with the planned 2024 increase in the NLW set to equal two-thirds of median hourly pay for those aged 21 and over, it is important to continue to investigate the employment effects of increases in the minimum wage and understand what factors explain the lack of employment effects so far observed.
3. This project investigated the role that imperfect competition in the labour market can play in explaining employment effects (or lack thereof) associated with minimum wage increases. In a perfectly competitive market, the elasticity of labour supply facing individual firms (i.e., workers’ responsiveness to a change in wages) is infinite[[1]](#footnote-2) and the wage equals the marginal product of labour. Under these conditions, classical labour theory predicts that, as long as the minimum wage is binding, increases in the minimum wage should unambiguously lead to a negative effect on employment and total hours worked. However, previous empirical work on the employment effects of increases in minimum wages has tended to show negligible or null impact on employment levels and some modest impact on the total hours worked (Manning 2021, Clemens 2019, Jardim et al 2018, Dube et al 2010, Dickens and Draca 2005, Card and Krueger 1993).
4. We investigated the link between different degrees of market concentration and minimum wage effects on the number of workers in low pay employment, total weekly hours worked among low pay workers, average hours per worker among low pay workers, and base hourly wages among low pay workers. A methodological contribution of this study was to use a novel data-driven sectoral definition of low pay labour markets, which grouped sectors together based on the volume of low pay job switches across sectors.
5. We find evidence that, following an increase in the minimum wage, employment and total hours increase in high employer concentration areas relative to in low concentration areas. This finding aligns with previous work, and with the theoretical discussion of the interaction between monopsony and minimum wage effects. However the magnitude and statistical significance of the results are sensitive to our modelling to the specification, and this is likely due to the generally low employer concentration in low pay labour markets, on our measure.
6. We find that hours per low pay worker and base wages do not exhibit a clear pattern across sectors with respect to monopsony and minimum wage effects. We find robust evidence that the NLW introduction increased low pay hourly wages (across low and high concentration labour markets).
7. We designed the analysis so that it covered all sectors, and this broad scope matches the remit of UK minimum wage policy. However, we find that monopsony likely interacts with minimum wage effects differently across different sectors and occupations, due to differences in public sector employment, in the elasticity of hours per worker, in the urban/rural geographic distribution of different sectors, and other factors. On our measures, there is low employer concentration in most sectors of the low pay labour market, and so any monopsony interactions with minimum wage policy are likely only present in quite specific sectors and local areas where employers have wage-setting power. Future work on monopsony effects could usefully focus on sectors or local areas with higher employer concentration.

# Aims and objectives

1. The Low Pay Commission is an independent public body that advises the Government on the National Living Wage (NLW) and the National Minimum Wage (NMW). The Low Pay Commission has an ongoing remit to monitor the operation of the NLW and the NMW and evaluate the effects brought about by changes in these wage floors.
2. Previous research on the employment effect of the NLW has tended to show modest to negligible impacts. Different explanations have been offered for this, including that the level of the NLW was not binding, or that businesses use other channels to adjust to increases in the NLW. With the level of the NLW increasing substantially in recent years, and the planned 2024 increase in the NLW set to be equal to two-thirds of median hourly pay for those aged 21 and over, it is important to continue to investigate the employment effects of increases in the minimum wage and understand what factors explain the lack of employment effects observed.
3. This project investigated the role that imperfect competition in the labour market can play in explaining employment effects (or lack thereof) associated with minimum wage increases. Specifically we investigated the link between different degrees of labour market concentration and employment in relation to minimum wage changes. This can help inform to what extent increases to the NLW in the UK can be expected to continue having modest or no employment effects going forward, and add to the LPC’s evidence base in making recommendations to the Government.

# Literature review

## Introduction

1. The National Minimum Wage (NMW) and the National Living Wage (NLW) have increased substantially since their inception in 1999 and 2016, respectively, in nominal and real terms. Recent increases in the NLW have been over and above average and median wages growth.
2. In a perfectly competitive market, the elasticity of labour supply facing individual firms (i.e., workers’ responsiveness to a change in wages) is infinite[[2]](#footnote-3) and the wage equals the marginal product of labour. Under these conditions, classical labour theory predicts that, as long as the minimum wage is binding, increases to the minimum wage should unambiguously lead to a negative effect on employment and total hours worked. However, previous empirical work on the employment effects of increases in minimum wages has tended to show a negligible or null impact on employment levels and some modest impact on the total hours worked (Manning 2021, Clemens 2019, Jardim et al 2018, Dube et al 2010, Dickens and Draca 2005, Card and Krueger 1993).

In the UK, recent research has also reported small or null employment effects, despite the recent substantial increases to the NLW (Dube et al 2019; Dolton et al 2015, Dolton et al 2012). With the exception of some studies finding adverse effects for certain labour market subgroups such as female part-time workers (Dickens et al 2015) or specific non-tradable sectors such as the residential care home sector (Draca, Machin and Van Reenan 2011, Machin, Manning and Rahman, 2003).

In a recent study in the UK, Cribb et al. (2021) investigated the introduction of the NLW and its subsequent increases. The authors used data from the Annual Survey of Hours and Earnings (ASHE) between 2016 and 2019 to compare employment changes along the wage distribution between low-wage areas and similar workers living in higher-wage areas that were less exposed to increases in the minimum wage. Overall, they found a negative but small, not statistically significant employment effect. However this overall effect masked substantial variation in the effect of increases in the minimum wage within the low pay end of the wage distribution, although small sample sizes limited their ability to identify the dynamics that led to this variation.

The magnitude and direction of the effect of minimum wages on employment depends on a range of factors, and we note four that have been highlighted in the literature: (1) pass-through between wages and labour costs, (2) elasticity of labour demand, (3) price elasticity of demand of final product, and (4) elasticity of labour supply faced by firms (Manning 2021, Clemens 2021):

* + **Low pass-through between wages and labour costs:** The effect of higher minimum wages on total factor costs can be mitigated by different channels. Firms can adjust non-wage labour costs in a variety of ways, including reducing non-wage benefits that contribute to workers’ full salaries,[[3]](#footnote-4) reducing the costs of measures that improve working conditions or reducing the volume and quality of employer-subsidised services for workers.[[4]](#footnote-5) Firms can also adjust firm productivity by reducing breaks during working hours, increasing staff shifts during unsocial hours to better utilise equipment, investing in training for employees or otherwise changing the skill mix of employees, or causing low-productivity employees to adjust their level of effort to avoid getting terminated. For example, Coviello, Deserranno and Persico (2020) found that workers employed by a large US retailer and paid based on performance increased their effort and were terminated less often after an increase in the minimum wage.
  + **Low elasticity of labour demand:** Firms can also absorb the effect of an increase in the minimum wage if the elasticity of labour demand (i.e., responsiveness of labour demand to a change in wages) is low which depends, among other factors, on the share of minimum wages in total costs and the elasticity of substitution of minimum wage workers with other inputs.[[5]](#footnote-6) If these two factors are low, firms might reduce their dependencies on low-skilled labour, increasing their reliance on capital, technologies or high-skilled labour, or increasing investments to enhance labour efficiency. When studying the effects of state minimum wage increases in the US between 2011 and 2016, Clemens, Kahn and Meer (2021) found evidence of substitution away from low-skilled labour as firms modified their minimum requirements in job postings. Increases in minimum wages might also be absorbed in the form of lower profits, especially in contexts when it is challenging for firms to adjust employment, prices or other non-wage labour costs.Machin (2018) found that firms in the UK experienced a reduction in market capitalisation comparable to a reduction in profits after the announcement in July 2015 of an unexpected large increase in the NMW in April 2016.
  + **Imperfectly competitive product markets:** Firms might face limited competition in their product markets (i.e., low price elasticity of demand), allowing them to raise prices or decrease the quality of their products to counter minimum wage increases. Frontier Economics (2020) assessed whether uplifts in the NLW between 2010 and 2020 were passed through to consumers in the form of higher prices of exposed products. The study reported no statistically significant effects on employment but found strong evidence of a statistically significant relationship between minimum wage uplifts and the prices of exposed products, suggesting that inflation might be an adjustment mechanism. There is evidence that these results are more likely to occur in non-tradable sectors, as when the relevant local product demand elasticity might be low and the share of minimum-wage workers is high (Manning, 2021). On the contrary, prices in tradable sectors (e.g., manufacturing) might be set internationally, so it might be challenging for firms to pass on any changes in minimum wages to customers (Dube, 2019).
  + **Monopsonistic[[6]](#footnote-7) labour markets:** Monopsony refers to the labour market case in which firms possess different degrees of wage-setting power. This wage-setting power stems from a low (inelastic) elasticity of labour supply to the firm, meaning that workers are relatively unresponsive to changes in their wages and have limited ability to switch jobs. Low job switching ability could be due to numerous reasons including job search frictions[[7]](#footnote-8), limited geographic mobility linked to high commuting costs, and heterogeneous preferences for amenities such as working conditions or commute length (Hirsh et al 2022, Manning, 2020).If firms have substantial discretion in setting wages, workers can be paid below their marginal productivity (in the absence of a minimum wage or other wage regulation), leading to levels of employment and wages below those that would prevail in a competitive market. In this situation, firms can absorb the introduction of and subsequent increases in a minimum wage without reducing their workforce, as long as this wage floor remains below the workers’ marginal productivity. This is possible at the cost of some profit reduction, as the introduction of a minimum wage bridges the gap between wages and marginal labour productivity. In other words, under monopsonistic conditions, theory suggests that the employment effects following an increase in the minimum wage are ambiguous and could even be positive.

1. The effect of different degrees of imperfect competition for low pay labour is the focus of this study. Below we review relevant literature on:

* Empirical evidence on imperfect competition in the UK labour market
* Summary of the theoretical effect of imperfect competition on low pay labour
* Empirical methods for investigating the effect of imperfect competition on low pay labour
* Empirical findings on the effect of imperfect competition on labour market outcomes

## Imperfect competition in the UK labour market

1. There is variation in labour market competitiveness between industries, occupations and geographical regions resulting in deviation from the perfectly competitive model (Manning 2020). Recent studies have explored the relationship between wages and measures of employment concentration as a proxy for monopsony power (see Section 2.4.2 for a discussion of empirical measures of monopsony). However, to the best of our knowledge there is limited evidence in the UK.
2. Bell and Tomlinson (2018) examined product and labour market concentration (i.e., concentration ratios) in the UK economy since the early 2000s. The authors measured product concentration in terms of the revenue share of the 5 largest UK firms in 600 sub-sectors. They estimated that across UK sectors, product concentration rose overall between 2003 and 2018, with substantial variation between subsectors. However, they found that labour market concentration – measured as the share of employees working in the top 5 biggest UK firms in each sub-sector – exhibited different trends from product market concentration. Labour market concentration declined slightly over the whole period under review, and this was driven largely by falling concentration within sectors (not changes in the relative size of sectors with different concentrations).
3. The authors tentatively suggest that the different trends in UK product and labour market concentration imply that firms that achieved large gains in revenue market share may have increasingly relied on outsourcing labour compared to smaller firms. This means that since the early 2000s, the largest UK firms have increased their market shares by using a relatively small amount of national labour while increasing their levels of turnover per employee. Importantly, labour concentration was substantially higher for low-paid workers and for low-pay sectors than the rest of the UK economy, and perhaps this is in part due to the difficulty of outsourcing certain low pay roles (e.g. service jobs). Based on these results, they note that labour market concentration and lack of employment options are more likely to be a concern for low pay workers than for the rest of the labour force.
4. In fact, Araki et al (2022) found that the UK’s share of business sector employment in concentrated labour markets (Herfindahl-Hirschman Index over 1,500) was lower than the OECD average in 2019. The authors also found variation within UK subsectors: UK rural labour markets were more concentrated than UK urban labour markets, and UK workers that can telework have substantially less concentrated labour markets than workers who cannot telework.

## Theoretical effect of imperfect competition for low pay labour

1. In a context where firms have some degree of monopsonistic power, the effect of an increase in the minimum wage is ambiguous and depends on three factors: (1) the baseline minimum wage level with respect to the marginal productivity of labour, (2) the magnitude of the change in the minimum wage (Naidu, Posner and Weyl 2018; Manning 2011) and (3) the degree of wage-setting power. In monopsonist markets, increases in wage floors can potentially increase employment (Azar et al 2019a, Bhaskar, Manning and To 2002, Bhaskar and To 1998).
2. In recent years there has been an increase in research interest in measuring monopsony power in labour markets and its effect on average wages. However, there are only a few studies that explore whether the level of competition in the labour market explains the negligible or null impact of changes in minimum wages on employment levels. Azar et al. (2019a) used a measure of labour market concentration (i.e., HHI) as a proxy for the level of labour market competition in a low-wage retail sector to analyse the minimum wage employment effect in the US. Munguia-Corella (2020) used a measure of market concentration (i.e., HHI) and job mobility to estimate the effect of minimum wages in the US. The authors found negative employment effects from increases in the minimum wage in low concentration markets, and a null or positive relationship in highly concentrated markets, which aligns with the theory outlined in Section 2.1.

## Empirical methods for investigating the effect of imperfect competition for low pay labour

1. The identification of the impact of the NMW on labour market outcomes in the UK is inherently difficult because there is no sizable excluded group from the NMW legislation, or differences across bordering areas that can be exploited. The typical approach applied to identify the impact of the NMW on the labour market is the ‘differential impacts’ approach which compares outcomes among groups of low-paid workers that experience different levels of minimum wage exposure either across regions or sectors, or at different points of the wage distribution (Dickens et al 2015).
2. A key challenge in implementing the ‘differential impact’ approach is that it assumes that employment outcomes amongst groups of low-paid workers would have evolved in a similar parallel way, absent of changes in the minimum wage. However, in some cases this assumption might not hold as there might be other exogenous factors that change simultaneously (e.g., changes in benefit systems). Additionally, this approach typically relies on self-reported or administrative data, and a potential shortcoming of these data is low-pay non- or under-reporting; an increase in the minimum wage could lead to an increase in non-reporting of low pay employees or non-reporting of some working hours.
3. Azar et al (2019a) noted, “an ideal design will study a (near) minimum-wage-earning occupation in a low-wage industry that has a range of high and low labour market concentration levels”. This highlights two additional key challenges for testing the relationship between minimum wages and employment in labour markets with monopsonistic characteristics: (1) accurately defining labour markets for low pay labour, and (2) measuring that monopsony power, which requires understanding of the drivers of wage-setting power. We discuss these two issues in detail below.
4. Recent relevant studies with high quality research designs are summarised in Table 1. The table includes the available evidence on how labour market power mediates the minimum wage employment effect (Azar et al 2019 and Munguia-Corella 2020) – both for the US. It also presents recent and highly cited studies using different approaches to define labour markers and measure market power.

### Labour market definition

1. Conceptually, the labour market for a worker encompasses the potential transitions of workers with similar skills between similar jobs. If the definition is too narrow, there might be a high number of job opportunities outside the defined market. Using data from the 2011 UK Census of Population and Census Area Statistics (CAS), we can utilise wards as the basic geographical unit. Manning and Petrongolo (2022) showed that labour market concentration is overestimated if worker mobility across segments is not considered. But if the market definition is too broad, it might overestimate the similarity of jobs within the market (Azar et al 2022). An appropriate market definition needs to strike the right balance between these two.
2. As shown in Table 1, most of the recent literature has defined relevant labour markets by interactions between commuting zones and/or geographical units and disaggregated industry and/or occupation classification codes to identify concentration local labour markers and/or low-mobility jobs. Which combination represents a better definition of the labour market depends on the ‘level of porosity’ across industries and occupations, and across locations (i.e., how likely and easy it is for workers to change occupations and industries, and to move or commute to other areas). For example, Manning and Petrongolo (2017) found that job search behaviours in the UK are quite local due to frictions associated with commuting between labour markets.
3. Studies of the impact of market concentration on labour (not specifically low pay labour) tend to use relatively granular sector segmentation in order to construct labour markets. Benmelech et al (2021) analysed the effect of local market concentration on wages in the US manufacturing sector at the industry level, under the assumption that specific skills restrict job searches. Azar et al (2019a), Azar et al (2020a) and Azar et al (2020b) used a dataset of US-wide online job vacancy postings from two labour market analytics firms to measure concentration at the level of six-digit occupation codes. However, low pay labour may be more fungible across sectors than higher pay labour, and sector-level market segmentation is unlikely to be appropriate for studying minimum wage effects. Azar (2019a) and Munguia-Corella (2020), aggregate sectors in order to study low pay labour.
4. In the US literature, it is common to segment labour markets at the county level, for example Benmelech et al (2021), Azar et al (2019a), Azar et al (2020a), Azar et al (2020b). Munguia-Corella (2020) found evidence that there is limited low pay labour mobility between US counties, and concluded that counties provide a reasonable low pay market definition. However, we note that commuting and mobility patterns among low pay labour may differ substantially between counties, as they depend on the local cost of transport, and results from the US may not be applicable to the UK.
5. Many recent studies have modelled local labour markets as discrete segments without taking into account that segment borders might be ‘porous’ and endogenous (Schubert et al 2021, Manning and Petrongolo 2017). In reality, workers may be willing to consider job opportunities in other local labour markets based on their geographical vicinity, skills transferability across occupations and industries and the level of the wage offer itself. Market definitions should be consistent with the level of cross-market transitions in the area of study (Azar et al 2022).

### Measuring labour market concentration

The most conceptually direct measure of monopsony power in labour markets is to estimate the elasticity of labour supply a given employer faces (Manning 2021, Manning 2011). There is a large literature that estimates labour supply elasticity, but as this approach is not the main focus of our study, we only include a high-level overview. The most common approach to estimating this elasticity is to use a dynamic monopsony model with search frictions or a static monopsony model with idiosyncratic worker preferences over non-wage job attributes (e.g., commuting distance or time) (Langella and Manning, 2021). In both cases, the elasticity of labour supply of a given firm can be written as the difference between the elasticity of recruitment and the elasticity of separations (Datta 2022, Hirsh et al 2022, Manning 2003). Due to limited data availability, most studies estimate either the recruitment elasticity – proxied by the applicant-wage elasticity – or the separation elasticity (Sokolova and Sorensen 2021).

1. However, estimating any of the elasticities mentioned above is challenging as they require exogenous variation in wages at the firm or establishment level (Datta 2022, Manning 2021). This is because there is substantial variation in wages across workers employed by the same firm due to differences in skills and other characteristics, or transitory shocks that affect job outcomes including wages (e.g., social networks, health, access to information).
2. In order to find suitable proxy measures for the wage elasticity of labour supply to the firm, it is important to understand the source of market power. Three main sources of monopsony power have been recognised in recent literature: (1) employer concentration or number of firms, (2) search frictions and (3) job differentiation (Azar et al 2019a, Manning and Petrongolo 2022). Given that all three measures imply a low wage elasticity of supply, theory suggests they should empirically correlate with monopsony power.
3. Many recent studies have explored the relationship between wages and measures of employment concentration. As shown in Table 1, most of these studies have constructed traditional measures of market concentration such as the HHI. The HHI is expressed as the sum of employment shares of all businesses in a given labour market and ranges from 0 to 10,000. Lower scores indicate higher levels of competition in the market. Specifically, the HHI is calculated as follows:

where is the employment share of firm in a given local market . HHI takes into account the entire distribution of businesses in each local market rather than focusing only on the biggest firms and gives a higher weight to businesses with larger shares. One of the main issues with using HHI is that it requires dividing local labour markets into discrete segments which assumes implicitly that workers cannot move across segments (Manning, 2021). In other words, the measure assumes that travel is costless within local markets and infinitely costly at the border (Datta 2022), and there is therefore a risk that job switching patterns among smaller subpopulations of workers are not well captured by a given labour market definition. However, the calculation for the HHI is simple and straightforward, requiring basic market information that can be obtained through national surveys. We have chosen to use HHI as a proxy measure for monopsony primarily because of data availability. By using HHI, our analysis can cover all sectors, for all geographic areas of the UK, and therefore deliver broader findings than would be possible with alternative monopsony proxy measures (discussed below in this subsection) that have greater data demands. Azar et al (2019b) estimated the relationship between the elasticity of labour supply and HHI measures and found that they are negatively associated. Furthermore, Azar et al (2020a), Rinz (2020) and Lipsius (2018) found a negative and significant relationship between wages and HHI, in line with monopsony theory. As mentioned above, when firms have substantial discretion in setting wages due to search frictions, firm-specific amenities or limited outside job opportunities, workers can be paid below their marginal productivity leading to levels of employment and wages below those that would prevail in a competitive market.

1. A key challenge in using market concentration as a proxy of monopsony power is that it might introduce endogeneity with respect to wages. This is because employer concentration may be correlated with supply and demand forces in specific labour markets, such as local economic conditions which also affect wages or employment, including productivity shocks. For example, a local increase in productivity for particular occupations would lead to firm market entry, decreased concentration and increased wages. Simultaneity bias might also arise between wages and market concentration, e.g. high wages might act as a barrier of entry for new firms or low-pay workers. To account for this issue, some studies have instrumented with labour supply or demand shifters at the national level; such as the number of job postings (vacancies) for the same type of occupations in other areas, or the national growth rate among very large employers (Rinz 2022, Azar et al 2020a, Schubert et al 2021).
2. Other studies have approximated monopsony power in labour markets by measuring labour force mobility across industries and/or occupations (i.e., how often workers switch to different industries when changing jobs). Low mobility can be a sign of labour search frictions[[8]](#footnote-9) that can result in monopsony power, as employees incur costs from job switching (Manning 2011), or that firms are paying above market rates. However, as with market concentration measures, using labour mobility as a proxy of monopsony power also has the same challenges around endogeneity. Munguia-Corella (2020) used two measures of monopsony power to analyse the effect of minimum wages in the US: within-sector job mobility and labour concentration (i.e., HHI). The author found similar patterns in monopsony power using both measures. The author found that the minimum wage had a significant negative elasticity to employment in perfectly competitive markets, and a positive but insignificant elasticity to employment under monopolistic conditions.
3. Workers can also have different preferences for non-wage benefits that contribute to their full salaries (Manning 2021, Card et al 2018). When jobs are differentiated by non-wage benefits, firms can gain wage-setting power. Azar et al (2022) estimated a differentiated jobs model using data on job applications and their findings suggested that non-wage job differentiation contributes to labour supply inelasticity. Manning and Petrongolo (2022) proposed a monopsony model of the labour market in which the source of market power stems from idiosyncratic worker preferences over non-wage attributes of jobs (i.e., commuting distance). The authors found that large metropolitan areas in the UK have lower concentration because workers need to commute relatively longer distances in urban areas.
4. Monopsony measures can be constructed from vacancies, applications or employment data, using industry and/or occupation codes. Online vacancies provide a rich source of data on firm’s hiring behaviour (e.g. including detailed information on skills, prerequisites, and job tasks) that typically is not collected through traditional surveys or databases (e.g., job titles, job descriptions, requirements, accurate posting dates). Additionally, online vacancies allow the assessment of job creation flows rather than stocks which can be slow to adjust to minimum wage changes (Clemens, Kahn and Meer 2021), especially when quitting is costly and recruitment is challenging. However, vacancy data only provides a partial view of employment outcomes as it does not contain information on quitting or separation rates. Overall, the choice between vacancy and employment measures depends on the available data and which one represents a better indication of the opportunities available in a given labour market (Manning, 2020). Concentration of employment is typically higher than concentration of vacancies, as only a proportion of firms will be hiring at any given time (Azar et al 2020a). According to Dey and Handwerker (2019), measures of HHI are similar when labour markets are defined using occupation or industry codes.

## Empirical findings

1. Estimates of the elasticity of labour supply found in the literature are often quite low, implying considerable monopsony power (Manning 2021) even in markets that are likely to be highly competitive such as online labour markets (Dube et al 2020). Sokolova and Sorensen (2021) present the findings of a meta-study of the elasticity of labour supply to the firm and found strong evidence of firms having monopsony power with workers producing as much as 12% more than their wage level. In a recent study, Azar et al (2022) estimated a firm level elasticity of 4.8, suggesting an implied markdown of 21% below workers’ productivity. Similar results were found by Datta (2022) who studies the extent of monopsony power in a low pay labour market using a novel human resources dataset from a large UK firm.
2. Several of the studies reviewed using market concentration measures as a proxy for market power have found a negative and significant relationship between wages and the HHI independently of the variables used to construct this index (employment, vacancies or applications). For example, Azar et al (2020a) found that going from the 25th percentile to the 75th percentile in concentration is linked with up to a 17% decline in wages. Rinz (2022) found that, from 1976 to 2015 in the US, increased local industrial concentration reduced earnings and increased inequality. However, other studies have found that this relationship is reduced for workers covered by a collective bargaining agreement (Benmelech et al 2018, Abel et al 2018).

Two US studies of the relationship between monopsony and minimum wage effects have found that monopsony seems to contribute to the negligible minimum wage employment effects found in the literature. Azar et al (2019a) found in the US that increases in the minimum wage are found to significantly decrease employment of workers in low concentration markets, but were estimated to be positive in the most highly concentrated markets. However, their results are limited to a few occupations in a low-paid retail sector[[9]](#footnote-10) and it does not cover all counties in the US. Manguia-Corella (2020) similarly found that minimum wage increases had a negative effect on teenage employment in areas with high competition, and positive effects on teenage employment in areas with a high degree of monopsony.

1. Our study builds on this literature to examine the role in the UK that the degree of market concentration in local labour markets plays in explaining the lack of observed employment effects after an increase in NMW/NLW. To the best of our knowledge, studies in the UK have focused on the measurement of monopsony power in the labour market and its impact on average wages (Manning and Petrongolo, 2022, Abel et al 2018, Manning and Petrongolo, 2017), but not on the interaction between monopsony and the effect of minimum wages on employment. The study would help clarify the extent to which local variation in low pay labour market structures leads to variation in local labour market responses to NMW/NLW increases. If selected local markets have higher levels of labour market concentration, then raising the minimum wage in these areas could result in higher wages without reducing employment or hours. This study focuses on labour market concentration (data availability allows us to conduct a UK-wide analysis), but investigating other sources of monopsony power in particular markets could be a useful area for future work.

|  |
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| Table 1 Summary of selected literature |

| 1. Author(s) | Country | Effect of interest | Definition of local labour markets | 1. Measurement of monopsony power | 1. Source of monopsony power | 1. Identification strategy | 1. Main findings |
| --- | --- | --- | --- | --- | --- | --- | --- |
| 1. Munguia-Corella (2020) | United States | 1. Effect of minimum wage on employment | 1. Combination of 4-digit NAICS[[10]](#footnote-11) code (industry) and counties by quarter | 1. HHI based on job vacancies and job mobility | 1. Labour market concentration and job mobility | 1. Two-way fixed effects (quarter and county) | 1. Under perfect competition, minimum wage has a significant elasticity to employment of -0.418. Under monopsonistic labour, effect of minimum wage is positive but insignificant (between 0.04 and 0.29 depending on degree) |
| 1. Azar et al (2019a) | United States | 1. Effect of minimum wage on employment | 1. Combination of 6-digit SOC[[11]](#footnote-12) level (occupation) in a 3-digit NAICS (industry) merchandise store retail sector and some counties by quarter | 1. HHI based on job vacancies | 1. Labour market concentration | 1. Fixed effect model (quarter and county) and state time trends | 1. Increases in the minimum wages significantly decreases employment in low concentration markets and become less negative (and even positive) as labour concentration increases |
| 1. Autor et al (2023) | United States | 1. Effect of labour market concentration on wages | 1. Combination of occupation and industries, and job changing patterns by month | 1. Elasticity of labour supply (separation) | 1. Dynamic job ladder model with search frictions | 1. Fixed effects model (state and period) | 1. Increase in labour market competition and elasticity of labour supply to the firm in the low-wage labour market following the peak of the Covid-19 pandemic 2. Wage-separation elasticity increases more among young non-college workers, who change employers and industries |
| 1. Manning and Petrongolo (2022) | UK | 1. Effect of labour market concentration on wages | 1. Combination of Census of Population and Census Area Statistics (CAS) and commuting patterns by year | 1. Concentration index based on employment | 1. Job differentiation and mobility within and across labour markets, based on spatial job search model | 1. Fixed effects model (ward and year) | 1. Labour market concentration would be overestimated without taking into account worker mobility across overlapping local markets 2. Concentration index is negatively and significantly correlated to local wages |
| 1. Datta (2022) | UK | 1. Effect of labour market concentration on wages | 1. Combination of 4-digit SOC level (occupation) and Build-Up Areas (BUAs) | 1. Elasticity of labour supply (recruitment and separation) | 1. Job differentiation and commuting within and across labour markets based on job search model | 1. Panel IV regression | 1. Strong evidence of monopsony power in the UK (20-25% markdown) which increases with commuting distance |
| 1. Azar et al (2022) | 1. United States | 1. Effect of labour market concentration on wages | 1. Combination of 6-digit SOC level (occupation) by commuting zone and year | 1. Elasticity of labour supply | 1. Job differentiation | 1. Nested logit model and IV | 1. Evidence of substantial job differentiation within and across occupations 2. Geographic distance between the job and the job seeker plays an important role in job differentiation 3. Firm level labour supply elasticity is 4.8 (21% markdown) |
| 1. Hershbein, Macaluso and Yeh (2022) | 1. United Stated | 1. Effect of labour market concentration on wages | 1. Combination of 4-digit SOC level (occupation) in manufacturing sector and metropolitan areas | 1. Plant-level markdowns and HHI based on job vacancies | 1. Job differentiation (variation in labour supply elasticities at the firm level) | 1. Production function estimation to calculate micro-level markdowns | 1. Average implied labour supply elasticity to the plant of 1.27 and average markdown 1.53 2. Substantial dispersion in markdowns across plants 3. Correlation between local markdowns and local labour market concentration over time is modest |
| 1. Schubert et al (2021) | 1. United States | 1. Effect of labour market concentration on wages | 1. Combination of 6-digit SOC level (occupation) and worker transition patterns by year | 1. Concentration index based on employment | 1. Labour market concentration and job mobility allowing for outward mobility based on wage bargaining model | 1. Panel IV regression | 1. Increases in employer concentration within a local occupation reduce wages by 6.5% on average, but substantial heterogeneity depending on degree of job mobility |
| 1. Azar et al (2020a) | 1. United States | 1. Effect of labour market concentration on wages | 1. Combination of 6-digit SOC level (occupation) and commuting zones by quarter | 1. HHI based on job vacancies | 1. Labour market concentration | 1. Fixed effect model and panel IV regression | 1. Average market is highly concentrated (above 2,500 HHI) 2. Going from the 25th percentile to the 75th percentile in concentration is associated with a 5% to 17% decline in posted wages |
| 1. Azar et al (2020b) | 1. United States | 1. Effect of labour market concentration on wages | 1. Combination of 6-digit SOC level (occupation) and commuting zones by quarter | 1. HHI based on job vacancies | 1. Labour market concentration | 1. OLS | 1. Average market has an HHI of 4,378. 60% of labour markets are highly concentrated (above 2,500 HHI) 2. Labour market concentration is negatively correlated with wages 3. No relationship between concentration and occupation’s skill level |
| 1. Benmelech et al (2020) | 1. United States | 1. Effect of labour market concentration on wages | 1. Combination of 4-digit SIC[[12]](#footnote-13) level (industry) and localised geographic areas by year | 1. HHI based on employment | 1. Labour market concentration | 1. Fixed effect model and panel IV regression | 1. Negative relation between local-level employer concentration and wages that strengthens over time 2. Relation increases when unionization rates are low |
| 1. Abel et al (2018) | 1. UK | 1. Effect of labour market concentration on wages | 1. Combination of 2-digit SIC levels (industry) and NUTS2 regions by year | 1. HHI based on employment | 1. Labour market concentration based on search and matching model | 1. OLS | Substantial cross-sectional variation in monopsony at the industry level  Link between labour market concentration and pay is greatly reduced for workers covered by a collective bargaining agreement |

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| Source: Various |

# Data

1. We used two microdata sources: the Business Structure Database (BSD) and the Annual Survey of Hours and Earnings (ASHE) from the ONS Secure Research service.[[13]](#footnote-14)
2. The **BSD** covers all VAT- or PAYE-registered firms, and around 98% of all UK economic activity. As it is essentially an annual census of all firms, it provides a longitudinal dataset suitable for various panel analysis methods. A particular advantage of the BSD is that all variables are collected at the level of the individual workplace (‘local unit’), as well as at the firm level (‘enterprise unit’). As local conditions will affect the impact of minimum wages, this means that the individual workplaces from firms operating in many locations can be included separately. The BSD is used to construct a measure of local monopsony in 2015 (i.e., the baseline year of the study); from employment data, enterprise unit locations and industry codes. The motivation for using data from the baseline year is to avoid endogeneity issues in the specification but this approach also happens to avoid any timeliness issues in BSD reporting.
3. The **ASHE** data set follows a sample of 1% of UK workers, randomly selected on the basis of their national insurance number (NINO). The same individuals are followed over time. The survey is completed by employers, so should align with payroll data. Hence, the pay data is likely more accurate than in respondent surveys (e.g. Labour Force Survey), which may suffer various inaccuracies, such as imperfect recall or other biases. ASHE covers in the range of 140,000 to 185,000 workers per year. The data set contains various measures of pay and hours worked. We note that there are various known issues with non-response in ASHE. Micro enterprises, private companies, younger firms are underrepresented; while jobs in Education and Health and Social Work are overrepresented, compared with BSD data (Stokes et al 2022). However, we rely on ASHE’s sampling weight estimation to correct for non-response accurately.

# Methods

We examined the association between changes in the minimum wage and employment changes in minimum wage sectors between 2015 and 2019, taking into account firm exposure to minimum wage increases, in local areas that are characterised by different levels of market concentration.

1. We defined low pay labour as a worker that earned an hourly rate that is less than or equal to the 2023 central forecast of the NLW that will be introduced in April 2024 in real terms (CPI), adjusted by 5 pence to account for data imprecision. We investigated the following outcomes, all constructed from ASHE data:
   * Number of workers in low pay employment
   * Total weekly hours worked among low pay workers
   * Average hours per worker among low pay workers
   * Mean wages excluding overtime among low pay workers

Workers can move in and out of the low pay category, and these ‘threshold’ effects may bias our estimates. We therefore include a sensitivity in which the outcome (and all calculations) are based on the entire working population including high pay workers.

The core regression specification follows Azar et al. (2019) and is as follows:[[14]](#footnote-15)

where *i* indicates the local geographic area, *s* is the SIC group, *t* is the time period (year, 2015-2019); and

* is the outcome of interest in Travel to Work Areas (TTWA) *i*, SIC cluster *s* and time *t* [ASHE data];
* is a dummy that takes the value 1 for periods after the introduction of the NLW (2016) and 0 otherwise;
* is a dummy measuring whether monopsony in local market TTWA *i*, SIC cluster *s* and time *t* is above the 75th percentile among local markets (i.e., high concentration areas), with 90th percentile investigated in sensitivities (i.e., very high concentration areas)[[15]](#footnote-16) [BSD data];
* is a dummy measuring whether the proportion of low pay workers paid at or below the incoming minimum wage level in TTWA *i*, SIC cluster *s* and time *t* is above the median for local labour markets [ASHE data];
* is the main variable of interest, measuring how the effect of the minimum wage on the outcome varies with employer market power among local labour markets with a high proportion of minimum wage workers;
* is the percentage of low pay workers that are employed by public sector employers. This is included because public sector wage schedules are subject to regulation and are normally set nationally, and so the relationship between wages and concentration is likely to be different among public sector employers and among private sector employers (although public/private employers compete with one another for workers);
* are geographic area fixed effects;
* is the error term, clustered by geographic area.

The main specification included FY2015-FY2019 to avoid effects of the pandemic on hours worked, and the distorting effects of furloughing on employment. CMA (2024) found that the COVID-19 pandemic generated an abrupt increase in labour market concentration, which aligns with our findings that the post-2019 years included exogenous shocks and noise in the data that made the findings including pandemic years difficult to interpret.

1. We present results for England and Wales only, because of inconsistencies in Scotland local geographic area definitions (i.e., TTWA) among the datasets that we used.

#### Geographic definition of local labour market

Low pay workers tend to be less geographically mobile than other workers (Green and Owen, 2006). They may have additional constraints on commuting to work (e.g. limited to public transport), and mobility over time (i.e. less likely to move house in order to change job).

1. We have focused on TTWA as local market definitions, as they are standard in the literature and aim to capture the characteristics of local labour markets summarised above. For example, Azar et al (2022), Azar et al (2020a) and Azar et al (2020b) use commuting zones to define geographic labour markets in the US which are clusters of counties built based on commuting patterns drawn from census data. Manning and Petrongolo (2022) characterised labour market segments in the UK based on Census Statistics Area wards and commuting patterns across Output Areas (OA) from the 2011 Census.
2. Defining disjoint (non-geographically-overlapping) labour markets reduces computational complexity relative to overlapping labour markets, but it (1) assumes that travel costs for all locations within a local market are similar, and (2) also may not capture the behaviour of workers who live near market boundaries. To investigate the extent to which disjoint labour market definitions may bias the results, we will include sensitivities with varying levels of geographic aggregation.
3. We use three TTWA definitions: standard TTWAs (167 in England and Wales) for the main specification, and TTWAs calculated based on low qualification workers (340 in England and Wales), and bus users (142 in England and Wales) to investigate larger and smaller geographic definitions. The standard TTWAs will be used in our main specification as the starting point because it represents a middle point between the two alternative TTWAs.
4. The standard TTWAs are geographical units created to reflect self-contained and non-overlapping areas with at least 3,500 economically active population in which at least 75% live and work (i.e., all commuting occurs within the boundary of that area). TTWAs were produced using an algorithm to identify commuting patterns from flow data[[16]](#footnote-17) by origin and destination for workers aged 16 and over, gathered in the Census 2011. This same method was applied to identify commuting patterns for low qualification workers and bus users to create the alternative TTWAs.[[17]](#footnote-18)

#### Sector/occupational definition of local labour markets

1. Low pay workers tend to have skill sets that match a wider array of occupations and sectors than higher pay workers have (i.e. less skill specialisation) (Longhi and Brynin 2010). However low pay workers are unlikely to have a skill set suited to all low pay jobs. For example, low pay workers with relatively stronger soft skills and physical skills may perform differently in the labour market (Aghion et al 2021). In order to estimate these types of labour market boundaries, we propose the following procedure:

* **First**, we define labour markets based on sectors (4-digit SIC). The advantage of basing labour market definitions on occupational codes instead would be that the skills required within a low pay occupation may be relatively more homogenous than they are within a sector. However, our measure of monopsony can only be calculated on a SIC basis (as it depends on BSD data, which does not include SOC). An analysis with SOC-based labour market definitions would be a useful area for future research.
* **Second**, we choose a method of estimating the ‘proximity’ between SICs, which measures the extent to which each pair of SICs belongs in the same market for low pay labour using ASHE data. We estimate the proximity from one SIC to another SIC as the estimated volume of low pay workers switching from one SIC to another (i.e., the number of workers switching from one SIC to another between adjacent and non-adjacent years). SICs with many job switches should have greater weight than SICs with fewer job switches, in defining the labour market. We aggregate the number of switches across the whole sample 2015-2019 to improve the precision of the estimates; it is unlikely that the low pay skills required by SICs would materially change over a short time period.
* **Third**, we choose a method of detecting labour markets based on the measure of proximity. The SIC/SOCs job switching data forms a network: the SIC/SOCs are nodes, and the volume of job switches are directional edges. We use a standard approach to community detection from network analysis, Louvain community detection (Blondel et al 2008). The number of communities that the algorithm detects is controlled by a user input (the resolution parameter), and we varied this parameter in sensitivity analysis.

1. Below we show the most common year-on-year SIC code switches among low pay workers in ASHE, to illustrate the kinds of related jobs that this approach aims to group together within a local labour market.

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| Table 2 Most common SIC code switches among low pay workers |

| 1. **#** | **SIC origin** | **SIC destination** |
| --- | --- | --- |
| 1. 1 | Primary education | General public administration |
| 1. 2 | Social work activities without accommodation for the elderly and disabled | Residential nursing care facilities |
| 1. 3 | Unlicenced restaurants and cafes | Licenced restaurants |
| 1. 4 | General secondary education | Primary education |
| 1. 5 | Unlicenced restaurants and cafes | Hotels and similar accommodation |
| 1. 6 | Activities of call centres | Management consultancy activities other than financial management |
| 1. 7 | Public houses and bars | Hotels and similar accommodation |
| 1. 8 | Other residential care activities n.e.c. | Residential nursing care facilities |
| 1. 9 | Other residential care activities n.e.c. | Residential care activities for the elderly and disabled |
| 1. 10 | Temporary employment agency activities | Other activities of employment placement agencies |
| 1. 11 | Residential care activities for the elderly and disabled | Residential nursing care facilities |
| 1. 12 | General cleaning of buildings | Combined facilities support activities |
| 1. 13 | Child day-care activities | Primary education |
| 1. 14 | Primary education | Retail sale in non-specialised stores with food, beverages or tobacco predominating |
| 1. 15 | Primary education | General cleaning buildings |
| 1. 16 | Other food services | Event catering activities |
| 1. 17 | Retail sale of clothing in specialised stores | Retail sale in non-specialised stores with food, beverages or tobacco predominating |
| 1. 18 | Social work activities without accommodation for the elderly and disabled | Other residential care activities n.e.c. |
| 1. 19 | Unlicenced restaurants and cafes | Retail sale in non-specialised stores with food, beverages or tobacco predominating |
| 1. 20 | Tour operator activities | Travel agency activities |

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| Source: ONS – ASHE (2015) |

1. The sector clusters used in our main specification are shown in Annex A.
2. This approach to low pay labour market construction has implications for how we account for exposure to minimum wage rises. A typical approach (e.g. in Azar et al 2019) is to restrict the analysis to particular low pay worker sectors, but as discussed above we would like to avoid this approach because of the ability of low skill workers to switch between sectors.

## Measuring monopsony

1. As discussed in Section 2.4.2, monopsony cannot be directly measured, and the literature has used a range of proxies. These include employment concentration (Manning and Petrongolo 2022, Rinz 2022, Schubert et al 2021, Benmelech et al 2020, Abel 2018) and variables that correlate with wage-setting power in job search models such as vacancies, hires, and unemployment rates (Hershbein, Macaluso and Yeh 2022, Munguia-Corella 2020, Azar et al 2020a, Azar et al 2020b) . CMA (2024) uses a labour leverage ratio, defined as the ratio of voluntary job terminations to involuntary job terminations, to measure the attractiveness of outside job options.
2. In our main specification, we construct an estimate of the low pay labour concentration in each local labour market taking into account companies with more than 5 employees. For each local market *we* calculate labour shares for each SIC present in the market (TTWA per SIC cluster) using BSD data and construct the HHI of total employment in each local market based on the following formula:

We explored using other proxies for monopsony that can be derived from ASHE data (i.e., low pay hires and job-search activity). However the sample size was not large enough to produce stable results with these measures. As the BSD is a census, it produces a more precise metric.

1. As discussion in Section 3.4.2, a challenge of using market concentration as a proxy of monopsony power is that it might introduce endogeneity with respect to wages, as employer concentration may be correlated with supply and demand forces in specific labour markets such as local economic conditions which also affect wages or employment, including productivity shocks. Simultaneity bias might also arise between wages and market concentration (e.g. high wages might act as a barrier of entry for new firms or low-pay workers).
2. To investigate the correlation between wages and concentration, we show the joint distribution of the minimum wage bite and log HHI in the figure below, where the observational unit is the local labour market. Results show that there is a low correlation between these variables (<0.03). However, a correlation between these variables may only be evident when conditioning on other features of local labour markets. We discuss this in Section 6.2 in the regression results.

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| * 1. Correaltion between minimum wage bite and log HHI, all workers |
|  |
| Source: ONS – BSD (2015), ASHE (2015) |

## Time period

1. There are several factors in considering a suitable time period for the analysis:

* Increasing the length of the time period increases statistical power and allow us to identify the stability of effects over time or short/long term dynamics
* Including time periods that saw substantial changes in the minimum wage, for example the increase in 2016, increases ability to detect effects
* Modelling the labour market during the COVID-19 pandemic introduces additional factors to be controlled for

We studied the time period FY2015-FY2019, to include 2016. We investigated including the pandemic years in the analysis. However, pandemic furloughing policy rendered hours worked and therefore pay per hour worked less informative. This led to several issues with the analysis, and we found the results that included the pandemic period to be unrobust.

## Sensitivity analysis

In this report, we include a set of key sensitivities that vary the regression specification which are presented in Annex B. These are:

* Reference model that omits the HHI measure and the MW bite variable (‘base model’).
* Reference model that omits the MW bite variable
* Includes all workers in local labour market construction and regressions (not just low pay workers)
* A narrower definition of ‘high’ employer concentration (local HHI > 90th percentile among local markets)
* More granular sectoral clusters to construct local labour markets (20 clusters)
* Less granular geographic areas to construct local labour markets (TTWAs based on bus users)
* More granular geographic areas to construct local labour markets (TTWAs based on low skill workers)
* Stratified by SIC cluster (9 separate models)
* Alternative model specification where the outcome variables are expressed in differentials and the NLW bite is lagged by one period

# Results

## Empirical distribution of HHI

1. According to the US Department of Justice and Federal Trade Commission, a high level of employer concentration is indicated by an HHI above 0.25 (on a scale where 1 represents complete concentration), or 2,500 (on a scale where 10,000 represents complete concentration).[[18]](#footnote-19) This corresponds to a log HHI of greater than -0.6.
2. Below is the average log HHI among all SICs, by TTWA. No TTWA has an average log HHI that qualifies as highly concentrated according to the DoJ/FTC definition. In some urban areas, including Greater London and Greater Manchester, employer concentration is very low. Employer concentration tends to be higher in rural areas, for example coastal Wales and Cornwall.

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| * 1. Employer concentration (all SICs) by TTWA |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets (TTWA x Clusters) with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

1. These results are in line with those found in CMA (2024) which uses a measure of labour market tightness (i.e. the labour leverage ratio – the ratio of voluntary job separations to involuntary job separations). The authors identified particular regions and occupations with higher concentration, noting that markets outside of London and the South East tend to be more concentrated (i.e., lower population density areas tend to have higher employer concentration). CMA (2024) and Abel et al (2018) found that UK labour market concentration has remained broadly stable over the last 20 years, in contrast to the US which has seen increased concentration. This finding on concentration stability is useful for our analytic approach, as we use baseline 2015 concentration in the regressions to reduce risks of endogeneity biases.
2. Below is the distribution of the HHI among the local labour markets defined by TTWA and SIC cluster, broken down by SIC cluster.[[19]](#footnote-20) As observed, HHI in these local labour markets tends to be low, but there is some variation in concentration by SIC cluster. Specifically, Cluster 5 (largely *health and social care*) and Cluster 6 (*facilities and support services*) show moderately high concentrations in certain TTWAs. In contrast, Cluster 2 (*hospitality*) has the lowest HHI distribution. These high concentration sectors have a mix of public services (e.g. hospitals) and private services (e.g. building cleaning). The distribution of HHIs is right skewed, indicating a tail of more concentrated areas.

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| --- |
| * 1. Distribution of HHI by SIC cluster |
|  |
| Source: ONS – BSD (2015)  Note: Figure presents minimum and maximum values for the 5th, 25th, 50thT, 75% and 95th percentile for each SIC cluster. Cluster 1: Retail, Cluster 2: Hospitality, Cluster 3: Wholesale and manufacturing, Cluster 4: Education and childcare, Cluster 5: Health and social care, Cluster 6: Facilities and support services, Cluster 7: Transport, Cluster 8: Construction and Cluster 9: Others |

1. CMA (2024) found that education, health and social care, agriculture and construction have had tight labour markets over the last fifteen years; and that manufacturing, information and communication services and finance were characterised by a low labour leverage ratio on average. The measure used in CMA (2024) is not directly comparable with ours, as it includes high pay workers and is a different labour market measure. For some sectors, our findings are consistent (i.e., agriculture, construction, and education have shown competitive labour markets) but in others results diverge. In particular, our measure indicates high concentration among health and social care employers, while CMA (2024) reports a high labour leverage ratio (indicating a high attractiveness of outside options).
2. This result highlights the conceptual discrepancies between the two measures: workers in the health and social care sector can exhibit high voluntary churn (e.g. due to dissatisfaction with working conditions) even if there are only a few similar employers in the local area, provided they are willing to switch sectors/professions. This is well-documented among nurses, who often start their careers with low pay.[[20]](#footnote-21) Arguably, if many nurses leave the profession voluntary, it suggests that their employers are not effectively competing for their labour, either through wages or non-monetary benefits.
3. This issue highlights that no single monopsony measure can capture all dimensions of labour market competition, and different metrics and studies serve complementary purposes.

## Regression results

1. Below are the key regression results for each outcome of interest (i.e., number of workers, total weekly hours worked, average hours per worker and mean wages excluding overtime), for the main model specification that includes just low pay workers and the sensitivity that includes all workers. The term of interest measures the minimum wage effect on the outcome in an area with high employer concentration, against an area with lower employer concentration. The coefficient on the interaction term of interest is shown in red.

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| Table 3 Results for main specification, including low pay workers only |

| 1. Variables | Log employment | Log total hours | Average hours per worker | 1. Mean wages excluding overtime |
| --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.07 | 1. 0.1 | 1. 0.61 | 1. 0.37 |
| 1. (SE, p) | 1. (0.02,<0.01) | 1. (0.02, <0.01) | 1. (0.2, <0.01) | 1. (0.02, <0.01) |
| 1. % public employer | 1. 0.66 | 1. 0.48 | 1. -4.42 | 1. -0.25 |
| 1. (SE, p) | 1. (0.1, <0.01) | 1. (0.1, <0.01) | 1. (0.82, <0.01) | 1. (0.05, <0.01) |
| 1. NLW bite | 1. 0.09 | 1. 0.00 | 1. -2.65 | 1. -1.38 |
| 1. (SE, p) | 1. (0.15,0.54) | 1. (0.17,1) | 1. (1.01,0.01) | 1. (0.04, <0.01) |
| 1. After NLW intro \* NLW bite | 1. -0.16 | 1. -0.25 | 1. -1.9 | 1. 0.92 |
| 1. (SE, p) | 1. (0.12,0.18) | 1. (0.12,0.04) | 1. (0.71,0.01) | 1. (0.04, <0.01) |
| 1. High HHI | 1. 0.05 | 1. 0.03 | 1. -1.2 | 1. -0.04 |
| 1. (SE, p) | 1. (0.05,0.29) | 1. (0.06,0.59) | 1. (0.44,0.01) | 1. (0.02,0.08) |
| 1. After NLW intro \* High HHI | 1. -0.14 | 1. -0.13 | 1. 0.18 | 1. 0.05 |
| 1. (SE, p) | 1. (0.05, <0.01) | 1. (0.05,0.01) | 1. (0.45,0.69) | 1. (0.03,0.09) |
| 1. High HHI \* NLW bite | 1. -0.23 | 1. -0.26 | 1. 0.59 | 1. 0.03 |
| 1. (SE, p) | 1. (0.27,0.38) | 1. (0.28,0.34) | 1. (1.81,0.74) | 1. (0.08,0.74) |
| 1. After NLW intro \* High HHI \* NLW bite | 1. 0.47 | 1. 0.52 | 1. 1.27 | 1. -0.03 |
| 1. (SE, p) | 1. (0.25,0.06) | 1. (0.26,0.05) | 1. (1.85,0.49) | 1. (0.09,0.77) |
| 1. Adj\_R2 | 1. 0.861 | 1. 0.833 | 1. 0.56 | 1. 0.353 |
| 1. \_N | 1. 10,288 | 1. 10,288 | 1. 10,288 | 1. 10,288 |

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| --- |
| Source: ONS – ASHE (2015-19) and BSD (2015)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity |
| Table 4 Results for secondary specification, including all workers |

| 1. Variables | Log employment | Log total hours | Average hours per worker | 1. Mean wages excluding overtime |
| --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.43 | 1. 0.43 | 1. 0.03 | 1. 1.28 |
| 1. (SE, p) | 1. (0.02,<0.01) | 1. (0.01,<0.01) | 1. (0.12,0.82) | 1. (0.23,<0.01) |
| 1. % public employer | 1. 1.01 | 1. 0.74 | 1. -9.07 | 1. -3 |
| 1. (SE, p) | 1. (0.06,<0.01) | 1. (0.05,<0.01) | 1. (0.4,<0.01) | 1. (1.61,0.06) |
| 1. NLW bite | 1. 2.66 | 1. 1.82 | 1. -28.07 | 1. -52.79 |
| 1. (SE, p) | 1. (0.34,<0.01) | 1. (0.33,<0.01) | 1. (1.68,<0.01) | 1. (13.33,<0.01) |
| 1. After NLW intro \* NLW bite | 1. -1.61 | 1. -1.47 | 1. 4.86 | 1. 10.78 |
| 1. (SE, p) | 1. (0.15,<0.01) | 1. (0.15,<0.01) | 1. (1.22,<0.01) | 1. (2.53,<0.01) |
| 1. High HHI | 1. 0.01 | 1. 0 | 1. -0.33 | 1. -0.72 |
| 1. (SE, p) | 1. (0.01,0.25) | 1. (0.01,0.81) | 1. (0.11,<0.01) | 1. (0.4,0.07) |
| 1. After NLW intro \* High HHI | 1. -0.01 | 1. -0.01 | 1. 0.14 | 1. -0.31 |
| 1. (SE, p) | 1. (0.02,0.35) | 1. (0.01,0.47) | 1. (0.14,0.29) | 1. (0.22,0.16) |
| 1. High HHI \* NLW bite | 1. -0.32 | 1. -0.16 | 1. 4.93 | 1. 17.38 |
| 1. (SE, p) | 1. (0.27,0.24) | 1. (0.29,0.58) | 1. (1.85,0.01) | 1. (9.04,0.05) |
| 1. After NLW intro \* High HHI \* NLW bite | 1. 0.34 | 1. 0.26 | 1. -2.26 | 1. -3.3 |
| 1. (SE, p) | 1. (0.17,0.05) | 1. (0.18,0.14) | 1. (1.57,0.15) | 1. (1.96,0.09) |
| 1. Adj\_R2 | 1. 0.881 | 1. 0.876 | 1. 0.526 | 1. 0.555 |
| 1. \_N | 1. 87,706 | 1. 87,706 | 1. 87,706 | 1. 87,706 |

|  |
| --- |
| Source: ONS – ASHE (2015-19) and BSD (2015)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity |

1. Below we summarise the results by outcome, and then summarise key limitations that should be considered when interpreting the results.

### Employment and total hours

1. The findings for employment and total hours are quite similar, although those related to total hours are in general somewhat more statistically significant. Since employer concentration is in general quite low, there is a limited small sample size of local labour markets with high HHI, which reduces the statistical significance and precision of the estimate.
2. In both specifications shown above, the triple interaction term of interest for employment is positive and has a material magnitude (ca. 60% increase in employment in the main specification), and is marginally statistically significant (p=0.06). The sign and magnitude of the term are generally robust across sensitivities (see Annex B); however, the term is not statistically significant in all specifications. For example, in the sensitivity that doubles the number of SIC clusters (i.e., granular labour markets), the term is not statistically significant, and the coefficient is negative. In the sensitivities that vary geographic markets (i.e., bus TTWAs and low skill TTWAs), the positive sign and magnitude of the term is consistent with the main specification, but slightly attenuated and underpowered.
3. This suggests that the results are very sensitive to different specifications of sector or occupation clusters, but they are more robust to changes in geographic market definitions. This finding is intuitive: irrespective of the definition of geographic markets, the variation in concentration that is driven by urban/rural variation will be retained across market definitions. In contrast, different SIC cluster definitions can substantially alter concentration patterns, depending on how sectors with high concentration with relatively small workforces are grouped with sectors that have low concentration and large workforces. For example, if a high concentration sector (e.g. mining) is clustered with a low concentration sector (e.g. warehousing/storage), this can mask some of the concentration variation in mining (which may be appropriate if mining and warehousing workers are considered to be in the same labour market).
4. When assessing the results of the main model by SIC clusters, we found that in 3 out of 9 clusters, the sign of the term of interest for employment is negative (*hospitality*, *facilities and support services*, *other*). This result is likely due to the atypical characteristics of these clusters: in *hospitality* there is little variation in HHI as the cluster is very unconcentrated; in *facilities and support services* there is atypically high HHI, and the *other* category includes all of the SIC codes that were not categorised into clusters and therefore are unlikely to form a coherent local labour market.

The sign of the term of interest for employment and total hours is consistent with previous studies: Azar et al (2019) in the US and Popp (2022) in Germany find that as labour markets become more concentrated, the dis-employment effect from the minimum wage is significantly reduced. Azar et al (2019) also found that the interaction between employer concentration and the minimum wage was most material in the upper tail of concentration, i.e. there is a non-linear effect.

The implication of this result is that any targeted policy to address ‘under-paying’ low pay workers due to monopsony should target local markets that are outliers in terms of high concentration. This is consistent with our findings. We found that monopsony effects on employment were not significant or material unless HHI is dichotomised using a relatively high threshold (we used the 75th percentile in the main specifications). We found a similar result using a higher threshold (90th percentile), but this sensitivity led to underpowering the statistical tests of significance.

### Average hours per worker

1. The term of interest is positive in the model for average hours per worker, but it is not statistically significant in the main model and across all sensitivities (see Annex B). In the models that stratify by SIC cluster, the term of interest is negative in half of the SIC clusters. It is likely that the behaviour of average hours per worker depends substantially on the type of low pay work, the type of company, and the mechanics of running the staff rota. Low pay work involving physical labour may differ from work that can be done for longer shifts. Average hours per worker has lower variance across SIC clusters than employment and total hours, which may contribute to an underpowered model and the lack of statistical significance.
2. Previous evidence suggests that the hours effects of minimum wage increases may be different for different subgroups of workers. Jardim et al (2018) found that minimum wage increases in Seattle decreased hours for low wage workers with less experience (i.e., shifting work to more experienced workers). If this type of dynamic were present in the data for this study, it could contribute to the mixed sign and non-statistically-significant results that we have observed. Dickens et al (2015) found that UK NMW increases reduced retention specifically among part-time female workers, which was also found by Cribb et al (2019). Differential effects on part-time workers may impact average hours per worker.

### Average wages excluding overtime

1. For the last twenty years, UK wages have been rising at a faster rate than productivity, across all income bands (CMA 2024). This is likely primarily due to labour supply shortages, but for lower income bands, the minimum wage increases since 2015 are likely a contributing factor. CMA (2024) found that higher employer concentration is associated with lower wages in the UK, which was also found by Benmelech et al (2021) in the US.
2. We did not find evidence of an interaction between employer concentration and average wages excluding overtime across the models. The term of interest was not statistically significant, and switched signs depending on the specification. We found that there was a positive, robust, and material impact of the introduction of the NLW on low pay wages.

### Joint distribution of concentration and minimum wage bite

1. The coefficients on the interaction term for HHI and NLW bite captures the relationship between increases in minimum wage workers and the outcomes in high concentration areas, after the introduction of the NLW in 2016. The coefficient is statistically significant for two specifications: mean hours and mean wages for the regressions that include all workers (but not only among low pay workers). This suggests that an increase in the NLW bite is associated with an increase in mean hours and mean wages particularly for higher pay workers in markets with high concentration, after the introduction of the NLW in 2016. There are various reasons why employers with monopsony power would react to an increase in their low pay wage bill by reducing hours and employment among low skill workers, and increasing the hours per worker and the wages per hour of higher skill workers. In many settings there are tasks that can be reasonably either performed by low skill workers or high skill workers depending on managerial decisions.
2. This effect is mostly driven by two SIC clusters: (1) hospital and social care, and (2) temp workers and logistics. Again, there are various potential reasons why this could be the case. For example, an increase in the cost of clerical and support staff combined with poor workforce management could cause hospitals and care homes to shift more administrative duties to clinicians, asking them to work more hours at overtime pay. There are widespread complaints about lack of administrative support among doctors, and excessive time spent on recordkeeping that could be done by administrative staff.[[21]](#footnote-22)
3. The effect of increases in the minimum wage on workforce management among high skill workers is an important area of research. Shifting low skill work onto high skill employees can be damaging to firm productivity in the long term, and difficult for firms to monitor and remedy if there is poor communication between frontline staff and management, or other budgetary pressures.

### Differential model with lagged minimum wage bite

We also analysed an alternative model specification where the outcome variables are expressed in differences and the NLW bite is lagged one period. The advantage of this specification is that the immediate impact of a NLW increase might not be fully realised in the same period it is implemented. Incorporating a lagged NLW bite, allows firms and workers to adjust their behaviour after the introduction of a NLW increase. It also helps address the issue of reverse causality, where changes in employment could potentially influence current minimum wage policies.

The sign of the term of interest for employment and total hours is consistent with the results from the main model (although smaller in magnitude and not statistically significant). However, we did find evidence of a large, positive and statistically significant effect on average wages in high employer concentration areas relative to low concentration areas. This is paired with a negative (albeit not significant) effect on average hours per low pay worker.

# Limitations

Brewer et al (2019) note that difference-in-difference type studies of the UK minimum wage tend in general to be statistically underpowered, which makes it difficult to draw robust conclusions. The statistical underpowering is in large part a result of the limited variation in the national UK minimum wage level, which eliminates the cross-sectional geographic variation in minimum wage level that is utilised in studies of other countries (e.g. the state-level variation exploited in US studies).

The national minimum wage policy not only reduces statistical power, but it also introduces potential biases. Time-varying national exogenous effects (i.e., that we cannot directly control for in the models) will confound our estimates of minimum wage effects and minimum wage interactions.

One potential issue of this type is the overall increase in labour market tightness that occurred between 2016 and 2019. This is likely to be a result of multiple factors such as the 2016 Brexit referendum, the decline in the attractiveness of the UK for EU workers, and the beginning of increasing restrictions of supply of labour from the EU, which particularly affected certain low pay labour markets.[[22]](#footnote-23) In our specifications, the effect of a national trend in labour market tightness would be attributed to our time-varying variable, the NLW introduction dummy. Labour market tightness would be expected to increase wages, hours, and employment, and so the association between NLW introduction and increases in these variables will be overstated in our estimates.

However our main term of interest is the interaction with employer concentration, and how a decrease in labour supply would interact with local employer concentration is ambiguous. The labour supply change due to Brexit was specifically among low pay workers that are geographically mobile, and so our local geographic definitions do not realistically capture their scope of employment options. It would be useful to validate these results in a post-pandemic period that has different dynamics in the supply of low skill workers (perhaps in some sectors or areas), when sufficient data becomes available for such an analysis. We note that post-pandemic UK migration in 2022-23 has been anomalously high, particularly in health and social care, which would complicate such an analysis.[[23]](#footnote-24)

The analysis could also be biased if the concentration measure is associated with a factor with a time trend that affects the outcomes of interest, but is conceptually separate from monopsony. This is because our geographic fixed effects control for baseline geographic differences, but not time trends. An example of this type of trend would be rural-urban divergence in economic performance, which would be correlated with monopsony (rural areas tend to be more concentrated), but the economic divergence is due to other factors (e.g. historical public investment). We do not have specific evidence that there is a material bias of this kind, but flag it as a potential caveat.

# Discussion

Manning (2021) notes that research on minimum wage effects has historically focused on the employment effects of minimum wage increases, and that it is difficult to isolate a specific type of circumstance in which the minimum wage has robust and predictable effects on employment. This study has aimed to identify such a circumstance. This study provides evidence that employer concentration interacts with minimum wage effects – higher concentration labour markets experience more positive effects of the minimum wage on employment – which is consistent with previous theoretical work on this subject.

1. We find evidence that, following an increase in the minimum wage, employment and total hours increase in high employer concentration areas relative to in low concentration areas. As discussed above, this finding aligns with previous work, and with the theoretical discussion of the interaction between monopsony and minimum wage effects. However the magnitude and statistical significance of the result are sensitive in our modelling to the chosen specification, and this is likely due to different sources of statistical underpowering: the limitations in minimum wage variation, and the generally low employer concentration in low pay labour markets.
2. We find that average hours per low pay worker and mean base wages excluding overtime do not exhibit a clear pattern with respect to monopsony and minimum wage effects across sectors. We find robust evidence that the NLW introduction increased low pay hourly wages (across low and high concentration labour markets).
3. We designed the analysis so that it covered all sectors, and this broad scope matches the remit of UK minimum wage policy. However, we find that monopsony likely interacts with minimum wage effects differently across different sectors and occupations, due to differences in public sector employment, in the elasticity of hours per worker, in the geographic distribution of different sectors, and other factors. There is low employer concentration in most sectors of the low pay labour market, and future work on monopsony effects could usefully focus on sectors or local areas with higher employer concentration. For example, based on our definition, hospitality and retail sectors are relatively unlikely to experience material monopsony effects due to the low concentration of those sectors; similarly workers in London or Core Cities are less likely to experience monopsony effects due to the density of employers.
4. Future analyses could build on this study in a number of different ways. A key contribution of this study is to attempt to construct local labour markets that realistically capture how low skill workers can switch between sectors/occupations that have similar skill requirements. This is important for accurately capturing local employer concentration; calculating monopsony metrics using single SIC and SOC codes may overstate concentration by failing to group together highly related SIC/SOCs, and is subject to the arbitrariness of SIC/SOC code granularity (e.g. that SIC codes are far more granular in manufacturing sectors than in service sectors, and the risk of miscoding occupations in SOC codes for each individual employee[[24]](#footnote-25)). The Department for Education (DfE) is currently developing a UK skills taxonomy[[25]](#footnote-26), and it could be interesting in the future to incorporate the skills taxonomy into the construction of local labour markets.
5. The UK NLW is only one of many possible approaches to mitigating welfare-reducing effects of local monopsony. Other types of interventions that are active areas of policy debate include regulations to improve working conditions, and policies to encourage effective and efficient collective bargaining (particularly for public sector and highly regulated services). Potential future work could investigate the interaction between other policies and monopsony for improving the welfare of low pay workers.

The corpus of minimum wage studies, which have struggled to estimate minimum wage effects that have broad external validity, highlight that minimum wage effects are likely to vary substantially by local area, due to a wide range of local idiosyncratic factors. Our findings show that the results are sensitive to geographic definitions of local labour markets.

To validate our results, it would be particularly useful to understand whether they hold for geographic definitions of local markets that offer significant improvements in accuracy and precision in capturing individuals’ work catchment areas (i.e., more sophisticated than alternative TTWAs). Individuals’ work catchment areas are highly localised and idiosyncratic (Manning & Petrongolo 2018). The catchment area depends on factors like car access, time available for transport, willingness to move house, and public transport access; and each individual belongs to a (slightly) different work catchment area. One way to reduce monopsony power is to increase work catchment areas, which may be particularly important in rural areas. The post-Covid role of public transport accessibility is currently an important area of policy research, to understand what types of public investment are the most important for reducing economic inactivity and regional disparities in economic inactivity.[[26]](#footnote-27) Low pay workers are more likely to rely on public transport for work access, and low pay workers in service jobs are more likely to have on-site jobs. Public transport quality is a direct policy lever which can be targeted in particular local areas. A more detailed study of the interaction between public transport access and monopsony effects would be informative for understanding the returns to different types of public transport investments in different areas.

Besides pay, other factors are also relevant for workers when choosing jobs and for employers when defining jobs (e.g., Blundell et al 2013, Kossek & Lautsch 2018, Martinez-Granado 2005, Clemens 2021). Staff rotas are particularly important (shift predictability, minimum hour contracts, shift time of day and flexibility), and labour market divisions may exist due to workers’ preferences for particular types of work, which might contribute to monopsony power. Understanding these more ‘hidden’ drivers of monopsony would be useful to inform any future interventions that aim to mitigate monopsony effects.

As discussed above, a key challenge in studying monopsony is constructing an appropriate proxy measure, and we have highlighted the conceptual and econometric shortcomings of the HHI measure that we have used. Future studies could usefully examine other monopsony measures that capture different aspects of vacancies and job switching rates. For example, CMA (2024) uses the labour leverage ratio, the ratio of voluntary job terminations to involuntary job terminations, to measure the attractiveness of outside job options. In addition to issues of endogeneity, there are also policy-motivated consideration for selecting a particular monopsony measure. Any changes in regulation that affect ease of hiring and firing may in the future introduce exogenous variation in monopsony measures based on vacancies and terminations, which could potentially be useful to exploit.

Lastly, there was some evidence that firms with monopsony power can react to increases in their low pay wage bill by increasing the wages and working hours of high skill staff, particularly among medical, social care, and temporary worker staff. This is potentially concerning if these firms are ‘cluttering’ the workload of high skill staff with tasks that can be more efficiently done by low skill staff. Although it would be challenging to design policy interventions to address firm management shortsightedness, this is an important area of future research.

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58. HHI empirical distribution
59. This Annex provides detail on each sectoral cluster used in the main regression specification.
    1. Cluster 1 (Retail)

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| --- |
| * 1. Mean log HHI for SICs in Cluster 1 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes. |

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| Table 5 SICs within Cluster 1 with the most low pay workers |

| 1. Rank | 1. SIC description |
| --- | --- |
| 1. 1 | 1. Retail sale in non-specialised stores with food, beverages or tobacco |
| 1. 2 | 1. Retail sale of clothing in specialised stores |
| 1. 3 | 1. Other retail sale in non-specialised stores |
| 1. 4 | 1. Hairdressing and other beauty treatments |
| 1. 5 | 1. Gambling and betting activities |
| 1. 6 | 1. Retail sale of flowers, plants, seeds, fertilisers, per animals and pet food in specialised stores |
| 1. 7 | 1. First-degree level higher education |
| 1. 8 | 1. Retail sale of bread, cakes, flour confectionary and sugar confectionary in specialised stores |
| 1. 9 | 1. Retail sale of furniture, lighting equipment and household articles in specialised stores |
| 1. 10 | 1. Retail sale of sports goods, fishing gear, camping goods, boats and bicycles |

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| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 2 (Hospitality)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 2 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

|  |
| --- |
| Table 6 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC description |
| --- | --- |
| 1. 1 | 1. Public houses and bars |
| 1. 2 | 1. Licenced restaurants |
| 1. 3 | 1. Unlicenced restaurants and cafes |
| 1. 4 | 1. Hotels and similar accommodation |
| 1. 5 | 1. Take-away food shops and mobile stands |
| 1. 6 | 1. Licenced clubs |
| 1. 7 | 1. Retail sale of meat and meat products in specialised stores |
| 1. 8 | 1. Growing of cereals (except rice), leguminous crops and oil seeds |
| 1. 9 | 1. Painting |
| 1. 10 | 1. Raising of horses and other equines |

|  |
| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 3 (wholesale and manufacturing)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 3 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

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| --- |
| Table 7 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC description |
| --- | --- |
| 1. 1 | 1. Temporary employment agency activities |
| 1. 2 | 1. Freight transport by road |
| 1. 3 | 1. Other activities of employment placement agencies |
| 1. 4 | 1. Manufacture of bread; manufacture of fresh pastry goods and cakes |
| 1. 5 | 1. Operation of warehousing and storage facilities for land transport activities of division 49 |
| 1. 6 | 1. Non-specialised wholesale of food, beverages and tabacco |
| 1. 7 | 1. Wholesale of other machinery and equipment |
| 1. 8 | 1. Other engineering activities |
| 1. 9 | 1. Other postal and courier activities: Unlicensed carriers |
| 1. 10 | 1. Wholesale of household goods (other than musical instruments) n.e.c. |

|  |
| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 4 (Education and Childcare work)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 4 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

|  |
| --- |
| Table 8 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC description |
| --- | --- |
| 1. 1 | 1. Primary education |
| 1. 2 | 1. Child day-care activities |
| 1. 3 | 1. General secondary education |
| 1. 4 | 1. Other social work activities without accommodation n.e.c. |
| 1. 5 | 1. General public administration activities |
| 1. 6 | 1. Other education n.e.c |
| 1. 7 | 1. Pre-primary education |
| 1. 8 | 1. Technical and vocational secondary education |
| 1. 9 | 1. Activities of households as employers of domestic personnel |
| 1. 10 | 1. Activities of religious organisations |

|  |
| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 5 (Health and Social care)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 5 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

|  |
| --- |
| Table 9 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC |
| --- | --- |
| 1. 1 | 1. Residential nursing care facilities |
| 1. 2 | 1. Residential care activities for the elderly and disabled |
| 1. 3 | 1. Social work activities without accommodation for the elderly and disables |
| 1. 4 | 1. Other residential care activities n.e.c. |
| 1. 5 | 1. Hospital activities |
| 1. 6 | 1. General medical practice activities |
| 1. 7 | 1. Dispensing chemist in specialised stores |
| 1. 8 | 1. Other human health activities |
| 1. 9 | 1. Fitness facilities |
| 1. 10 | 1. Residential care activities for learning difficulties, mental health and substance abuse |

|  |
| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 6 (Facilities and Support services)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 6 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

|  |
| --- |
| Table 10 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC |
| --- | --- |
| 1. 1 | 1. General cleaning of buildings |
| 1. 2 | 1. Other food services |
| 1. 3 | 1. Combined facilities support activities |
| 1. 4 | 1. Event catering activities |
| 1. 5 | 1. Private security activities |
| 1. 6 | 1. Other cleaning services |
| 1. 7 | 1. Activities of head offices |
| 1. 8 | 1. Washing and (dry-) cleaning of textile and fur products |
| 1. 9 | 1. Operation of historical sites and buildings and similar visitor attractions |
| 1. 10 | 1. Service activities incidental to air transportation |

|  |
| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 7 (Transport)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 7 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

|  |
| --- |
| Table 11 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC description |
| --- | --- |
| 1. 1 | 1. Maintenance and repair of motor vehicles |
| 1. 2 | 1. Sale of new cars and light motor vehicles |
| 1. 3 | 1. Wholesale trade of motor vehicle parts and accessories |
| 1. 4 | 1. Solicitors |
| 1. 5 | 1. Retail sale of automotive fuel in specialised stores |
| 1. 6 | 1. Retail trade of motor vehicle parts and accessories |
| 1. 7 | 1. Taxi operation |
| 1. 8 | 1. Other urban, suburban or metropolitan area passenger land transport (not incl. underground, metro and the like) |
| 1. 9 | 1. Other passenger land transport |
| 1. 10 | 1. Renting and leasing of cars and light motor vehicles |

|  |
| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 8 (construction)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 8 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

|  |
| --- |
| Table 12 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC |
| --- | --- |
| 1. 1 | 1. Retail sale of hardware, paints and glass in specialised stores |
| 1. 2 | 1. Wholesale of wood, construction materials and sanitary equipment |
| 1. 3 | 1. Construction of domestic buildings |
| 1. 4 | 1. Retail sale via mail orders houses or via internet |
| 1. 5 | 1. Landscape service activities |
| 1. 6 | 1. Construction of other civil engineering projects n.e.c. |
| 1. 7 | 1. Other professional, scientific and technical activities n.e.c. |
| 1. 8 | 1. Joinery installation |
| 1. 9 | 1. Wholesale of hardware, plumbing and heating equipment and supplies |
| 1. 10 | 1. Collection of non-hazardous waste |

|  |
| --- |
| Source: ONS – ASHE (2015) |

* 1. Cluster 9 (Others)

|  |
| --- |
| * 1. Mean log HHI for SICs in Cluster 9 |
|  |
| Source: ONS – BSD (2015)  Note: Local labour markets with less than 100 employees are omitted. Areas highlighted in light grey are dropped due to inconsistencies in TTWA codes |

|  |
| --- |
| Table 13 SICs within the cluster with the most low pay workers |

| 1. Rank | 1. SIC description |
| --- | --- |
| 1. 1 | 1. Operation of sports facilities |
| 1. 2 | 1. Activities for sports clubs |
| 1. 3 | 1. Other business support services activities n.e.c. |
| 1. 4 | 1. Activities of call centres |
| 1. 5 | 1. Activities of other membership organizations n.e.c. |
| 1. 6 | 1. Management consultancy activities other than financial management |
| 1. 7 | 1. Recreational vehicle parks, trailer parks and camping grounds |
| 1. 8 | 1. Electrical installation |
| 1. 9 | 1. Accounting and auditing activities |
| 1. 10 | 1. Other personal service activities n.e.c. |

|  |
| --- |
| Source: ONS – ASHE (2015) |

1. Regression results
2. This annex contains regression outputs for the following outcomes:
   * Total employment
   * Total hours worked
   * Average hours worked
   * Average wages
3. We also provide an alternative model specification where the outcomes variables are expressed in differentials and the NLW bite is lagged one period.
4. The observational units are low pay local labour markets. Each observational unit was defined by year, by Travel to Work Area, and by SIC grouping (cluster of sectors). We had 9 SIC groupings in each TTWA, except for the sensitivity ‘Granular labour markets’, which had 20 SIC groupings.
5. Each column in the below tables corresponds to a regression model, and the final row of the table shows the unweighted observations in each regression.
6. In this output we have omitted the geographic area fixed effects.
   1. Log total employment

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 14 Results for log total employment, for each model specification |

| 1. Variables | 1. Base | 1. Without MW bite | 1. Narrower high concentration definition | 1. Main model | 1. Granular labour markets | 1. Bus TTWAs | 1. Low skill TTWAs | 1. All workers |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.02 | 1. 0.02 | 1. 0.05 | 1. 0.07 | 1. 0.03 | 1. 0.07 | 1. 0.07 | 1. 0.43 |
|  | 1. (0.01,0.01) | 1. (0.01,0.03) | 1. (0.02,0.01) | 1. (0.02,<0.01) | 1. (0.02,0.07) | 1. (0.02,<0.01) | 1. (0.02,<0.01) | 1. (0.02,<0.01) |
| 1. % public employer | 1. 0.6 | 1. 0.65 | 1. 0.65 | 1. 0.66 | 1. 0.67 | 1. 0.81 | 1. 0.64 | 1. 1.01 |
|  | 1. (0.1,<0.01) | 1. (0.11,<0.01) | 1. (0.1,<0.01) | 1. (0.1,<0.01) | 1. (0.08,<0.01) | 1. (0.13,<0.01) | 1. (0.08,<0.01) | 1. (0.06,<0.01) |
| 1. Very high HHI |  | 1. 0 | 1. 0.01 |  |  |  |  |  |
|  |  | 1. (0.07,0.97) | 1. (0.1,0.91) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI |  | 1. 0.02 | 1. -0.1 |  |  |  |  |  |
|  |  | 1. (0.05,0.66) | 1. (0.09,0.3) |  |  |  |  |  |
| 1. NLW bite |  |  | 1. 0.06 | 1. 0.09 | 1. -0.02 | 1. 0.08 | 1. 0.12 | 1. 2.66 |
|  |  |  | 1. (0.14,0.68) | 1. (0.15,0.54) | 1. (0.12,0.86) | 1. (0.18,0.65) | 1. (0.13,0.37) | 1. (0.34,<0.01) |
| 1. After NLW intro \* NLW bite |  |  | 1. -0.1 | 1. -0.16 | 1. 0.03 | 1. -0.17 | 1. -0.16 | 1. -1.61 |
|  |  |  | 1. (0.11,0.34) | 1. (0.12,0.18) | 1. (0.09,0.75) | 1. (0.14,0.22) | 1. (0.11,0.15) | 1. (0.15,<0.01) |
| 1. Very high HHI \* NLW bite |  |  | 1. -0.07 |  |  |  |  |  |
|  |  |  | 1. (0.43,0.87) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI \* NLW bite |  |  | 1. 0.35 |  |  |  |  |  |
|  |  |  | 1. (0.41,0.4) |  |  |  |  |  |
| 1. High HHI |  |  |  | 1. 0.05 | 1. 0.03 | 1. 0 | 1. -0.04 | 1. 0.01 |
|  |  |  |  | 1. (0.05,0.29) | 1. (0.04,0.52) | 1. (0.05,1) | 1. (0.05,0.38) | 1. (0.01,0.25) |
| 1. After NLW intro \* High HHI |  |  |  | 1. -0.14 | 1. 0.02 | 1. -0.08 | 1. -0.05 | 1. -0.01 |
|  |  |  |  | 1. (0.05,<0.01) | 1. (0.04,0.52) | 1. (0.05,0.09) | 1. (0.04,0.23) | 1. (0.02,0.35) |
| High HHI \* NLW bite |  |  |  | 1. -0.23 | 1. 0.16 | 1. -0.18 | 1. -0.04 | 1. -0.32 |
|  |  |  |  | 1. (0.27,0.38) | 1. (0.22,0.47) | 1. (0.29,0.54) | 1. (0.23,0.87) | 1. (0.27,0.24) |
| 1. After NLW intro \* High HHI \* NLW bite |  |  |  | 1. 0.47 | 1. -0.09 | 1. 0.36 | 1. 0.23 | 1. 0.34 |
|  |  |  |  | 1. (0.25,0.06) | 1. (0.19,0.62) | 1. (0.26,0.16) | 1. (0.21,0.26) | 1. (0.17,0.05) |
| 1. Adj\_R2 | 1. 0.862 | 1. 0.861 | 1. 0.861 | 1. 0.861 | 1. 0.839 | 1. 0.809 | 1. 0.812 | 1. 0.881 |
| 1. \_N | 1. 12,162 | 1. 10,288 | 1. 10,288 | 1. 10,288 | 1. 19,490 | 1. 8,418 | 1. 13,964 | 1. 87,706 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity |

* 1. Log total employment, stratified by SIC cluster

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 15 Results for log total employment (main model only), stratified by SIC cluster |

| 1. Variables | 1. Cluster 1 | 1. Cluster 2 | 1. Cluster 3 | 1. Cluster 4 | 1. Cluster 5 | 1. Cluster 6 | 1. Cluster 7 | 1. Cluster 8 | 1. Cluster 9 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.21 | 1. 0.26 | 1. 0.02 | 1. 0.1 | 1. -0.04 | 1. -0.2 | 1. -0.01 | 1. 0.03 | 1. 0.04 |
|  | 1. (0.06,<0.01) | 1. (0.07, <0.01) | 1. (0.06,0.71) | 1. (0.04,0.01) | 1. (0.09,0.62) | 1. (0.24,0.4) | 1. (0.06,0.84) | 1. (0.06,0.6) | 1. (0.06,0.51) |
| 1. High HHI | 1. -2.01 | 1. -1.23 | 1. 0.42 | 1. -0.97 | 1. 1.34 | 1. 1.37 | 1. -1.32 | 1. -1.02 | 1. 1.34 |
|  | 1. (0.13,<0.01) | 1. (0.32,<0.01) | 1. (0.12,<0.01) | 1. (0.13,<0.01) | 1. (0.09,<0.01) | 1. (0.29,<0.01) | 1. (0.17,<0.01) | 1. (0.16,<0.01) | 1. (0.11,<0.01) |
| 1. NLW bite | 1. -0.3 | 1. -0.26 | 1. 0.26 | 1. 0.96 | 1. 0.08 | 1. -0.32 | 1. -0.16 | 1. -0.14 | 1. 0.09 |
|  | 1. (0.2,0.15) | 1. (0.18,0.15) | 1. (0.2,0.2) | 1. (0.37,0.01) | 1. (0.4,0.85) | 1. (0.56,0.58) | 1. (0.19,0.41) | 1. (0.25,0.59) | 1. (0.24,0.71) |
| 1. % public employer | 1. -1.72 | 1. -0.18 | 1. -1.04 | 1. 0.73 | 1. -0.22 | 1. 0.79 | 1. -0.14 | 1. 0.09 | 1. 0.25 |
|  | 1. (1.49,0.25) | 1. (0.39,0.64) | 1. (0.21,<0.01) | 1. (0.11,<0.01) | 1. (0.17,0.21) | 1. (1.19,0.51) | 1. (0.87,0.87) | 1. (0.4,0.82) | 1. (0.59,0.67) |
| 1. After NLW intro \* High HHI | 1. -0.25 | 1. 1.54 | 1. -0.1 | 1. -0.16 | 1. -0.07 | 1. 0.17 | 1. -0.06 | 1. 0.09 | 1. 0.08 |
|  | 1. (0.14,0.08) | 1. (0.65,0.02) | 1. (0.15,0.53) | 1. (0.13,0.22) | 1. (0.11,0.5) | 1. (0.29,0.55) | 1. (0.19,0.74) | 1. (0.21,0.68) | 1. (0.13,0.56) |
| 1. After NLW intro \* NLW bite | 1. -0.48 | 1. -0.15 | 1. -0.19 | 1. -1.15 | 1. 0.34 | 1. 0.37 | 1. 0.26 | 1. 0.32 | 1. 0.05 |
|  | 1. (0.23,0.04) | 1. (0.17,0.39) | 1. (0.21,0.38) | 1. (0.38,<0.01) | 1. (0.44,0.44) | 1. (0.57,0.52) | 1. (0.21,0.22) | 1. (0.25,0.2) | 1. (0.28,0.86) |
| 1. High HHI \* NLW bite | 1. -0.52 | 1. 2.82 | 1. -0.18 | 1. -0.63 | 1. -0.19 | 1. -0.02 | 1. 0.05 | 1. -0.69 | 1. -0.1 |
|  | 1. (0.51,0.3) | 1. (0.58,0) | 1. (0.47,0.71) | 1. (2.16,0.77) | 1. (0.56,0.74) | 1. (0.65,0.98) | 1. (0.57,0.93) | 1. (0.54,0.2) | 1. (0.55,0.85) |
| 1. After NLW intro \* High HHI \* NLW bite | 1. 1.04 | 1. -3.52 | 1. 0.13 | 1. 1 | 1. 0.15 | 1. -0.15 | 1. 0.13 | 1. 0.59 | 1. -0.19 |
|  | 1. (0.56,0.06) | 1. (1.01,<0.01) | 1. (0.56,0.82) | 1. (2.24,0.66) | 1. (0.58,0.8) | 1. (0.66,0.82) | 1. (0.57,0.82) | 1. (0.58,0.31) | 1. (0.55,0.73) |
| 1. Adj\_R2 | 1. 0.913 | 1. 0.933 | 1. 0.871 | 1. 0.889 | 1. 0.886 | 1. 0.899 | 1. 0.827 | 1. 0.847 | 1. 0.876 |
| 1. \_N | 1. 1,199 | 1. 1,187 | 1. 1,151 | 1. 1,181 | 1. 1,180 | 1. 1,038 | 1. 1,107 | 1. 1,086 | 1. 1,159 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity. Cluster 1: Retail, Cluster 2: Hospitality, Cluster 3: Wholesale and manufacturing, Cluster 4: Education and childcare, Cluster 5: Health and social care, Cluster 6: Facilities and support services, Cluster 7: Transport, Cluster 8: Construction and Cluster 9: Others |

* 1. Log total hours

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 16 Results for log total hours, for each model specification |

| 1. Variables | 1. Base | 1. Without MW bite | 1. Narrower high concentration definition | 1. Main model | 1. Granular labour markets | 1. Bus TTWAs | 1. Low skill TTWAs | 1. All workers |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0 | 1. 0 | 1. 0.08 | 1. 0.1 | 1. 0.05 | 1. 0.1 | 1. 0.1 | 1. 0.43 |
|  | 1. (0.01,0.94) | 1. (0.01,0.77) | 1. (0.02,<0.01) | 1. (0.02,<0.01) | 1. (0.02,<0.01) | 1. (0.02,<0.01) | 1. (0.02,<0.01) | 1. (0.01,<0.01) |
| 1. % public employer | 1. 0.49 | 1. 0.53 | 1. 0.47 | 1. 0.48 | 1. 0.55 | 1. 0.6 | 1. 0.46 | 1. 0.74 |
|  | 1. (0.1,<0.01) | 1. (0.11,<0.01) | 1. (0.1,<0.01) | 1. (0.1,<0.01) | 1. (0.08,<0.01) | 1. (0.12,<0.01) | 1. (0.09,<0.01) | 1. (0.05,<0.01) |
| 1. Very high HHI |  | 1. -0.04 | 1. -0.01 |  |  |  |  |  |
|  |  | 1. (0.07,0.6) | 1. (0.11,0.92) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI |  | 1. 0.05 | 1. -0.12 |  |  |  |  |  |
|  |  | 1. (0.06,0.4) | 1. (0.11,0.27) |  |  |  |  |  |
| 1. NLW bite |  |  | 1. -0.04 | 1. 0 | 1. -0.13 | 1. -0.02 | 1. 0.02 | 1. 1.82 |
|  |  |  | 1. (0.16,0.81) | 1. (0.17,1) | 1. (0.13,0.32) | 1. (0.2,0.94) | 1. (0.13,0.87) | 1. (0.33,<0.01) |
| 1. After NLW intro \* NLW bite |  |  | 1. -0.2 | 1. -0.25 | 1. -0.03 | 1. -0.25 | 1. -0.25 | 1. -1.47 |
|  |  |  | 1. (0.11,0.07) | 1. (0.12,0.04) | 1. (0.09,0.71) | 1. (0.14,0.07) | 1. (0.11,0.03) | 1. (0.15,<0.01) |
| 1. Very high HHI \* NLW bite |  |  | 1. -0.13 |  |  |  |  |  |
|  |  |  | 1. (0.47,0.78) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI \* NLW bite |  |  | 1. 0.49 |  |  |  |  |  |
|  |  |  | 1. (0.45,0.28) |  |  |  |  |  |
| 1. High HHI |  |  |  | 1. 0.03 | 1. 0.03 | 1. -0.01 | 1. -0.07 | 1. 0 |
|  |  |  |  | 1. (0.06,0.59) | 1. (0.05,0.54) | 1. (0.06,0.83) | 1. (0.05,0.19) | 1. (0.01,0.81) |
| 1. After NLW intro \* High HHI |  |  |  | 1. -0.13 | 1. 0.05 | 1. -0.08 | 1. -0.03 | 1. -0.01 |
|  |  |  |  | 1. (0.05,0.01) | 1. (0.04,0.28) | 1. (0.05,0.1) | 1. (0.05,0.53) | 1. (0.01,0.47) |
| 1. High HHI \* NLW bite |  |  |  | 1. -0.26 | 1. 0.14 | 1. -0.2 | 1. -0.04 | 1. -0.16 |
|  |  |  |  | 1. (0.28,0.34) | 1. (0.23,0.53) | 1. (0.3,0.5) | 1. (0.24,0.88) | 1. (0.29,0.58) |
| 1. After NLW intro \* High HHI \* NLW bite |  |  |  | 1. 0.52 | 1. -0.17 | 1. 0.42 | 1. 0.21 | 1. 0.26 |
|  |  |  |  | 1. (0.26,0.05) | 1. (0.21,0.4) | 1. (0.26,0.11) | 1. (0.23,0.36) | 1. (0.18,0.14) |
| 1. Adj\_R2 | 1. 0.831 | 1. 0.832 | 1. 0.832 | 1. 0.833 | 1. 0.777 | 1. 0.79 | 1. 0.767 | 1. 0.876 |
| 1. \_N | 1. 12,162 | 1. 10,288 | 1. 10,288 | 1. 10,288 | 1. 19,490 | 1. 8,418 | 1. 13,964 | 1. 87,706 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity |

* 1. Log total hours, stratified by SIC cluster

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 17 Results for log total hours (main model only), stratified by SIC cluster |

| 1. Variables | 1. Cluster 1 | 1. Cluster 2 | 1. Cluster 3 | 1. Cluster 4 | 1. Cluster 5 | 1. Cluster 6 | 1. Cluster 7 | 1. Cluster 8 | 1. Cluster 9 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.22 | 1. 0.26 | 1. -0.01 | 1. 0.14 | 1. -0.03 | 1. -0.18 | 1. 0 | 1. 0.04 | 1. 0.05 |
|  | 1. (0.07,0) | 1. (0.07,0) | 1. (0.06,0.92) | 1. (0.04,0) | 1. (0.09,0.76) | 1. (0.26,0.48) | 1. (0.07,0.99) | 1. (0.06,0.5) | 1. (0.06,0.46) |
| 1. High HHI | 1. -2.34 | 1. -0.95 | 1. 0.47 | 1. -0.93 | 1. 1.5 | 1. 1.01 | 1. -1.01 | 1. -0.9 | 1. 1.33 |
|  | 1. (0.16,0) | 1. (0.43,0.03) | 1. (0.11,0) | 1. (0.15,0) | 1. (0.1,0) | 1. (0.3,0) | 1. (0.18,0) | 1. (0.17,0) | 1. (0.12,0) |
| 1. NLW bite | 1. -0.5 | 1. -0.46 | 1. 0.12 | 1. 1.24 | 1. -0.56 | 1. -0.62 | 1. -0.35 | 1. -0.36 | 1. 0.06 |
|  | 1. (0.22,0.02) | 1. (0.18,0.01) | 1. (0.22,0.57) | 1. (0.41,0) | 1. (0.57,0.33) | 1. (0.59,0.29) | 1. (0.21,0.09) | 1. (0.27,0.19) | 1. (0.28,0.82) |
| 1. % public employer | 1. -1.55 | 1. -0.23 | 1. -1.81 | 1. 0.56 | 1. -0.17 | 1. 0.39 | 1. -0.01 | 1. 0.3 | 1. 0.25 |
|  | 1. (1.3,0.23) | 1. (0.42,0.58) | 1. (0.19,0) | 1. (0.11,0) | 1. (0.21,0.4) | 1. (1.01,0.7) | 1. (1.23,0.99) | 1. (0.4,0.45) | 1. (0.75,0.73) |
| 1. After NLW intro \* High HHI | 1. -0.26 | 1. 1.44 | 1. -0.13 | 1. -0.07 | 1. -0.09 | 1. 0.24 | 1. -0.12 | 1. 0.16 | 1. 0.07 |
|  | 1. (0.16,0.12) | 1. (0.64,0.03) | 1. (0.16,0.44) | 1. (0.13,0.57) | 1. (0.12,0.45) | 1. (0.32,0.44) | 1. (0.21,0.57) | 1. (0.26,0.54) | 1. (0.15,0.64) |
| 1. After NLW intro \* NLW bite | 1. -0.48 | 1. -0.23 | 1. -0.14 | 1. -1.48 | 1. 0.73 | 1. 0.4 | 1. 0.29 | 1. 0.38 | 1. -0.07 |
|  | 1. (0.25,0.05) | 1. (0.18,0.2) | 1. (0.22,0.54) | 1. (0.42,0) | 1. (0.5,0.14) | 1. (0.62,0.51) | 1. (0.23,0.2) | 1. (0.27,0.15) | 1. (0.3,0.82) |
| 1. High HHI \* NLW bite | 1. -0.56 | 1. 2.35 | 1. -0.17 | 1. -1.03 | 1. 0.2 | 1. -0.02 | 1. 0.12 | 1. -0.55 | 1. -0.55 |
|  | 1. (0.6,0.35) | 1. (0.84,0.01) | 1. (0.42,0.68) | 1. (1.88,0.58) | 1. (0.72,0.79) | 1. (0.7,0.98) | 1. (0.64,0.85) | 1. (0.62,0.38) | 1. (0.67,0.41) |
| 1. After NLW intro \* High HHI \* NLW bite | 1. 1.03 | 1. -3.09 | 1. 0.22 | 1. 1.33 | 1. -0.03 | 1. -0.3 | 1. 0.07 | 1. 0.39 | 1. 0.22 |
|  | 1. (0.62,0.1) | 1. (0.88,0) | 1. (0.53,0.67) | 1. (1.9,0.49) | 1. (0.65,0.96) | 1. (0.72,0.68) | 1. (0.65,0.91) | 1. (0.72,0.58) | 1. (0.68,0.74) |
| 1. Adj\_R2 | 1. 0.91 | 1. 0.933 | 1. 0.86 | 1. 0.879 | 1. 0.832 | 1. 0.863 | 1. 0.809 | 1. 0.821 | 1. 0.809 |
| 1. \_N | 1. 1,199 | 1. 1,187 | 1. 1,151 | 1. 1,181 | 1. 1,180 | 1. 1,038 | 1. 1,107 | 1. 1,086 | 1. 1,159 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity. Cluster 1: Retail, Cluster 2: Hospitality, Cluster 3: Wholesale and manufacturing, Cluster 4: Education and childcare, Cluster 5: Health and social care, Cluster 6: Facilities and support services, Cluster 7: Transport, Cluster 8: Construction and Cluster 9: Others |

* 1. Average hours per low pay worker

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 18 Results for average hours per low pay worker, for each model specification |

| 1. Variables | 1. Base | 1. Without MW bite | 1. Narrower high concentration definition | 1. Main model | 1. Granular labour markets | 1. Bus TTWAs | 1. Low skill TTWAs | 1. All workers |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. -0.59 | 1. -0.63 | 1. 0.69 | 1. 0.61 | 1. 0.46 | 1. 0.7 | 1. 0.62 | 1. 0.03 |
|  | 1. (0.1,<0.01) | 1. (0.11,<0.01) | 1. (0.18,<0.01) | 1. (0.2,<0.01) | 1. (0.16,<0.01) | 1. (0.18,<0.01) | 1. (0.18,<0.01) | 1. (0.12,0.82) |
| 1. % public employer | 1. -3.01 | 1. -3.06 | 1. -4.41 | 1. -4.42 | 1. -2.69 | 1. -4.97 | 1. -4.23 | 1. -9.07 |
|  | 1. (0.7,<0.01) | 1. (0.73,<0.01) | 1. (0.82,<0.01) | 1. (0.82,<0.01) | 1. (0.8,<0.01) | 1. (0.94,<0.01) | 1. (0.76,<0.01) | 1. (0.4,<0.01) |
| 1. Very high HHI |  | 1. -1.2 | 1. -1.01 |  |  |  |  |  |
|  |  | 1. (0.43,<0.01) | 1. (0.65,0.12) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI |  | 1. 0.98 | 1. -0.69 |  |  |  |  |  |
|  |  | 1. (0.39,0.01) | 1. (0.66,0.29) |  |  |  |  |  |
| 1. NLW bite |  |  | 1. -2.44 | 1. -2.65 | 1. -2.5 | 1. -3.13 | 1. -2.49 | 1. -28.07 |
|  |  |  | 1. (0.97,0.01) | 1. (1.01,0.01) | 1. (0.75,<0.01) | 1. (1.15,0.01) | 1. (0.77,<0.01) | 1. (1.68,<0.01) |
| 1. After NLW intro \* NLW bite |  |  | 1. -2.05 | 1. -1.9 | 1. -1.39 | 1. -1.71 | 1. -1.83 | 1. 4.86 |
|  |  |  | 1. (0.68,<0.01) | 1. (0.71,0.01) | 1. (0.57,0.01) | 1. (0.73,0.02) | 1. (0.64,<0.01) | 1. (1.22,<0.01) |
| 1. Very high HHI \* NLW bite |  |  | 1. -0.55 |  |  |  |  |  |
|  |  |  | 1. (2.48,0.83) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI \* NLW bite |  |  | 1. 4.35 |  |  |  |  |  |
|  |  |  | 1. (2.39,0.07) |  |  |  |  |  |
| 1. High HHI |  |  |  | 1. -1.2 | 1. -0.21 | 1. -0.63 | 1. -1.11 | 1. -0.33 |
|  |  |  |  | 1. (0.44,0.01) | 1. (0.4,0.6) | 1. (0.47,0.18) | 1. (0.43,0.01) | 1. (0.11,<0.01) |
| 1. After NLW intro \* High HHI |  |  |  | 1. 0.18 | 1. -0.02 | 1. -0.18 | 1. 0.18 | 1. 0.14 |
|  |  |  |  | 1. (0.45,0.69) | 1. (0.38,0.97) | 1. (0.45,0.69) | 1. (0.41,0.66) | 1. (0.14,0.29) |
| 1. High HHI \* NLW bite |  |  |  | 1. 0.59 | 1. -0.02 | 1. -0.25 | 1. 0.55 | 1. 4.93 |
|  |  |  |  | 1. (1.81,0.74) | 1. (1.53,0.99) | 1. (1.7,0.88) | 1. (1.63,0.74) | 1. (1.85,0.01) |
| 1. After NLW intro \* High HHI \* NLW bite |  |  |  | 1. 1.27 | 1. 0.67 | 1. 2.13 | 1. 0.74 | 1. -2.26 |
|  |  |  |  | 1. (1.85,0.49) | 1. (1.48,0.65) | 1. (1.71,0.21) | 1. (1.63,0.65) | 1. (1.57,0.15) |
| 1. Adj\_R2 | 1. 0.518 | 1. 0.547 | 1. 0.56 | 1. 0.56 | 1. 0.433 | 1. 0.59 | 1. 0.48 | 1. 0.526 |
| 1. \_N | 1. 12,162 | 1. 10,288 | 1. 10,288 | 1. 10,288 | 1. 19,490 | 1. 8,418 | 1. 13,964 | 1. 87,706 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity |

* 1. Average hours per low pay worker, stratified by SIC cluster

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 19 Results for average hours per low pay worker (main model only), stratified by SIC cluster |

| 1. Variables | 1. Cluster 1 | 1. Cluster 2 | 1. Cluster 3 | 1. Cluster 4 | 1. Cluster 5 | 1. Cluster 6 | 1. Cluster 7 | 1. Cluster 8 | 1. Cluster 9 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.26 | 1. -0.43 | 1. -0.9 | 1. 0.78 | 1. 0.12 | 1. 0.52 | 1. 0.25 | 1. 0.18 | 1. 0.26 |
|  | 1. (0.54,0.63) | 1. (0.84,0.61) | 1. (0.57,0.11) | 1. (0.5,0.12) | 1. (0.64,0.85) | 1. (1.37,0.71) | 1. (0.87,0.78) | 1. (0.65,0.78) | 1. (0.74,0.72) |
| 1. High HHI | 1. -2.88 | 1. 5.49 | 1. 0.98 | 1. -0.05 | 1. 3.72 | 1. -14.78 | 1. 9.23 | 1. 4.38 | 1. -0.53 |
|  | 1. (1.15,0.01) | 1. (3.44,0.11) | 1. (1.92,0.61) | 1. (1.91,0.98) | 1. (0.76,<0.01) | 1. (1.95,<0.01) | 1. (1.69,<0.01) | 1. (2.45,0.07) | 1. (1.05,0.62) |
| 1. NLW bite | 1. -5.14 | 1. -6.24 | 1. -4.85 | 1. 8.17 | 1. -8.2 | 1. -7.7 | 1. -5.84 | 1. -7.04 | 1. 0.38 |
|  | 1. (2.53,0.04) | 1. (2.15,<0.01) | 1. (2.31,0.04) | 1. (5.7,0.15) | 1. (4.4,0.06) | 1. (4.02,0.06) | 1. (2.34,0.01) | 1. (3.3,0.03) | 1. (2.77,0.89) |
| 1. % public employer | 1. 6.9 | 1. -6.87 | 1. -22.23 | 1. -3.96 | 1. 2.83 | 1. -7.15 | 1. 3.54 | 1. 5.33 | 1. -3.73 |
|  | 1. (12.38,0.58) | 1. (4.85,0.16) | 1. (3.24,<0.01) | 1. (1.05,<0.01) | 1. (1.82,0.12) | 1. (7.66,0.35) | 1. (13.78,0.8) | 1. (4.45,0.23) | 1. (7.72,0.63) |
| 1. After NLW intro \* High HHI | 1. -0.01 | 1. -1.69 | 1. -1.1 | 1. 1.84 | 1. -0.28 | 1. 1.68 | 1. -1.41 | 1. 2.1 | 1. -1.08 |
|  | 1. (1.2,0.99) | 1. (3.07,0.58) | 1. (2.44,0.65) | 1. (1.36,0.18) | 1. (0.88,0.75) | 1. (2.07,0.42) | 1. (1.97,0.47) | 1. (3.14,0.5) | 1. (1.45,0.46) |
| 1. After NLW intro \* NLW bite | 1. 0.22 | 1. -0.53 | 1. 1.79 | 1. -8.21 | 1. 6.25 | 1. 0.85 | 1. 1.69 | 1. 2.6 | 1. -3.64 |
|  | 1. (2.65,0.93) | 1. (2.19,0.81) | 1. (2.42,0.46) | 1. (5.63,0.14) | 1. (4.33,0.15) | 1. (3.78,0.82) | 1. (2.53,0.51) | 1. (3.19,0.42) | 1. (2.89,0.21) |
| 1. High HHI \* NLW bite | 1. -2.49 | 1. -9.3 | 1. 1.22 | 1. -3.71 | 1. 3.91 | 1. 4.01 | 1. 0.4 | 1. 4.54 | 1. -13.8 |
|  | 1. (5.09,0.63) | 1. (8.58,0.28) | 1. (6.97,0.86) | 1. (23.46,0.87) | 1. (5.71,0.49) | 1. (5.19,0.44) | 1. (6.92,0.95) | 1. (13.42,0.73) | 1. (5.53,0.01) |
| 1. After NLW intro \* High HHI \* NLW bite | 1. 0.38 | 1. 8.37 | 1. 3.55 | 1. 3.07 | 1. -0.39 | 1. -3.93 | 1. -1.25 | 1. -5.03 | 1. 13.57 |
|  | 1. (5.25,0.94) | 1. (9.91,0.4) | 1. (8.01,0.66) | 1. (22.57,0.89) | 1. (5.64,0.94) | 1. (5.04,0.44) | 1. (7.02,0.86) | 1. (12.83,0.7) | 1. (5.94,0.02) |
| 1. Adj\_R2 | 1. 0.235 | 1. 0.395 | 1. 0.282 | 1. 0.352 | 1. 0.274 | 1. 0.355 | 1. 0.294 | 1. 0.277 | 1. 0.318 |
| 1. \_N | 1. 1199 | 1. 1187 | 1. 1151 | 1. 1181 | 1. 1180 | 1. 1038 | 1. 1107 | 1. 1086 | 1. 1159 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity. Cluster 1: Retail, Cluster 2: Hospitality, Cluster 3: Wholesale and manufacturing, Cluster 4: Education and childcare, Cluster 5: Health and social care, Cluster 6: Facilities and support services, Cluster 7: Transport, Cluster 8: Construction and Cluster 9: Others |

* 1. Mean base wages

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 20 Results for mean base wages excluding overtime, for each model specification |

| 1. Variables | 1. Base | 1. Without MW bite | 1. Narrower high concentration definition | 1. Main model | 1. Granular labour markets | 1. Bus TTWAs | 1. Low skill TTWAs | 1. All workers |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.46 | 1. 0.46 | 1. 0.38 | 1. 0.37 | 1. 0.44 | 1. 0.37 | 1. 0.4 | 1. 1.28 |
|  | 1. (0.01,0) | 1. (0.01,0) | 1. (0.02,0) | 1. (0.02,0) | 1. (0.02,0) | 1. (0.02,0) | 1. (0.01,0) | 1. (0.23,0) |
| 1. % public employer | 1. -0.04 | 1. -0.05 | 1. -0.25 | 1. -0.25 | 1. -0.2 | 1. -0.22 | 1. -0.18 | 1. -3 |
|  | 1. (0.04,0.38) | 1. (0.05,0.28) | 1. (0.05,0) | 1. (0.05,0) | 1. (0.03,0) | 1. (0.06,0) | 1. (0.04,0) | 1. (1.61,0.06) |
| 1. Very high HHI |  | 1. -0.02 | 1. 0.01 |  |  |  |  |  |
|  |  | 1. (0.03,0.57) | 1. (0.04,0.82) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI |  | 1. 0.03 | 1. 0.01 |  |  |  |  |  |
|  |  | 1. (0.03,0.29) | 1. (0.04,0.83) |  |  |  |  |  |
| 1. NLW bite |  |  | 1. -1.37 | 1. -1.38 | 1. -1.38 | 1. -1.39 | 1. -1.42 | 1. -52.79 |
|  |  |  | 1. (0.04,0) | 1. (0.04,0) | 1. (0.03,0) | 1. (0.05,0) | 1. (0.04,0) | 1. (13.33,0) |
| 1. After NLW intro \* NLW bite |  |  | 1. 0.91 | 1. 0.92 | 1. 0.79 | 1. 0.94 | 1. 0.87 | 1. 10.78 |
|  |  |  | 1. (0.04,0) | 1. (0.04,0) | 1. (0.03,0) | 1. (0.04,0) | 1. (0.04,0) | 1. (2.53,0) |
| 1. Very high HHI \* NLW bite |  |  | 1. -0.03 |  |  |  |  |  |
|  |  |  | 1. (0.14,0.86) |  |  |  |  |  |
| 1. After NLW intro \* Very high HHI \* NLW bite |  |  | 1. 0.02 |  |  |  |  |  |
|  |  |  | 1. (0.15,0.89) |  |  |  |  |  |
| 1. High HHI |  |  |  | 1. -0.04 | 1. 0.05 | 1. -0.01 | 1. -0.06 | 1. -0.72 |
|  |  |  |  | 1. (0.02,0.08) | 1. (0.02,0) | 1. (0.02,0.73) | 1. (0.02,0) | 1. (0.4,0.07) |
| 1. After NLW intro \* High HHI |  |  |  | 1. 0.05 | 1. -0.01 | 1. 0 | 1. 0.09 | 1. -0.31 |
|  |  |  |  | 1. (0.03,0.09) | 1. (0.02,0.57) | 1. (0.03,0.87) | 1. (0.03,0) | 1. (0.22,0.16) |
| 1. High HHI \* NLW bite |  |  |  | 1. 0.03 | 1. -0.04 | 1. -0.02 | 1. 0.12 | 1. 17.38 |
|  |  |  |  | 1. (0.08,0.74) | 1. (0.06,0.46) | 1. (0.1,0.83) | 1. (0.07,0.11) | 1. (9.04,0.05) |
| 1. After NLW intro \* High HHI \* NLW bite |  |  |  | 1. -0.03 | 1. -0.04 | 1. 0.1 | 1. -0.19 | 1. -3.3 |
|  |  |  |  | 1. (0.09,0.77) | 1. (0.07,0.52) | 1. (0.11,0.37) | 1. (0.09,0.03) | 1. (1.96,0.09) |
| 1. Adj\_R2 | 1. 0.276 | 1. 0.281 | 1. 0.352 | 1. 0.353 | 1. 0.32 | 1. 0.359 | 1. 0.322 | 1. 0.555 |
| 1. \_N | 1. 12,162 | 1. 10,288 | 1. 10,288 | 1. 10,288 | 1. 19,490 | 1. 8,418 | 1. 13,964 | 1. 87,706 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity |

* 1. Mean base wages, stratified by SIC cluster

*Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 21 Results for mean base wages, excluding overtime (main model only), stratified by SIC cluster |

| 1. Variables | 1. Cluster 1 | 1. Cluster 2 | 1. Cluster 3 | 1. Cluster 4 | 1. Cluster 5 | 1. Cluster 6 | 1. Cluster 7 | 1. Cluster 8 | 1. Cluster 9 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1. After NLW intro | 1. 0.38 | 1. 0.5 | 1. 0.25 | 1. 0.35 | 1. 0.26 | 1. 0.09 | 1. 0.34 | 1. 0.34 | 1. 0.38 |
|  | 1. (0.04,0) | 1. (0.05,0) | 1. (0.04,0) | 1. (0.03,0) | 1. (0.06,0) | 1. (0.1,0.37) | 1. (0.05,0) | 1. (0.05,0) | 1. (0.04,0) |
| 1. High HHI | 1. 0.21 | 1. -0.02 | 1. -0.08 | 1. -0.11 | 1. -0.21 | 1. -0.31 | 1. 0.58 | 1. -0.79 | 1. -0.08 |
|  | 1. (0.06,0) | 1. (0.05,0.68) | 1. (0.08,0.35) | 1. (0.11,0.33) | 1. (0.06,0) | 1. (0.09,0) | 1. (0.12,0) | 1. (0.38,0.04) | 1. (0.08,0.33) |
| 1. NLW bite | 1. -0.81 | 1. -1.06 | 1. -1.11 | 1. -1.76 | 1. -1.37 | 1. -1.06 | 1. -1.25 | 1. -1.7 | 1. -1.28 |
|  | 1. (0.16,0) | 1. (0.1,0) | 1. (0.14,0) | 1. (0.33,0) | 1. (0.22,0) | 1. (0.17,0) | 1. (0.16,0) | 1. (0.23,0) | 1. (0.14,0) |
| 1. % public employer | 1. -1.9 | 1. -0.18 | 1. 0.68 | 1. -0.25 | 1. -0.98 | 1. 0.27 | 1. -1.14 | 1. -2.87 | 1. -0.28 |
|  | 1. (1.15,0.1) | 1. (0.22,0.42) | 1. (0.13,0) | 1. (0.09,0) | 1. (0.11,0) | 1. (0.33,0.41) | 1. (0.87,0.19) | 1. (0.61,0) | 1. (0.62,0.64) |
| 1. After NLW intro \* High HHI | 1. 0.08 | 1. 0.28 | 1. 0.23 | 1. 0.18 | 1. 0.06 | 1. 0.3 | 1. -0.04 | 1. 0.38 | 1. 0.2 |
|  | 1. (0.07,0.23) | 1. (0.28,0.31) | 1. (0.1,0.02) | 1. (0.1,0.08) | 1. (0.07,0.38) | 1. (0.14,0.03) | 1. (0.14,0.76) | 1. (0.42,0.37) | 1. (0.11,0.07) |
| 1. After NLW intro \* NLW bite | 1. 0.93 | 1. 0.55 | 1. 1.08 | 1. 0.99 | 1. 1.44 | 1. 1.26 | 1. 0.84 | 1. 1.02 | 1. 0.61 |
|  | 1. (0.16,0) | 1. (0.11,0) | 1. (0.14,0) | 1. (0.34,0) | 1. (0.23,0) | 1. (0.24,0) | 1. (0.15,0) | 1. (0.23,0) | 1. (0.15,0) |
| 1. High HHI \* NLW bite | 1. -0.46 | 1. 0.71 | 1. 0.29 | 1. 2.61 | 1. -0.53 | 1. -0.16 | 1. -1.1 | 1. 1.18 | 1. 0.32 |
|  | 1. (0.24,0.05) | 1. (0.18,0) | 1. (0.23,0.21) | 1. (1.22,0.03) | 1. (0.33,0.11) | 1. (0.24,0.5) | 1. (0.72,0.13) | 1. (1.34,0.38) | 1. (0.35,0.35) |
| 1. After NLW intro \* High HHI \* NLW bite | 1. 0.09 | 1. -0.91 | 1. -0.68 | 1. -2.5 | 1. 0.1 | 1. -0.43 | 1. 0.93 | 1. -0.86 | 1. -0.69 |
|  | 1. (0.25,0.7) | 1. (0.58,0.12) | 1. (0.27,0.01) | 1. (1.24,0.04) | 1. (0.31,0.74) | 1. (0.31,0.16) | 1. (0.75,0.21) | 1. (1.21,0.48) | 1. (0.37,0.06) |
| 1. Adj\_R2 | 1. 0.435 | 1. 0.396 | 1. 0.362 | 1. 0.312 | 1. 0.314 | 1. 0.398 | 1. 0.275 | 1. 0.369 | 1. 0.197 |
| 1. \_N | 1. 1,199 | 1. 1,187 | 1. 1,151 | 1. 1,181 | 1. 1,180 | 1. 1,038 | 1. 1,107 | 1. 1,086 | 1. 1,159 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021)  Note: We use robust standard errors to account for serial correlation and heteroskedasticity. Cluster 1: Retail, Cluster 2: Hospitality, Cluster 3: Wholesale and manufacturing, Cluster 4: Education and childcare, Cluster 5: Health and social care, Cluster 6: Facilities and support services, Cluster 7: Transport, Cluster 8: Construction and Cluster 9: Others |

* 1. Model in differences with lagged bite

1. *Regression covariates are displayed in rows, and models are shown in columns. Below each point estimate is the (standard error, p-value) associated with that estimate.*

|  |
| --- |
| Table 22 Banded rows |

| 1. Variables | 1. ∆ Log employment | 1. ∆ Log total hours | 1. ∆ Average hours per low pay worker | 1. ∆ Mean wages excluding overtime |
| --- | --- | --- | --- | --- |
| 1. % public employer | 1. -0.08 | 1. -0.05 | 1. 0.85 | 1. -0.08 |
|  | 1. (0.02,<0.01) | 1. (0.02,0.01) | 1. (0.17,<0.01) | 1. (0.02,<0.01) |
| 1. High HHI | 1. -0.01 | 1. 0 | 1. 0.7 | 1. -0.09 |
|  | 1. (0.02,0.55) | 1. (0.03,0.85) | 1. (0.34,0.04) | 1. (0.03,<0.01) |
| 1. Lagged NLW bite | 1. -0.27 | 1. -0.22 | 1. 1.34 | 1. -0.09 |
|  | 1. (0.05,<0.01) | 1. (0.05,<0.01) | 1. (0.29,0) | 1. (0.07,0.21) |
| 1. Lagged NLW bite \* High HHI | 1. 0.13 | 1. 0.08 | 1. -1.49 | 1. 0.32 |
|  | 1. (0.08,0.09) | 1. (0.09,0.36) | 1. (1.02,0.15) | 1. (0.08,<0.01) |
| 1. Adj\_R2 | 1. 0.008 | 1. 0.004 | 1. 0.002 | 1. 0.007 |
| 1. \_N | 1. 9,003 | 1. 9,003 | 1. 9,003 | 1. 9,003 |

|  |
| --- |
| Source: BSD (2015), ASHE (2015-2021) |

1. 

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1. If one company slightly reduces wages, all of its workers leave to work for another organisation. [↑](#footnote-ref-2)
2. If one company slightly reduces wages, all of its workers leave to work for another organisation. [↑](#footnote-ref-3)
3. Includes commissions, bonuses, overtime, non-statutory sick pay, non-statutory parental pay, employer pension contributions. [↑](#footnote-ref-4)
4. Includes quality of healthcare, childcare, disability accessibility, and pension services for employees. [↑](#footnote-ref-5)
5. Other drivers of the ability to absorb the effect of increases in the minimum wage include the elasticity of demand for the product, and the elasticity of supply of other factors. [↑](#footnote-ref-6)
6. Monopsony is technically defined as a market with one buyer of labour (firm) and many sellers (workers). The term is typically used more generally to indicate the case where employers have wage-setting power in imperfectly competitive labour markets. In this study, we use the term monopsony in this more general sense. [↑](#footnote-ref-7)
7. In search and matching labour models, increases in the minimum wage have two opposing effects on job creation. On the one hand, it reduces the labour demand by increasing the marginal cost of hiring a new worker leading to lower hiring rates. But on the other hand, it increases labour supply as expected returns of employment improve relative to unemployment, leading to additional search efforts from unemployment workers. The increased labour supply also improves the quality of matches between employers and employees. Therefore the net effect of an increase in wage floors is ambiguous (Meer and West, 2016). [↑](#footnote-ref-8)
8. It takes time for employers that are currently recruiting to be matched with workers that are perfect substitutes of current workers (Manning, 2011) [↑](#footnote-ref-9)
9. Three low-wage occupations in the merchandise store sector which include large firms like Walmart and Target. [↑](#footnote-ref-10)
10. North American Industry Classification System (NAICS) is a US hierarchical classification of business establishments by type of economic activity/production process (up to 6-digits), based on the primary business activity. The NAICS includes 20 business sectors. [↑](#footnote-ref-11)
11. Standard Occupational Classification (SOC) System is a US hierarchical coding framework used to classify occupations (up to 6-digits). It assigns all jobs a four-digit code based on the skills and qualifications needed for the job. It reflects the current occupational structure in the United States and it includes 840 occupational types. [↑](#footnote-ref-12)
12. Standard Industrial Classification (SIC) was a US hierarchical classification of business establishments (up to 4-digits) based on their largest product lines. It was replaced by the NAICS code system in 1997, except in some government agencies. [↑](#footnote-ref-13)
13. We investigated using the Annual Population Survey (APS), but found that the sample size was insufficient to construct monopsony metrics in local areas. [↑](#footnote-ref-14)
14. We use robust standard errors to account for serial correlation and heteroskedasticity. [↑](#footnote-ref-15)
15. We used relatively high percentile thresholds for HHI because the distribution of concentration is right-skewed, and it is likely that the effects of monopsony particularly impact markets with very few employer options. [↑](#footnote-ref-16)
16. Data showing the movement of people between locations including commuting patterns [↑](#footnote-ref-17)
17. [Travel to work area analysis in Great Britain: 2016](https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/traveltoworkareaanalysisingreatbritain/2016) [↑](#footnote-ref-18)
18. <https://www.justice.gov/atr/herfindahl-hirschman-index> [↑](#footnote-ref-19)
19. For more detail on sector clusters used in our main specification, please see Annex A. [↑](#footnote-ref-20)
20. <https://www.nursingtimes.net/news/workforce/early-departure-of-thousands-of-nurses-deeply-worrying-13-02-2023/> [↑](#footnote-ref-21)
21. See for example: <https://www.bmj.com/content/367/bmj.l6381> [↑](#footnote-ref-22)
22. For a summary of post-Brexit-referendum labour statistics, see for example <https://www.ecb.europa.eu/pub/economic-bulletin/articles/2023/html/ecb.ebart202303_01~3af23c5f5a.en.html> [↑](#footnote-ref-23)
23. <https://migrationobservatory.ox.ac.uk/resources/briefings/long-term-international-migration-flows-to-and-from-the-uk/> [↑](#footnote-ref-24)
24. For example, see the discussion in <https://wonkhe.com/blogs/how-do-you-solve-a-problem-like-soc-coding/> for graduate jobs. [↑](#footnote-ref-25)
25. <https://assets.publishing.service.gov.uk/media/652fdb9d92895c0010dcb9a5/A_skills_classification_for_the_UK.pdf> [↑](#footnote-ref-26)
26. For example, see the transport section of the DLUHC Levelling Up Missions (2024). <https://www.gov.uk/government/publications/statement-of-levelling-up-missions/statement-of-levelling-up-missions> [↑](#footnote-ref-27)