Essays on Monopsony Power, Wage Floors and Atypical Work Arrangements

Nikhil Datta

A dissertation submitted in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

of

University College London.

Department of Economics

University College London

June 8, 2022

To Anil, Anup and Ruchi for being there from the start.

To sobriety for saving me.

To Bella, for she is meri jaan, and my partner on this journey.

Abstract

This thesis studies the role of monopsony power, wage floors and atypical work arrangements in modern labour markets. Chapter two studies the extent of monopsony power in a low pay labour market and explores its determinants. I emphasise the role of the spatial distribution of activity and workers' distaste for commuting in generating imperfect substitutability between jobs, and heterogeneity in monopsony power. Estimates show strong evidence of monopsony power, with wage markdowns of 20-25%, and a sizeable distaste for commuting amongst workers. Structural estimates of a job search model suggest that commutes are responsible for approximately 1/3 of the wage markdown. Chapter three studies the impact of a Living Wage on wages and intensive margin employment for workers within a large local services firm, with a focus on heterogeneous impacts across age groups. I show the Living Wage raised wages but did not affect aggregate hours, however there is evidence of a reallocation of hours by age arising from differential eligibility to be paid the Living Wage. Chapter four studies the evolving nature of atypical work arrangements, and the interaction with labour wage floors is also explored in the context of the 2016 introduction of the UK's National Living Wage. Chapter five investigates the extent to which labour supply preferences are responsible for the marked rise in atypical work arrangements in the UK and US. In particular I estimate the distribution for preferences and willingness-to-pay over various job attributes. The list of attributes includes key distinguishing factors of typical and atypical work arrangements, such as security, work-related benefits, flexibility, autonomy and taxation implications. The results are indicative that the majority of the population prefer characteristics associated with traditional employee-employer relationships, and this preference holds even when analysing just the sub-sample of those in atypical work arrangements.

Impact Statement

This thesis contributes to the understanding of the mechanisms underpinning the functioning of modern day labour markets. The research developed for, and contained within this thesis is of benefit to academia and policymakers.

For academics working on topics related to labour markets, the theories postulated and empirically tested concerning the wage setting behaviour of the firm, the driving forces behind wage markdowns, and how they vary across space will help the continued development of more accurate modelling. Furthermore, the results contribute to our collective understanding of how minimum wages can improve wage outcomes for workers while not damaging their employment outcomes. The methodologies developed concerning spatial labour market size will hopefully aid labour economists improve definitions of spatial labour markets which in turn can provide more accurate measures of concentration.

The results are also of key interest to policy makers. The work concerning minimum wages and Living Wages has previously been presented to members of the Low Pay Commission so as to assist in minimum wage determination rates for the UK. It has additionally been presented to members of the Welsh Government, who were exploring Living Wage legislation for the social care sector. The estimates of monopsony power in low skilled labour markets in the UK could also be of future use for policy makers considering legislation to improve worker power and wages for the lowest earners in society. The analysis showing that workers have, in general, strong preferences for secure, stable work can in turn complement the government's own commissioned research on modern working practices as laid out in the Taylor review.

Acknowledgements

I am incredibly grateful to my supervisors Uta Schönberg and Christian Dustmann, and my supervisor-in-all-but-title Stephen Machin for their guidance and support throughout this work. I thank my colleagues and contemporaries at the Department of Economics and Centre for Research and Analysis of Migration at UCL for the formal teaching, support and constructive feedback I have received.

My gratitude goes to the research community and staff at the Centre for Economic Performance at LSE who created a welcoming, friendly, and stimulating research environment which I have been lucky enough to call my second academic home for more than half a decade.

I am grateful to Alison Andrews, Jan David Bakker, Joshua De-Lyon, and Simon Fuchs for their comments and input, but more importantly for their friendship and companionship.

For financial support I am grateful to the Economic and Social Research Council, the Centre for Economic Performance, the Department of Economics at UCL, and to my wife who kindly housed and fed me.

I am particularly grateful to Bella Datta and James Duckworth, for keeping me sane and putting up with some of my horrendous moods during this process.

Contents

1 Introduction

Wages and contract structure are two of the most important features of a job in a modern labour market and have a strong ability to impact the welfare of workers. Wages are the main determinant of household income in developed economies, in the UK and US they account for between 80-90% of total income for median working-age households. Contractual relations between workers and firms determine aspects of job security, longevity, flexibility, autonomy and taxation implications, all of which are likely to impact workers.

This thesis explores questions related to these two features of modern jobs and their interaction. A focus is placed on wage determination, and the role of monopsony power in suppressing wages down from their marginal product for workers as was first envisioned by Pigou (1924) and Robinson (1933). It extends this tradition by taking an empirical approach to measure the size of markdowns, and a theoretical approach to examine the underlying mechanisms and marries these two approaches by employing structural estimation techniques. The thesis also explores the role of wage floors in determining wages for low paid workers, and asks if minimum wages are able to improve pay conditions, and if so by how much. In addition it asks what other margins of adjustment might occur for workers, as understanding these adjustments would be key for a full picture of welfare impacts for workers. Given evidence of monopsony power, a particular focus is placed on employment adjustments along the extensive and intensive margin, as well as how minimum wages may effect the structure of contractual relations for workers. As a final point of examination, this thesis examines the state of atypical work arrangements in the UK and US economies, in particular looking at zero-hours contracts, and solo self-employment arrangements such as contracting and the gig-economy. With this descriptive evidence in mind, it seeks to estimate worker valuations for different types of contractual relationships. This thesis ties together this complementary work on monopsony power, minimum wages and atypical work arrangements, and comprises of four separate chapters.

Chapter two studies the extent of monopsony power in a low pay labour market and explores its determinants. I emphasise the role of the spatial distribution of activity and workers' distaste for commuting in generating imperfect substitutability between jobs, and heterogeneity in monopsony power. Using detailed HR data for a firm with hundreds of establishments across the UK, coupled with two sources of job-establishment level exogenous wage variation, including a Living Wage floor, I estimate both the recruitment and separation elasticities as well as the commuting-wage elasticity. Estimates show strong evidence of monopsony power, with wage markdowns of 20-25%, and a sizeable distaste for commuting amongst workers. To formalise the role of commutes in generating monopsony power I develop a job search model where utility depends on wages, commutes and an idiosyncratic component. The model endogenously defines probabilistic spatial labour markets which are point specific and overlapping, and generates labour supply to the firm elasticities which vary across space. Distaste for commuting is shown to increase monopsony power, but does so heterogeneously, increasing monopsony power in rural areas more than in denser urban areas. Spatial heterogeneity in market-power predicted by the model is evidenced in both causal estimates using the HR data and descriptive estimates using a nationally representative dataset. Structurally estimating the model using spatial variation in monopsony power I find that commutes are responsible for approximately 1/3 of the wage markdown.

Chapter three considers an emerging, highly policy relevant feature of minimum wages, studying what happens when a wage floor significantly higher than a nationally legislated minimum is imposed. The consequences of age-wage discontinuities and wage floors higher than mandated minimum wages are explored in the context of a Living Wage being introduced to a large UK organisation through time. Between 2011 and 2019, the Company was exposed to a Living Wage Rate higher than the statutory National Minimum Wage, which was sequentially introduced into some of its establishments and had the effect of boosting wages and strongly increasing the age-wage discontinuity from age-related pay grades. The analysis finds positive labour supply responses at the age discontinuity before Living Wage treatment, but a fall in hours at the discontinuity following treatment. The Living Wage raised wage costs but did not affect aggregate hours, showing a within-establishment reallocation of hours by age arising from differential eligibility to be paid the Living Wage.

Chapter four studies the evolving nature of atypical work arrangements. A particular focus is placed on one such form of work relation: zero hour contracts (ZHCs). The chapter uses existing secondary data and new survey data collected for the specific purpose of studying alternative work arrangements to describe the nature of ZHC work in the UK labour market. The interaction with labour wage floors is also explored, in the context of the 2016 introduction of the UK's National Living Wage. ZHC work is shown to be an important feature of today's work arrangements, and a higher minimum wage has resulted in an increased use of ZHCs in the UK social care sector, and in low wage sectors more generally.

Chapter five investigates the extent to which labour supply preferences are responsible for the marked rise in atypical work arrangements in the UK and US. By employing vignettes in a discrete job choice experiment in a representative survey, I estimate the distribution for preferences and willingness-to-pay over various job attributes. The list of attributes includes key distinguishing factors of typical and atypical work arrangements, such as security, work-related benefits, flexibility, autonomy and taxation implications. The results are indicative that the majority of the population prefer characteristics associated with traditional employee-employer relationships, and this preference holds even when analysing just the sub-sample of those in atypical work arrangements. Additionally, preferences across the UK and US are very similar, despite differences in labour market regulations. Rather than suggesting that labour supply preferences have contributed to the increase in atypical work arrangements, I find that the changing nature of work is likely to have significant negative welfare implications for many workers.

Overall I find that modern labour markets show strong evidence of being monopsonistic, and wage floors can go some way in mitigating these issues without causing detrimental effects on workers' employment outcomes. That said, in certain highly exposed industries, such as the social care sector, there is some evidence that a higher wage floor has caused an increase in the proliferation of atypical work arrangements, which workers on average would prefer to avoid for a more secure employee-employer contractual relationship.

2

Local Monopsony Power

Abstract

This paper studies the extent of monopsony power in a low pay labour market and explores its determinants. I emphasise the role of the spatial distribution of activity and workers' distaste for commuting in generating imperfect substitutability between jobs, and heterogeneity in monopsony power. Using detailed HR data for a firm with hundreds of establishments across the UK, coupled with two sources of job-establishment level exogenous wage variation, I estimate both the recruitment and separation elasticities as well as the commuting-wage elasticity. Estimates show strong evidence of monopsony power, with wage markdowns of 20-25%, and a sizeable distaste for commuting amongst workers. To formalise the role of commutes in generating monopsony power I develop a job search model where utility depends on wages, commutes and an idiosyncratic component. The model endogenously defines probabilistic spatial labour markets which are point specific and overlapping, and generates labour supply to the firm elasticities which vary across space. Distaste for commuting is shown to increase monopsony power, but does so heterogeneously, increasing monopsony power in rural areas more than in denser urban areas. Spatial heterogeneity in market-power predicted by the model is evidenced in both causal estimates using the HR data and descriptive estimates using a nationally representative dataset. Structurally estimating the model using spatial variation in monopsony power I find that commutes are responsible for approximately 1/3 of the wage markdown.

2.1 Introduction

Wages account for 84% of total income for the median working-age household in the UK. The wage-setting behaviour of firms is therefore of first-order economic importance. In a perfectly competitive market where firms are price takers, workers receive their marginal product. But in markets where firms have wage-setting power, workers receive a marked-down percentage of their marginal product, and the size of that markdown depends on the extent of monopsony power their employer exercises.[1] The sources of monopsony power are still not well known and are of key importance in understanding what generates inefficiencies in labour markets, heterogeneity in markdowns and how to to design optimal labour market policy. This paper estimates the extent of monopsony power for a firm with hundreds of establishments across the UK and examines a source of monopsony power, workers' distaste for commuting.

To estimate the extent of monopsony power I am interested in examining two key elasticities; the recruitment-wage elasticity and the separation-wage elasticity, which combined give the labour supply elasticity to the firm. A large labour supply elasticity to the firm suggests a more competitive market, while a low elasticity suggests large markdowns. To estimate workers' distaste for commuting I am interested in estimating the commuting-wage elasticity. To estimate these parameters I utilise a novel dataset for a large UK based firm, which contains rich human resources (HR), vacancy, and applicant data. In addition to the usual information such as wages, tenure, and demographic characteristics, the dataset includes detailed data on specific job roles, entire vacancy text, and worker and applicant home location, so commutes can be accurately calculated.

Estimating the above three elasticities has historically been challenging as they require exogenous wage variation at the establishment-level as a minimum. This is because to isolate the elasticities, we require to see how recruits, separations or willingness-to-commute respond when only the wage in a single establishment changes, and the rest of the market's wages remain unchanged.

To overcome endogeneity concerns I use two novel instruments to establish exogenous variation in the wage at the job-establishment-time level, and the advert-job-establishment-time level respectively. The first a location specific Living Wage floor that only affects firms who are engaged in council procurement contracts and thus affects a fraction of a percentage of firms and workers in the area. The Living Wage is however binding for The Company's establishment in that location, and only affects jobs that were previously paying less than the Living Wage. As the Company's local main competitors all operate

[1]For canonical texts on this see Pigou (1924), Robinson (1933) and Manning (2003).

purely in the private sector, the location specific Living Wage floor essentially operates as an establishment-job-time wage shifter for those jobs where the Living Wage is binding. The second is an instrument related to the saliency of the advertised wage in a job advert. By law in the UK all jobs must pay 28 days annual leave and some firms decide to pay this as an hourly wage top-up, which works out to 12.07%. The Company pays this annual leave top-up to all their casual staff, however only some of the advertised positions include the top-up in the posted wage. This is as a result of the member of HR staff who was posting vacancies that day, and thus induced by idiosyncrasies in The Company's HR department. The instrument has the effect of inducing variation in the posted wage randomly for the same jobs, within the same establishment.

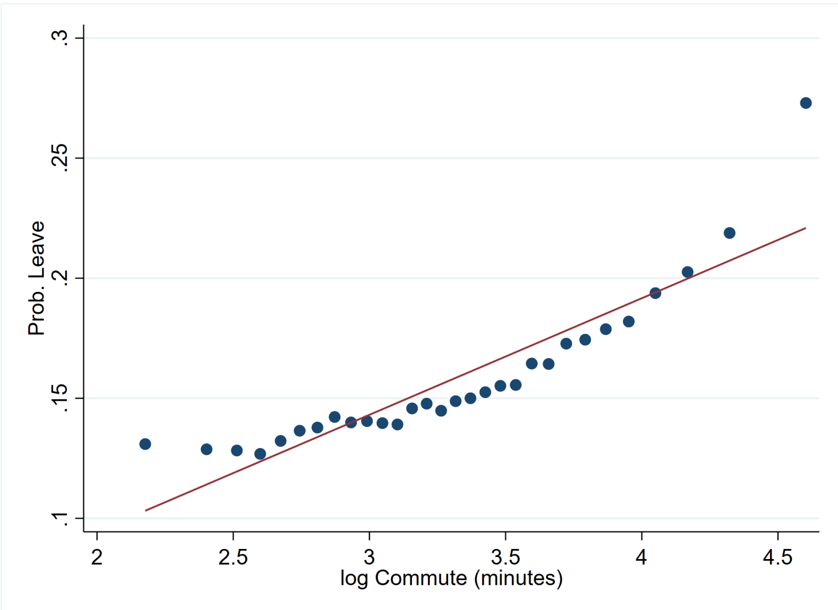
Previous estimates of the labour supply elasticity to the firm have relied on a result from Manning (2003) that the recruitment elasticity and separation elasticity are equal in absolute value under certain restrictive assumptions. This paper is the first to estimate both elasticities separately for the same firm utilising exogenous variation in the wage. In doing so I am able to assess whether there are asymmetries in market power over incumbent workers versus new recruits. I find a separation-wage elasticity of -1.7 and an application-wage elasticity of approximately 3.7, suggesting firms exercise more monopsony power over incumbent workers than in attracting new applicants. This is suggestive of the presence of greater frictions for incumbent workers. However, as the increase in applicants only effects recruitment via increasing the probability of filling a vacancy, the recruitment and separation elasticity are found to be of similar size. The baseline estimates suggest an average markdown in the region of 20-25%. I additionally find workers have a very strong distaste for commuting. In particular I find a commuting-wage elasticity of approximately 1, which implies a minimum wage worker would require an extra £0.47 ($0.55) per hour for an extra 5 minute commute.

The role of commutes in generating monopsony power is straightforward. The length of commute to a place of work is a non-wage factor that can affect the utility from a job, and therefore generate imperfect substitutability between differently located jobs. Figure 2.1 plots the probability of separation against log commutes for a large representative sample of British workers for the period 2003-2019. As can be seen length of commute is strongly positively correlated with separations, which is suggestive that distance to work is an important factor in worker preferences over jobs.[2] The importance of commutes is determined by the size of the commuting-wage elasticity. If there is evidence of a strong distaste for commuting (a low elasticity), there is scope for this to generate geographical

[2]This correlation is unchanged when including a barrage of controls including wage, age, sex, part time and temporary contracts, and fixed effects fo year, occupation and industry, as shown in figure 2.B.1 in the appendix.

heterogeneity in monopsony power as jobs and workers are not equally spaced across the spatial economy. To formalise this mechanism I develop a job search model of "local monopsony power", where utility depends on the wage, commuting and an idiosyncratic component. The model endogenously defines spatial labour markets which are continuous and overlapping and generates labour supply to the firm elasticities which arise endogenously and vary across space. The model suggests that as distaste for commuting increases, monopsony power increases, but does so heterogeneously across space. Rural areas where job options are more limited are shown to be less competitive than denser more urban areas, as a result of commutes. To validate the model I show that the model predictions in heterogeneity in monopsony power across space are consistent with heterogeneity found in my causal estimates. I additionally show that model predictions for monopsony power across 7,250 Built Up Areas in the UK are strongly negatively correlated with wages and worker density for the low pay retail market. I then structurally estimate the model and show that commutes are responsible for approximately 1/3 of the wage markdown.

Figure 2.1: Separations vs Commutes



Note: *The figure plots the probability of separation within a year against commutes measured in minutes. Commutes are measured using the Open Street map dataset for Great Britain and ArcGIS's networking tool. The sample is based on 1,429,376 worker-year observations from the Annual Survery of Hours and Earnings 2003-2019.*

This paper makes three contributions. Firstly, the empirical section on estimating the labour supply elasticity to the firm, and thus the extent of monopsony power, contributes to the empirical literature on measuring imperfect competition. Till now studies have typically either attempted to estimate the recruitment elasticity, using applicant data,[3] or the separation elasticity[4] and relied on a result from Manning (2003) that states that they are equal in absolute value. There are reasons to believe this result might not hold[5] which would mean estimates of the labour supply elasticity to the firm relying on that result are incorrect. This study is the first to estimate both the recruitment and separation elasticity for the same firm, and assess asymmetries in market power between incumbent and new workers. Furthermore, rather than assuming that the application-wage elasticity is synonymous with the recruitment-wage elasticity this study is also the first to examine how the the number of applications impacts the probability of filling a vacancy. Using these results I offer a range of markdown estimates, where the lowest relates to a firm which employs all its applicants (16%), and the highest relates to a firm with only a single vacancy to fill (25%).

Secondly, it contributes theoretically to the sources of monopsony power. There are two strands of literature on this front, one which attributes monopsony power to search frictions (Burdett and Mortensen, 1998; Manning, 2003), and a newer strand borrowing foundations from Industrial Organization where firms are imperfect substitutes for workers due to idiosyncratic preferences over non-wage aspects of a job (Card et al., 2018).[6] This study belongs to the latter of these two, though develops it by splitting the role of location and commutes out from the single idiosyncratic parameter, which recent research suggests is the most important non-wage aspect of a job for workers (Caldwell and Oehlsen, 2018; Blundell, 2020), and formally models them. In a job search model of labour supply where utility is in part dependent on the commuting distance between the location of the worker and the location of the firm, I show spatial labour markets become point specific and weaken over distances. Monopsony power is increasing in the variance of the idiosyncratic component of utility, and the role of the spatial distribution of activity in generating monopsony power depends on the commuting-wage elasticity. As distaste for commuting increases, so does monopsony power, though heterogeneously across locations. Areas with few local job opportunities, where workers need to commute for work, exercise greater monopsony power than more congested city areas. Firms in more congested city areas are still able to exercise some local monopsony power, as even small commutes within a city generate disutility.

[3]For examples see Dal Bó et al. (2013); Belot et al. (2018); Pörtner and Hassairi (2018); Azar et al. (2019); Banfi and Villena-Roldan (2019); Dube et al. (2020a); Marinescu and Wolthoff (2020)

[4]Notable recent papers include Ransom and Sims (2010); Dube et al. (2016, 2019) and for a recent survey see Sokolova and Sorensen (2021).

[5]It is derived for a market rather than an individual firm, and relies on assumptions that recruitment from unemployment is invariant to the wage, and that the recruitment and separation elasticity are both constant.

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

The above result contributes to the literature on the spatial determinants of wages in urban economics. The seminal paper from Glaeser and Mare (2001) noted that urban workers earn on average 33% more than their non-urban counterparts, and this is in part due to level differences in wages (Heuermann et al., 2010; de la Roca and Puga, 2017). Much of the literature has attributed this urban wage premium to productivity gains from agglomeration (Ciccone and Hall, 1996; Glaeser, 1998; Puga, 2010; Moretti, 2011) in a competitive labour market setting. This study adds to new evidence from Hirsch et al. (2020) that part of the premium is likely driven by differences in monopsony power as the thick labour market in urban areas have more jobs in close proximity such that they are closer substitutes, and provides a micro-foundation for this.

Thirdly, it contributes by empirically assessing the sources of monopsony power. The IV estimates of the commuting-wage elasticity are the first I am aware of utilising exogenous wage variation, and suggest a strong distaste for commuting and that a firm's geographic labour market size only mildly responds to wage increases. The estimate suggests that even identical jobs, but differently located, within the same city are imperfect substitutes as workers have very strong travel preferences. By exploiting geographic variation in the location of establishments I additionally show that the model does a good job of spatially predicting more and less competitive areas, giving credibility to the mechanism suggested by the model. A structural estimation exercise matching the model predicted elasticities with the empirically estimated elasticities, additionally enables me to estimate the variance parameter related to the distribution of idiosyncratic preferences. A simple transformation into a logit model suggests that in the absence of commutes the firm's application-elasticity would be equal to this parameter, and therefore approximately 80% larger. A short-run partial-equilibrium counterfactual exercise which shrinks all commutes to zero, but holds incumbent wages constant gives a result similar in size. Estimates imply that in the absence of commutes, markdowns would be approximately 10 percentage points lower. Thus, the above mechanism concerning the role of commutes appears to be an important one.

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

The analysis also speaks to the recent surge in literature and policy debates concerning employer concentration and market power in the labour market.[7] Until now studies have generally relied on the discretisation of labour markets into non-overlapping, relatively large areas with travel assumed to be costless within this area and infinitely costly at the border. This has recently come under criticism (Berry et al., 2019; Rose, 2019), partly due to the very local nature of labour markets (Manning and Petrongolo, 2017). In the UK this is generally done at the Travel To Work Area (TTWA) and in the US at the Commuting Zone (CZ) level. The mean area for TTWAs is 1,064 km^2 and travel distances within TTWAs can exceed 90 minutes. The results for the commuting-wage elasticity suggest that by using the aforementioned definitions of a spatial labour market, employer concentrations are likely to be underestimated. This is an important development given the increased calls for a stronger regulatory response to market concentration (Krueger and Posner, 2018; Naidu et al., 2018; Marinescu and Hovenkamp, 2019; Marinescu and Posner, 2019). Furthermore, within sizeable discretised areas firms' labour market power are likely to be highly heterogeneous. For example, despite both being within the same TTWA, a firm located in Soho, London is unlikely to have the same labour market power as a firm in the commuter town of Brookmans Park, Hertfordshire. By using a continuous framework with overlapping labour markets a much more accurate and granular measure of labour market power is possible. With that measure in place policy makers will be better suited to choose optimal policies to increase worker power, whether it be through labour market regulation, area specific minimum wages or collective bargaining.

The remainder of this paper is organised as follows. Section 2.2 introduces the data, discusses the identification strategy, and presents estimates of monopsony power and the commuting-wage elasticity. In section 2.3 I formally develop the model of local monopsony power, discuss its implications, and provide evidence of its validity using both causal and observational data. Section 2.4 structurally estimates the parameter relating to the distribution of idiosyncratic preferences and quantifies the role of commutes in generating monopsony power. Section 5.7 concludes.

[7] Examples of work in this vein includes Schubert et al. (2021); Naidu and Posner (2021); Azar et al. (2020b); Azkarate-Askasua and Zerecero (2020); Arnold (2020); Azar et al. (2020a); Benmelech et al. (2020); Nimczik (2020); Berger et al. (2019); Jarosch et al. (2019); Qiu and Sojourner (2019); Rinz et al. (2018); Abel et al. (2018); Lipsius (2018); Hershbein et al. (2018).

2.2 Evidence of Monopsony Power and Distaste for Commuting

This section has two main aims. First, it assesses the extent of monopsony power in a low pay labour market in the UK by estimating the labour supply elasticity to the firm, a key parameter for establishing market power and markdowns. It does this by estimating three separate elasticities, the separation-wage elasticity, the application-wage elasticity and the vacancy fill-application elasticity. The second and third of these elasticities combines to give the recruitment elasticity, which when added to the negative of the separation elasticity gives the labour supply elasticity to the firm[8].

Second, it estimates the commuting-wage elasticity, a parameter for establishing workers' distaste for commuting. This parameter is of interest as commutes have the potential of being a key driver in giving rise to imperfect substitutability between jobs, and therefore generating monopsony power (Caldwell and Danieli, 2020). Furthermore, if there is evidence of a strong distaste for commuting, there is scope for this to generate geographical heterogeneity in monopsony power as jobs and workers are not equally spaced across the spatial economy.

2.2.1 Data and Identification

2.2.1.1 Data

I utilise a rich bespoke dataset for a large UK based services firm (The Company) with operations in over 300 establishments across the UK. Establishments are centrally operated by the same company using the same structure of operations and management, but there is establishment level autonomy over employment and workforce composition decisions. While The Company's main competitors are firms operating in the private sector, a large part of the firm's business is government procurement contracts. The dataset includes HR data for the period 2011-2019, and vacancy and applicant data for the period 2016-2019. The HR data covers approximately 31,000 employees and includes information on demographics, job roles, pay, start and leave dates and home location. The vacancy data includes all information that is contained in a job advert including, job role, wage, location and all text within the advert, as well as whether the position was filled or not. The applicant data includes the number of applicants for each vacancy, and details on the applicants including home location, gender, ethnicity and whether the applicant was internal or external. The combination of these three datasets allows me to explore separations, applications, vacancy-filling and commutes, and how they respond to wages.

[8]See Manning (2003) for more details.

Table 2.1 presents summary statistics for The Company in March 2019 along with comparative statistics from the Labour Force Survey (LFS). As can be seen 60% of the firm's workforce are female, marginally higher than the national average. The Company's workforce are also younger when compared to the national average. The median worker is 33 years old, while the median worker in the LFS is 42 years old. Almost half of the firm's workers are classified as "Entry-Level". These jobs are typically minimum-wage jobs in the UK, and would be considered unskilled. The Company has a very large number of workers on zero-hours contracts[9], only about 30% of the workforce have permanent contracts, which is much smaller than the national average. These types of contracts are however more prevalent in minimum wage jobs (Datta et al., 2019). The average wage in the firm is £12.88, and this is around 16% lower than the national average. The mean commute for workers in the firm is 24.3 minutes while the median is considerably less at 16.8 minutes. Approximately half of the firm's workforce are based in establishments located in London.

Table 2.1: Summary Statistics, March 2019

Variable	**The Company**			**LFS**		
	Mean	S.D.	Median	Mean	S.D.	Median
Female	0.60			0.52		
Age	35.9	14.3	33.0	41.9	13.2	42.0
Entry-Level	0.49					
Permanent	0.28			0.94		
Hourly Rate (£)	12.88	5.87	10.20	15.10	10.11	12.03
Commute (minutes)	24.3	17.0	16.8			
London	0.53			0.12		
N						
Workers	18,773			36,125		
Establishments	362					

Note: *The table presents worker-level summary statistics for The Company and the related statistics from the nationally representative Labour Force Survey, as of March 2019.*

Table 2.A.1 in the appendix contains summary statistics on the vacancy data which unsurprisingly shows a very similar pattern to those from 2.1. It additionally shows that the advertised vacancies receive 19 applications on average.

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

2.2.1.2 Exogenous Wage Variation

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

Between 2012 and 2019 107 local government units gained accreditation. For example, of the 32 London Boroughs, 17 have received accreditation, the earliest (Islington) receiving accreditation in May 2012, and the most recent (Redbridge) receiving accreditation in November 2018[10]. As figure 2.2 shows, this setting gives a large amount of variation in Living Wage treatment for establishments run by The Company. In particular, over the period for which we have HR data, approximately 140 establishments went from being untreated to treated, while run by The Company. The living wage rates for London (LLW) and the rest of the UK (UKLW) are calculated each year by the LWF and the Resolution Foundation and have typically been considerably higher than the mandatory National Minimum Wage (NMW) and National Living Wage (NLW). The LLW rate

[10]Correct as of July 2019.

has typically been approximately 30-35% higher than the mandatory minimums, while the UKLW has been about 15-20% higher as can be seen by figure 2.B.2 in the appendix .

Figure 2.2: Living Wage Roll-out

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

To ensure that this instrument can causally identify the recruitment, separation and commuting elasticities, it's necessary to ensure that the Living Wage adoption within an area only affects a very few number of jobs. If for example, it affected all low pay jobs in the area the relative wage offered by the establishment would remain unchanged, and therefore it would be reasonable to assume this would have little affect on separations, recruitment and commutes. It's important to highlight therefore that when a council signs up to the LWF's living wage it only affects council employees and those who are subcontracted to do work for the council. Council employment makes up approximately 3% of employment and is usually made up of workers more skilled than would be affected by the wage floor. As an example table 2.A.2 in the appendix gives estimates of the employment counts and shares for the London Borough of Hackney, and shows council employment accounts only for 3.3% of total employment in the borough. Furthermore, examination of the pay scale documentation for the borough show that the lowest paid point is 8% above the binding LLW for 2019. This is suggestive that the council adoptions of the Living Wage affects only a fraction of a percentage of workers in the area. While a significant portion of The Company's business comes from procurement contracts with the council, their main competitors are private sector firms which would not be affected by the Living Wage adoption by the council. Finally, though The Company employs thousands of workers across the UK, their average establishment only has about 25 entry-level workers. Therefore, when an establishment gets treated, there are not concerns regarding wage spillovers to other firms in the local area, as may be the case with very large employers (Derenoncourt et al., 2021).

Secondly, I utilise an instrument related to saliency of the wage posted. In the UK, whether a job has a permanent or zero-hours contract, the firm is required by law to give the worker 28 days paid annual leave. Due to the nature of non-permanent work, many firms opt to give the statutory annual leave as a top up to the wage, which calculates to a wage supplement of 12.07%. Within the vacancy data, some non-permanent jobs (approximately 20%) are advertised with the annual leave top-up included in the advertised wage, while the text of the adverts stay constant. Discussions with the HR team at The Company concluded that this occurred due to idiosyncrasies in whomever happened to be posting the job that day onto the HR system[11]. This lends itself for use as a seemingly random instrument. This instrument however can only be used for non-permanent jobs, as it is not well defined for permanent jobs. Furthermore, it can only be used for the recruitment and commuting elasticity estimates, as it is not relevant to separations.

2.2.2 Estimates of Monopsony Power

2.2.2.1 Empirical Framework

To estimate the labour supply elasticity to the firm I estimate the recruitment and separation elasticities separately and then add the negative of the separation elasticity to the recruitment elasticity.

To estimate the recruitment elasticity I consider two settings, one where a firm hires all applicants and thus the application-wage elasticity reflects the recruitment elasticity, and one where a vacancy reflects a single opening, and thus an increase in applicants increases the probability of filling a vacancy. To assess whether it's reasonable to treat the application elasticity as the recruitment elasticity would depend on both the firm's production function and on the demand for their output product. For example, in online task based markets where all workers willing to work at the given wage rate are taken on to carry out a homogenous task, such as in Dube et al. (2020a,b), the responsiveness of applicants to wages is precisely the recruitment elasticity. On the other hand, for a firm which has a Leontief production function, and only one spare unit of capital (for

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

example, a garden maintenance company with a vacant lawnmower), the recruitment elasticity would be akin to the vacancy fill-wage elasticity, which would be less than the applicant-wage elasticity.[12] For The Company however, the latter of these will be more relevant as their structure of vacancy openings more closely resembles this. That is, a vacancy opening generally relates to a single fillable position, and the increase in applicants enables a greater likelihood of filling that vacancy.

To estimate the recruitment elasticity I estimate:

$$log(Apps_{ajemy}) = \beta_1 log(Wage_{ajemy}) + \gamma_{je} + \lambda_{ey} + \nu_{ym} + \theta_{jy} + \epsilon_{ajemy} \tag{2.1}$$

and

$$Filled_{ajemy} = \beta_2 log(Apps_{ajemy}) + \gamma_{je} + \lambda_{ey} + \nu_{ym} + \theta_{jy} + \epsilon_{ajemy} \tag{2.2}$$

where $Apps_{ajemy}$ is the number of applicants applying to advert a advertising for job-role j in establishment e in month-year my, $Filled_{ajemy}$ is a binary variable indicating whether the position was filled, $Wage_{ajemy}$ refers to the advertised hourly wage (in £), γ_{je} are job-role establishment fixed effects, λ_{ey} and θ_{jy} are time-varying establishment and job-role fixed effects [13], ν_{ym} are year-month fixed effects.

To estimate the separation elasticity I regress a linear probability model (LPM) of the form:

$$Leave_{ijemy} = \beta_3 log(Wage_{ijemy}) + \gamma_{je} + \lambda_{emy} + \theta_{jmy} + \epsilon_{ijemy} \tag{2.3}$$

where $Leave_{ijemy}$ is an indicator variable equal to 1 if individual i leaves job-role j in establishment e in a particular year-month ym, and equal to 0 otherwise.[14]

Equations (2.1), (2.2) and (2.3) utilise variation within the same job role-establishment combination while controlling for establishment-level time shocks, and job-level time shocks. They are akin to a triple-difference specification. Though these specifications are very flexible, concerns relating to endogeneity still exist. Job-location specific time shocks are still conceivable, which in turn could be correlated with wages, recruitment and separations (see Belot et al. (2018); Marinescu and Wolthoff (2020) for evidence of this). As a result I instrument $log(Wage)$ in equations (2.1) and (2.3) and $log(Apps)$ in

[12] This point is discussed analytically in section 2.3.2. However intuitively it can be seen by the fact that the fill-wage elasticity would be equal to the applicant-wage elasticity multiplied by the fill-applicant elasticity, and the fill-applicant elasticity would be less than 1.

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

[14] A recent survey from Sokolova and Sorensen (2021) found that results estimated using the more straightforward LPM were not statistically different from results utilising non-linear estimation techniques.

equation (2.2) with the two instruments outlined in section 2.2.1.2. The first LW_{jewm}, the Living Wage instrument which is defined at the establishment-job-time level, and the second, AL_{ajemy}, the annual leave wage saliency instrument which is defined at the advert level.

$$LW_{jemy} = \begin{cases} 1 & \text{if establishment is subject to LW \& LW was binding for job} \\ 0 & \text{otherwise} \end{cases} \tag{2.4}$$

$$AL_{ajemy} = \begin{cases} 1 & \text{if advert included annual leave in hourly rate} \\ 0 & \text{otherwise} \end{cases} \tag{2.5}$$

Assuming parameters β_1, β_2 and β_3 are identified, and we assume that a vacancy only relates to one fillable position, then

$$\varepsilon_{nw} = \underbrace{\varepsilon_{rw}}_{\frac{\hat{\beta}_2}{E[\widehat{Filled_{ajemy}}]}*\hat{\beta}_1} - \underbrace{\varepsilon_{sw}}_{\frac{\hat{\beta}_3}{E[\widehat{Leave_{ijemy}}]}} \tag{2.6}$$

however, in a setting where all applicants are employed $\varepsilon_{rw} = \hat{\beta}_1$. One could also use these two estimates of the recruitment elasticity to place upper and lower bounds on the parameter. While the structure of a company's vacancies may lend itself more to the interpretation as in equation (2.6) it's also worth noting that an increase in wages may lead to an increase in quality of applicants (Dal Bó et al., 2013), and therefore an increase in the effective units of labour which would imply $\frac{\hat{\beta}_2}{E[\widehat{Filled_{ajemy}}]} * \hat{\beta}_1$ underestimates the elasticity.

2.2.2.2 Results

Table 2.2 reports estimates of $\hat{\beta}_1$ from (2.1), column (1) reports OLS estimates and columns (2-5) where $log(Wage)$ is instrumented using one or both of the two instruments discussed in section 2.2.1.2. It also reports the relevant first stage coefficients for the specifications where only one of the two instruments are employed. Column (2) reports the specification utilising the entire sample and the living wage instrument, column (3) utilising only the sample of non-permanent adverts and the annual leave instrument, column (4) the non-permanent sample and the living wage instrument, and column (5) the non-permanent sample using both instruments. The specifications using the smaller sample do not include job-year fix effects to reduce saturation concerns.

All specifications report a statistically significant applicant-wage elasticity, with estimates ranging between 2.4 to 4.7, aside from the OLS specification which underestimates the

Table 2.2: Application - Wage Estimates

	(1) log(Apps)	(2) log(Apps)	(3) log(Apps)	(4) log(Apps)	(5) log(Apps)
log(Wage)	0.560**	4.706**	2.407***	3.679**	2.753***
	(0.238)	(2.154)	(0.662)	(1.414)	(0.622)
First Stage	-	0.030***	0.085***	0.066***	-
		(0.005)	(0.008)	(0.009)	
Job-Establishment FE	Yes	Yes	Yes	Yes	Yes
Establishment-Year FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Job-Year FE	Yes	Yes	No	No	No
N	5487	5487	2376	2376	2376
First Stage F-Stat.	-	61.35	385.8	127.1	288.4
Hansen J Stat.	-	-	-	-	0.714
Instrumented With *AL*	No	No	Yes	No	Yes
Instrumented With *LW*	No	Yes	No	Yes	Yes
Sample	All	All	Non-Perm	Non-Perm	Non-Perm

Note: *The table presents estimates of $\hat{\beta}_1$ from equation (2.1) via OLS or where $log(Wage)$ is instrumented with either LW_{jemy}, AL_{ajemy} or both instruments. If only one instrument is used the table reports the accompanying implied first stage coefficient. If both instruments are used the table reports the over identifying test statistic. All columns report the first stage Cragg-Donald F statistic. Standard errors are reported in parentheses and are clustered at the establishment-job. Col (1) includes a control for whether the job advert was for a salaried position.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

elasticity, a finding similar to other recent studies (e.g. Marinescu and Wolthoff (2020)). A possible explanation of this is that firms adjust wages to match local market conditions, and therefore wage changes within the firm are correlated to outside wage options. The midpoint of the IV estimates implies that a 10% increase in the posted wage would increase applicants by 37%. All specifications report a sizeable Cragg-Donald F-statistic, demonstrating strength in both instruments. Specification (5) additionally reports the Hansen J statistic exploiting the fact the equation is overidentified. The reported χ^2 statistic confirms that the validity of the instruments cannot be rejected.

Table 2.3 reports estimates of $\hat{\beta}_2$ from (2.2). Column (1) reports the OLS estimates while column (2) the specification using both instruments. Given the instruments are impacting $log(Apps)$ through two steps[15] the first stage is considerably weaker, and therefore only the specification with both is reported. The implied fill-applicant elasticity is effec-

[15] I.e. they act on wages, which in turn acts on applicants.

Table 2.3: Filled-Applicants Estimates

	(1) Filled	(2) Filled
log(Apps)	0.248***	0.250**
	(0.0127)	(0.127)
Job-Centre FE	Yes	Yes
Centre-Year FE	Yes	Yes
Job-Year FE	Yes	No
Year-Month FE	Yes	Yes
N	4859	2115
R^2	0.522	-
First Stage F-Stat.	-	16.37
Hansen J Stat.	-	1.415
Instrumented With AL	No	Yes
Instrumented With LW	No	Yes
Sample	All	Non-Perm
Mean of Dep. Var	0.698	0.663

Note: *The table presents estimates of $\hat{\beta}_2$ from equation (2.2). Column (1) reports the OLS specification and column (2) reports the specification where $log(Apps)$ is instrumented with LW_{jemy} and AL_{ajemy}, and additionally reports the over identifying test statistic and the first stage Cragg-Donald F statistic. Standard errors are reported in parentheses and are clustered at the establishment.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tively identical across the two specifications. By calculating $\frac{\hat{\beta}_2}{E[\widehat{Filled_{ajemy}}]}$ one can see the elasticity ranges from $0.36 - 0.38$. This implies a 10% increase in the number of applicants would increase the likelihood of filling the vacancy by 3.7%. Similar to table 2.2 the reported Hansen J statistic implies we can not reject the validity of the instrument. Taking the midpoint of the range of estimates of the applicant-wage elasticity from table 2.2, 3.7, and a fill-applicant elasticity of 0.37 suggests the recruitment elasticity, ε_{rw} lies between 1.4 and 3.7. The structure of the vacancies for this firm are such that a job posting typically relates to a single opening, and therefore the lower end of this is more likely to be reasonable.

Table 2.4 presents estimates of $\hat{\beta}_3$ from (2.3) via OLS and using the living wage instrument, as well as $E[\widehat{Leave_{ijemy}}]$. Column (1) reports OLS estimates without controls, Column (2) reports IV estimates without controls, while column (3) reports IV estimates with controls for gender, ethnic minority status, whether permanent or not, tenure and age. The OLS estimate as before underestimates the elasticity. The IV estimate is robust to the inclusion of controls and implies an ε_{sw} of approximately -1.7, implying a 10%

Table 2.4: Separation-Wage estimates

	(1) Leave	(2) Leave	(3) Leave
log(Wage)	-0.0234***	-0.0791**	-0.0854***
	(0.0032)	(0.0317)	(0.0323)
First Stage	-	0.0625***	0.0594***
		(0.003)	(0.003)
Job-Centre FE	Yes	Yes	Yes
Centre-Time FE	Yes	Yes	Yes
Job-Time FE	Yes	Yes	Yes
Controls	No	No	Yes
N	1055521	1055521	1055521
First Stage F-Stat.	-	4404.8	4793.3
Instrumented With *LW*	No	Yes	Yes
Mean of Dep. Var		0.048	

Note: *The table presents estimates of $\hat{\beta}_3$ from equation (2.3) where log(Wage) is instrumented with LW, the accompanying first stage coefficient and the first stage Cragg-Donald F statistic. Standard errors are reported in parentheses and are clustered at the establishment. Col (2) includes controls include Gender, BAME, Contract, Tenure and Age.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

increase in the wage reduces the likelihood of separation in any month by 17%.

Combining the estimates that $\varepsilon_{rw} \in [1.4,\ 3.7]$ and $\varepsilon_{sw} \approx -1.7$ this implies $\varepsilon_{nw} \in [3.1,\ 5.4]$. According to the traditional wage markdown (μ) equation[16] the estimates suggests a wage markdown ranging between 16-25%. As discussed, the upper end of this markdown estimate is likely to be more accurate. These results suggest considerable market power in a low wage labour market where frictions such as firm-specific capital are less likely to play a role.

2.2.2.3 Discussion

The estimate of the labour supply elasticity to the firm above makes two advances on the existing literature. First, it does not rely on the result from Manning (2003) that $\varepsilon_{rw} = -\varepsilon_{sw}$ which relies on a number of restrictive assumptions, including recruitment from unemployment is invariant to the wage, and that the recruitment and separation

[16] $\mu = 1 - \frac{\varepsilon_{nw}}{1+\varepsilon_{nw}}$.

elasticity are both constant [17]. It is possible there may be differences in firm's monopsony power over new recruits and separations, and the above results test this. My findings suggest that the application-wage elasticity is approximately twice the size of the separation-wage elasticity, and therefore firms exercise more monopsony power over incumbent workers than in attracting new recruits. This is an interesting finding and the source of this deserves investigation which is beyond the scope of this paper. However, a possible explanation is that incumbent workers are likely to have invested time in their existing job (e.g. through building relationships with colleagues, getting to know specifics of the firm) which they place a value on, which in turn creates a greater friction when responding to wages. That said due to the firm's hiring structure (increases in applicants only effects recruitment via increasing the probability of filling vacancies), the recruitment and separation elasticity are similar in size. Second, utilising the information on both applicants and whether the vacancy is filled I offer a range of markdown estimates, where the lowest relates to a firm which employs all its applicants (16%), and the highest relates to a firm with only a single vacancy to fill (25%)

The aforementioned results bare some similarity to recent estimates of monopsony power from the literature, and may also be instructive as to whether restrictions employed in the literature are reasonable. In terms of application and recruitment elasticities the results are within a similar range to some recent studies utilising data on applications (e.g. Dal Bó et al. (2013); Falch (2017); Azar et al. (2019)) and higher than some others (e.g. Dube et al. (2020a); Belot et al. (2018)). That said the results suggest using an application elasticity as synonymous with the recruitment elasticity as done in Azar et al. (2019) is likely to underestimate the extent of monopsony power. The separation elasticity is of a similar magnitude to recent papers with a clear identification strategy. Bassier et al. (2020) report that low pay sectors generally have lower separation elasticities and range from -1.2 to -1.4, which are very similar to those estimated here. Similarly Dube et al. (2019) estimate a separation elasticity of -2.3. The latter of these studies utilises data on a single firm operating in the retail sector in the US and so is similar in set up to this study.

The results are robust to a number of potential issues which are explored further in section 5.6.5 in the appendix. Using a triple-difference event study design I show parallel pre-trends and no evidence of announcement effects in the separation elasticity estimates (see figure 2.C.1). Additionally, I address the concerns recently raised regarding the workings of two-way fixed effect estimators, with staggered treatment timing (Borusyak and Jaravel, 2017; Sun and Abraham, 2020; Callaway and Sant'Anna, 2020; Goodman-Bacon,

[17] The latter of these is a particularly strong assumption as it is not obvious that a firm in a minimum wage labour market in the UK would expect the same proportional response in recruits when increasing wages from £10 to £11, as when increasing wages from £20 to £22

2021). Despite the fact this study employs a more flexible estimation strategy (akin to a triple-difference estimator), as a matter of caution I check whether any of the issues raised in the aforementioned studies could be sullying the results when using the Living Wage instrument. I do this by comparing a traditional two-way fixed effect event study estimator at the establishment level with a robust estimator (similar to that from Sun and Abraham (2020)), examining the impacts on wages. Figure 2.C.3 plots the two sets of estimates and as can be seen there is very little noticeable difference between the two panels. Given these results it is unlikely that the more flexible specifications utilising a triple-difference estimator will suffer from the aforementioned issues.

2.2.3 Estimates of the Commuting-Wage Elasticity

2.2.3.1 Empirical Framework

To estimate the commuting-wage elasticity I regress

$$log(Comm_{iajemy}) = \beta_4 log(Wage_{ajemy}) + \delta' X_{imy} + \gamma_{je} + \lambda_{ey} + \nu_{ym} + \theta_{jy} + \epsilon_{iajemy} \quad (2.7)$$

where $Comm_{iajemy}$ is the commuting time measured in minutes between applicant i's home and address of the establishment. Commutes are measured using the Google Maps API and are calculated for an arrival time of 9am so as to account for traffic. Commuting times utilised in this exercise are therefore considerably more accurate than typical "as the crow flies" distances calculated via GIS software. Given the popularity of google maps for routing[18] it is also a reasonable approximate of expected commuting times by job searchers. Commuting time was calculated for both car and public transport, and it is assumed that workers choose the fastest method of the two options.[19] $log(Wage_{ajemy})$ is, as before, instrumented with LW_{jemy} and AL_{ajemy}, and X_{ia} is a set of controls including individual's gender, ethnicity, and whether they were internal or external applicants, and whether the advert was for a non-salaried job.[20]

2.2.3.2 Results

Table 2.5 presents results from estimating equation (2.7). Aside from column (1) which reports the OLS estimates (and is again underestimated), point estimates across all specifications are consistent and imply a commuting-wage elasticity $\varepsilon_{cw} \approx 1$. Specifications

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

[19]In practice this means that many people working in London are assumed to utilise public transport which is a reasonable assumption.

[20]This control was only included for specifications using the entire sample.

Table 2.5: Commuting - Wage Estimates

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

Note: *The table presents estimates of $\hat{\beta}_4$ from equation (2.7) where $log(Wage)$ is instrumented with either LW_{jemy}, AL_{ajemy} or both instruments. If both instruments are used the table reports the over identifying test statistic. All columns report the first stage Cragg-Donald F statistic. Standard errors are reported in parentheses and are clustered at the advert. Regressions are weighted by the inverse number of applicants for each job. Controls include gender, ethnicity, whether applicants were internal and whether the advert was for a permanent job.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

containing the annual leave instrument are more precisely estimated, and the specification with both instruments is statistically significant to a 5% level. All specifications have a sizeable first stage F-stat, and the over-identified specifications in column (4) indicates as before that the validity of the instruments cannot be rejected.

The estimated commuting-wage elasticity suggests a strong distaste for commuting, and that a firm's geographic labour market size is only mildly responsive to wage increases. For an hourly wage of £7.50 (\$9.67) (the NMW for the midpoint of the sample period) and average commute of 25 minutes, a commuting-wage elasticity ≈ 1 implies an extra 5 minutes of total commute would require an extra £3.00 (\$4.06) per day[21], or £0.37 (\$0.50) per hour assuming an 8 hour work day. The results are suggestive that commuting distances are likely to be a strong factor in generating imperfect substitutability between jobs.[22]

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

[22]The results imply a WTP considerably larger than recent estimates from Le Barbanchon et al. (2021) but similar in size to higher end values of the Value of Travel Time used by the British Deparment of

To ascertain robustness of the aforementioned results section 5.6.5 in the appendix explores the assumption of a constant, linear in logs, relationship between wages and commutes as well as the impacts of the higher wage across the distribution of commutes. The results suggest the assumed relationship is reasonable one, and that the impacts across the majority of the distribution are constant, aside from at the tail ends and the CDF under a higher wage would stochastically dominate a CDF under a lower wage, as expected.

2.3 The Role of Commutes in Generating Monopsony Power: Theoretical Framework

The estimates from section 2.2 suggest strong monopsony power in the labour market and a strong distaste for commuting. It is reasonable to see how the latter of these can cause the former: the length of commute to a place of work is a non-wage factor affecting the utility from a job, and therefore generates imperfect substitutability between differently located jobs. The following section formalises this mechanism in a job search model. I additionally show how this mechanism is not only a factor in generating monopsony power, but that it generates monopsony power heterogeneously across space depending on the spatial distribution of workers and firms. I then validate the model by showing how the model predictions of heterogeneity in monopsony across space are consistent with heterogeneity found in the data used in section 2.2. I additionally show that model predictions for monopsony power across 7,250 Built Up Areas are strongly negatively correlated with wages, worker density and population as one would expect, for the low pay retail labour market. Given the validity of the model, I then structurally estimate the model in section 2.4 to quantify how much of monopsony power is due to commutes.

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

Transport (Batley et al., 2019) and earlier estimates from the literature (Timothy and Wheaton, 2001; Van Ommeren and Fosgerau, 2009).

in the appendix in section 2.F. The main take away from this model is that distaste for commuting is a key factor in generating monopsony power but does so heterogeneously. As distaste for commuting increases, rural areas with less outside opportunities experience greater monopsony power than denser urban areas where many firms and workers are located in close proximity; though the latter still sees increases in monopsony power.

2.3.1 Model Setup

There are many firms j and workers i, spatially located across the economy, l_i, l_j. Firm and worker locations are treated as given and fixed. Firms consider themselves as small and therefore I abstract away from strategic interaction. Furthermore, it's assumed that firms can not wage discriminate workers. In the following subsection I concentrate on the applying (recruitment) worker problem, however results for the maintaining (separation) problem are very similar and can be found in section 2.E in the appendix. Additionally, while the model can flexibly include search costs, I shall predominantly focus on a version where search costs are assumed to be zero. Derivations including search costs can be found in the appendix in section 2.F.

2.3.2 The Firm Problem

Firm's gain profits from job j according to:

$$\Pi_j = (p_j - w_j)n_j(w_j) \tag{2.8}$$

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

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

$$w_j = p_j \frac{\varepsilon_{nw_j}}{1 + \varepsilon_{nw_j}} \tag{2.9}$$

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

In the steady-state, employment is such that

$$n_j = \frac{r_j(w_j)}{s_j(w_j)} \tag{2.10}$$

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

$$\varepsilon_{nw_j} = \varepsilon_{rw_j} - \varepsilon_{sw_j} \tag{2.11}$$

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

$$r_j(w_j) = \Phi(A_j(w_j)) \tag{2.12}$$

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

$$\varepsilon_{rw_j} = \varepsilon_{\Phi A}\varepsilon_{Aw_j} \tag{2.13}$$

Equation 2.13 demonstrates what was discussed in section 2.2. If the firm hired a constant ratio of workers then $\varepsilon_{\Phi A} = 1$ and $\varepsilon_{rw_j} = \varepsilon_{AW_j}$. However, assuming there is only one vacancy to fill as per The Company, then $\varepsilon_{\Phi A} < 1$. I shall assume going forward the latter of these is the case.

Workers are homogenous in productivity, however some worker-firm matches are determined “unsuitable”. Therefore there is a non-zero probability of a vacancy being unfilled despite $A_j \geq 1$, as is a feature of the data used in section 2.2.2.2. In particular I assume the probability of some worker being suitable to be q, which is independent of any other characteristics of the workers and unknown to the worker before applying. Thus

$$\Phi(A_j) = 1 - (1-q)^{A_j} \quad [23] \tag{2.14}$$

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

2.3.3 The Worker Problem

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

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

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

$$u_{ij} = w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \nu_{ij} \tag{2.15}$$

where $d_{ij} = |l_i - l_j|$ is a measure of distance between the worker and the job. ν_{ij} is an idiosyncratic utility component known only to the worker[24] and is distributed iid following some distribution $F(v_{ij})$, defined over the support $[0, \infty]$. ν_{ij} could be thought of as j specific characteristics and i's preferences over them, for example, management style, flexibility and firm ethics. The parameter ε_{cw} is the commuting-wage elasticity and reflects the importance of commutes in determining worker utility. The utility function in equation (2.15) reflects how workers will see jobs as imperfect substitutes as a result of idiosyncratic preferences and the commuting distance and the importance of these two factors will be determined by the size ε_{cw} and the variance of $F(v_{ij})$.

A worker i, who is currently in job j[25] will choose to apply to posted job j' if the expected utility of doing so is greater than not applying:

$$P(A_{j'})u_{ij'} + (1 + P(A_{j'}))u_{ij} \geq u_{ij} \tag{2.16}$$

where $P(A_{j'})$ is the probability of getting the job, which is a function of the total number of applicants to job j', $A_{j'}$[26]

Rearranged worker i will apply to j' if

$$\nu_{ij'} \geq \underbrace{\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}}}_{\equiv x_{ijj'}} \tag{2.17}$$

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

$$Pr(Apply_{ij}^{j'}) = 1 - F(x_{ijj'}) \tag{2.18}$$

Note that $x_{ijj'}$ here is a measure of relative utility between the incumbent job j, and the potential job j'. Additionally note in equation 2.17 the idiosyncratic component related to the incumbent job is normalised to $\bar{\nu}$, which in practice will be treated as the median draw.[27]

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

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

[26] This drops out in this setting but is important when search costs are introduced as explored in section 2.F.

[27] This normalisation is required for tractability reasons, as distributions under study do not have a

2.3.4 The Individual's Elasticity

The first key observation here relates to the elasticity of applying for the individual. Under the assumption the distribution $F(x)$ is such that $\frac{\partial h(x)x}{\partial X} \geq 0$, where $h(x)$ is the hazard function related to $F(x)$[28] the individual specific application elasticity is given by

$$\varepsilon_{Aw_{ij}^{j'}} = h(x_{ijj'})x_{ijj'} \tag{2.19}$$

and is decreasing in potential relative utility. The above assumption on the distribution of ν_{ij} is not a restrictive one and is fulfilled by commonly used distributions including Weibull, exponential, lognormal, loglogistic and Frechet.[29]

The above formulation of the individual's responsiveness of applying with respect to wages has a number of interesting and important features. Firstly, it can be seen that as the posted wage increases, $x_{ijj'}$ decreases and therefore the elasticity of applying to wages decreases. Given that the probability of applying is bounded between 0 and 1, this result is intuitive.[30] Secondly, the smaller the standard deviation of idiosyncratic preferences, the closer the behaviour of the individual to the perfectly competitive benchmark, and vice versa.[31] Both of these points are demonstrated graphically in figure (2.B.4) in the appendix.

Thirdly, the lower the elasticity of commuting to wages[32], ε_{cw}, the more important commutes are in determining the elasticity of applying to wages for the individual. For example, assuming $\varepsilon_{cw} < \infty$, the inelastic part of the curve occurs when a firm offers higher wages, or is located relatively nearer to workers than their current job. This would suggest that workers which currently have to commute far, but a job opening comes up close by to them, would have a more inelastic labour supply curve to the posted job.

neat closed form for the ratio of two random variables. The key patterns from the simulation exercises in sections 2.3.4 and 2.3.5 are however unchanged when allowing the incumbent idiosyncratic component to be a random variable.

[28]I.e. $h(x) = \frac{f(x)}{[1-F(x)]}$

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

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

[31]It can in fact be shown that in the absence of commuting costs, the shape parameter related to the weibull distribution will equate to the labour supply elasticity facing the firm, which is outlined in greater detail in section 2.3.5

[32]I.e. The greater the preference for a smaller commute.

The lower the commuting elasticity, the greater the impact of space on the application elasticity. This is exemplified in figures 2.B.5 and 2.B.6 in the appendix which present a simulated distribution of two workers and their respective labour supply curves.

2.3.5 The Elasticity of Labour Supply To The Firm

The labour supply to the firm can be calculated by summing equation (2.18) over all relevant workers in the economy, which gives

$$A_{j'} = \sum_{i,j} [1 - F(x_{ijj'})] \tag{2.20}$$

Equation (2.20) reflects the lack of need to discretise the economy into geographical labour markets. Labour markets are endogenously constructed, point specific, become continuous, and weaken over distances. Ceteris paribus workers close by to the advertised job are more likely to apply and workers farther away from the job are less likely to apply, and the extent of this factor is dependent on their disutility for commuting. Furthermore, it also accounts for workers' incumbent options. For example, if a firm is located far from workers, but those workers are currently commuting a similar distance, the size of the labour market would be larger than a situation where a firm is close to workers and those workers only currently commute a small distance.

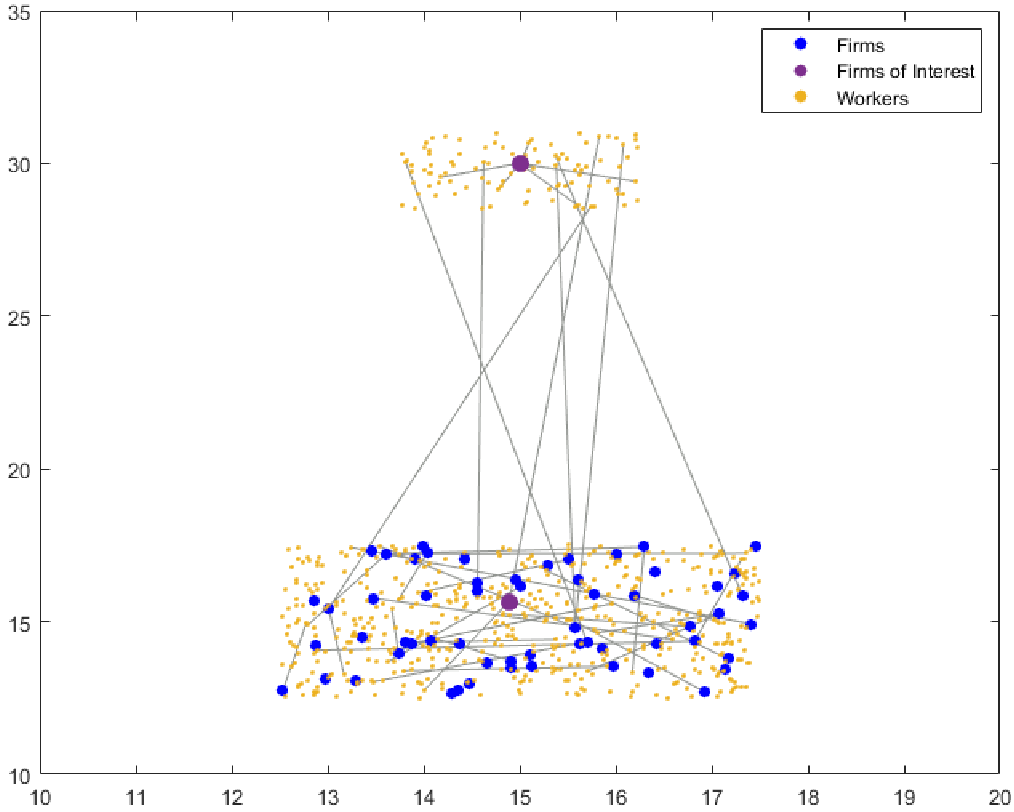
It can be shown that the application elasticity to the firm is

$$\varepsilon_{Aw^{j'}} = \frac{\sum_{(i,j)} \varepsilon_{Aw^{j'}_{ij}} [1 - F(x_{ijj'})]}{\sum_{(i,j)} [1 - F(x_{ijj'})]} \tag{2.21}$$

which is simply a weighted average of the individual level elasticity from equation (2.19), where the weights are the probability of applying to the job. Therefore workers who are more likely to apply to the job (and therefore have a lower individual elasticity) will receive higher weights than those relatively less likely to apply.

As the application elasticity to the firm is a weighted average of the individual level elasticities, many of the features of the individual level elasticities outlined in section 2.3.4 aggregate up to the firm level. Thus, the larger the spread of idiosyncratic preferences over jobs, the lower the elasticity of labour supply to the firm, and the greater the monopsony power. Additionally, the lower the commuting-wage elasticity, the greater the monopsony power and the more important the spatial distribution of activity in generating heterogeneities in monopsony power. Both of these last two points can be demonstrated in a similar simulation exercise as seen in figures 2.B.5 and 2.B.6.

Figure 2.3: Spatial Heterogeneity in Labour Supply To the Firm I



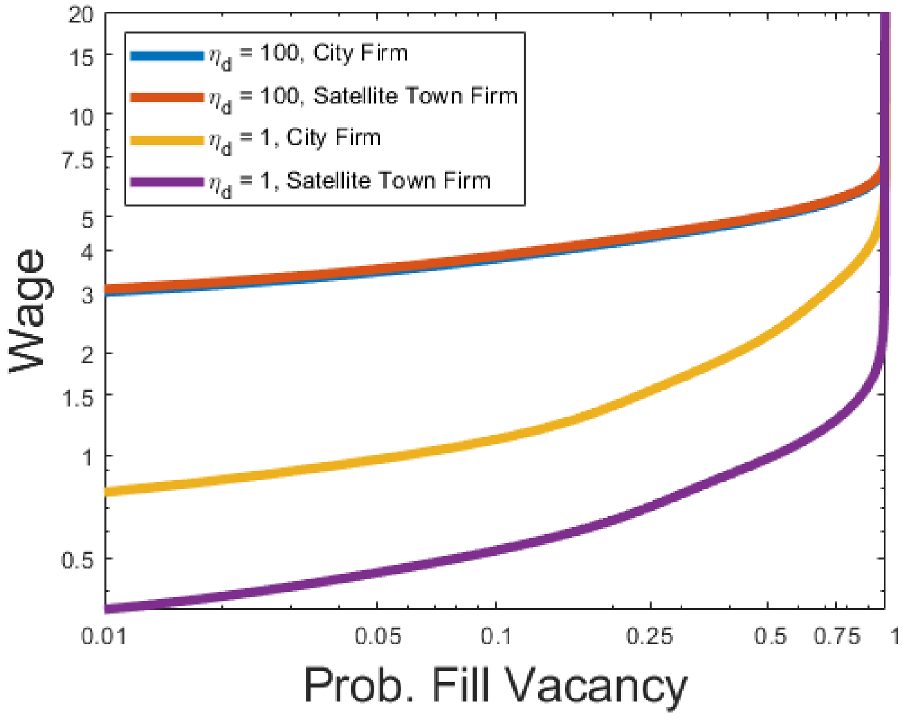
Note: *The figure presents a simulated spatial distribution of 600 workers, and 60 firms. 500 workers and 59 firms are located in the "city" while 100 workers and 1 firm is located in the "satellite town". Lines are drawn to demonstrate some of the existing commutes.*

Figure 2.3 presents a simulated spatial distribution of 600 workers and 60 firms, where 500 of the workers and 59 firms are located in a "city" while 100 workers and 1 firm is located in a "satellite town". Each firm has a labour force of 10 workers, lines demonstrate existing commutes for some workers and as can be seen some workers living in the satellite town commute into the city for work. As before it's assumed that all workers are currently in jobs with a wage of £10[33]. To explore the impact of commuting on monopsony power I examine the labour supply curve to two firms, one city firm and the satellite town firm, when posting a new vacancy.

As seen in figure 2.4 in the setting where a worker's commuting elasticity is extremely large ($\varepsilon_{cw} = 100$) there is virtually no difference between the labour supply to the two

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

Figure 2.4: Spatial Heterogeneity in Labour Supply To the Firm II



Note: *The figure plots the labour supply to the firm curves as per figure 2.3 under different parameterisations of* ε_{cw}*, calculated according to equation (2.20) and (2.14), against the advertised wage on log scales. Parameterisation is such that* $c = 0$ *and* $\nu_{ij} = median(\nu_{ij})$*.* F *is assumed to follow a weibull distribution with shape parameter* $k = 5$ *and scale parameter* $\lambda = 1$*, and the exogenous suitability parameter* $q = 0.075$*.*

firms. This is generated by the fact that worker's incumbent utilities would be almost identical across space, as would their potential utility from the advertised job. Put another way, when the commuting elasticity is large, the location differences do not generate any heterogeneity in utility. The advertising firms would still have considerable monopsony power under this parameterisation which is generated by the idiosyncratic term.

The parameterisation where $\varepsilon_{cw} = 1$ represents a scenario where workers have a strong distaste for commuting as per the estimates from sectio 2.2.3. This scenario has two effects, it increases monopsony power for both firms, but does so heterogeneously. At any given wage rate the satellite town firm experiences a more inelastic labour supply curve than the city firm. As many workers living in the satellite town have to commute into the city due to lack of local options, when a job opening appears locally, that job exercises considerable local monopsony power. While the satellite town firm experiences more, both firms experience greater monopsony power (a more inelastic slope) at any given wage rate in comparison to the $\varepsilon_{cw} = 100$ scenario and would therefore be able to markdown wages more than in the high commuting elasticity scenario. This is driven by the fact that distance plays an important role in determining utility from a job, so even the city firm would still enjoy some local monopsony power, as even small commutes within the city generate disutility.

2.3.6 Model Implications

A key result of this model is that all firms[34] would likely experience some local monopsony power, and therefore some of the monopsony power observed in empirical studies is likely driven by distaste for commuting coupled with the spatial locations of firms and workers. Models which coarsely discretise the spatial economy and treat commuting within areas as costless, and across boundaries as (infinitely) costly are likely to be misspecified, especially given the estimate of $\varepsilon_{cw} \approx 1$ from section 2.2. For example, many recent models rely on idiosyncratic preferences (typically assumed extreme value distributed) to generate monopsony power and lump distance to work within those idiosyncratic preferences (e.g. Lamadon et al. (2019); Berger et al. (2019); Card et al. (2018); Azar et al. (2019)). However, there is a strong reason to believe that these preferences are not idiosyncratic but rather systematic with clear spatial patterns as outlined above.

The model additionally gives rise to heterogeneity in monopsony power across space, and denser urban areas are likely to see less monopsony power than rural areas with fewer outside options. The model therefore offers a new micro-founded explanation for the urban wage premium. Specifically that markdowns in cities are likely to be smaller in size due to the more competitive nature of the markets. That said, each firm located at a specific point would have its own specific level of monopsony power, and this would likely vary even within a city. Typically labour market analysis has been done at the TTWA level in the UK and the mean area for TTWAs is 1,064 km^2, and the above model suggests there is likely to be considerable heterogeneity within that area.

Figure 2.B.7 in the appendix shows the map for the TTWA for London[35], and its surrounding TTWAs, and exemplifies the issue. A study of monopsony power in the UK labour market with discretised areas into TTWAs would suggest the travel time between Rickmansworth (in the North West of London) and Gravesend (in the South East) is costless whereas google-maps estimates a travel time of 90 minutes utilising either car or public transport. Additionally, using a model where distance to work is lumped into the idiosyncratic component, though allowed to vary by area, would result in a firm located on the edge of the TTWA (e.g. Potters Bar) as having the same degree of competitiveness

[34]Except in the extreme case where a firm is relatively located far from all workers.
[35]This TTWA represents almost a sixth of the Great Britain working population.

as a firm operating in central London (e.g. Holborn), which seems unlikely.

Another result of this model is that the labour supply elasticity to the firm is no longer a structural parameter, as elasticities are an endogenous result of the spatial distribution of activity.[36] While the labour supply elasticities are still a function of the idiosyncratic component (which could now be assumed to be constant across areas), they are also determined by the spatial distribution of activity, and the wage-commuting elasticity. It's worth noting that if workers did not care about commuting, and $\varepsilon_{cw} = \infty$ then the model would collapse to the typical logit model utilised in other studies, and this is shown in section 2.G.

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

The sources of monopsony explored in the above exposition focus entirely on imperfect substitution between jobs, unlike some of the original literature which focused on dynamic search frictions (see Manning (2003)). The model however can flexibly introduce search frictions and is done so in section 2.F of the appendix. Monopsony power is shown to be weakly increasing in search costs, but more interestingly it is shown that the individual level elasticity can actually be negative in some instances.

2.3.7 Model Validation

2.3.7.1 Model Predicted Elasticities vs Empirical Elasticties

To validate the model I first use the data and empirical framework from section 2.2 and the estimated commuting-wage elasticity from section 2.2.3.2 to check whether job adverts predicted to be more elastic by the model are. To do this I calculate a version of equation (2.21) assuming a Weibull distribution, for each job advert, and split the sample of adverts in half at the median based on the model calculated $\varepsilon_{AWj'}$, labelling the top half "high". I then interact this variable in the application-wage elasticity regression from section 2.2.2.1.

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

Specifically I calculate

$$\varepsilon_{Aw_{ajemy}} = \frac{\sum_{i,j} k \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{\lambda w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k exp \left(- \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{\lambda w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \right)}{\sum_{i,j} exp \left(- \left(\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \bar{\nu}}{\lambda w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \right)^k \right)} \tag{2.22}$$

using a value of $\varepsilon_{cw} = 1$ given the estimates from section 2.2.3. For the incumbent value of ν_{ij}, I assume it is equal to the median value of the distribution $ln(2)^{\frac{1}{k}}$[37], and to ensure robustness I calculate 2.22 using three different values of $k \in \{3, 5, 7\}$.

I use data from the Annual Survey of Hours and Earnings for 2016-2019 for Great Britain (Office for National Statistics, 2020)[38] for information on w_j, d_{ij} and $d_{ij'}$. d_{ij} and $d_{ij'}$ are calculated at the 6-digit postcode level.[39] I additionally utilise the Open Street map dataset for Great Britain and ArcGIS's networking tool for commute calculation. This allows for a very accurate time of commute between home and work postcodes.[40] For each job advert j', workers with the same occupation code[41] that job j' related to was included in the calculation of (2.22). Summary statistics for (2.22) are reported in table 2.A.3 in the appendix.

Allocating adverts to the high elasticity group such that

$$HighElast = \begin{cases} 1 \text{ if } \varepsilon_{AW_{ajemy}} \geq med(\varepsilon_{AW_{ajemy}}) \\ 0 \text{ otherwise} \end{cases} \tag{2.23}$$

I regress

$$\begin{aligned} log(Apps_{ajemy}) = & \beta_5 log(Wage_{ajemy}) + \beta_6 log(Wage_{ajemy}) X HighElast_{ajemy} \\ & + \beta_7 HighElast_{ajemy} + \gamma_{je} + \lambda_{ey} + \theta_{my} + \epsilon_{ajemy} \end{aligned} \tag{2.24}$$

[37]I use the median rather than the mean ($\lambda\Gamma(1 + \frac{1}{k})$) to avoid the need to utilise the gamma function.

[38]The data does not contain information on Northern Ireland and therefore the sample is marginally smaller than that used in section 2.2.2.2.

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

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

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

utilising the two instruments used previously, LW_{jemy} and AL_{ajemy}. Table 2.6 presents the parameter estimates for $\hat{\beta}_5$, $\hat{\beta}_6$ and $\hat{\beta}_7$ for the three values of k. The model predicted high group has almost double the elasticity of the low group, suggesting the model does a good job of predicting more and less competitive job adverts. Additionally, the estimate of $\hat{\beta}_7$ is negative as the model would predict.[42] Estimates across all three specifications are consistent, parameter estimates are not statistically significantly different across the various parametrisations of k. This is unsurprising as varying k is only able to alter the model predicted relative difference between the high and low groups' elasticities (as seen in table 2.A.3). It would not be able to fundamentally manipulate the composition of the high and low elasticity groups.

Table 2.6: Model Validation Interaction

	(1) log(Apps)	(2) log(Apps)	(3) log(Apps)
log(Wage)	1.854**	1.864**	2.070***
	(0.788)	(0.844)	(0.701)
log(Wage)X HighElast	1.558**	1.635**	1.549**
	(0.686)	(0.808)	(0.628)
HighElast	-3.752**	-3.925**	-3.550**
	(1.655)	(1.951)	(1.528)
Job-Centre FE	Yes	Yes	Yes
Centre-Year FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
N	2239	2239	2239
First Stage F-Stat.	60.40	35.82	56.48
Hansen J Stat.	4.456	3.009	1.146
Instrumented With AL	Yes	Yes	Yes
Instrumented With LW	Yes	Yes	Yes
k	3	5	7

Note: *The table presents estimates of* $\hat{\beta}_5$,$\hat{\beta}_6$ *and* $\hat{\beta}_7$ *from regression equation (2.24) utilising both the LW and AL instrument. High and low groups are defined according to the model predicted elasticities* $\varepsilon_{AW_{ajemy}}$ *from equation 2.22, with varying values of k. Standard errors are reported in parentheses and are clustered at the establishment.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.3.7.2 Descriptive Correlations for Retail Shop Workers

As a secondary test of validation I look at the relationship between the degree of competitiveness as predicted by the model (i.e. the application-wage elasticity) for different

[42] Those jobs with higher elasticties should be on the flatter part of their labour supply curve and therefore have a lower number of applicants in comparison to the low elasticity group.

geographic locations across England and Wales, and measures of wages, density and population.

Choice of geographic locations for this exercise is non-trivial. Typically for the UK one would use centroids of TTWAs or Local Authorities (LA), however, the model is particularly granular, and therefore using such large areas carries a high risk of measurement error.[43] On the other hand the choice of specific points to calculate competitiveness for any country is effectively infinite, and some structure would be beneficial. I therefore utilise the ONS's geography of Built-Up Areas and their subdivisions (BUAs). BUAs are defined as land which is "irreversibly urban in character" (Harding et al., 2013) and comprise of villages, towns or cities. Approximately 95% of the population of England and Wales live in BUAs and the land area of BUAs only makes up 9.6% of the total land. The smallest BUA has a population of just over 100, while the largest is Greater London with almost 10 million, though for the following analysis however London is split into many subdivisions to improve granularity. Figure 2.B.8 in the appendix presents a map of the BUAs and where appropriate, their subdivisions for England and Wales. In total there are 7,625 areas.

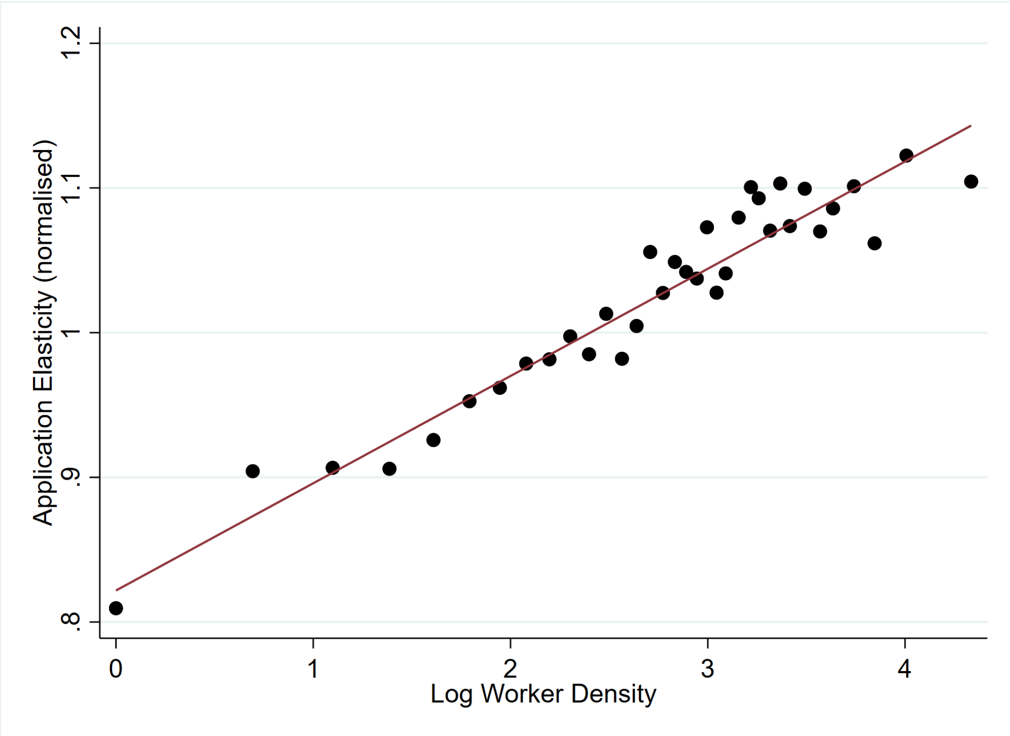
For each BUA I take the centroid point and calculate equation 2.22 using the same parameter values as before ($\varepsilon_{cw} = 1$ and $k \in \{3, 5, 7\}$), for the market of retail shop workers present in ASHE for the year 2019. I choose this occupation as it represents the largest occupation group of minimum wage jobs for the UK, in total there are 10,138 workers located across England and Wales in the dataset. As before distances are measured in minutes utilising the Open Street map data and ArcGIS, incumbent wages are taken from ASHE and the elasticities are calculated at the point of the LWF's Living Wages for 2019.[44]

Figure 2.5 presents binned scatter plots of the worker density against the normalised model predicted application elasticity, and the normalised model predicted elasticity against wages, respectively, for the value of $k = 3$. Worker density is measured by the number of retail workers within a 25 minute drive of the centroid in the sample, while wages is the mean of those workers' wages. Both plots show a strong positive correlation which is reassuring. Denser areas are expected to be more competitive due to the close proximity of outside options, and similarly areas that are more competitive should have higher wages. The slope relating the application elasticity to wages is likely to be slightly muted due to the existence of a national minimum wage policy, however it still shows a

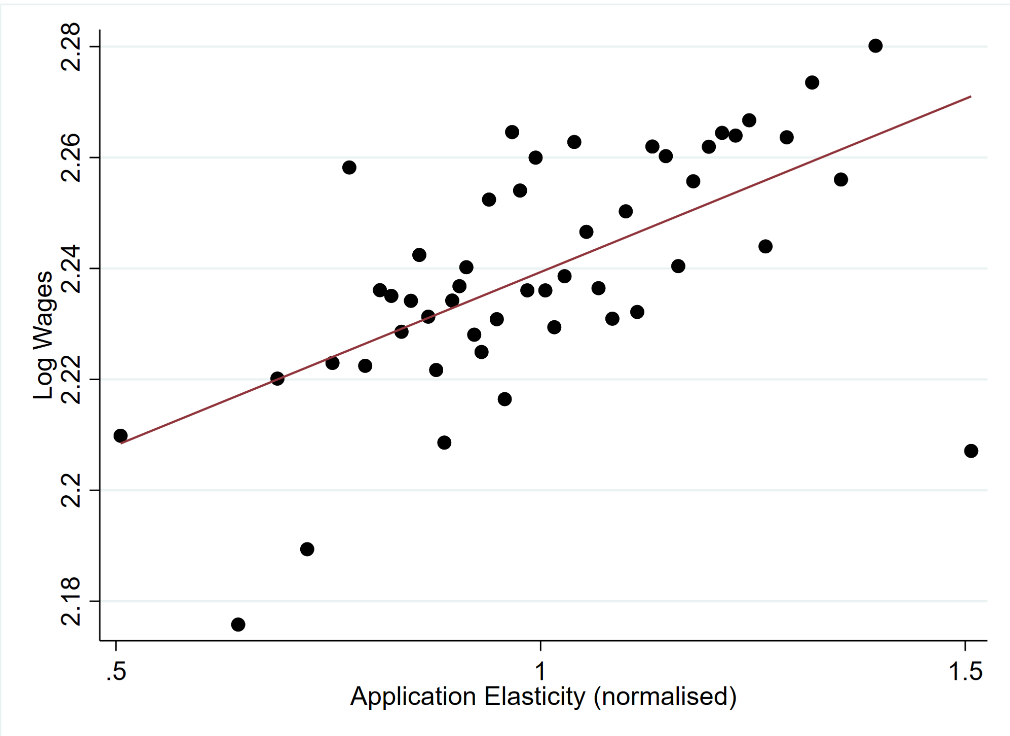
[43]By using the centroid of a TTWA or LA it's not clear that specific point would be representative of the rest of the geographic area. For example the centroid of a LA could be agricultural land located between two major towns.

[44]£9.30 for non-London areas and £10.75 for London.

Figure 2.5: Model Predicted Elasticities vs Density and Wages



Slope = 0.103, Std. error = 0.003



Slope = 0.062, Std. error = 0.008

Note: *The figure presents binned scatter plots of the application elasticity (normalised by dividing by its mean) as calculated by equation 2.22 using values of $k = 3$ for centroids of 7,625 BUAs and BUASDs for the market of retail workers against worker density and average log wages. Worker density is measured by those workers within a 25 minute drive of the centroid and wages are calculated by the mean hourly wage of those individuals.*

strong robust relationship. The strong correlation is invariant to the value of k as shown in figures 2.B.9 and 2.B.10 in the appendix. The positive relationship between the application elasticity also holds when using measures at the BUA level, such as residential density and population as shown in figures 2.B.11 and 2.B.12 in the appendix. These results are suggestive that denser more populated areas are likely to experience more competitive labour markets, and thus higher wages, and may go some way in explaining the urban wage premium. They additionally give credence to the mechanism suggested by the model, that distaste for commuting is a key factor in generating monopsony power.

2.4 Structural Estimation and The Relative Importance of Commutes

In the following section I structurally estimate the model to estimate the value of the Weibull parameter k by matching the model predicted elasticities to the empirical elasticities. By doing so I can comment on the relative importance of commutes in determining monopsony power. Thanks to the relationship between the Weibull distribution and the Extreme Value Type-I (EV) distribution, the Weibull shape parameter $k = \frac{1}{\beta}$ where the variance of the EV distribution is $\frac{\pi^2}{6}\beta^2$. Thus as shown in section 2.G, k has a neat interpretation of being the application elasticity in the absence of commutes. As a secondary step I also use the model and the estimated parameters to examine the effect on competitiveness and markdowns of shrinking all commutes to zero, while holding incumbent wages constant.

2.4.1 Method

To elicit the parameter k I use a minimum distance estimator, that minimises the difference between the model predicted elasticities and the empirically estimated elasticities. I additionally introduce a log-scaling parameter α. In practice this parameter ensures that the elasticities match in absolute-value, rather than in just relative value. The parameter, therefore allows for a clearer interpretation of the following results.

The labour supply function (in logs) then becomes

$$log(A_{j'}) = \alpha \ log\Big(\sum_{ij}[1 - F(x_{ijj'})]\Big) \tag{2.25}$$

and for each job advert the empirical counterpart becomes

$$\tilde{\varepsilon}_{Aw_{ajemy}} = \alpha * \varepsilon_{Aw_{ajemy}} \tag{2.26}$$

where $\varepsilon_{Aw_{ajemy}}$ is defined in equation 2.22. For a given k, I calculate 2.26 using the same data and method as outlined in section 2.3.7.1.

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

1. Guess parameters k and α.
2. Calculate equation (2.26) for each job advert using the guessed parameters.
3. Split the sample in half at the median based on the model calculated $\tilde{\varepsilon}_{Aw_{ajemy}}$, labelling the top half "high".
4. Estimate regression equation

$$\begin{aligned} log(Apps_{ajemy}) = & \beta_1 log(Wage_{ajemy}) + \beta_2 log(Wage_{ajemy}) X HighElast._{ajemy} \\ & + \beta_3 HighElast._{ajemy} + \gamma_{je} + \lambda_{ey} + \theta_{my} + \epsilon_{ajemy} \end{aligned}$$

   with the high group as calculated from step 3 and with $log(Wage_{ajemy})$ instrumented with the two instruments discussed in section 2.2.1.2.

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

$$Euclidean\ distance = \sqrt{(\hat{\beta}_1 - \bar{\varepsilon}_{Aw,low})^2 + (\hat{\beta}_1 + \hat{\beta}_2 - \bar{\varepsilon}_{Aw,high})^2}. \qquad (2.27)$$

6. Repeat steps 1-5 until equation (2.27) in step 5 is minimised.

Identification of k comes through the variation the parameter induces in the relative difference between the model predicted elasticities of the high and low group. This is exemplified in table 2.A.3 in the appendix which documents the relative difference between the high and low group elasticities. The higher the value of k, the larger the relative difference between the high and low group elasticities. This is consistent with intuition. The lower the value of k the larger the variance of the idiosyncratic term ν_{ij}, and the more important the idiosyncratic term is in determining monopsony power in comparison to location and commutes. Thus, the more similar the levels of monopsony power between the high and low group. Identification of α comes through matching the absolute levels of the elasticities.

2.4.2 Results

Table 2.7 presents estimates of the structural parameters using the algorithm outlined in section 2.4.1. k is estimated to be 5.49, which is reasonable as it would suggest in the absence of commutes the application elasticity would be equal to approximately 5.5 (see section 2.G). Table 2.8 presents the model implied elasticities along with the empirically estimated counterparts, which are similar in value to the specification with $k = 5$ in the regression table 2.6.

Table 2.7: Structural Parameter Estimates

k	α
5.49	2.44

Note: *The table presents the structural estimates for the remaining model parameters, based off the algorithm outlined in section 2.4.1. The sample includes 2,239 non-permanent job adverts for The Company, and 1,062,022 worker-advert pairs from ASHE.*

Table 2.8: Model vs Empirical Elasticities

		Elasticity	
	Mean	High	Low
Model	2.93	3.95	1.91
Empirical	3.03	3.71	2.34

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

The model does a good job of matching the respective empirical elasticities, and gives support to the mechanisms suggested by the model in section 2.3.5.

2.4.3 Shrinking Commutes to Zero

The model lends itself to an exercise where all commutes are assumed to shrink to zero[45]. That is, the model can look at the effect on incumbent and potential utilities, and therefore job specific elasticities when commutes are assumed away (or $\varepsilon_{cw} = \infty$), but incumbent wages are held constant. The following analysis does not therefore take into account general equilibrium effects; i.e. the fact that firms would also change wages for their incumbent workers, as their optimal wage would also change. One interpretation of the following exercise is, what would happen to the labour supply elasticity to the firm and therefore markdowns, if all workers were immediately assumed to work from home, and incumbent wages were unchanged in the short run. Another interpretation is that the resulting elasticities will go some way in explaining how much of monopsony power

[45] Or all workers and firms were to be located at the exact same point.

is generated by commutes and the spatial distribution of activity.

Methodologically, the exercise is straightforward and is based off equation 2.26. Using the parameter estimates of $k = 5.49$, $\alpha = 2.44$, and $\varepsilon_{cw} = 1$, I compare the model predicted elasticities with the predicted elasticities where $\varepsilon_{cw} = \infty$. This is equivalent to assuming both d_{ij} and $d_{ij'}$ equal 1.[46]

Table 2.9 presents the mean advert-level application-elasticities under the true parametrisation of $\varepsilon_{cw} = 1$ and the alternative of $\varepsilon_{cw} = \infty$, where the alternative is equivalent to assuming away all commutes. The average application elasticity is approximately two thirds higher in the counterfactual scenario and suggests that commutes are a key source of monopsony power. Interestingly, under the no-commute counterfactual, the mean application elasticity is close in size to the estimated parameter k, which as discussed previously would be the application elasticity in the absence of commutes in an EV logit model. This gives additional reassurance to the credibility of the exercise.

Table 2.9: True vs Work form Home Elasticities

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

Note: *The table presents the mean of the advert-level elasticities calculated via equation 2.22 under the true parametrisation of $\varepsilon_{cw} = 1$ and counterfactual of $\varepsilon_{cw} = \infty$ utilising the sample of 2,239 non-permanent job adverts for The Company, 1,062,022 worker-advert pairs from ASHE and the structurally estimated parameter values of $k = 5.49$ and $\alpha = 2.44$.*

Assuming a recruitment-application (i.e. fill-application) elasticity of 0.37 as estimated in section 2.2.2.2, that $\varepsilon_{rw} = \varepsilon_{ra} * \varepsilon_{aw}$[47] and assuming an equality between the separation and recruitment-elasticity (which is a reasonable assumption given results in section 2.2.2.2) markdowns can be calculated according to

$$\mu = 1 - \frac{2 * 0.37 * \varepsilon_{AW}}{1 + 2 * 0.37 * \varepsilon_{AW}}. \tag{2.28}$$

The back of the envelope calculation suggests that markdowns would be approximately 10 percentage points lower in a scenario with no commutes.

These results indicate the spatial distribution of activity and distaste for commuting are a key contributor to monopsony power. The results imply that commutes are responsible for about one third of the markdown of wages. It is reasonable to assume however, that

[46] As utility is multiplicative assuming they become 0 would not be practical.

[47] Note that this is the lower bound as discussed in section 2.2.2.2.

this is a lower bound, as incumbent wages would be expected to rise which would in turn lower markdowns further for the advertising firms, if incumbent wage responses were considered.

2.5 Conclusion

This paper provides new evidence and theory on the extent, and sources, of monopsony power in the labour market. Utilising two instruments and a rich bespoke dataset that contains HR, vacancy and applicant information for a firm with hundreds of establishments across the UK I evaluate the firm's labour supply elasticity, a key measure of monopsony power, estimating both the recruitment and separation elasticity. Estimates suggest a markdown between 16% - 25%. I additionally estimate the commuting-wage elasticity, and results suggest worker's have a strong distaste for commuting. The estimate for preferences over commuting suggests commutes could be a key factor in generating imperfect substitutability between jobs and monopsony power.

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

I validate the model by showing how the model predictions of heterogeneity in monopsony across space are consistent with heterogeneity found in the causal estimates. I additionally show model consistent measures of competitiveness for Built Up Areas in England and Wales are shown to be strongly correlated with worker and residentail density, residential population, and wages. I then structurally estimate the model by matching the model predicted elasticities with the empirically estimated elasticities. The results of the estimation and an exercise which shrinks all commutes to zero suggests that commutes are responsible for 1/3 of the wage markdown.

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

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

Appendix

2.A Additional Tables

Table 2.A.1: Summary Statistics, Adverts

Variable	Mean	S.D.	Median
Hourly Rate (£)	11.07	11.07	10.20
Entry Level	0.48		
No Applicants	18.5	28.9	10
London	0.55		
N	5487		

Note: *The table presents summary statistics for the job adverts for The Company for the period of 2016-2019.*

Table 2.A.2: London Borough of Hackney, Employment

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

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

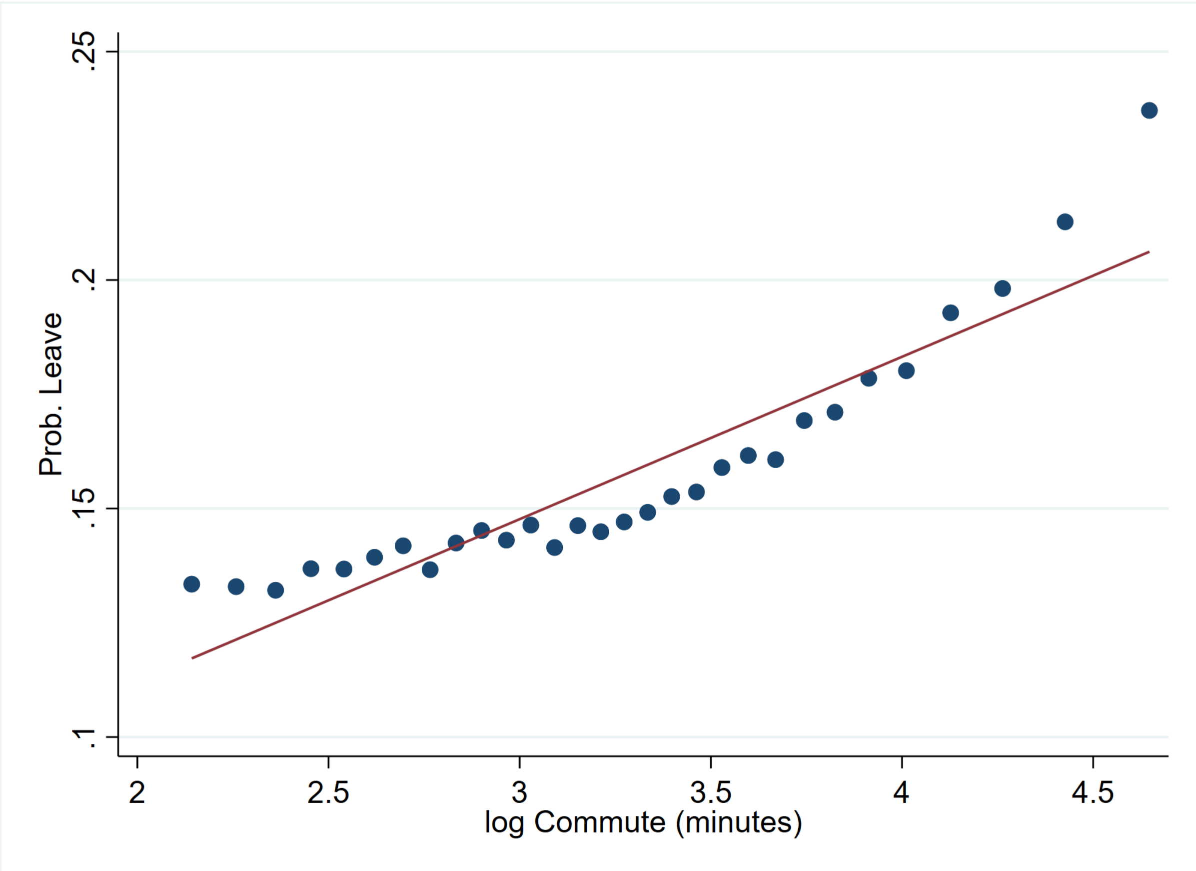
Table 2.A.3: Model Elasticity Estimates

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

Note: *The table presents descriptive statistics for the pooled, high group and low group for estimates of* $\varepsilon_{AWj'}$ *based on equation 2.22 under different values of* k*, for a sample of 2,239 non-permanent job adverts.*

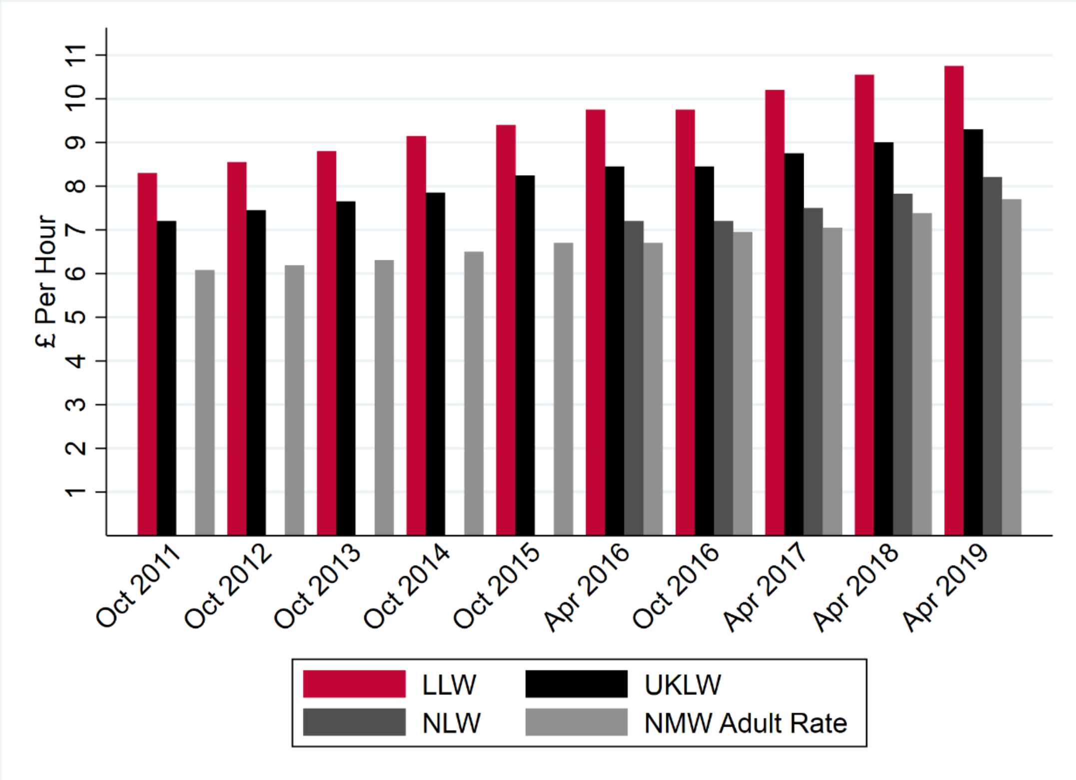
2.B Additional Figures

Figure 2.B.1: Separations vs Commutes with controls



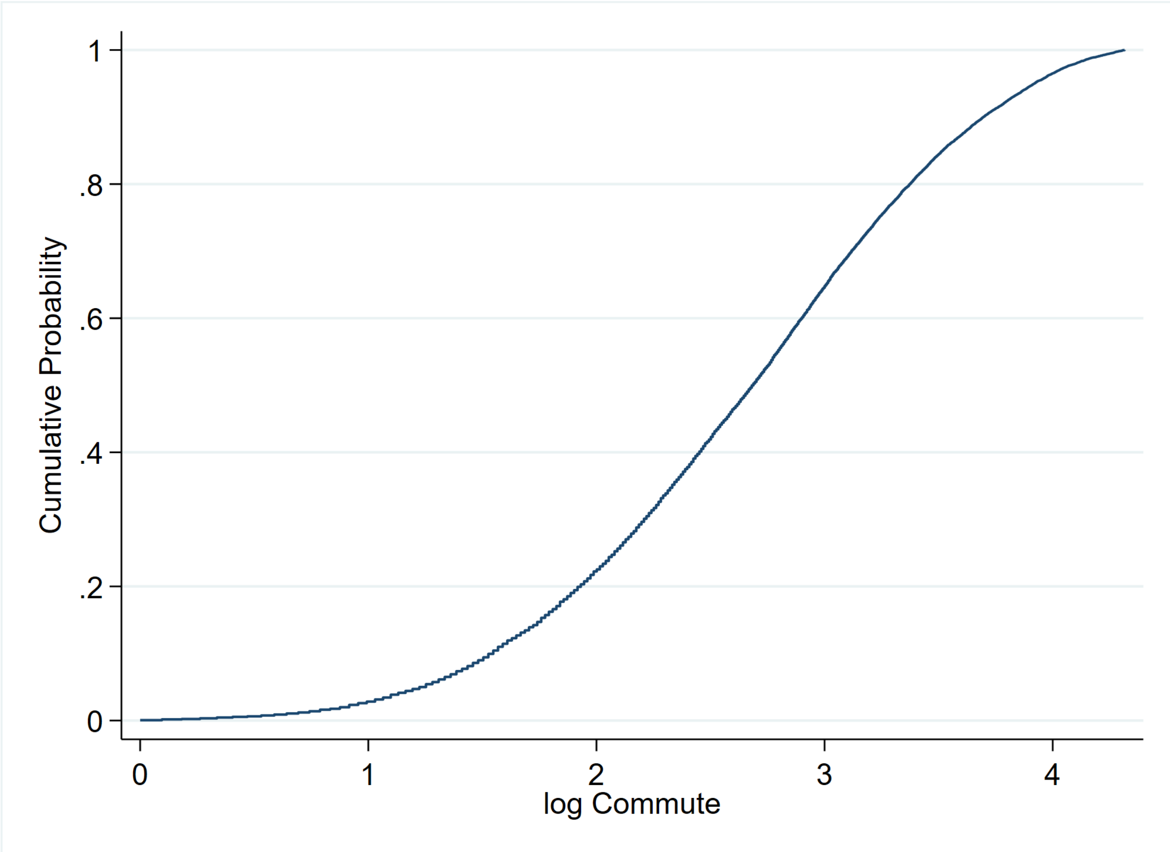
Note: *The figure plots the probability of separation within a year against commutes measured in minutes controlling for wage, age, sex, part time and temporary contracts, year, occupation and industry. Commutes are measured using the Open Street map dataset for Great Britain and ArcGis's networking tool. The sample is based on 1,429,376 worker-year observations from the Annual Survery of Hours and Earnings 2003-2019.*

Figure 2.B.2: Living Wage and Minimum Wage Rates



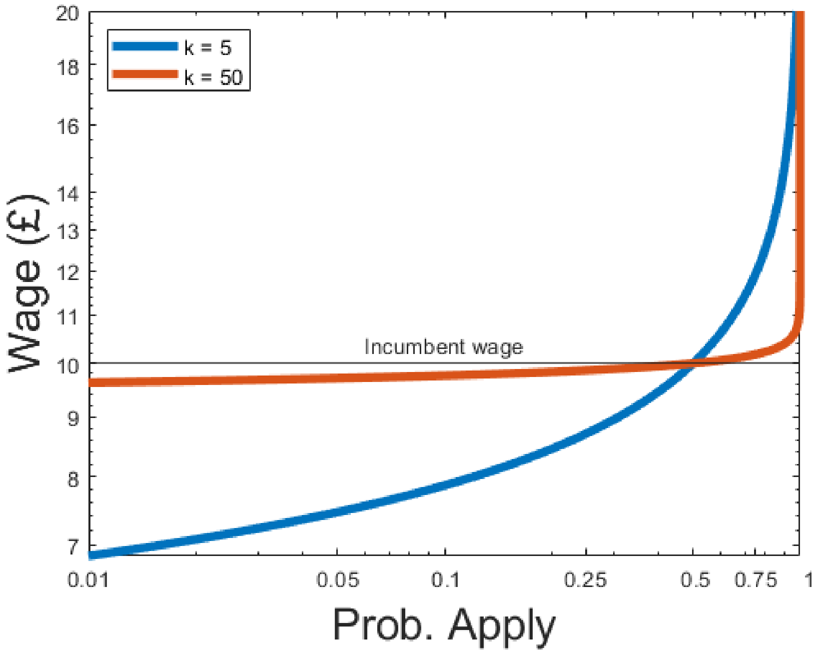
Note: *The figure shows the Living Wage Foundations' London and UK wide rates, as well as the statutory National Living Wage and National Minimum Wage adult rate for 2011 - 2019.*

Figure 2.B.3: Log Commute CDF



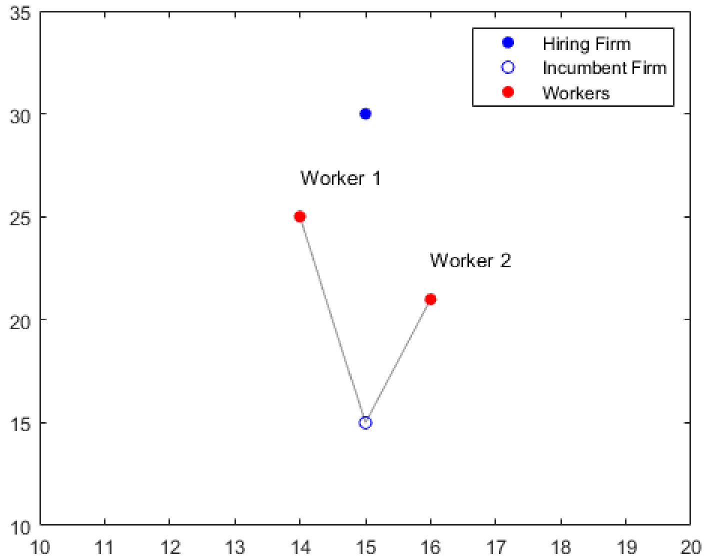
Note: *The figure presents the CDF of log commutes for job applicants for The Company between 2016 and 2019.*

Figure 2.B.4: Individual Labour Supply To the Firm



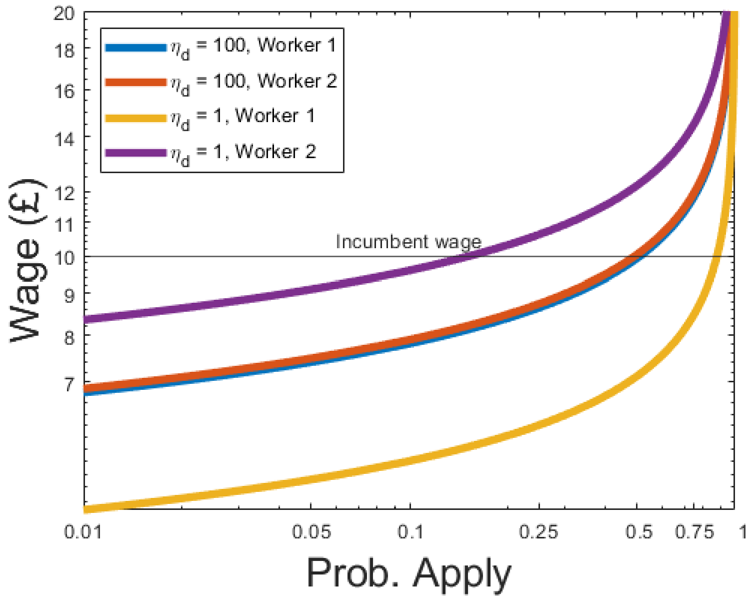
Note: *The figure plots the probability of applying for the worker as per equation (2.18), against the advertised wage on log scales. Parameterisation is such that* $\varepsilon_{cw} = \infty$ *and* $\nu_{ij} = median(\nu_{ij})$. *F is assumed to follow a weibull distribution with scale parameter* $\lambda = 1$ *and the figure plots for both shape parameter values of* $k = 5$ *and* $k = 50$.

Figure 2.B.5: Spatial Heterogeneity in Individual Labour Supply To the Firm I



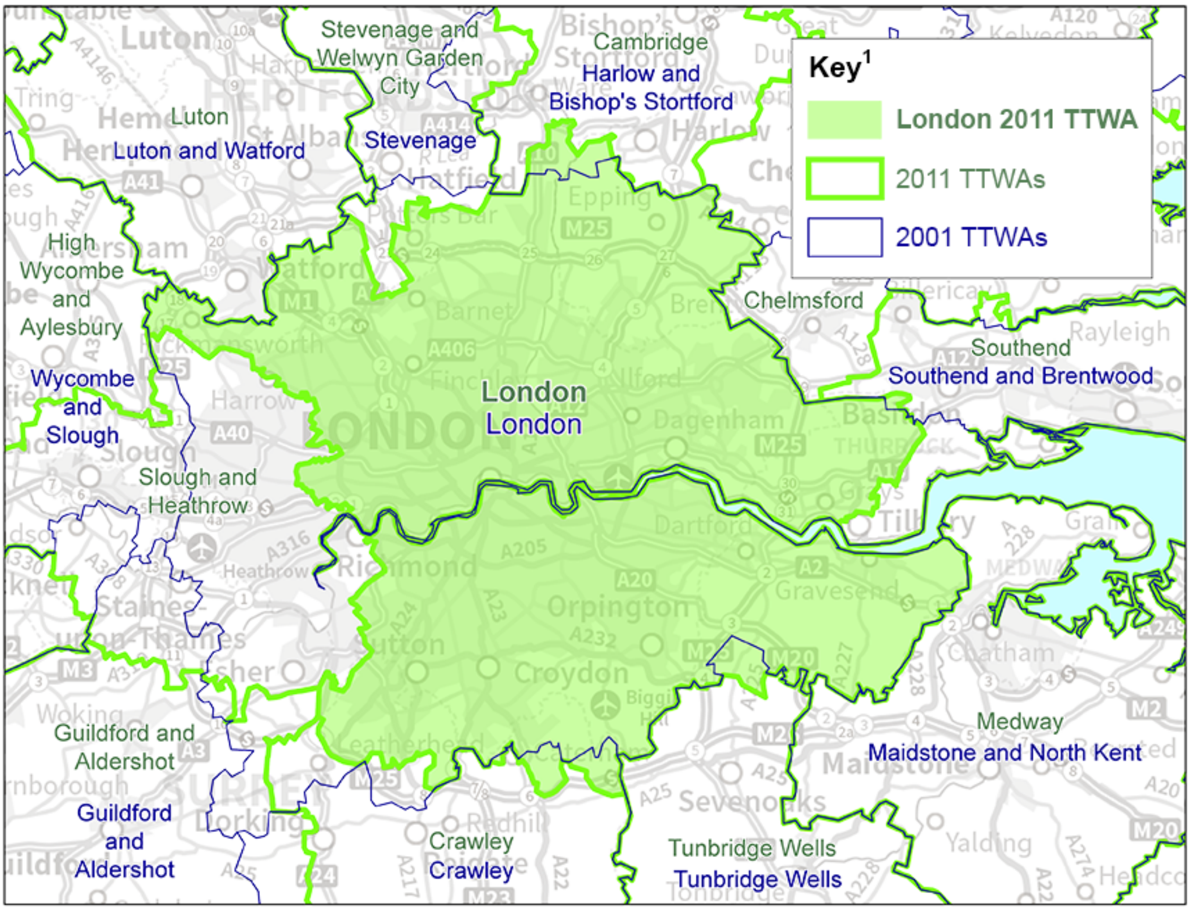
Note: *The figure presents a simulated spatial distribution of two workers with current wage of £10, their incumbent firm and a hiring firm.*

Figure 2.B.6: Spatial Heterogeneity in Individual Labour Supply To the Firm II



Note: *The figure plots the probability of applying to the hiring firm for the two workers spatially located as per figure 2.B.5 under different parameterisations of ε_{cw}, calculated according to equation (2.18), against the advertised wage on log scales. Parameterisation is such that $c = 0$ and $\nu_{ij} = median(\nu_{ij})$. F is assumed to follow a weibull distribution with shape parameter $k = 5$ and scale parameter $\lambda = 1$. When $\varepsilon_{cw} = 100$, where distance plays little role in determining utility, the supply curves are close to identical. When $\varepsilon_{cw} = 1$ where worker 2 experiences a lower elasticity of labour supply to the firm for any given wage than worker 1.*

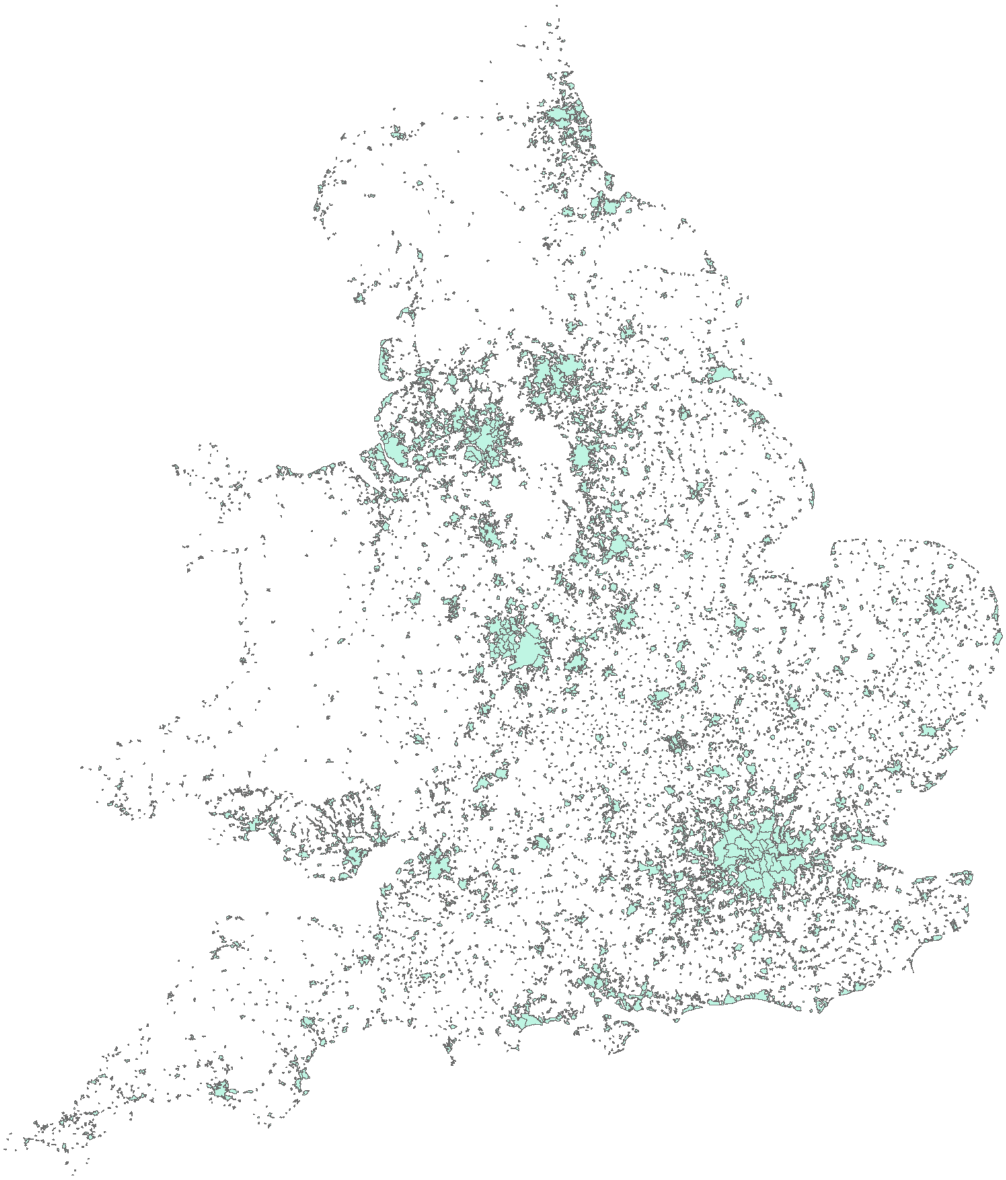
Figure 2.B.7: London TTWA



1 Travel to Work Area (TTWA).

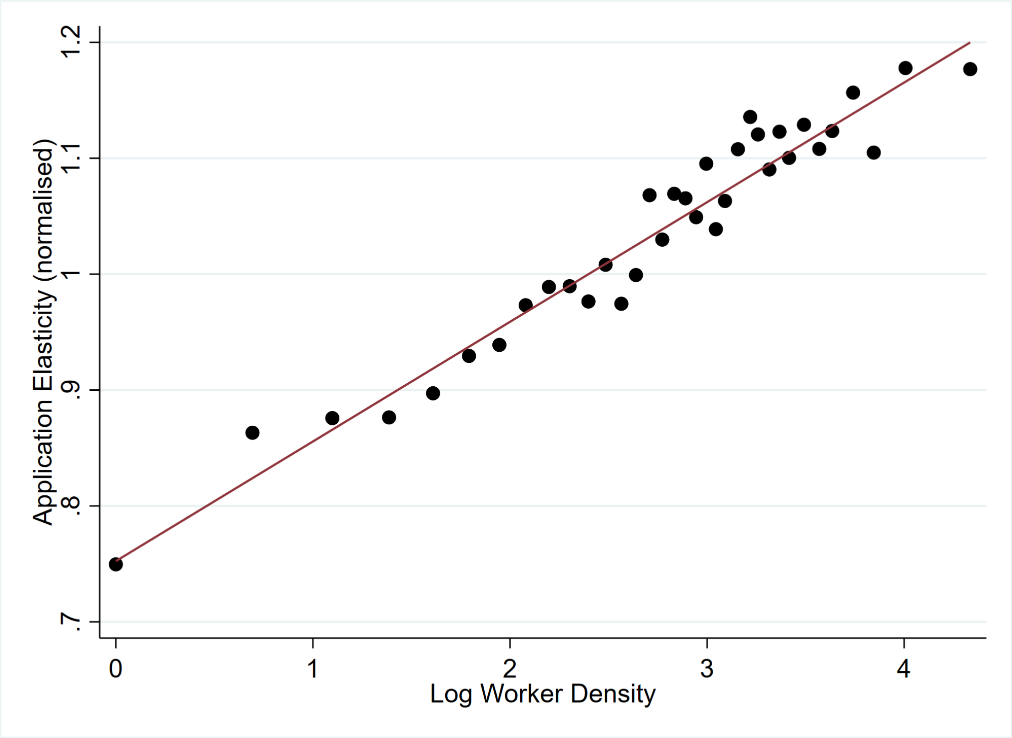
Note: *The figure presents the map of the London TTWA for the years 2001 and 2011.*

Figure 2.B.8: Built Up Area Sub Divisions for England and Wales

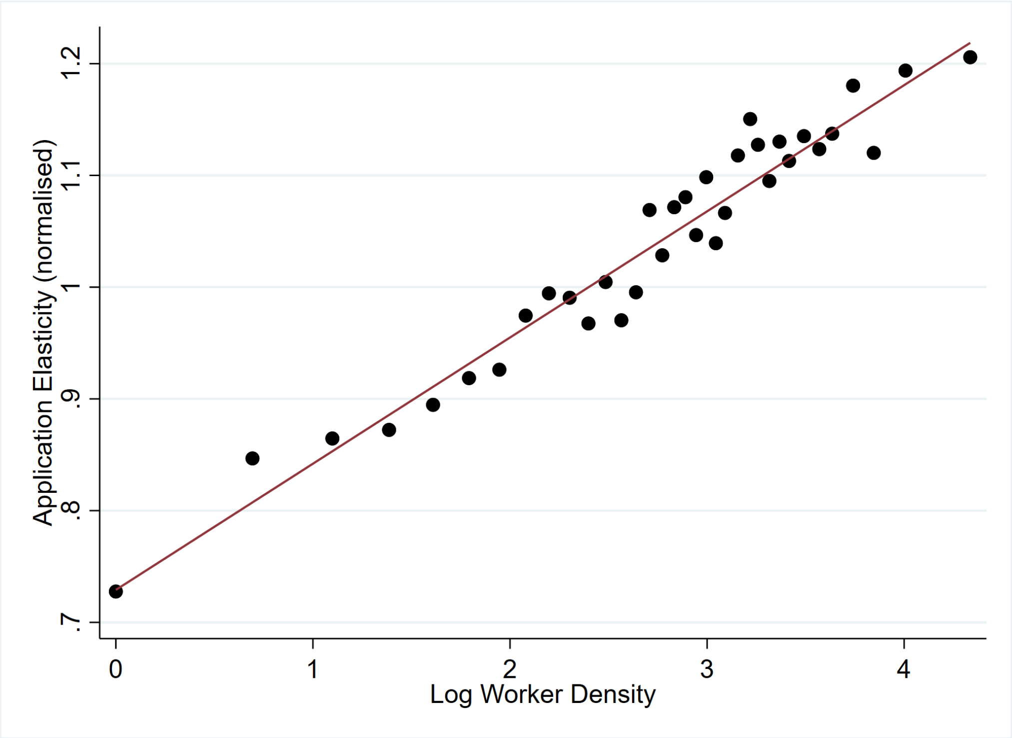


Note: *The figure presents a map of the Built Up Area and Built Up Area Sub Divisions for England and Wales.*

Figure 2.B.9: Model Predicted Elasticities vs Worker Density



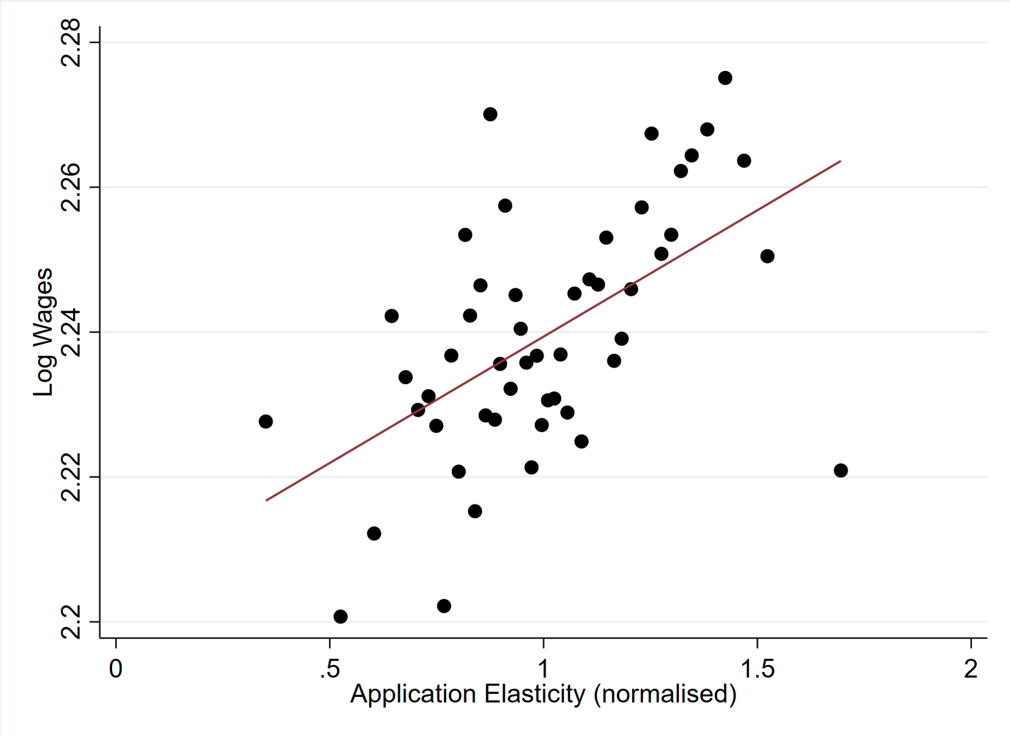
Slope = 0.074, Std. error = 0.002



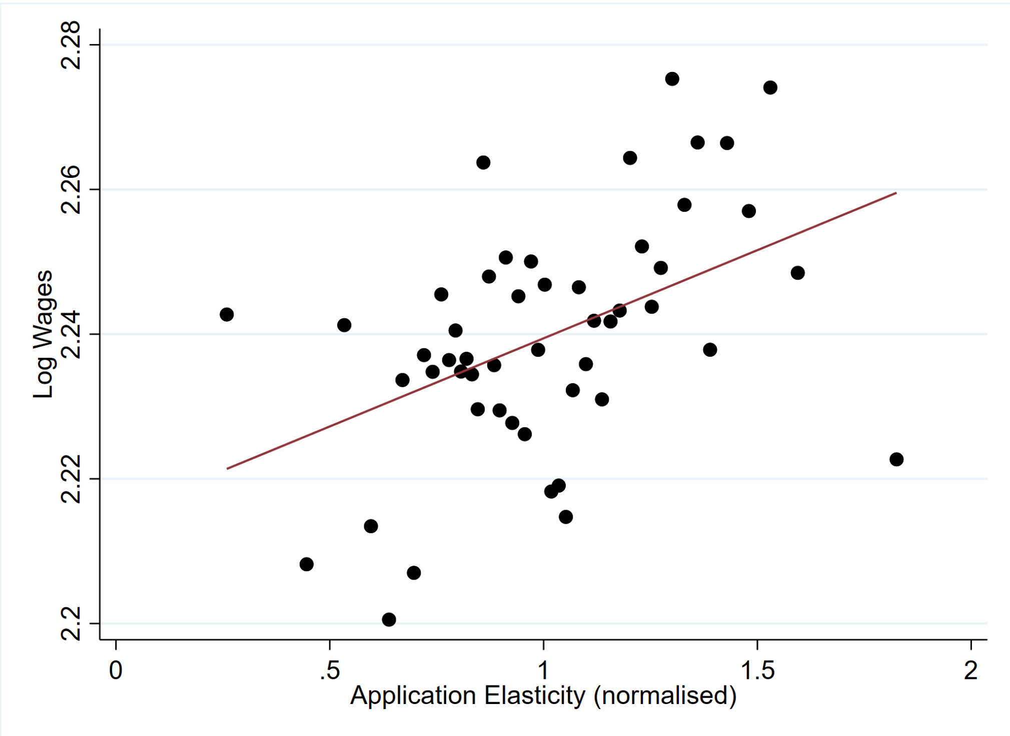
Slope = 0.113, Std. error = 0.003

Note: *The figure presents binned scatter plots of the application elasticity (normalised by dividing by its mean) as calculated by equation 2.22 using values of $k = 5$ and $k = 7$ for centroids of 7,625 BUAs and BUASDs for the market of retail workers against log worker density. Worker density is measured by those workers within a 25 minute drive of the centroid.*

Figure 2.B.10: Model Predicted Elasticities vs Wages



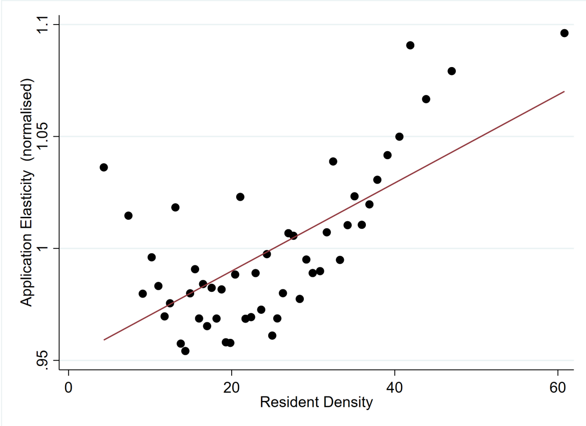
Slope = 0.035, Std. error = 0.006



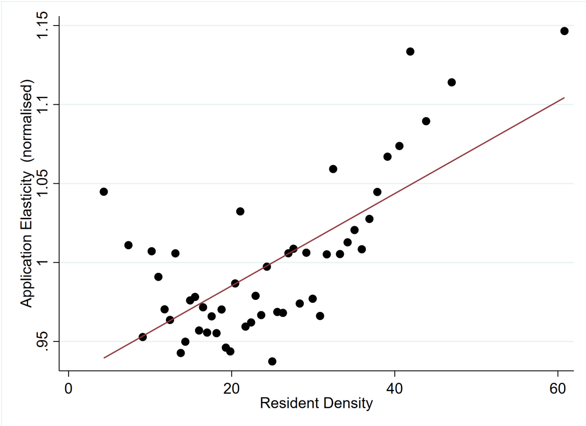
Slope = 0.024, Std. error = 0.005

Note: *The figure presents binned scatter plots of the application elasticity (normalised by dividing by its mean) as calculated by equation 2.22 using values of* $k = 5$ *and* $k = 7$ *for centroids of 7,625 BUAs and BUASDs for the market of retail workers against log average wages. Average wages are measured by the mean wage of workers within a 25 minute drive of the centroid.*

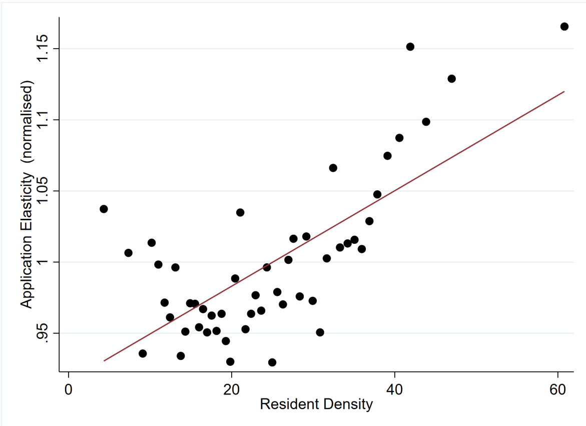
Figure 2.B.11: Model Predicted Elasticities vs Residential Density



Slope = 0.0020, Std. error = 0.0002



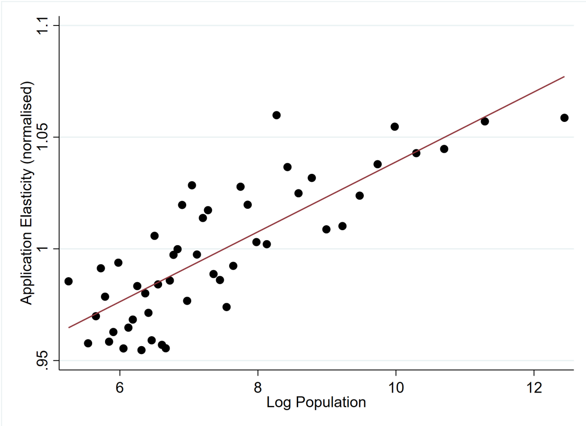
Slope = 0.0029, Std. error = 0.0002



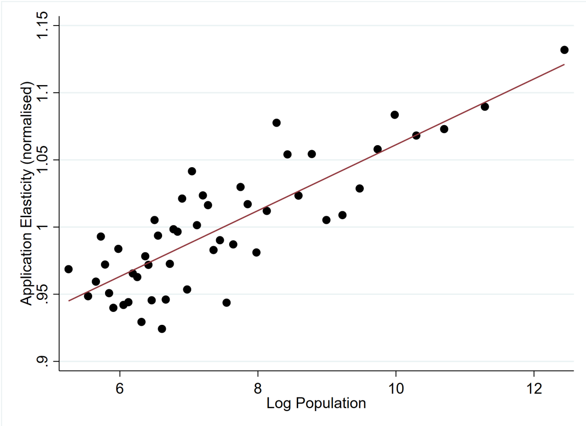
Slope = 0.0030, Std. error = 0.0003

Note: *The figure presents binned scatter plots of the application elasticity (normalised by dividing by its mean) as calculated by equation 2.22 using values of* $k = 3$, $k = 5$, *and* $k = 7$ *for centroids of 7,168 BUAs and BUASDs for the market of retail workers against residential density. Residential density measures from Census 2011 data from NOMIS.*

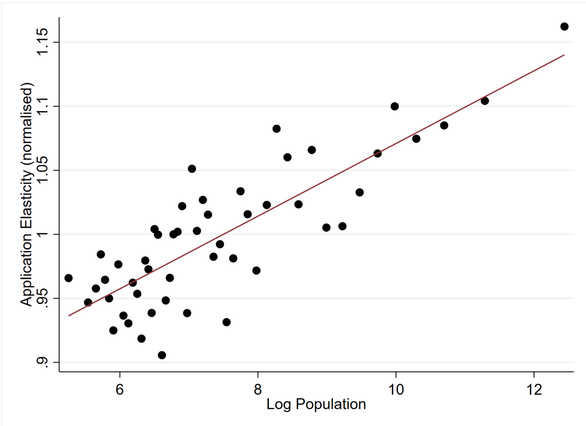
Figure 2.B.12: Model Predicted Elasticities vs Population



Slope = 0.0157, Std. error = 0.002



Slope = 0.0245, Std. error = 0.002



Slope = 0.0284, Std. error = 0.002

Note: *The figure presents binned scatter plots of the application elasticity (normalised by dividing by its mean) as calculated by equation 2.22 using values of* $k = 3$, $k = 5$, *and* $k = 7$ *for centroids of 7,168 BUAs and BUASDs for the market of retail workers against log population. Population measures from Census 2011 data from NOMIS.*

2.C Robustness

2.C.1 Estimating the Elasticity of Labour Supply to the Firm

To strengthen the credibility of the identification strategy employed and therefore results discussed in section 2.2.2.2 and 2.2.3, I perform a number of robustness checks.

2.C.2 Parallel Trends and Anticipation Effects

Firstly, one may have a concern that an announcement effect may cause a bias towards zero in the separation elasticity estimates. Specifically, if workers' employed by The Company in a particular establishment find out many months before the introduction of the Living Wage that they are to receive a substantial pay increase, they may decide to stay on with the firm longer. Discussions with the director of human resources suggests this is unlikely to be a concern treated workers only found out relatively near to the treatment date. However, it is prudent to empirically test for anticipation effects. Figure 2.C.1 graphically presents the transformed event study parameter estimates of the reduced-form estimating equation

$$Leave_{ijemy} = \sum_{l \neq -1,-11} \beta_{4,l} LW_{je,my+l} + \gamma_{je} + \lambda_{emy} + \theta_{jmy} + \epsilon_{ijemy} \tag{2.29}$$

where $l \in \{-12, ..., 12\}$ and the end points are binned such that $LW_{je,my+12} = 1 \; \forall \; \{l \geq 12 : LW_{je,my+l} = 1\}$ and $LW_{je,m-12} = 1 \; \forall \; \{l \leq -12 : LW_{je,my+l} = 1\}$.[48] Monthly effects are aggregated to the quarter, q such that

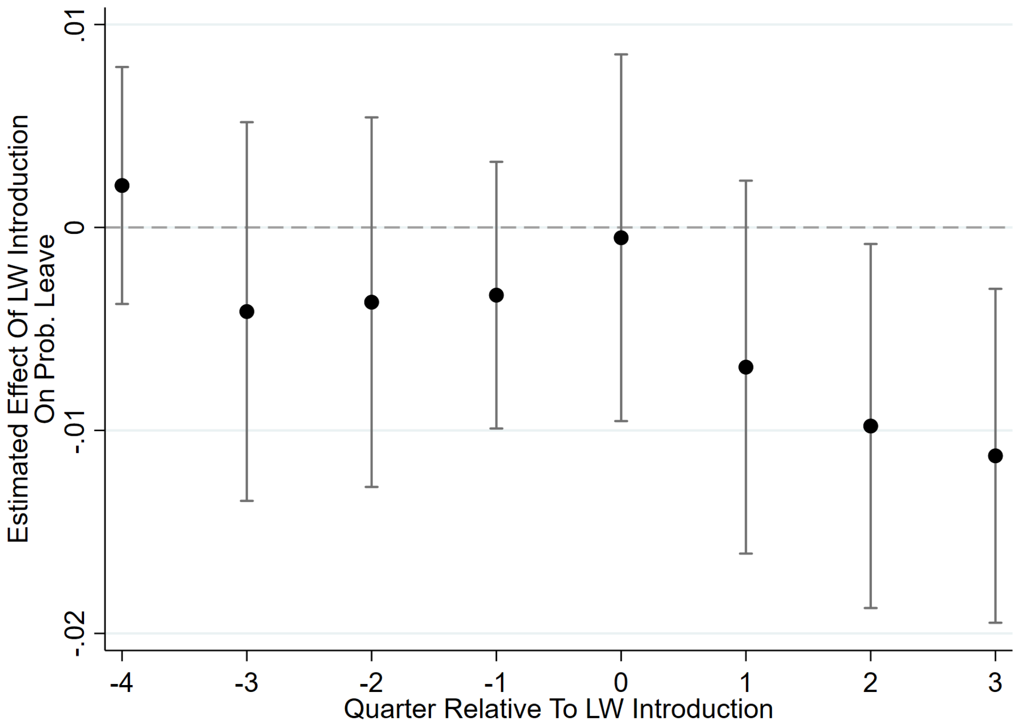
$$\hat{\beta}_4^q = \sum_{l \in q} \frac{1}{3} \hat{\beta_{4,l}} \tag{2.30}$$

and one may note that the monthly parameter effects are normalised to two periods, -1 and -11, as recommended in Borusyak and Jaravel (2017).

Figure 2.C.1 suggests that the restriction of parallel pre-trends can not be rejected, and therefore there is no evidence of anticipatory effects. The figure additionally shows that after one quarter of the introduction of the Living Wage, there is a clear drop in the rate of separations which continues to fall during the second and third quarter proceeding the introduction. For completeness figure 2.C.2 reports the similar exercise for the first stage. The estimation is identical to equation 2.29 and 2.30 except with the dependent variable changed to $log(Wage)$.

[48]This implies that the first and last parameter estimate in 2.C.1 contain longer run pre and post effects.

Figure 2.C.1: Separations Event Study

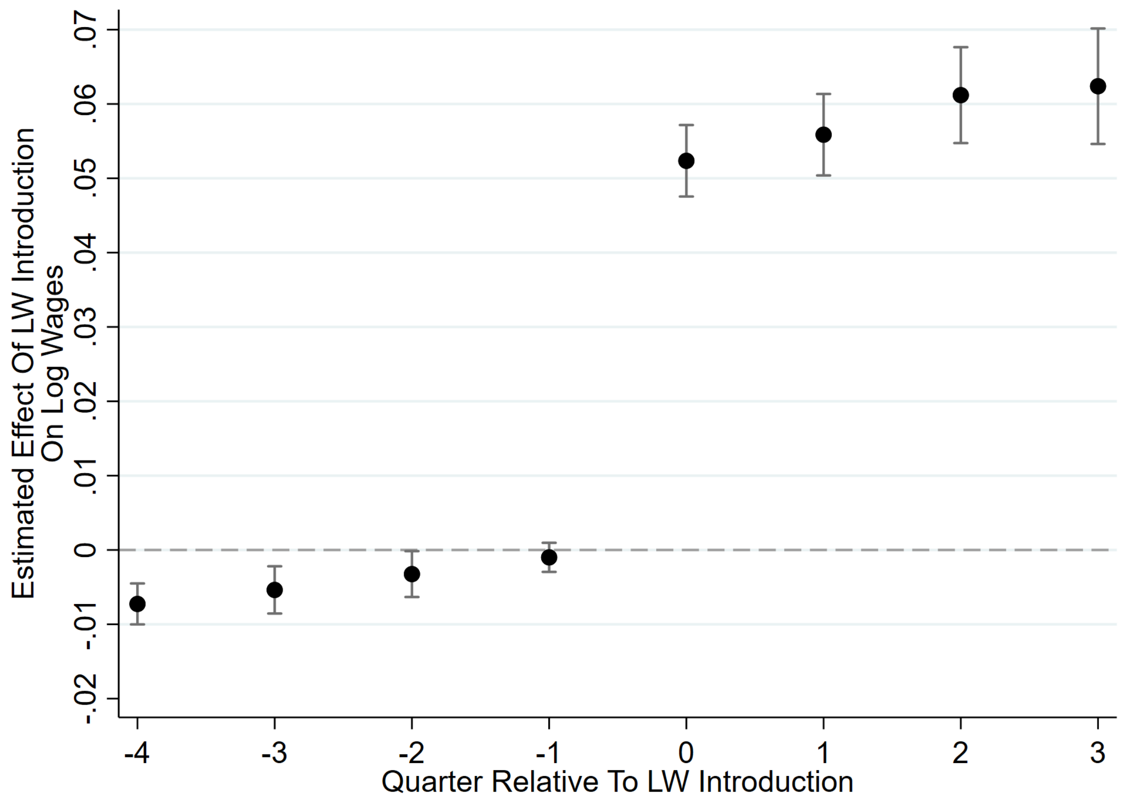


Note: *The figure presents estimates and 95% confidence intervals for parameters* $\hat{\beta}_4^q$ from equation 2.30.

2.C.3 Staggered Treatment Timing

There has been a recent interest in the workings of two-way fixed effect estimators, in particular utilising staggered treatment times (Borusyak and Jaravel, 2017; Sun and Abraham, 2020; Callaway and Sant'Anna, 2020; Goodman-Bacon, 2021). Concerns raised include: issues identifying the linear component of the path of pre-trends in traditional event study specifications (Borusyak and Jaravel, 2017), contamination of lead and lag coefficients from other period effects (Sun and Abraham, 2020), biased estimates of treatment effects when the control group contains treated units when dynamic treatment effects are present (Goodman-Bacon, 2021) and the structure of weights assigned across treatment cohorts when estimating dynamic treatment effects (Sun and Abraham, 2020). The approach in this paper is more flexible than a two-way fixed effect estimator, and when utilising just the Living Wage instrument, akin to a triple-difference estimator. Additionally, it is not obvious why some of these issues would be present in the current setting. For example, dynamic treatment effects are unlikely when studying the response of number of applicants in response to wage changes. Despite this fact, as a matter

Figure 2.C.2: Wages Event Study



Note: *The figure presents estimates and 95% confidence intervals for parameters of* $\hat{\beta}_4^q$ from equation 2.30 where the dependent variable in equation 2.29 is $log(Wage_{ijemy})$.

of caution to check whether any of these issues could be sullying the estimated effects when using the Living Wage instrument I implement a two-way fixed effects event study estimator at the establishment level akin to that suggested in Sun and Abraham (2020) while also implementing adjustments as recommended in Borusyak and Jaravel (2017). This estimator is the same implemented in Datta and Machin (2021). I compare these results to a traditional two-way fixed effects event-study estimator at the establishment level to see if there is a fundamental difference between the results.

The robust estimator is as follows. Borrowing notation from Sun and Abraham (2020), let Y_{et} denote some outcome for unit e at time t with treatment status $D_{et} \in \{0, 1\}$: $D_{et} = 1$ if e is treated in period t and $D_{et} = 0$ otherwise, where treatment is absorbing, and therefore $D_{es} \leq D_{it}$ for $s < t$. A unit's treatment path can therefore be characterised by $K_e = min\{t : D_{et} = 1\}$, and where we let $K_e = \infty$ if the unit is never treated. Units can therefore be categorized into disjoint cohorts $k \in \{t_{min}, \ldots, t_{max}, \infty\}$, where units in cohort k are first treated at the same time $\{e : K_e = k\}$. Y_{et}^k is the potential outcome in period t when unit e is first treated at time k and Y_{et}^{∞} is the potential outcome at time t if unit e never receives treatment. A cohort-specific average treatment effect on the treated l periods from treatment is thus:

$$CATT_{k,l} = E[Y_{e,k+l} - Y^{\infty}_{e,k+l} | K_e = k] \tag{2.31}$$

This notation allows treatment effect heterogeneity across cohorts, which in this setting may be important as the bite of the living wage may change over time. I am then interested in some weighted average of 2.31, for some $l \in g$, to construct a relative period coefficient. As is often the case when firms face a shock to the wage floor, we are interested in the average dynamic effects (which allows an analysis of the pre-trends).

For analysing the average dynamic effects I focus on the weighted average similar to that proposed in Sun and Abraham (2020).

$$v_g = \frac{1}{|g|} \sum_{l \in g} \sum_{k} CATT_{k,l} Pr\{K_e = k | K_e \in l\} \tag{2.32}$$

which effectively uses weights according to the size of the treated cohort that experiences l periods relative to treatment.

In practice 2.32 is estimated using the following methodology:

1. For each treatment cohort I estimate an adjusted form of the typical, two-way fixed effect, event study specification, where t is in months and I limit l to 12 months before and after the cohort treatment period.

$$Y_{et} = \alpha_e + \lambda_t + \sum_{l \neq = -1, -12} \delta_{k,l} LW_{i,t+l} + \beta' X_{et} + \epsilon_{et} \tag{2.33}$$

   Where α_e is the establishment fixed effect, λ_t is a year-month fixed effect, LW_{et} is a dummy variable which represents whether an establishment pays the Living Wage and X_{et} is a set of time varying establishment level controls. For each treatment cohort e, the control group is restricted such that they have not received treatment within the past two years, or will not receive treatment within two years of the relevant treatment cohort treatment date. This is to ensure no overlap of dynamic effects between the treated and control groups. As per the suggestion of Borusyak and Jaravel (2017), I normalise the dynamic effects to two periods, -1 and -12, to deal with the underidentification issues they raise.

2. I estimate the weights $Pr\{K_e = k | K_e \in l\}$ by sample shares of each cohort in the relevant relative period l.

3. I combine steps 1 and 2, and aggregate monthly effects l, to the level of quarters g,

for graphical representation by taking a simple equal weighted mean. In particular

$$\hat{v}_g = \frac{1}{3}\sum_{l\in g}\sum_{k}\hat{\delta}_{k,l}\hat{Pr}\{K_e = k|K_e \in l\} \tag{2.34}$$

The above methodology comes with a number of benefits. Firstly, it is completely transparent about what weights are being used between treatment cohorts in the estimation of the parameters of interest. These weights are guaranteed to be convex and non-negative, which in the typical event study specification with variation in timing is not necessarily the case Sun and Abraham (2020). Secondly, there is clarity in terms of which groups are being used as treatment and control groups in both the dynamic, and long run treatment effect estimation. Thirdly, it deals with underidentification problems raised previously in the literature.

The top panel of figure 2.C.3 presents estimates of $\hat{v}_g$ from equation 2.34, using the more transparent methodology outlined above. The bottom panel of figure 2.C.3 presents estimates using a standard pooled two-way fixed effects event study estimator,

$$Y_{et} = \alpha_e + \lambda_t + \sum_{l\neq=-1,-12}\delta_l LW_{e,t+l} + \beta' X_{et} + \epsilon_{et} \tag{2.35}$$

with monthly effects aggregated to the month per

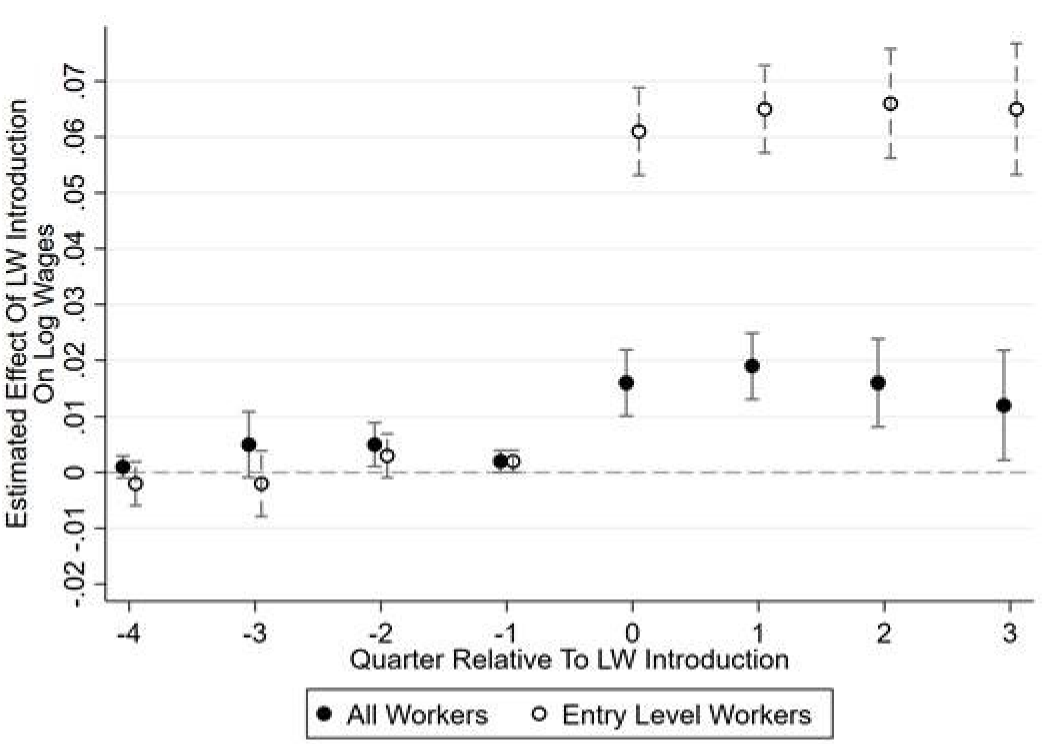
$$\hat{v}_g^{pooled} = \sum_{l\in q}\frac{1}{3}\hat{\delta}_l \tag{2.36}$$

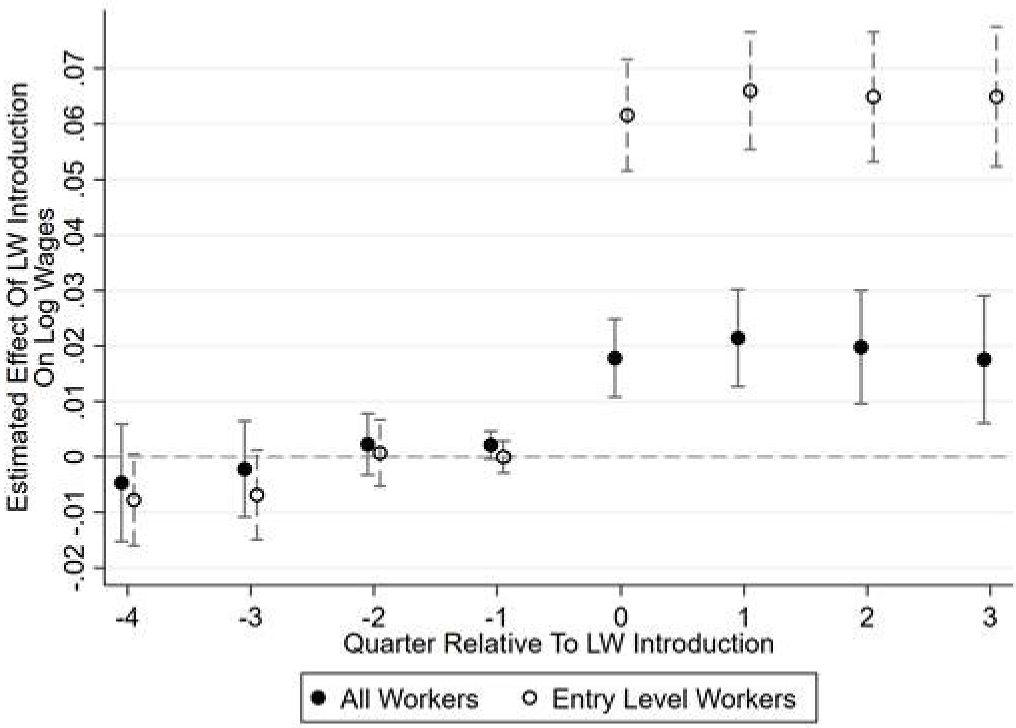
There is little obvious difference between the two panels for both impacts on all workers' and entry-level workers' wages at the establishment level. Both suggest parallel pre-trends, and stable dynamic treatment effects, with entry level workers experiencing 6% greater wage growth in treated establishments. This result is also consistent with the triple-difference first stage estimate from table 2.4 and 2.C.2. Given these results it is unlikely that the more flexible specifications utilising a triple-difference estimator will suffer from the aforementioned issues.

2.D Estimating the Commuting-Wage Elasticity

It's reasonable to suspect that assuming a constant, linear in logs, relationship between wages and commutes is a strong assumption. Analysis using observational data however, suggests it is unlikely to be problematic. Figure 2.D.1 presents a scatter plot of log commutes against log wages, both orthogonalized against year and industry fixed

Figure 2.C.3: Event Study Robustness

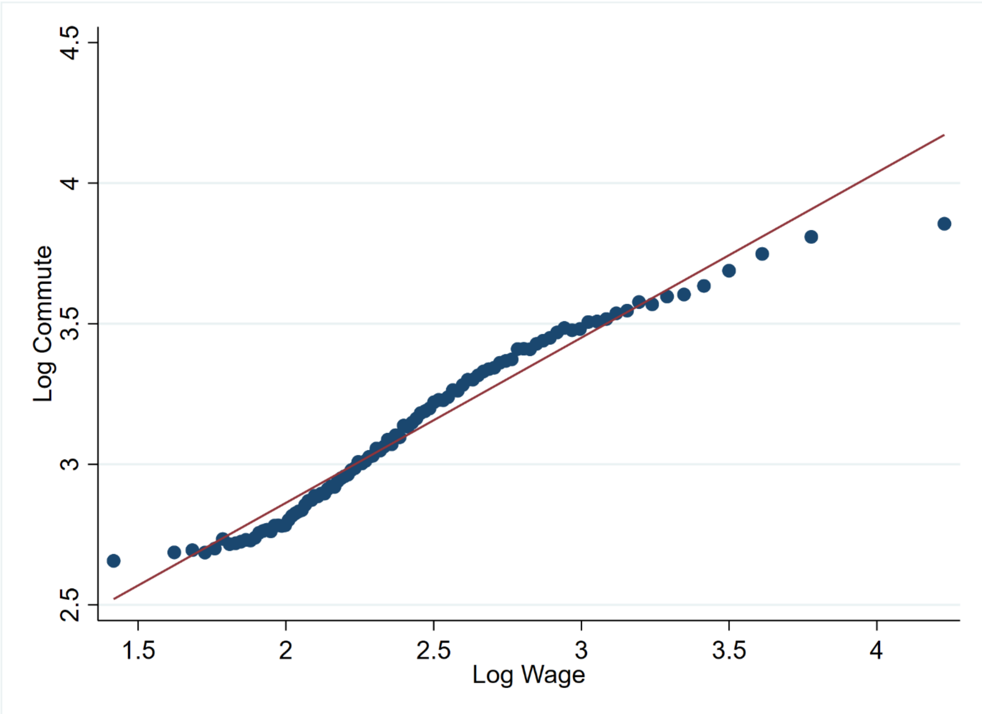




Note: *The top panel presents estimates from equation 2.34, while the bottom panel presents results from equation 2.36. Both panels use a sample of establishments run by The Company active between January 2011 and April 2019, and are based off 17,879 establishment year-month observations. The vertical bars indicate 95% confidence intervals. For the top panel these are based on 1000 bootstraps.*

effects, gender, age, part time and temporary, using data from the nationally representative Annual Survey of Hours and Earnings. There is a clear positive correlation and is approximated well by a linear relationship, except perhaps at the extreme tails.

Figure 2.D.1: Log Commutes vs Log Wage



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

Further to this end figure 2.B.3 and table 2.D.1 in the appendix presents the CDF of log commutes for the sample used in columns (2) - (4) in table 2.5 and the results from the instrumented regression[49]

$$P(log(Commute_{iajemy}) \leq x) = \beta_5^x log(Wage_{jemy}) + \delta' X_{ia} + \gamma_{je} + \lambda_{ey} + \nu_{ym} + \epsilon_{iajemy} \quad (2.37)$$

The estimates from equation (2.37) show that the CDF under a higher wage would stochastically dominate a CDF under a lower wage, as expected. Furthermore, effects are sizeable across most of the distribution aside from the tail ends. The estimates imply a 10% increase in wages would reduce the probability of being lower than a specific value by between 3-6% between the 10th percentile up to the 75th percentile. Therefore, allowing

[49]Ideally one would look at the effects across the distribution using a quantile regression, however at the time of writing this IV quantile regression with high dimensional fixed effects is not possible.

Table 2.D.1: Commuting - Wage Distribution Estimates

	(1) x = 1	(2) x = 1.5	(3) x = 2	(4) x = 2.5	(5) x = 3	(6) x = 3.5	(7) x = 4
log(Wage)	-0.05	-0.33**	-0.33*	-0.63**	-0.56**	-0.06	-0.03
	(0.07)	(0.16)	(0.20)	(0.26)	(0.25)	(0.18)	(0.10)
Job-Centre FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Centre-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19585	19585	19585	19585	19585	19585	19585
Inst. W/ AL	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inst. W/ LW	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Non-Perm	Non-Perm	Non-Perm	Non-Perm	Non-Perm	Non-Perm	Non-Perm

Note: *The table presents estimates of* $\hat{\beta}_5^x$ *from equation (2.37). Standard errors are reported in parentheses and are clustered at the establishment. Regressions are weighted by the inverse number of applicants for each job. Controls include gender and ethnicity.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

for a non-parametric relationship between commutes and wages would most likely only marginally improve accuracy, while complicating estimation of the model and losing a degree of analytical tractability.

2.E The Maintaining Worker Problem

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

$$\varphi_{ijj'}(w_j) = 1 - P(A_{j'})(1 - F(x_{ijj'})) \tag{2.38}$$

This implies

$$\varepsilon_{\varphi w_{ijj'}} = \frac{P(A_{j'})f(x_{ijj'})}{1 - P(A_{j'})(1 - F(x_{ijj'})}\tilde{x}_{ijj'} \tag{2.39}$$

Note that

$$\varepsilon_{sw} = -\frac{\varphi}{1-\varphi}\varepsilon_{\varphi w} \tag{2.40}$$

$$\varepsilon_{sw_{ijj'}} = -h(x_{ijj'})x_{ijj'} \tag{2.41}$$

It is straight forward to see how the above is the inverse of the hiring problem and particularly obvious when looking at equation 2.39. As incumbent utility increases, $x_{ijj'}$ increases .

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

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

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

$$\varphi_{(ij)}(w_j) = \sum_{j'} \varphi_{(ij),j'}(w_j) \tag{2.42}$$

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

2.F Introducing Search Costs

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

$$P(A_{j'})u_{ij'} - (1 + P(A_{j'}))u_{ij} - c \geq u_{ij} \tag{2.43}$$

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

$$\nu_{ij'} \geq \underbrace{\frac{w_j d_{ij}^{\frac{-1}{\varepsilon_{cw}}} \nu_{ij} + \frac{c}{P(A_{j'})}}{w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}}}_{\equiv \tilde{x}_{ijj'}} \tag{2.44}$$

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

2.F.1 The Individual's Elasticity

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

$$\tilde{\varepsilon}_{AW_{ij}^{j'}} = h(\tilde{x}_{ijj'}) \left(\tilde{x}_{ijj'} + \frac{c}{P(A_{j'}) w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \varepsilon_{PA} \, \tilde{\varepsilon}_{AW^{j'}} \right) \tag{2.45}$$

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

One can see a key change with the addition of search costs that as more workers apply for a job, they have an externality on other worker's choice decision, and this in turn can have a negative impact on the size of the responsiveness of an individual worker applying for a job. Intuitively, if a wage is posted much higher than the going market rate, some workers may not apply as they believe that the probability of getting the job goes down, and this matters when applications are costly. The size of this externality depends on two factors c and ε_{PA}. The role of the first of these is trivial while the latter depends somewhat on the production function of the firm. For example, if firms hire all workers that apply for a vacancy (such as on some online task markets) then $\varepsilon_{PA} = 0$ and the problem collapses to a similar framework as in section 2.3. In the situation where a firm only has one job vacancy on the other hand, $\varepsilon_{PA} > 0$ and any increase in applicants would reduce the probability of getting an offer. Additionally, without imposing any additional restrictions it is not clear that $\varepsilon_{AW_{ij}^{j'}}$ is positive for all individuals, nor that the elasticity is decreasing in the posted wage.

2.F.2 The Elasticity of Labour Supply To The Firm

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

$$\tilde{\varepsilon}_{AW^{j'}} = \frac{\varepsilon_{AW^{j'}}}{1+S^{j'}} \tag{2.46}$$

such that

$$S^{j'} = |\varepsilon_{PA}| \frac{\sum_{(i,j)} S^{j'}_{i,j}(1-F(x_{ijj'}))}{\sum_{(i,j)}(1-F(x_{ijj'}))} \tag{2.47}$$

and

$$S^{j'}_{i,j} = h(x_{ijj'}) \frac{c}{P(A_{j'}) w_{j'} d_{ij'}^{\frac{-1}{\varepsilon_{cw}}}} \tag{2.48}$$

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

2.G Relationship with Logit Models of Monopsony

A number of recent studies have used logit models of search (Card et al., 2018; Azar et al., 2019; Lamadon et al., 2019) to illustrate monopsony power in the labour market. The utility function set up in this setting with a Weibull distribution speaks directly to these models due to the relationship between the Extreme Value Type 1 distribution and the Weibull distribution.

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

$$\hat{u}^*_{ij} = log\ w_j - \frac{1}{\varepsilon_{cw}} log\ d_{ij} + \xi^*_{ij}. \tag{2.49}$$

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

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

$$\hat{u}_{ij} = \frac{1}{\beta} log\ w_j + \xi_{ij} \tag{2.50}$$

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

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

$$P_{ij} = Pr(\xi_{ij'} - \xi_{ij} < w_j - w_{j'}) \forall j' \neq j \in \mathcal{J} \tag{2.51}$$

Which gives the logit formulation

$$P_{ij} = \frac{exp(\frac{1}{\beta} w_j)}{\sum_{j'} exp(\frac{1}{\beta} w_{j'})} \tag{2.52}$$

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

$$A_j = L * \frac{exp(\frac{1}{\beta} w_j)}{\sum_{j'} exp(\frac{1}{\beta} w_{j'})} \tag{2.53}$$

Taking logs, equation (2.53) can be re written as

$$a_j = log(L) + \frac{1}{\beta} w_j - log\Big(\sum_{j'} exp(\frac{1}{\beta} w_{j'})\Big). \tag{2.54}$$

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

$$\varepsilon_{AW} = \frac{1}{\beta}(1 - s_j) \tag{2.55}$$

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

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

3

Living wages and age discontinuities for low-wage workers [1]

Abstract

This paper considers an emerging, highly policy relevant feature of minimum wages, studying what happens when a wage floor significantly higher than a nationally legislated minimum is imposed. The consequences of age-wage discontinuities and wage floors higher than mandated minimum wages are explored in the context of a Living Wage being introduced to a large UK organisation through time. Between 2011 and 2019, the Company was exposed to a Living Wage Rate higher than the statutory National Minimum Wage, which was sequentially introduced into some of its establishments and had the effect of boosting wages and strongly increasing the age-wage discontinuity from age-related pay grades. The analysis finds positive labour supply responses at the age discontinuity before Living Wage treatment, but a fall in hours at the discontinuity following treatment. The Living Wage raised wage costs but did not affect aggregate hours, showing a within-establishment reallocation of hours by age arising from differential eligibility to be paid the Living Wage.

[1] Joint work with Stephen Machin.

3.1 Introduction

Study of minimum wages, and their economic effects, has once again become a common preoccupation of researchers. There are a number of reasons why. Many countries are experiencing low real wage growth and a minimum wage policy is one that can directly boost the wages of low-wage workers. Viewed through this lens, minimum wages have become the policy tool of choice as some places – like US and UK cities – have raised local minimum wages above the presiding national or state legislated minimum wage. Some companies (for example, Amazon, IKEA, Wal-Mart) have raised their own lowest wage above the mandated minimum. And in the recent past some countries, most notably Germany in 2015, that did not previously have a national minimum wage have introduced one at a relatively high level.

These features of minimum wages have resulted in a sizable upsurge of recent research which has broadened the remit in this area. A clear focus has been placed on studying newer questions relative to the very sizeable past research literature that placed a principal focus on studying the employment effects of minimum wages.[2] Because of the widespread finding from a range of studies that the employment effects tend to be modest, if they exist at all, more recent research looks at other forms of adjustment to the wage cost shock that minimum wages induce (see, for example, Draca et al. (2011), Hirsch et al. (2015), Bell and Machin (2018), and Harasztosi and Lindner (2019)), on changes in the composition of worker wages and employment (Giuliano (2013), Dustmann et al. (2022), and Giupponi and Machin (2021)) and on local minimum wages (Dube and Lindner (2021)).

This paper studies an emerging, highly policy relevant feature of minimum wages. It studies what happens when a significantly higher wage floor than a nationally legislated minimum is imposed. It is able to adopt a research design where some establishments of a firm progressively raised their minimum wage floor to a level higher than the prevailing national minimum wage. The setting is the UK, where the company studied was exposed to a Living Wage Rate higher than the statutory National Minimum Wage sequentially as it was introduced into some of its establishments in a staggered sequence between 2012 and 2019. The Company is an employer of a large number of low-wage workers with over 300 establishments across the UK and operates in the service sector. While the Company's main competitors are firms operating in the private sector, a large part

[2]The various phases of minimum wage research are summarised well in reviews by Brown et al. (1982) on the first generation of time series studies, by Card and Krueger (1994) on the second generation of so-called "revisionist" quasi-experimental research and by Brown (1999) on both. See also a review making closer links between minimum wage research and monopsony in the labour market by Manning (2021).

of the firm's business is government procurement contracts.

A new focus has emerged in recent years on living wages, wage rates which are required to meet minimum standards given the costs of living. In the UK this is exemplified by the Living Wage Foundation which calculates rates for London and the rest of the UK and has accredited over 7,000 employers. In the US MIT operate a living wage calculator for different states, cities and metro areas (Glasmeier, 2020 [Online]) and hundreds of cities have passed living-wage ordinances (Dube and Lindner, 2021; Sosnaud, 2016).[3] This interest has emerged at least in part as a result of claims that national minimum wage levels (or federal and state minima in the US) have not been adequate to meet the cost of living (Iacurci, 2021 [Online]). This paper presents a detailed account of how firms respond to a "true" living wage, calculated according to a consumption basket of goods and services deemed necessary for an acceptable standard of living.[4]

The paper studies the impact of introducing the Living Wage Rate on wages and hours in The Company, leveraging two sources of credibly exogenous variation: a staggered mandated Living Wage treatment and a discontinuity in the age-wage profile. Due to age eligibility criteria for the Living Wage the interaction of these two effects results in differential discontinuities in the age-wage profile for treated and untreated establishments. Thus, the setting lends itself to an event study research design, a regression discontinuity design, and the interaction of these two which is referred to as a "difference-in-discontinuity" design. The analysis finds that the Living Wage raised wages but did not damage aggregate jobs and hours. It did, however, result in a reallocation of workers by age because of differential eligibility to be paid the Living Wage. In particular we find that younger workers around the age eligibility cut-off experience a loss of hours and, in some cases, earnings as the firm is able to substitute them with older workers, as a direct result of the Living Wage introduction.

3.2 Experimental Setting

The Living Wage Foundation (LWF) is a charitable organisation in the UK, established in 2011, that campaigns for employers to pay workers a living wage. Each year the LWF calculates and publishes a Living Wage rate for London (LLW) and the rest of the UK (UKLW). The LLW rate has typically been approximately 30-35% higher than the official

[3]Many of these US city living wage ordinances are lower than the rate as recommended by the MIT Living Wage Calculator for the area and are more precisely de facto higher local minimum wages, not living wages.

[4]For details of the methodology underpinning the calculation, and the history of the UK Living Wage, see D'Arcy and Finch (2019).

statutory National Minimum Wage (NMW) applicable to over 21s, or National Living Wage (NLW) applicable to over 25s, while the UKLW has been about 15-20% higher as can be seen in figure 3.B.1 of the Appendix. However, unlike the statutory NMW, the LLW and UKLW comprise only of a single rate which is applicable to all workers over the age of 18, with 16 and 17 year olds in work not being covered by the Living Wage. The NMW on the other hand is currently comprised of 4 different age-specific rates: age 16-17, age 18–20, age 21-24 and age 25+.

Organisations voluntarily sign up to become Living Wage employers and following appropriate audits by the LWF can achieve accredited status. As of July 2020, the LWF lists 6,562 accredited employers and included in this list are 107 local government units.[5] When public bodies achieve accreditation, they are given an amnesty on existing procurement contracts, but are expected to enforce the living wage at the start, renegotiation or renewal of contracts.

The Company operates in the service sector and the majority of their business is through procurement contracts with local councils.[6] As the firm operates hundreds of establishments across the UK, different establishments become contractually obliged to pay the LLW and UKLW at different times. This is dependent on whether, and when, the local government unit has voluntarily signed up to the LWF's Living Wage, as well as idiosyncratic timings of contractual renewal or renegotiation.

Between 2012 and 2019, 107 local government units gained accreditation. For example, of the 32 London Boroughs, 17 have received accreditation, the earliest (Islington in North London) receiving accreditation in May 2012, and the most recent (Redbridge in the East of the city) receiving accreditation in November 2018.[7] As figure 3.2.1 shows, this setting gives substantial variation in Living Wage treatment for establishments run by The Company. In particular, over the period for which we have HR data approximately 140 establishments went from being untreated to treated, while run by The Company. The remainder never pay Living Wages and therefore the relevant minimum wage floor to them is the UK National Minimum Wage.

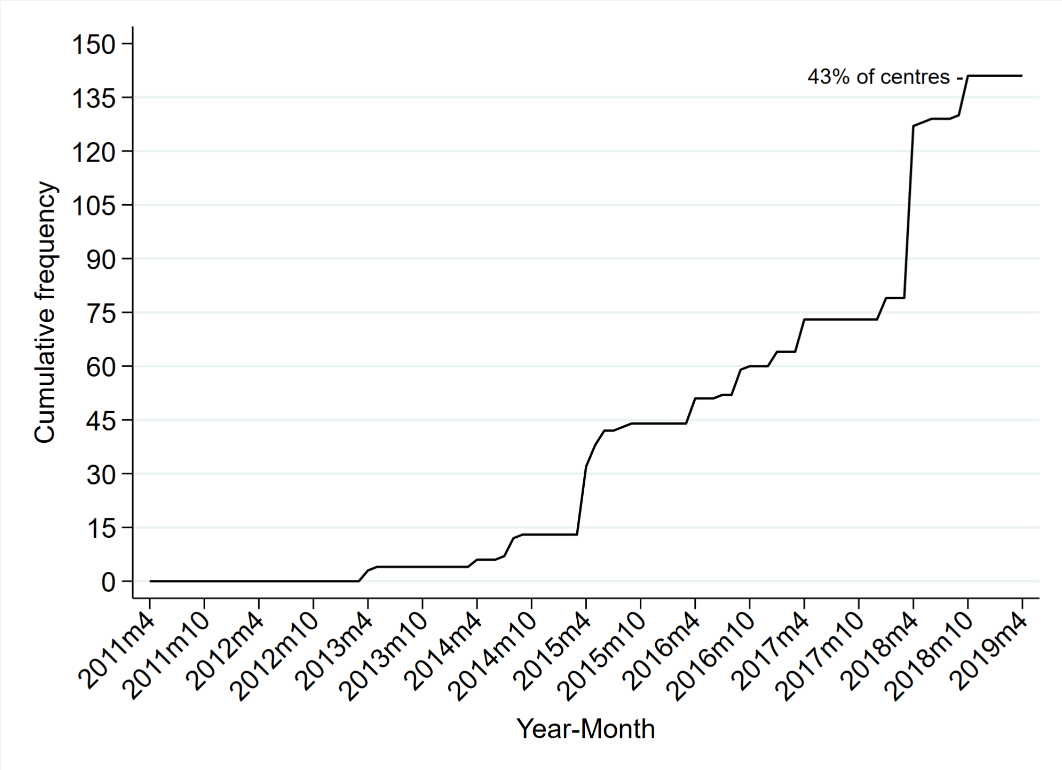
This variation in Living Wage treatment is combined with the fact that The Company has an already existent pay structure which operates an age-related pay scale for their

[5] These include London Boroughs, Unitary Authorities, Metropolitan Districts, County Councils, District Councils, Local Government Districts and Parish Councils.

[6] Councils here refer to Principal Councils which are local government authorities carrying out statutory duties in England and Wales. They are responsible for a wide range of public services including transport, education, planning, and cultural services, and operate local tax collection. There are 355 principal councils in England and Wales and this includes 33 London boroughs.

[7] Correct as of July 2019.

Figure 3.2.1: Living Wage Treatments Over Time



Note: *The figure reports the number of treated establishments over time. The figure only includes which were treated while run by The Company. Some establishments were already subjected to the Living Wage when taken over by The Company.*

entry-level[8] (unskilled) jobs.[9] In particular, similar to the NMW, their pay-scale has a sizeable discontinuity at age 18.[10] The Living Wage treatment, which only treats those over 18, therefore has the effect of increasing the size of this age-wage discontinuity. It is thus possible to implement a "Differences-in-Discontinuity" design, exploiting both an exogenous treatment to wages as well as a seemingly arbitrary discontinuity in wages as a function of age, where the treatment effects the size of the discontinuity.

The setting combined with the dataset allows a novel analysis of how a wage floor could affect highly exposed young workers employed on casual contracts (specifically on zero-hours contracts[11]) where hours adjustments face no frictions, both in terms of wages and

[8]Entry-level jobs are essentially unskilled jobs. Roles with this classification would typically be considered "minimum wage" jobs in the UK.

[9]This pay-scale is centrally determined, however establishments have independent control over both intensive and extensive margin employment, as well as employment composition.

[10]Many companies have a sizeable discontinuity at this particular age, when individuals become adults in UK law. The NMW for example as of April 2020 implies a statutory rate of £4.55 for under 18s and a statutory rate of £6.45 for age 18-20.

[11]Such contracts mean firms are not obligated to give workers hours, and when offered them workers are not obligated to work them. For a fuller description of the of what these types of contracts entail see Datta et al. (2019).

employment along the intensive margin. The presence of the discontinuity at age 18 would likely result in both supply and demand effects, where young workers would be willing to supply more labour just after the age 18 cut-off, and budget conscious managers would be less willing to give such workers as many hours. Furthermore, when an establishment is exposed to a higher wage floor it is likely that labour supply to the establishment across the whole age range would increase, potentially suppressing demand for younger workers.[12] By comparing the size of the discontinuity in wages and hours before and after treatment, the analysis is able to disentangle which of these effects dominates, and thus assess the impact on young workers.

As all establishments are operated by the same company using the same structure of operations and management, but with establishment level autonomy over employment and workforce composition, a true counterfactual when comparing treated and untreated establishments can be estimated. Additionally, and unlike in many minimum wage papers, the approach can isolate the impact of just the individual establishment being exposed to a higher wage floor, rather than the entire market. This is because when a local government unit voluntarily signs up to the LWF's Living Wage, private companies and non-council public employees in the area remain untreated.[13] Furthermore, the establishment located within the treated council would not be contractually obliged to the Living Wage until renewal or renegotiation, introducing further idiosyncrasies in when the establishment must raise wages. Thus, the estimates presented here will not be contaminated by general equilibrium effects that could be present in other settings.

3.3 Data and Empirical Method

3.3.1 Data

This study analyses a novel dataset which contains the complete HR data of The Company for the period of 2011–2019. As stated in the introduction, The Company operates in the service sector and a large portion of its turnover is from government procurement contracts, for local council services. It is worth noting that the council services they provide are not typical natural monopolies, and other private firms compete in the same local markets.

The HR data contains very detailed information on all workers in each of The Company's establishments. In addition to the usual information such as job tenure, wages,

[12] See chapter 2 for evidence of this.

[13] The proportion of workers treated within a local authority is a small fraction of a percentage. Council employment only makes up approximately 3% of employment and typical council jobs are paid above the wage floor. For more information see chapter 2.

age and demographic characteristics, there is very detailed data on the specific job role that each worker carries out, the precise dates of wage changes, and exact hours worked from timesheet data.

Table 3.A.1 in the Appendix presents summary statistics for workers employed by The Company as of 2019. The Company is big, employing approximately 19,000 workers and has a large proportion of female workers (60%). Half of the workers are based in London and 5% of all workers are less than 18 years old, this proportion is considerably higher for casual entry-level workers (12%). The workforce is younger on average (36 years) than the national average (43 years), and this is more pronounced at 31 years old for entry-level workers. Three quarters of entry-level workers are on casual contracts which puts The Company in a very flexible position to adjust employment along the intensive margin.

The average hourly wage is £12.88 per hour, which is approximately 25% lower than the average hourly wage for the UK in 2019.[14] The average hourly wage for entry-level workers is £9.38, almost half of the UK mean and about 15% higher than the UK National Living Wage shown in Appendix figure 3.B.1. The average worker works approximately only one quarter of full-time hours, casual entry-level workers only work on average about 5 hours per week. Given the large proportion of casual staff the summary statistics suggest that permanent employees work much closer to full time hours (the exact figure is 132 hours per month for the mean permanent employee). This is in line with the national average.[15]

3.3.2 Empirical Method 1 – Differences-in-Discontinuity

The first part of the empirical analysis leverages a "Differences-in-Discontinuity" research design, to estimate the effect of the key variables – the Living Wage, the age discontinuity at age 18 and the interaction of the two - on the wages and hours of entry-level casual workers. Age is normalised around 18 such that $age = age^* - 18$, where age^* is the true measure of age, the discontinuity (D) is defined $D = 1[age \geq 0]$, and treatment from Living Wage introduction ($T = 1$ when introduced), the wage equation for entry-level casual worker i employed at establishment e in year y and month m takes the form

$$\begin{aligned}\ln(wage)_{ieym} &= \beta_1 D_{ieym} x T_{eym} + \beta_2 D_{ieym} + \alpha_1 T_{eym} + \alpha_2 age_{ieym} \\ &+\alpha_3 age_{ieym} x D_{ieym} + \alpha_4 age_{ieym} x T_{eym} \\ &+\alpha_5 age_{ieym} x D_{ieym} x T_{ieym} + \gamma_e + \lambda_{ym} + \xi_{ieym}\end{aligned} \tag{3.1}$$

This equation has the same format as a typical regression discontinuity design with a

[14]This stood at £17.27, as calculated from the Annual Survey of Hours and Earnings.
[15]140 hours per week, as calculated from the Annual Survey of Hours and Earnings.

linear predictor for the running variable (age in months above/below 18) either side of the discontinuity. In addition, however, the specification allows for the pre 18 and post 18 slopes to differ based on whether the Living Wage treatment has been applied. Additionally, equation (3.1) includes both establishment (γ) and year-month fixed effects (λ), as is conventional in a difference-in-difference specification.

The main parameters of interest are β_1 and β_2. In specification (1), β_2 identifies the impact of the age discontinuity in the pay-scale schedule on wages, while β_1 identifies the impact of the Living Wage treatment on the size of this wage discontinuity. If the Living Wage raises wage levels and generates an additional premium for reaching age 18, β_1 is expected to be positive and this is the first key hypothesis to be tested in the analysis.

After the first stage wage equation, the analysis then considers whether there is an intensive margin employment response to Living Wage introduction. This first stage of wages and second stage of labour adjustment, of course, is predicated on the same logical basis as the way the big literature on minimum wages and employment proceeds, except here we are looking at a wage floor higher than the mandated minimum. To investigate this second stage, the same structure specification (1) is adopted, except now with hours worked as the dependent variable:

$$\begin{aligned} \ln(hours)_{ieym} = \beta_3 D_{ieym} x T_{eym} + \beta_4 D_{ieym} + \alpha_6 T_{eym} + \alpha_7 age_{ieym} \\ + \alpha_8 age_{ieym} x D_{ieym} + \alpha_9 Age_{ieym} x T_{eym} \\ + \alpha_{10} Age_{ieym} x D_{ieym} x T_{ieym} + \gamma_e + \lambda_{ym} + \xi_{ieym} \end{aligned} \tag{3.2}$$

Now the two main parameters of interest are β_3 and β_4. In (2), β_4 identifies the impact of the age discontinuity in the pay-scale schedule on hours, while β_3 identifies the impact of the Living Wage treatment on the size of the hours discontinuity. Equation (3.1) and equation (3.2) are estimated on both a wide window of 24 months either side of the age cut-off (i.e. on the sample of 16 to 20 year olds), and a smaller window of 12 months either side of the age cut-off (i.e. for 17 to 19 year olds).

As discussed above, the impact of the increase on wages on hours worked is ex ante ambiguous. This is because an increase in wages should in theory have oppositely signed labour supply and demand responses. In the case of $\beta_4 > 0$, this would suggest the labour supply response of the age-wage discontinuity dominating the labour demand response, and vice versa. Similarly, $\beta_3 < 0$ would suggest that the Living Wage is resulting in some intensive margin unemployment effects for those workers around the age 18 discontinuity. Furthermore, depending on the sign of β_3, it is possible to place lower bounds on the labour supply elasticity to the firm, by dividing the respective parameter by its counterpart parameter from specification (1). For example, if $\beta_4 > 0$, then $\frac{\beta_4}{\beta_2}$ gives a lower bound on the labour supply elasticity for casual youth workers. This is because the labour demand response can be reasonably assumed to be weakly negative and β_4 would contain both supply and demand effects.

3.3.3 Empirical Method 2 – Event Study

The approach in Empirical Method 1 is informative for generating evidence about local impacts around the age 18 cut-off. This enables the analysis to precisely showing how the Company is able to adjust to the LW introductions. To study how this local adjustment translates into an impact for the establishment as a whole, and therefore to ascertain whether the Living Wage has an impact on aggregate wages, employment and hours on the intensive margin, an event study estimator is implemented at the establishment level which, because of its staggered nature, treats the multiple treatment timing of the setting with due caution.

Borrowing notation from Sun and Abraham (2020), let Y_{eym} denote an outcome of interest for establishment e at year-month ym with treatment status $T_{eym} \in \{0, 1\} : T_{eym} = 1$ if e is treated in period ym and $T_{eym} = 0$ otherwise, where treatment is absorbing, and therefore $T_{es} \leq T_{eym}$ for $s < ym$. An establishment's treatment path can therefore be characterised by $K_e = min\{ym : T_{eym} = 1\}$, and $K_e = \infty$ if the establishment is never treated. Establishments can therefore be categorized into disjoint cohorts k$\in ym_{min}, ..., ym_{max}, \infty$, where establishments in cohort k are first treated at the same time $e : K_e = k$. Y^k_{eym} is the potential outcome in period ym when establishment e is first treated at time k and Y^∞_{eym} is the potential outcome at time ym if establishment e never receives treatment. A cohort-specific average treatment effect on the treated l periods from treatment is thus:

$$CATT_{k,l} = E\left[Y_{e,k+l} - Y^\infty_{e,k+l}\right| K_i = k] \tag{3.3}$$

This notation allows for treatment effect heterogeneity across cohorts, which in this setting may be important as the bite of the living wage may change over time. The key estimate of interest is then some weighted average of (3), for $l \in g$, to construct a relative period coefficient. As is often the case when firms face a shock to the wage floor, the interest is in the average dynamic effects (which allows an analysis of the pre-trends).
For analysing these average dynamic effects, a weighted average similar to that proposed in Sun and Abraham (2020) is

$$v_g = \frac{1}{|g|}\sum_{l\in g}\sum_{k} CATT_{k,l} Pr\{K_e = k | K_e \in l\} \tag{3.4}$$

which effectively uses weights according to the size of the treated cohort that experiences l periods relative to treatment.

In practice, (4) is estimated using the following methodology in three steps:

1. For each treatment cohort estimate an adjusted form of the typical, two-way fixed effect event study specification, limiting l to 12 months before and after the treatment period.

$$Y_{eym} = \gamma_e + \lambda_{ym} + \sum_{l \neq -1,-12} \delta_{k,l} T_{e,ym+l} + \beta' X_{eym} + \varepsilon_{eym} \tag{3.5}$$

   where variables are the same as above, and X_{eym} is a set of time varying establishment level controls. For each treatment cohort k, the control group is restricted such that they have not received treatment within the past two years or will not receive treatment within two years of the relevant treatment cohort treatment date. This is to ensure no overlap of dynamic effects between the treated and control groups. As per the suggestion of Borusyak and Jaravel (2017), the dynamic effects are normalised to two periods, -1 and -12, to deal with the underidentification issues they raise.

2. Estimate the weights $Pr\{K_e = k | K_e \in l\}$ by sample shares of each cohort in the relevant relative period l.

3. Combine steps 1 and 2, and aggregate monthly affects l, to the level of quarters, g, for graphical representation by taking a simple equal weighted mean. In particular

$$\hat{v_g} = \frac{1}{3} \sum_{l \in g} \sum_{k} \hat{\delta}_{k,l} \hat{Pr}\{K_e = k | K_e \in l\} \tag{3.6}$$

There has been a recent surge in interest in the workings of difference-in-difference and event study estimators, especially when like here there is variation in treatment timing and heterogenous treatment effects (for example, see Callaway and Sant'Anna (2020); Goodman-Bacon (2021); Sun and Abraham (2020); and Borusyak and Jaravel (2017)). Concerns raised include: issues identifying the linear component of the path of pre-trends in traditional event study specifications (Borusyak and Jaravel, 2017); contamination of lead and lag coefficients from other period effects (Sun and Abraham, 2020); biased estimates of treatment effects when the control group contains treated units when dynamic treatment effects are present (Goodman-Bacon, 2021); and the structure of weights assigned across treatment cohorts when estimating dynamic treatment effects (Sun and Abraham, 2020). The estimator used here is akin to that suggested in Sun and Abraham

(2020) and also implements adjustment as recommended in Borusyak and Jaravel (2017) in an attempt to overcome the aforementioned issues.[16]

3.3.4 Empirical Method - Robustness

The approach used in the main estimating equations (3.1) and (3.2) is more flexible than the standard two-way fixed effect estimator used in a typical difference-in-difference setting as it exploits variation in both Living Wage treatment and the discontinuity at age 18. Despite this, as a matter of caution we additionally implement a robustness check where we compare the Living Wage impacts on wages from the event study estimates using the Sun and Abraham (2021) style estimator with a traditional event study regression of the form:

$$ln(Wage)_{eym} = \gamma_e + \lambda_{ym} + \sum_{l \neq -1,-12} \delta_l LW_{e,t+l} + \beta' X_{et} + \varepsilon_{et} \tag{3.7}$$

aggregated to quarterly effects according to

$$\hat{v}_g = \frac{1}{3} \sum_{l \in g} \hat{\delta}_l \tag{3.8}$$

Assuming the estimates of $\hat{v}_g$ from equation (3.8) are similar to those from equation (3.6), which is robust to the aforementioned issues, this is suggestive that the main estimating equations (3.1) and (3.2) are unlikely to suffer from the above issues.

3.4 Results

This section presents the findings, beginning with the first and second stage wage and hours differences-in-discontinuity-based estimates, moving to consider aggregate establishment level impacts, and then offering an interpretation of the key results.

3.4.1 Wages

The top panel of figure 3.4.1 reports scatter plots of the mean log wage by months relative to age 18 for entry-level casual workers in establishments treated and untreated with the Living Wage, orthogonalized against time and year fixed effects. There is a clear discontinuity at age 18 in both cases, and either side of the discontinuity the wage to age correlation appears mostly flat. The size of the discontinuity for workers in treated

[16]For a more complete discussion of some of the discussed issues and how the implemented event study estimator deals with these, see Datta and Machin (2021).

centres (approximately 18 log points) is considerably larger than the discontinuity in untreated centres (approximately 12 log points).

Columns (1) and (2) of Table 3.4.1 present results from the counterpart regressions to the top panel of figure 3.4.1, from estimating specification (1). The parameter estimates suggest in untreated establishments as an entry-level casual worker moves from age 17 to 18 they experience a 12% increase in wages. For those in treated establishments the increase in wages is considerably higher, at about 20%. Workers within the sample also experience on average 4-5% higher wages from Living Wage treatment. This figure is likely to be higher when considering all entry-level workers rather than those just around the age 18 cut-off, given the proportion receiving direct treatment would be larger. The estimates of the main parameters of interest for specification (1) do not fundamentally vary based on the width of the window considered around the age 18 cut-off and all are highly statistically significant.

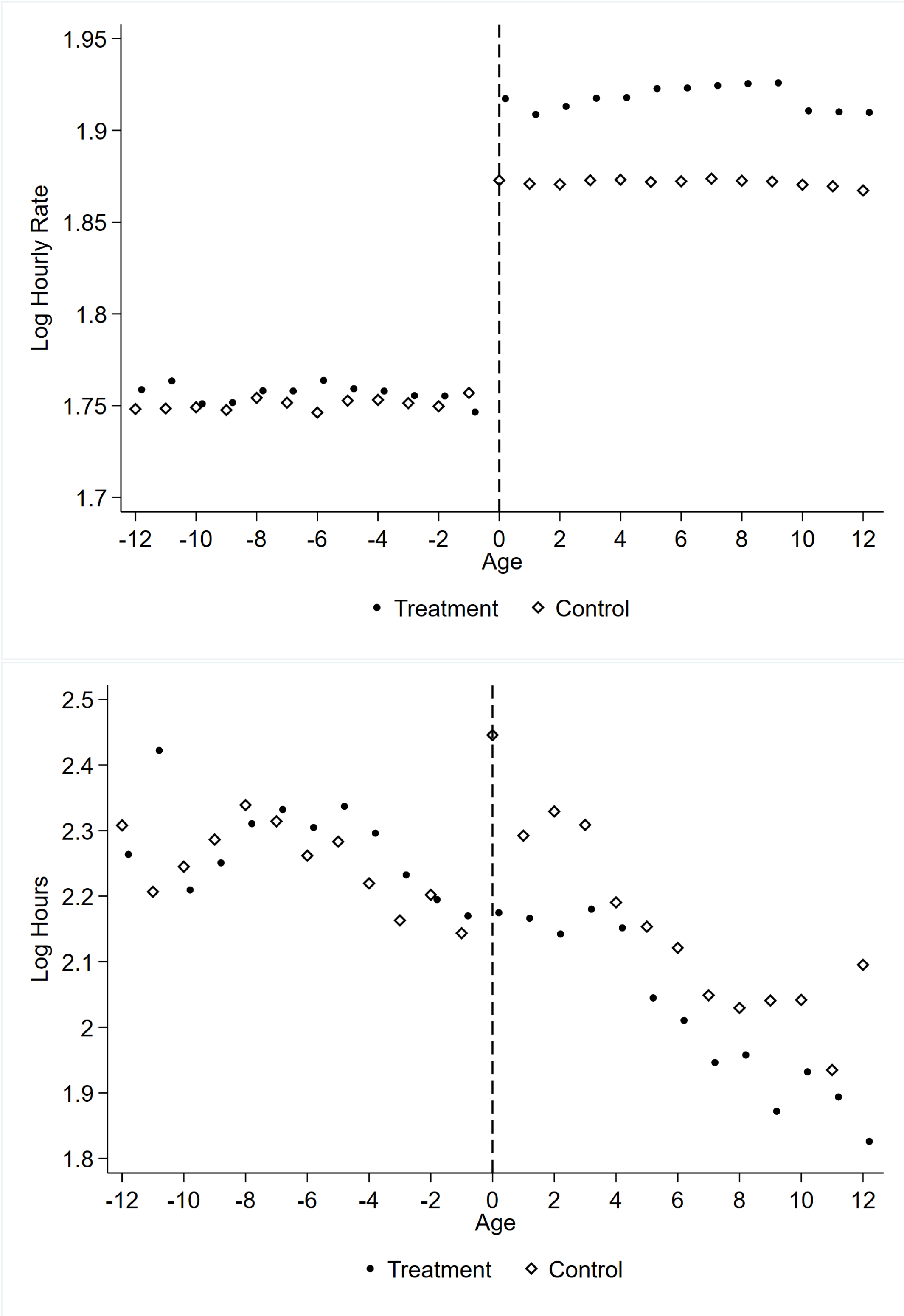
3.4.2 Hours

The bottom panel of figure 3.4.1 is of the same form as the top panel for wages, but instead shows mean log hours by months relative to age 18. Unsurprisingly, the number of log hours worked features more noise than its wage counterpart. But the figure shows a positive discontinuity in log hours at age 18 for workers untreated with the Living Wage, and a structural difference in this discontinuity for those treated with the Living Wage. The difference in hours between the treatment and control group for post age 18 workers is relatively consistent across the year following the discontinuity, with all control group age bins working more hours than their treated counterparts.

It is also clear this difference for the two groups did not exist prior to the age 18 cut-off. The year following turning 18 workers have a downward trend in the number of hours they work, reducing average hours worked by approximately 2 hours over the year. This is likely driven in part because many of this age group would still be engaged in full time, pre-university, education and examination assessments take place during their eighteenth year. Importantly however, the trend is consistent across both groups. This gives additional credence to the identification strategy which exploits the difference in hours between treated and untreated centres, as well as the age 18 cutoff.

Columns (3) and (4) of table 3.4.1 report parameter estimates for specification (2) to confirm this. In particular, the estimates show that as casual entry-level workers move from age 17 to 18, they work 10-17% more hours. The positive sign and size of this parameter suggests a strong labour supply response from casual youth workers. In the

Figure 3.4.1: Wage and Hours Discontinuities



Note: *The top and bottom figures respectively report log wages and log hours controlling for establishment and year-month fixed effects, by months relative to age 18 for 2 years before and after the cut-off, for those treated and untreated with the Living Wage. The dashed line marks the age 18 cutoff. The sample is a panel of entry-level casual workers employed by The Company active between January 2011 and April 2019.*

Table 3.4.1: Wage and Hours Equations

	(1) Log Wage	(2) Log Wage	(3) Log Casual Hours	(4) Log Casual Hours
Eighteen X Treated	0.072 (0.015)	0.072 (0.015)	-0.326 (0.102)	-0.266 (0.093)
Eighteen	0.121 (0.007)	0.128 (0.007)	0.097 (0.045)	0.166 (0.046)
Treated	0.056 (0.015)	0.052 (0.014)	0.099 (0.126)	0.084 (0.125)
Age/100	0.120 (0.037)	-0.024 (0.048)	-0.655 (0.314)	-0.801 (0.504)
Age/100 X Eighteen	-0.143 (0.042)	-0.007 (0.005)	-.1.679 (0.427)	-2.502 (0.631)
Age/100 X Treated	-0.057 (0.068)	-0.090 (0.096)	1.472 (0.700)	0.381 (1.046)
Age/100 X Eighteen X Treated	0.109 (0.082)	0.122 (0.120)	-0.721 (0.940)	0.377 (1.325)
Centre FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Sample Size	94606	55176	94606	55176
R2	0.740	0.754	0.179	0.180
Window	±24 Months	±12 Months	±24 Months	±12 Months

Note: *The table reports parameter estimates from model (3.1) and (2) under different sample windows around the age 18 cut-off. Standard errors are clustered at the establishment and are reported in parentheses.*

presence of no demand effects, this would imply a labour supply elasticity to the firm of approximately 1.3 according to the specification using the smaller window.[17]

For those in treated establishments, the discontinuity in casual hours drops between 26-33 percentage points, indicative that the change in hours around the discontinuity becomes negative. According to the specification using the ±12 month window, hours fall for workers as they move to the positive side of the discontinuity by approximately 10% in treated establishments. Both columns 3 and 4 therefore reveal a strong negative impact on intensive margin employment for casual youth workers just over the age 18 cut-off as a result of a higher wage floor. Parameter estimates for β_1 and β_3 imply that casual youth workers around the age 18 cut-off experience a 7% increase in wages due to the Living Wage treatment, but a fall in hours of 26-33%.[18]

3.4.3 Aggregate Effects

Figure 3.4.2 shows the coefficients from (6) and examines the aggregate effects at the establishment level of the Living Wage on intensive margin employment. Column (1) in Table 3.A.2 in the appendix presents the counterpart point estimates and standard errors. As can be seen there is an absence of differing pre-trends suggesting that the common time trend assumption necessary in such settings is not violated. Following the Living Wage introduction there is no change in aggregate intensive margin employment. Figures 3.B.2[19] and 3.B.3 in the Appendix, present event study plots for log wages using parameter estimates from equations (3.6) (the robust estimator) and (3.8) (the traditional estimator) respectively. Columns (2)-(5) in Table 3.A.2 in the appendix present the counterpart point estimates and standard errors. The figures show a sharp, statistically significant rise in wages for all workers (approximately 1.5%) and entry-level workers (approximately 6.5%) which is roughly consistent throughout the year following treatment. The results between the two estimators are strikingly similar which suggests our main estimating equations are unlikely to be biased by the issues mentioned in the previous section.

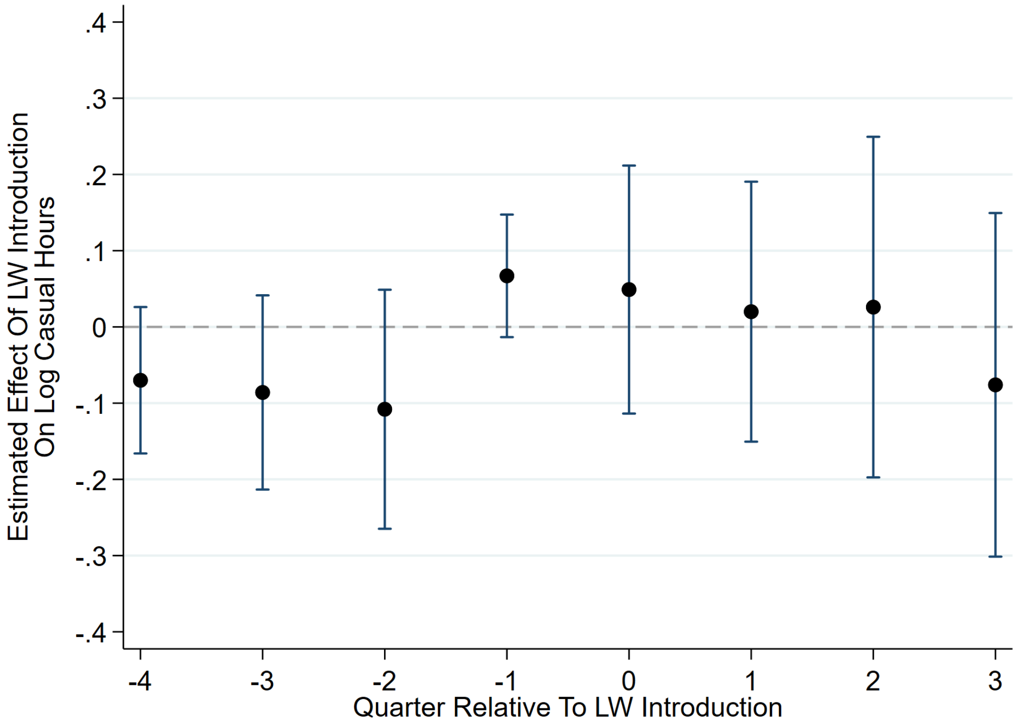
These results suggest that the Living Wage introduction acted to affect the way that hours are distributed across workers within the establishment, but not the total number

[17]The elasticity when using the wider window is 0.8 which, even if a little smaller in magnitude, still very clearly supports the interpretation of a strong supply side response to the Living Wage.

[18]patial heterogeneity analysis suggests that workers around the age 18 cut-off in London experienced a 10.3% increase in wages due to the Living Wage treatment (standard error 0.027), and a fall in hours of 36.5% (standard error 0.131). The parameter estimates of β_2 (0.098, standard error 0.007)) and β_4 (0.126, standard error 0.068) for the 12-month window for those in London suggest a lower bound labour supply elasticity of 1.3, identical to the main specification.

[19]Impacts on aggregate employment are reported in Datta and Machin (2021) and similarly show no effects.

Figure 3.4.2: Living Wage Effect on Total Casual Hours



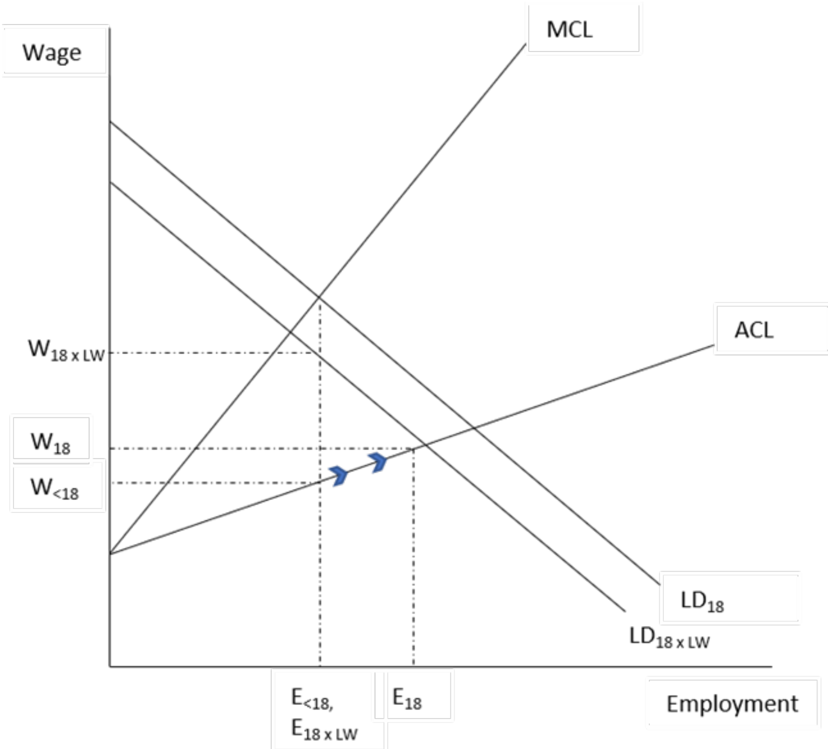
Note: *The graph reports the estimates coefficient from model (3.6). The sample is a panel of establishments run by The Company active between January 2011 and April 2019. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors. Parameters are normalised to month -1 and -12.*

of hours worked. In particular, hours are shifted away from casual workers who have just crossed the age 18 boundary where the Living Wage becomes binding. Those in treated centres crossing the boundary experience a 19% increase in wages, and a drop in hours of 10-22% depending on specification, suggesting the impact on earnings could be negative. Against the counterfactual of those in untreated centres, who experience a 12% increase in wages and an increase in hours of 10-16% the fall in earnings is even more pronounced.

3.4.4 Discussion

The above results can be rationalised and explained in a simple model of a firm with monopsony power in the labour market. This is illustrated in figure 3.4.3. The coefficients on β_4 and β_2 imply a lower bound on the labour supply elasticity to the firm for 18 year olds of approximately 1.3. On the figure this corresponds to the movement from E¡18 to E18 under demand condition LD18. When the establishment is required to pay the Living Wage, the wage for 18 years olds increases as well as the wages for all older workers in entry-level positions. As the firm has monopsony power, this induces a positive labour supply response from older workers to the firm as the firm is able to substitute younger 18 year olds for older workers, thus reducing demand for 18 year olds. Therefore, employment for 18 year olds falls back to the original level due to the movement along and shift in of the labour demand curve. Additionally, as employment is unaffected at the establishment level, the fall from E18 to E18 x LW must in turn have a 1:1 increase across older workers. Assuming a positive relationship between age and productivity, it is clear why a firm would substitute 18-year olds for older workers.

Figure 3.4.3: Monopsony Market for 18 Year Olds



Note: *The figure presents a basic model of monopsony, with changes in the wage due to changing age from just less than 18 (W¡18) to just over 18 (W18), and an increase due to the Living Wage which only affects those over 18 (W18 x LW), and how this impacts employment (E). The figure has lines representing the Marginal Cost of Labour (MCL), Average Cost of Labour (ACL), Labour Demand for those around age 18 (LD18) and Labour Demand for those around age 18 when the establishment is subject to the living wage (LD18 X LW).*

3.5 Conclusion

Living wages have increasingly been receiving attention in the news and in policy circles in both the US and UK. This has come about from concerns regarding the existing mandated minimum wages arguing that they are simply too low for families to live on (Glasmeier, 2015 [Online]) . Interest has been magnified by concerns about stagnating real wages. Recently we have seen companies in the UK such as IKEA pledging to pay a living wage. The landscape appears to be changing in this regard. In the UK The Living Wage is a policy tool being considered at a governmental level. The Welsh government, for example, recently set up the Social Care Fair Work Forum, where one of their positions is to ensure all care workers are paid the Living Wage.

This paper offers novel evidence on how firms respond to a living wage, specifically the Living Wage Foundation's Living Wage, which is considerably higher than the UK mandated minimum wage. Using a bespoke dataset for a large service sector firm with hundreds of establishments across the UK that are as good as randomly exposed to a Living Wage, this paper shows that the Living Wage had a strong impact on wages and no aggregate impact on total hours worked. However, utilising discontinuities in the age-wage profile for The Company which change in size as a result of exposure to the Living Wage, the analysis demonstrates that exposed establishments reallocate hours away from workers just over the age 18 cut-off. Because of this hours reallocation, the results suggest that workers just over the age 18 cut-off actually experience a loss of earnings as a result of the living wage introduction, and establishments are able to do this due to increased labour supply from older, possibly more productive, workers.

The results in this paper should be interpreted carefully, at least partly because they apply to a single firm. In a setting where all (or more) firms are exposed to a higher minimum wage it is not clear that firms would be able to reallocate hours in the same way, as labour supply responses would likely be muted. Likewise, for an industry specific Living Wage, for example the case of social care referred to above, the extent of hours reallocation will depend on the labour supply elasticity to the market rather than the firm, which is also likely to be considerably smaller. The main finding of the paper does, however, suggest that there are settings where firms can absorb higher wage costs in adjustment to a living wage level higher than the prevailing mandated minimum wage, and in the one studied here this seems largely due to the presence of monopsony power.

Appendix

3.A Additional Tables

Table 3.A.1: Summary Statistics

	2019			
	All		Entry-level	
	Mean	S.D.	Mean	S.D.
Female	0.60	0.49	0.55	0.50
BAME	0.22	0.42	0.25	0.43
Age	35.94	14.31	31.43	13.86
<18	0.05	0.22	0.09	0.29
<18 - Casual	0.07	0.25	0.12	0.32
London	0.53	0.50	0.50	0.50
Casual	0.72	0.45	0.75	0.43
Tenure (weeks)	194.10	214.15	139.04	157.08
Hourly Wage (£)	12.88	5.87	9.38	3.24
Hourly Wage (£) - Casual	13.17	6.12	9.34	3.63
Hours (monthly)	35.76	64.48	28.95	56.92
Hours – Casual (monthly)	14.54	26.83	19.13	29.84
Number of Workers	18,773		9,183	

Note: *The table reports parameter estimates from model (3.6) for log(casual hours) and log(wages) and from model (3.8) for log(wages) for different samples of workers, and are the counterpart estimates for figure 3.4.2, figure 3.B.2 and figure 3.B.3. Columns (1), (2) and (3) report bootstrapped standard errors in parentheses and columns (4) and (5) report standard errors clustered at the establishment in parentheses. Columns (2) and (4) include controls for the proportion of entry-level workers.*

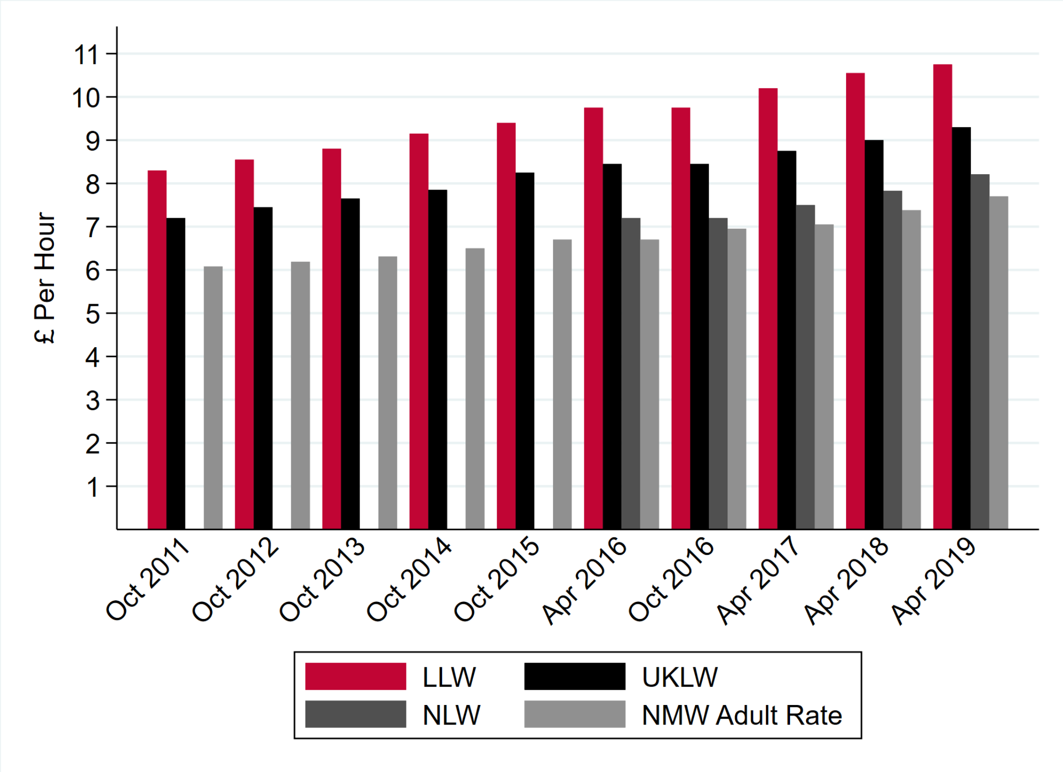
Table 3.A.2: Event Study Estimates

	(1) log(casual hours)	(2) log(wage)	(3) log(wage)	(4) log(wage)	(5) log(wage)
Treated x Quarter					
-4	-0.070 (.049)	0.001 (.001)	-0.002 (.002)	-0.005 (.005)	-0.008 (.004)
-3	-0.086 (.065)	0.005 (.003)	-0.002 (.003)	-0.002 (.004)	-0.007 (.004)
-2	-0.108 (.080)	0.005 (.002)	0.003 (.002)	0.002 (.003)	0.001 (.003)
-1	0.067 (.041)	0.002 (.001)	0.002 (.001)	0.002 (.001)	0.000 (.001)
0	0.049 (.083)	0.016 (.003)	0.061 (.004)	0.018 (.004)	0.062 (.005)
1	0.020 (.087)	0.019 (.003)	0.065 (.004)	0.021 (.004)	0.066 (.005)
2	0.026 (.114)	0.016 (.004)	0.066 (.005)	0.020 (.005)	0.065 (.006)
3	-0.076 (.115)	0.012 (.005)	0.065 (.006)	0.018 (.006)	0.065 (.006)
Centre FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Sample Size	17,879	17,879	17,879	17,879	17,879
Estimating Equation	(6)	(6)	(6)	(8)	(8)
Sample of Workers	All	All	Entry-Level	All	Entry-Level

Note: *The table reports parameter estimates from model (3.6) for log(casual hours) and log(wages) and from model (3.8) for log(wages) for different samples of workers, and are the counterpart estimates for figure 3, figure 3.B.2 and figure 3.B.3. Columns (1), (2) and (3) report bootstrapped standard errors in parentheses and columns (4) and (5) report standard errors clustered at the establishment in parentheses. Columns (2) and (4) include controls for the proportion of entry-level workers.*

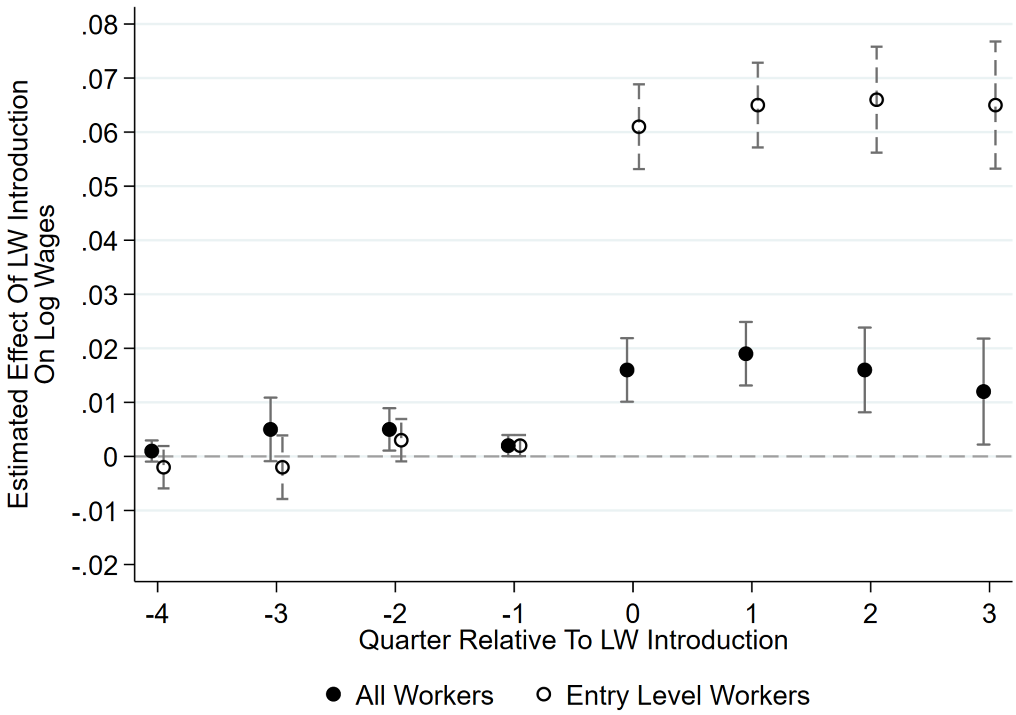
3.B Additional Figures

Figure 3.B.1: Living and Minimum Wage Rates



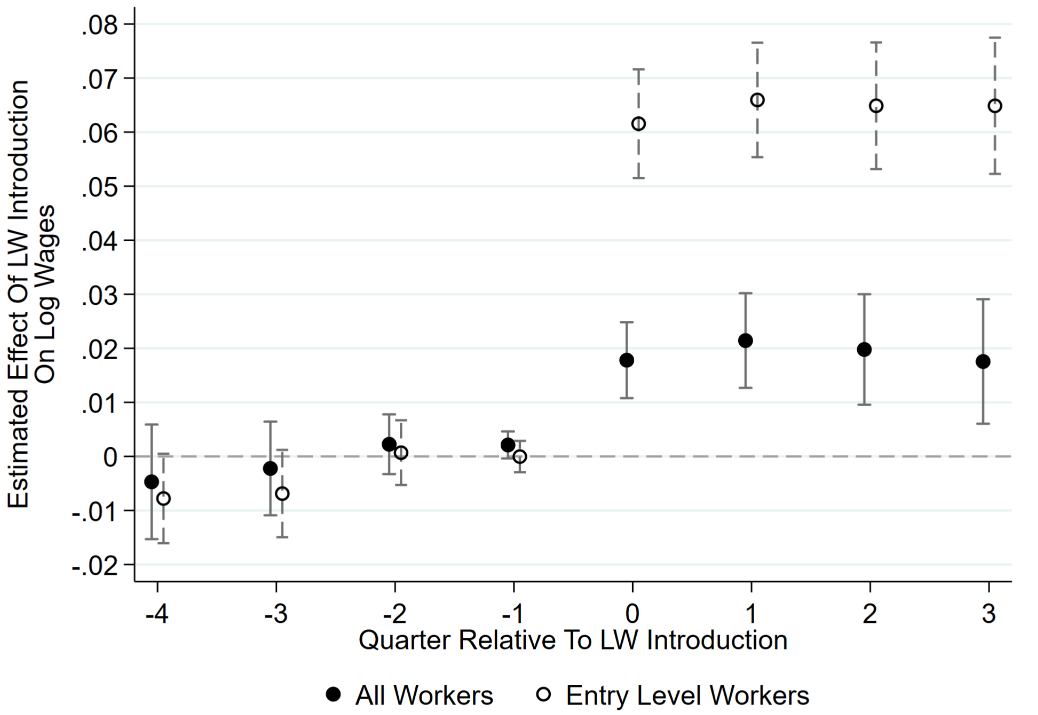
Note: *The figure presents the hourly wage rate of the nationally mandated 21+ minimum wage (NMW Adult rate), the 25+ minimum wage (NLW) and the Living Wage Foundation's non-London UK rate (UKLW) and the London rate (LLW).*

Figure 3.B.2: Living Wage Effect on Wages I



Note: *The graph reports the estimates coefficient from model (3.6). The sample is a panel of establishments run by The Company active between January 2011 and April 2019. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors. Parameters are normalised to month -1 and -12.*

Figure 3.B.3: Living Wage Effect on Wages II



Note: *The graph reports the estimates coefficient from model (3.8). The sample is a panel of establishments run by The Company active between January 2011 and April 2019. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors. Parameters are normalised to month -1 and -12.*

4

Zero Hours Contracts and Labour Market Policy [1]

Abstract

The evolving nature of atypical work arrangements is studied. A particular focus is placed on one such form of work relation: zero hour contracts (ZHCs). The paper uses existing secondary data and new survey data collected for the specific purpose of studying alternative work arrangements to describe the nature of ZHC work in the UK labour market. The interaction with labour market policy is also explored, in the context of the 2016 introduction of the UK's National Living Wage. ZHC work is shown to be an important feature of today's work arrangements, and a higher minimum wage has resulted in an increased use of ZHCs in the UK social care sector, and in low wage sectors more generally.

[1] Joint work with Giulia Giupponi and Stephen Machin.

4.1 Introduction

Contemporary labor markets feature the use of "atypical" work arrangements. Some of these – like self-employment and agency work – have emerged in their current format as an evolution of previous work structures. Others – like short hours and zero hours contracts – reflect more the work demands of the modern age, with their introduction driven by technical and social change.[2] The increased incidence of this kind of work has led to discussions of there being a trade-off between additional flexibility and the emergence of low wage, dead end jobs, which function outside the job legislation offered in conventional forms of employment.

From a research perspective, it is important to try to determine which side of this trade-off dominates, and if it differs by work arrangement. In this paper, we consider the case of the UK labor market where the rise of atypical work has been a key feature of the post-financial crisis period. The focus is placed specifically on one kind of alternative work arrangement that has increasingly entered the UK setting, namely zero hours contracts (ZHCs). Almost a million people are on ZHCs at the time of writing, out of a total workforce of 32 million. Many of these ZHC work positions are prominent in the low-wage sectors of employment. Their relevance to labor market policy that affects low wage levels is therefore high.

The principal focus of the paper is placed upon developing a better understanding of ZHCs and labor market policy. More specifically, in doing this, the paper has two main aims. The first is to empirically document the evolution and characterization of ZHCs in the UK setting. There are two parts to this, the first drawing on data from the Quarterly Labour Force Survey and the second on newly collected survey data on alternative work arrangements. Part of the latter survey is devoted to ZHCs, which are only limitedly surveyed and understood in existing survey data sources (Abraham and Amaya (2018)) and - consequently - in the literature, and the intention is to fill this gap with new evidence.

The second aim is to explore the extent to which labor market institutions have the scope to be, at least partly, responsible for the increased diffusion of flexible work arrangements, or – conversely – whether the latter are a consequence of factors that have little to do with labor market institutions and rigidities. In this paper, a particular policy focus is placed on minimum wages, where we are interested in understanding whether higher minimum wages have potential to induce a larger utilization of alternative work arrangements by firms and, consequently, a shift in the composition of their workforce towards

[2] Workers on zero hours contracts agree to be available for work as and when required, with no guaranteed hours or times of work.

more flexible, but also insecure jobs.

In Europe, the rise of alternative work arrangements and gig-economy jobs is often considered an expression of the duality of the labor market, whereby the existence of rigidities in the "primary" market creates the conditions for an expansion of more flexible contractual relationships in the "secondary" market. Alternative work arrangements have also grown in the US, where labor markets are overall less rigid than in Europe, but minimum wages are an important component of labor market policies. By providing direct evidence on the role – or lack thereof – of minimum wage policies on the incidence of flexible work arrangements, this paper contributes to understanding a policy question relevant to both the US and European labor markets.

In the first part of the paper, survey-based evidence is presented to show that ZHCs are a key contract type in some, predominantly low wage, sectors of the UK labor market. They are characterized by the flexibility/dead end jobs trade-off already introduced above. They also feature, in different guises or by different names, in other countries' employment structures. The second part of the paper analyzes minimum wage policy and ZHC utilization by exploiting a substantial increase in the minimum wage rate for workers aged 25 and over that took place in the UK in April 2016, when a new minimum wage rate – the National Living Wage (NLW) – was introduced (Bell and Machin (2018); Giupponi and Machin (2018)). In the UK setting, ZHC usage by employers does seem to have been affected by changes in labor market policy, as the sizable hike of the minimum wage that occurred when the NLW was introduced did shift more workers onto ZHC positions in the adult social care sector (and in low wage sectors more generally). To our knowledge, this is the first study connecting minimum wage changes to employer use of different types of job contracts.

The rest of the paper is structured as follows. In Section 4.2, a description of the atypical work arrangement under study, ZHCs, is given, together with a discussion of the extent to which other countries have similar job contracts. In Section 4.3, the relevant literature to the subject matter of the paper is discussed. Section 4.4 reports the analysis that documents the patterns of ZHC coverage in the UK labor market. Section 4.5 describes the evidence on minimum wages and ZHC jobs. Section 4.6 concludes.

4.2 Atypical Work Arrangements: Zero Hours Contracts

4.2.1 Zero Hours Contracts in the UK

ZHCs are an employment contract under which a worker is not guaranteed any hours and is only paid for work carried out. It can be viewed as a form of on-call working, as workers can be offered hours at short notice, as and when an employer needs them. Workers are not obliged to accept work that has been offered to them and, similarly, employers are not obliged to offer any work.[3] Thus, ZHCs offer flexibility to both the employer and the employee, and, as a result, some workers may prefer them to typical fixed hour employment contracts. Conversely, due to the lack of security and guaranteed income, they are unlikely to be suitable for many workers. Such contracts have become prevalent in particular industries such as retail, health, and hospitality.

ZHCs have, in theory, always been possible to be used by employers in the UK and have no specific legal status, rather being an informal term to refer to a type of contract. Their use has seen an increase over the past decade. Estimates from the Office of National Statistics (ONS) suggest that in 2008 143,000 employees were on ZHCs whereas by 2017 this figure was 883,000. Until 1998, ZHCs were often used to "clock off" workers during quiet periods nonetheless expecting them to stay on site, though this exploitative practice was ended in 1998 with the passing of the Working Time Regulations.
Table 4.2.1 presents a breakdown of various legislation coverage for different forms of employment relation in the UK setting. While ZHC workers are covered by some employment legislation, such as minimum wage coverage and holiday pay, legal complications have arisen due to the nature of the contract. One key area of contention has been whether a worker is also considered an "employee", which would in turn grant them additional rights, such as unfair dismissal protection (Adams et al. (2018)).[4] While the contract itself would not classify workers as employees, case law in the UK to date has concentrated more on whether there is a pattern of regular work being accepted, and if so the employee classification would be granted (Pyper and Powell (2018)).

ZHCs have received a fair amount of attention both in the UK media and from the UK Parliament. The Conservative-Liberal Democrat coalition government that was in power from 2010 to 2015 launched a review of the use of ZHCs in 2013. This raised four main areas of concern – exclusivity clauses, transparency of contracts offered to workers, uncertainty of earnings and an imbalance in the employment relationship. Up to now, the

[3] It is questionable however, whether all ZHC roles afford workers this ability in practice (Wakeling (2014)).

[4] Workers are still afforded a number of core employment rights, unlike for example, those gig economy workers who are officially self-employed and thus are not covered.

Table 4.2.1: Forms of Employment in the UK

	Permanent employment	Zero hours contract	Self-employment
National Insurance contributions	Employers pay NI contributions on their employee's earnings and benefits, above the threshold of £162 a week, at a rate of 13.8%. Employees pay NI on their earnings and benefits above the threshold of £162 a week at a rate of 12%. Above the earnings threshold of £892 a week this drops to 2%	Employers pay NI contributions on their employee's earnings and benefits, above the threshold of £162 a week, at a rate of 13.8%. Employees pay NI on their earnings and benefits above the threshold of £162 a week at a rate of 12%. Above the earnings threshold of £892 a week this drops to 2%	Contributions are only made by the worker. Above the yearly profit threshold of £6,205 there is a flat rate of £2.95 per week. Between £8,424 and £46,350 there is a rate of 9% and above £46,350 the rate drops to 2%
Minimum wage	Covered	Covered	Not covered
Holiday pay	Full-time employees are entitled to 28 days paid holiday leave per year, and part time employees the pro-rata equivalent	Entitled to the same degree of holiday pay as permanent employees. Due to the nature of ZHC work, many firms include holiday pay in the workers hourly wage rate	Not entitled to holiday pay
Sick pay	Entitled to statutory sick pay, only if they earn at least £116 per week	Entitled to statutory sick pay, only if they earn at least £116 on average from one employer	Not entitled sick pay
Unfair dismissal protection, Minimum notice periods and Statutory redundancy pay	Protected against unfair dismissal, covered by statutory minimum notice periods, and entitled to statutory redundancy pay	Employer could offer zero hours in perpetuity, thus effectively no protection against unfair dismissal, no minimum notice period, no redundancy pay	Not covered by unfair dismissal protection, minimum notice periods or statutory redundancy pay

Notes: National Insurance contributions build up your state pension, whilst also helping to pay for the NHS and other welfare services. Reports from the UK's Citizens Advice Bureau suggests some employers attempt to avoid paying out sick pay to ZHC workers, and stop hours for those workers who do try to claim. Some instances of case law in the UK have tried to establish that ZHC workers who work regular hours may be eligible for aspects of dismissal protection.
Source: UK Government Website.

only area which has been legislatively addressed is that concerning exclusivity clauses, i.e. clauses that prevented workers on ZHCs from working for more than one employer. As of March 2015, the *Small Business, Enterprise and Employment Act 2015* came into force and effectively banned exclusivity clauses on ZHCs.

4.2.2 Zero Hours-Like Contracts: the International Setting

As stated above there is no legal definition in the UK for ZHCs, and thus international comparisons rely on assessing qualitative similarities. This can often be problematic due to the differences in terminology, legal status and governance. Similar atypical working arrangements however do exist and there is varied diffusion across Europe and other developed economies, though they often operate under different names, and levels of regulation. Caution should nonetheless be taken when drawing parallels as the welfare implications of such arrangements will also rely on factors such as union coverage and domestic economic performance.

Probably the largest proportion of such atypical contracts exists in Australia, where "casual employment" contracts are a legal classification and approximately 25 percent of employees are on such contracts. Around half of workers on these contracts receive variable earnings from one period to the next, and around a third would like more hours (A and T (2018)). Australia is however an outlier in this case, since most developed economies where zero hours-like contracts are used generally have usage rates in the same region as the UK. In Canada 3.2 percent of employment is in "casual employment" and in the US approximately 2.6 percent is "on-call". In Europe, Finland reported 4 percent of employees on ZHCs and Norway 0.8 percent; in Netherlands 6.4 percent are "on-call", and the Irish Quarterly National Household Survey reports that approximately 5.3 percent of Irish employees have constant variation in their working hours.[5] Given the varied definition and sometimes lack of a legal classification, equivalent statistics do not necessarily exist for all countries where there is diffusion.

The attention these types of contracts have received in the media and political sphere are not unique to the UK. Following union pressure, New Zealand passed regulation in 2016 which stipulated that firms needed to outline a minimum number of guaranteed hours each week and employee refusal of hours beyond that should not result in any detriment to the worker. Furthermore, it introduced the requirement of compensation to the worker if shifts were cancelled at short notice. In Finland, a citizen's initiative gathered

[5] Figures for the Netherlands are from 2016; for Finland, Ireland and the US from 2015, and for Norway from 2010.

50,000 supporters to ban ZHCs, and though it was rejected by the parliament, a number of proposals have been made in order to regulate such employment relationships. The most recent looks to ensure that employers present a valid reason (relating to demand fluctuations) as to why they require to use a ZHC. Extensive regulation was introduced in 2012 and 2013 to "on-call" work in Italy and has severely restricted the use of zero hours-like contracts to only older and younger age groups, and in 2014 further regulation was introduced in both the Netherlands and France.

Table 4.2.2 presents a comparative set of descriptions and associated regulations for zero hours-like contracts in Western Europe (where they are present) and for the US. Western Europe generally experiences significant regulation of zero hours-like contracts. For example, while proliferation in the EU is largest in the Netherlands, workers there enjoy regulations that ensure a minimum number of hours of work whenever they are called to work, as well as agreed hour adjustments based on the previous three months of work. Conversely, unlike the UK, employees must work when called upon. Such idiosyncrasies exemplify how outwardly similar contractual agreements may have very different implications when in action. What is evident, however, is that the UK, Sweden and the US (aside from some specific cities) appear to have the least regulation of zero hours-like contracts. Union density in Sweden is high (around 70 percent), but in both the UK and the US rates are much lower (23.2 percent and 10.7 percent respectively). Thus, proliferation of zero hours (-like) contracts in the UK and the US, where workers' real wage growth has been weak, are likely to have the most significant welfare implications.

4.3 Related Literature

4.3.1 Atypical Work Arrangements

Employment relationships such as ZHCs, diverging from the standard full-time, permanent, regular and single employer set-up have been characterized as "atypical" (Eurofund (2017)) and such working arrangements have seen a large amount of growth in the past two decades in a number of developed economies (Eichhorst and Tobsch (2013); Gielen and Schils (2014); LSE Growth Commission (2017); Katz and Krueger (2019b)). The concept of "atypical" work arrangements has always been somewhat nebulous, but spans a variety of working practices including part-time, agency, contract, fixed-term, contingent and independent contracting. Studies have demonstrated the large heterogeneity across these types of employment relationships, though part time and temporary work fare relatively badly in terms of wages when compared to their standard counterpart (Kalleberg (2000)).

Table 4.2.2: Zero Hour-Like Contracts in Europe and the United States

Country	Contract type	Description and/or regulation
France	N/A	ZHCs are outlawed in most cases. All part-time contracts must include the number and distribution of hours. Collective bargaining agreements require a minimum of 24 hours per week but can be reduced at the request of the employee. Exceptions for youth in education and temporary agency workers
Germany	On-call work	Generally, contracts must specify weekly and daily working hours. If agreed by the employer and employee (or employee representative) a contract could avoid specifying weekly working hours, in which case 10 weekly working hours are deemed to be agreed. If the daily working hours are not specified, the employer is bound to call the employee for at least 3 consecutive hours per day
Italy	On-call work	Contracts exist but are heavily regulated. Contracts must be justified by reference to production cycles and organization needs, and companies who use them must notify the ministry of labour. Banned from public administration, weekend work and bank holiday work. Only workers under 25 and over 55 can be placed on them. Limits to 400 working days over 3 years and then automatic conversion into full-time permanent contract
Sweden	On-call work	These contracts give no fixed hours and the employer can vary the working hours. No known regulation
Norway	Zero hours contract	Until recently such contracts made up around 0.8% of the workforce. Case law from 2005 and 2017 has deemed the use of permanent contracts where employees were to work only on-call as illegal and evading temporary employment law (which has strict usage and limitations). New regulation has been proposed by government to explicitly prohibit ZHCs
Netherlands	Zero hours contract	Unlike the UK, there is an obligation on behalf of the employee to work when called upon. Each time an employee is called to worker, they must be paid a minimum of 3 hours wages (even if there is less than 3 hours work for them). Following 3 months of continuous employment on a ZHC, the agreed number of hours adjusts to the average number of hours during the previous 3 months
	Min-max contract	Employees are given a guaranteed number of hours – weekly, monthly or annually. These are always paid even if the employer is unable to provide work. If the guaranteed number of hours per week is 15 hours or less, then similar regulation to the ZHCs is enforceable. During periods of high demand, employers and employees can agree upon extra hours
United States	On-call/ "Just-in-time" schedules	Diffusion of on-call working arrangements have increased from 1.6% in 1995 to 2.6% in 2015 (Katz and Krueger (2019b)). There is no federal regulation, however eight states operate "show-up pay" laws, where employers are required to pay workers for a minimum number of hours (no matter how long they work), if they have been called to work. Coverage however varies across these eight states, and a number of exemptions exist. A few cities (e.g. San Francisco, Seattle, New York) operate fair scheduling ordinances. For example, San Francisco requires new employees to receive a written estimate of their expected days and hours of shifts. Schedules must be posted at least two weeks in advance, changes with less than a week notice results in compensation entitlement for the employee, and employees required to be on call but not working are also entitled to some compensation. If employers have available hours, these must be offered to current part-time employees before hiring additional part-time workers

Source: Eurofund (2015); O'Sullivan et al. (2015); McCrate (2018).

ZHCs most closely match the definition for contingent work, and early literature suggested that atypical working arrangements, especially in the form of temporary or contingent work, offered workers lower wages, fewer benefits, less security and little scope for human capital development (Rodgers and Rodgers (1989); M. Beard and R. Edwards (1995); Nollen (1996); Kalleberg (2000)).[6] Conversely, however, more recent (albeit weak) evidence has suggested that atypical work may serve as a stepping stone to more stable employment in the long run, when faced between an option of continued job search and atypical employment (Addison and Surfield (2008)).

The past few years have seen a growth in the interest in atypical or "alternative" work arrangements with a small portion of the literature presenting descriptive evidence as well as trying to understand the mechanisms driving the shift to such types of work. Factors that have been suggested to be contributors include weak demand conditions, worker's preferences and technological change; where the latter may work by reducing transaction costs. Since transaction costs – such as search, monitoring and enforcement costs – are, according to Coase (1937), factors that lead to the creation of the firm, it is likely that technological change would lead to a blurring of the boundaries of the firm.

Katz and Krueger (2019b) found that, over the ten year period between 2005 and 2015, the proportion of workers engaged in some form of alternative work arrangement grew by 10-20 percent in the United States, while analysis of the UK labor market has shown a growth in both the prevalence of ZHCs as well as individuals described as "self-employed with no employees" (LSE Growth Commission (2017)).

Katz and Krueger (2017) report US findings that individuals who suffer periods of unemployment are 7-17 percent more likely to be employed in alternative work arrangements 1 to 2.5 years later than their observational counterparts who did not experience such unemployment. These results suggest that at least one factor that could be driving the supply side of the atypical labor market is a weakening of market power for workers. Additionally, Mas and Pallais (2017) use a discrete choice experiment to elicit willingness to pay for alternative work arrangements for call center workers and find that the average worker is willing to give up a fifth of their wages to avoid an employer dictated work schedule. This gives further evidence that low paid workers finding themselves in contingent work arrangements are likely to be engaged in such work out of necessity rather than choice.

[6]Contingent work is defined as "any job in which an individual does not have an explicit or implicit contract for long-term employment or one in which the minimum hours worked can vary in a non-systematic manner" (Polivka and Nardone (1989)).

To our knowledge there is little recent research concerning the factors driving labor demand for contingent work arrangements. There are obvious benefits to employers, in particular the ability to reduce wage liabilities and cope with seasonal and weekly fluctuating demand conditions. Dube et al. (forthcoming) present evidence demonstrating significant monopsony power on an online labor market platform, though it should be noted such self-employed "HIT" work does have some key differences to more traditional sectors, which generally offer more on-going work.

4.3.2 Minimum Wages

Over its long existence as a key research area in labor economics, the minimum wage literature has evolved along three main lines of research. The primary and most traditional focus has been on the employment and unemployment effects of minimum wages, which have proven elusive to detect in many cases. Early studies based mostly on US time-series work found negative employment effects among teenagers (Brown et al. (1982)). However, apart from those, the vast majority of quasi-experimental micro-based work that started in the early 1990s in the US and the UK (Card and Krueger (1994); Machin et al. (2003); Stewart (2004); Giupponi and Machin (2018)), and of more recent analyses based on spatial identification in the US find hardly any evidence of disemployment effects of minimum wages (Dube et al. (2010); Baskaya and Rubinstein (2015); Dube et al. (2016); Clemens and Wither (2019)).[7]

Partly in response to this fairly widespread inability to find evidence of disemployment effects, a second strand of research has investigated other margins through which firms can adjust to the wage cost shock induced by the minimum wage increase. Examples of such margins of adjustment are prices (Aaronson (2001); MaCurdy (2015); Harasztosi and Lindner (2019)), profits (Draca et al. (2011)), firm value (Bell and Machin (2018)) and the quality of services provided (Giupponi and Machin (2018)). A third body of the literature has looked at the impact on wage inequality at the bottom of the distribution, and at wage spillover effects up the wage distribution and onto legally unaffected workers (DiNardo et al. (1996); Lee (1999); Autor et al. (2016); Giupponi and Machin (2018)).

To the best of our knowledge, this is the first paper examining the impact of a minimum wage change on contractual arrangements. We thus contribute to the existing literature by assessing the impact of minimum wages on workers' employment conditions (other than pay) and on the utilization of flexible contractual forms by firms that can act as

[7] In a rather different context of union bargained minima, Kreiner et al. (2017) study the effect of a change in the youth minimum wage in Denmark and find an employment elasticity to the wage rate of -0.8.

buffers against the wage cost shock. We do this by exploiting the introduction of the National Living Wage (NLW) in the UK in April 2016. The NLW is the mandated minimum wage rate for workers aged 25 and over; it was set at £7.20 an hour from April 2016 to March 2017, then uprated to £7.50 in April 2017.[8] As demonstrated by Figure 4.B1 in Appendix 4.B, while the UK has had various national minimum wages (NMW) in place since 1999, the NLW introduction represented a substantial (7.5 percent) increase in the wage floor for those aged 25 and over.

4.4 Survey Evidence of Zero Hours Contracts

4.4.1 ZHCs in the Labour Force Survey

The Labour Force Survey (LFS) is a quarterly cross-sectional survey of the UK labor market. Each quarter contains data on approximately 35,000 employees, some of whom could be on a ZHC. Questions relating to flexible work arrangements are asked only in quarters April-June and October-December therefore in each year it is only these two quarters that are analyzed.

Table 4.4.1 presents summary statistics for both all employees and ZHC employees for 2017. Of all workers in 2017, around 2.7 percent are recorded as being on ZHCs. ZHC workers are on average more likely to be younger, female, and still in full time education, though still a large proportion (over 80 percent) have completed their full-time education. It is unsurprising that female workers experience a higher incidence of ZHCs given they are more prevalent amongst part-time employees. Typically, ZHC workers have lower tenure, though it is unclear whether this is due to higher ZHC worker turnover rates or if longer tenured ZHC workers are more likely to be placed on more secure contracts. The mean hourly wage for ZHC workers is around £5 lower than the equivalent for all workers, and they work on average 10 hours less per week than the average employee. Interestingly, the median hourly wage for ZHC workers is very close to the 2017 NLW of £7.50 per hour, within approximately 5 percent.

Figure 4.4.1 and Table 4.4.2 exemplify the importance of the NLW for ZHC workers. Figure 4.4.1 shows there to be a very sizable spike in the wage distribution for ZHC workers at the 2017 NLW of £7.50 an hour. Table 4.4.2 shows that, while the NLW is important for a significant proportion of all employees, with around 6 percent paid exactly the NLW and 20 percent likely to be affected by the subsequent minimum wage uprating, the 2016

[8] Further details on UK minimum wage policies and the National Living Wage will be provided in Section 4.5.

Table 4.4.1: LFS Descriptive Statistics

	All Employees 2017		ZHC Employees 2017	
	Mean	S.D.	Mean	S.D.
Age	43.43	13.39	38.22	16.67
Prop. female	0.49	0.50	0.59	0.49
Prop. in full-time education	0.03	0.17	0.17	0.38
Age when completed full-time education	18.63	3.10	18.32	3.05
Median tenure	5-10 yrs		1-2 yrs	
Prop. part-time	0.29	0.45	0.67	0.47
Prop. aged under 25	0.09	0.29	0.31	0.46
Hourly wage	14.73	11.78	9.77	7.46
Hourly wage (aged 25+)	15.42	12.13	10.76	7.96
Hourly wage (aged under 25)	8.24	3.63	7.47	5.50
Hourly wage (median)	11.50		7.90	
Weekly hours	31.40	17.38	21.33	16.98
Prop. wanting more hours	0.08	0.27	0.25	0.43
Observations	71,604		1,907	

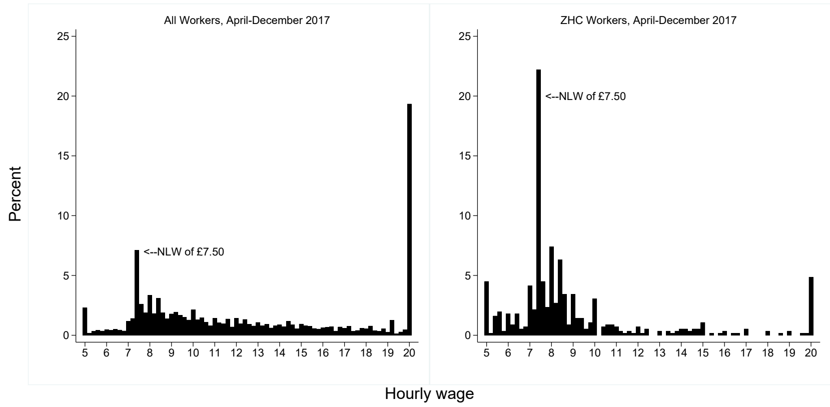
Notes: The table reports the mean and standard deviation of a set of individual characteristics for the employees from the LFS, for both all employees and ZHC workers, in 2017. The ZHC indicator only appears in April-June and October-December quarters of the LFS. Thus the above statistics use only those two quarters for each year. Wage data only appears in two waves of the survey, thus wage stats are based off approximately one third of the number of observations.
Source: LFS.

and 2017 upratings affected a lot more – around half – of all ZHC workers. This latter figure could increase when one considers the possibility of wage spillover effects up the distribution.[9] While the NLW is age specific and mandatory only for those aged 25 and over, there is strong evidence that there are spillovers for workers aged under 25 (Giupponi and Machin (2018)). Indeed, one can see that the proportion paid exactly the NLW is identical for all employees and for those aged 25 and over. This identity is lost, but only marginally, when considering ZHC workers.

The LFS also has a panel version of the survey, albeit with a much smaller sample size. We use this to produce transition Tables 4.4.3 and 4.4.4, which detail flows into/out of ZHC positions from/to different types of economic activity. As can be seen by the diagonals in both tables, ZHCs have the lowest persistence of all working arrangements presented. Over the period analyzed (2015-2018) just over a third of ZHC workers remained in ZHC positions after five quarters and, of ZHC workers, only a quarter were ZHC workers five quarters before. ZHC workers are most likely to transition from and to

[9]For evidence on the existence (or lack thereof) of spillover effects in the UK see Stewart (2012), Low Pay Commission (2009) and Butcher et al. (2012).

Figure 4.4.1: Hourly Wage Distribution for all Workers and Workers on ZHC



Notes: The graphs show the distribution of hourly wages for all workers and workers who declare to be on a ZHC. The distribution is censored at £5 and £20.00. The data are binned into £0.20 bins. NLW denotes the level of the National Living Wage.
Source: LFS.

Table 4.4.2: The Bite of the National Living Wage

	All Employees				ZHC Employees			
	2016		2017		2016		2017	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Prop. paid below next NLW	0.20	0.40	0.20	0.40	0.54	0.50	0.49	0.50
Prop. paid below next NLW (25+)	0.16	0.37	0.16	0.36	0.41	0.49	0.39	0.49
Prop. paid at NLW	0.06	0.23	0.06	0.24	0.18	0.38	0.20	0.40
Prop. paid at NLW (25+)	0.05	0.23	0.06	0.24	0.21	0.41	0.22	0.42
Observations	20,638		21,102		606		554	

Notes: The table reports the mean and standard deviation of proportions of employees impacted by the NLW, for both all employees and ZHC workers, for the years 2016 and 2017.
Source: LFS.

Table 4.4.3: Transitions out of ZHC Work (Between Quarter T and T+5)

Status in T	Status in T+5							
	Inactive	Unempl	Emp FT	Emp PT	Self FT	Self PT	ZHC	Total
Inactive	84.89	3.79	2.23	5.68	0.38	1.82	1.21	100.00 [2,641]
Unempl	21.20	36.71	19.94	15.19	0.63	1.90	4.43	100.00 [316]
Emp FT	2.47	1.13	88.91	4.41	1.79	0.49	0.81	100.00 [4,697]
Emp PT	7.20	1.55	9.50	76.22	0.75	1.55	3.22	100.00 [1,737]
Self FT	2.58	0.49	8.11	0.86	79.85	6.88	1.23	100.00 [814]
Self PT	11.50	1.47	2.95	6.19	10.03	66.08	1.77	100.00 [339]
ZHC	15.17	4.83	16.55	20.00	4.14	2.76	36.55	100.00 [145]
Total	24.62 [2,632]	2.92 [312]	42.69 [4,563]	16.71 [1,786]	7.47 [799]	3.63 [388]	1.96 [209]	100.00 [10,689]

Notes: For each type of economic activity today, the table reports the percentage of respondents by working arrangement in 5 quarters time. The data is pooled from the LFS panel survey, from January 2015 to March 2018. For all those in some form of employment, their primary job is reported. Sample sizes reported in square brackets.
Source: LFS.

other forms of part time employment, full time employment and inactivity.

These patterns of work dynamics act to confirm the somewhat precarious nature of ZHCs as a form of employment. One issue that emerges is whether workers who move from ZHCs into more secure working arrangements (part-time and full-time employment) do so by changing employer, or if after a period of time their employer offers a more secure contract. Equally, there is the question of whether those in "regular" work get reclassified by employers onto ZHCs. Sample size issues preclude any systematic and robust probing of this question with the data we have available, but when we investigated the interaction between job changes and changes in ZHC status for non-job changers, we found there to be a roughly half and half mixture of job moves and reclassifications. Clearly both are happening, but this remains suggestive as reaching a firmer conclusion would require more detailed and larger sample size longitudinal data than we are currently able to study.

Table 4.4.4: Transitions into ZHC Work (Between Quarter T and T+5)

Status in T	Status in T+5							
	Inactive	Unempl	Emp FT	Emp PT	Self FT	Self PT	ZHC	Total
Inactive	85.18	32.05	1.29	8.40	1.25	12.37	15.31	24.71 [2,641]
Unempl	2.55	37.18	1.38	2.69	0.25	1.55	6.70	2.96 [316]
Emp FT	4.41	16.99	91.52	11.59	10.51	5.93	18.18	43.94 [4,697]
Emp PT	4.75	8.65	3.62	74.13	1.63	6.96	26.79	16.25 [1,737]
Self FT	0.80	1.28	1.45	0.39	81.35	14.43	4.78	7.62 [814]
Self PT	1.48	1.60	0.22	1.18	4.26	57.73	2.87	3.17 [339]
ZHC	0.84	2.24	0.53	1.62	0.75	1.03	25.36	1.36 [145]
Total	100.00 [2,632]	100.00 [312]	100.00 [4,563]	100.00 [1,786]	100.00 [799]	100.00 [388]	100.00 [209]	100.00 [10,689]

Notes: For each type of economic activity today, the table reports the percentage of respondents by working arrangement 5 quarters before. The data is pooled from the LFS panel survey, from January 2015 to March 2018. For all those in some form of employment, their primary job is reported. Sample sizes reported in square brackets.
Source: LFS.

4.4.2 ZHCs in the LSE-CEP Survey of Alternative Work Arrangements

In order to better understand the role of alternative work arrangements in the UK, between February 5^{th} and March 2^{nd} 2018, we ran the "LSE-CEP Survey of Alternative Work Arrangements" using an online platform. While the survey was designed to be representative of the UK population aged 18-65, its main goal was to collect information on both the types of jobs and characteristics of workers involved in alternative work arrangements. The survey questionnaire is reproduced in Appendix 4.C. The survey questioned approximately 20,000 individuals, of which just fewer than 19,000 remained in the cleaned sample.[10]

Table 4.A1 in Appendix 4.A presents descriptive statistics for the sample of respondents of the LSE-CEP survey. The survey is equally represented across sex and the age distribution, with a slightly lower participation rate for the ends (18-24 and 55-65) of the surveyed age distribution. Additionally, there is a healthy mixture of qualification attainment as well as regional representativeness across the UK. Around half of our sample are employed by a private company, a further quarter are employed by either a non-profit or government and the remainder are split between some form of self-employment or not working. Sample attrition during cleaning does not appear to fundamentally change any of these statistics.

Table 4.4.5 presents descriptive statistics for ZHC workers, for the cleaned sample. ZHCs are spread roughly equally across the sexes of respondents, which is marginally different to the LFS proportion shown earlier in Table 4.4.1. ZHC workers in our survey are on average younger than the average worker, though surprisingly share a similar distribution of educational qualifications as all workers in the survey. One may have assumed that workers experiencing more insecure employment contracts would be those with lower skill sets and thus market power, however these summary statistics suggest otherwise. On the whole, a region's share of ZHC workers is roughly the same as their share of workers overall. However, London appears to be anomalous in that its share of ZHC workers is about four fifths higher than its share of workers. Interestingly, a large proportion of ZHC workers (42 percent in the cleaned sample) hold multiple jobs, and around a third hold a job with a more secure contract. This is suggestive that ZHC jobs may act as a form of "top up" income for some workers, and additionally some ZHC workers may hold multiple ZHC jobs as a form of insurance due to the possibility of lack of hours.

Hourly wages for ZHC workers in our survey are paid an average of £11.63 per hour; this is slightly higher than the same figure produced by the LFS for ZHC workers (£9.77).

[10] Respondents were excluded from the cleaned sample if they responded with gibberish to any open questions and/or did not answer the attention questions correctly.

Table 4.4.5: Sample of ZHC Workers in LSE-CEP Survey

	Mean	S.D.
Female	0.53	0.50
Age	36.28	13.21
Age 18-24	0.26	0.44
Age 25-34	0.25	0.43
Age 35-44	0.19	0.39
Age 45-54	0.18	0.38
Age 55-65	0.13	0.33
No qualifications	0.02	0.13
Some GCSE/O levels	0.10	0.30
5 or more GCSE/O levels	0.13	0.34
Trade/technical/vocational training	0.11	0.31
A levels	0.23	0.42
Bachelor's degree	0.27	0.45
Master's degree	0.11	0.31
Doctorate degree	0.03	0.16
North East	0.05	0.22
North West	0.12	0.32
Yorkshire and Humberside	0.06	0.23
East Midlands	0.08	0.27
West Midlands	0.09	0.29
Eastern England	0.08	0.26
London	0.19	0.40
South East	0.12	0.33
South West	0.08	0.27
Wales	0.04	0.20
Scotland	0.07	0.26
Northern Ireland	0.02	0.15
Married/Cohabiting	0.44	0.50
Widow/Separated/Divorced	0.10	0.30
Never married	0.45	0.50
Children	0.55	0.50
White	0.84	0.37
Mixed/Multiple ethnic group	0.04	0.20
Asian/Asian British	0.06	0.23
Black/African/Caribbean/Black British	0.06	0.23
Arab	0.00	0.06
Observations	1,167	

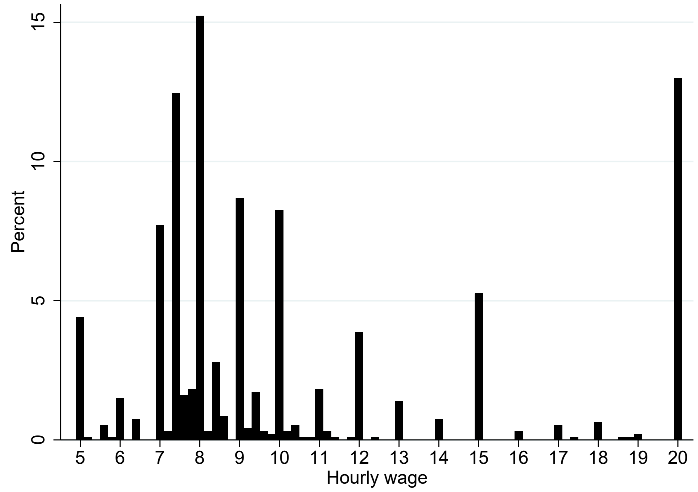
Table 4.4.5 Continued: Sample of ZHC Workers in LSE-CEP Survey

	Mean	S.D.
Multiple employers (ZHC jobs)	0.42	0.49
Non-ZHC job holder	0.34	0.47
Agriculture, forestry and fishing	0.01	0.08
Mining and quarrying	0.01	0.08
Manufacturing	0.07	0.25
Electricity, gas, steam and air conditioning supply	0.02	0.15
Water supply, sewerage, waste management	0.01	0.10
Construction	0.06	0.24
Wholesale and retail trade, repair of motor vehicles	0.09	0.29
Transportation and storage	0.06	0.24
Accommodation and food service activities	0.11	0.32
Information and communication	0.05	0.22
Financial and insurance activities	0.03	0.18
Real estate activities	0.01	0.07
Professional, scientific and technical activities	0.03	0.16
Administrative and support service activities	0.05	0.23
Public administration and defense	0.01	0.10
Education	0.09	0.29
Human health and social work activities	0.15	0.36
Arts, entertainment and recreation	0.06	0.24
Other service activities	0.06	0.23
Activities of households as employers of domestic personnel	0.01	0.12
Activities of extraterritorial organizations	0.00	0.07
Other	0.01	0.07
Hourly wage	11.63	8.16
Hourly Wage (median)	8.64	
Hours worked in previous week	18.62	13.67
Different days worked per week	4.06	1.71
Proportion doing unpaid hours	0.32	0.47
Average weekly unpaid hours	7.08	9.02
Less than one year of working experience	0.05	0.23
1-3 years of working experience	0.17	0.38
3-5 years of working experience	0.15	0.36
More than 5 years of experience	0.62	0.48
Less than one year of working experience in ZHC	0.52	0.50
1-3 years of working experience in ZHC	0.21	0.41
3-5 years of working experience in ZHC	0.14	0.35
More than 5 years of experience in ZHC	0.13	0.34
Received work-related training in the last year	0.55	0.50
Observations	1,167	

Notes: The table reports the mean and standard deviation of a set of individual characteristics for the sample of respondents who declared to be on a ZHC in the week prior to taking the survey.
Source: LSE-CEP survey.

Figure 4.4.2 presents the hourly wage distribution for ZHC workers in our survey. It can be seen that the modal hourly rate is £8 and that there is a large proportion of individuals paid around the region of the NLW rate of £7.50. Thus, it is likely to be the thicker right tail that is driving up the mean wage in the CEP survey compared to the LFS, rather than the entire distribution being centered higher.

Figure 4.4.2: Hourly Wage Distribution for Workers on ZHC

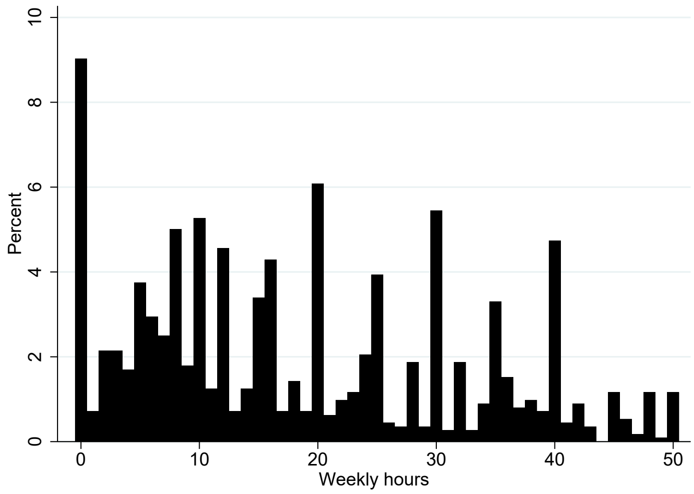


Notes: The graph shows the distribution of hourly wages for respondents who declare to be on a ZHC. The distribution is censored at £5.00 and £20.00. The data are binned into £0.20 bins.
Source: LSE-CEP survey.

The average number of hours worked is low (around 19 per week) and similar to the figure found in the LFS. This further concretes the fact that many ZHC workers are working less than full time. Figure 4.4.3 presents the weekly hours distribution. There is a large spread of the hours performed, with almost 10 percent of workers not doing any hours the previous week, which may well be reflective of the insecurity related to some ZHC jobs. There does appear to be a selection of workers performing full-time (or above full-time) hours, whether these hours are regular is however unclear.

What is striking is that around one third of ZHC workers do unpaid work each week, averaging at 7 hours per week. This would imply the average worker is losing out on approximately £80 per week. Such losses may be particularly important for social care workers (who we study in more detail below). As discussed in Rubery and G. Hebson (2014) domiciliary carers for example only get paid for face to face time, and time spent driving between clients may result in what they call a “fragmented time contract”. Almost two thirds of ZHC workers have been working for over five years. Conversely, over half of those sampled have less than one year experience on a ZHC, suggesting that an

Figure 4.4.3: Weekly Hours Distribution for Workers on ZHC



Notes: The graph shows the distribution of weekly hours of work for respondents who declare to be on a ZHC. The distribution is trimmed at the 95^{th} percentile.
Source: LSE-CEP survey.

abundance of those on ZHCs have previously held non-ZHC working arrangements.

There are a few industries which stand out as having a large share of workers on ZHCs. In particular, retail, education, accommodation and food services, and health and social work. For retail and accommodation and food services this is unsurprising, as these professions are characterized by having a larger proportion of workers on part-time contracts and may be subject to seasonal fluctuations. The health and social work sector has the highest proportion of ZHC workers (15 percent). The social care sector, which falls under this heading, has not only a large number of low paid staff, but also faces an informal price cap for its output good, as a large proportion of those receiving social care are council funded. It is thus a perfect sector to analyze to assess whether firms facing growing wage bills due to the NLW are likely to use ZHCs to reduce their wage liability.

4.4.3 LSE-CEP Survey Representativeness

Table 4.A2 in Appendix 4.A presents demographic variables (similar to those in Table 4.4.5 and Table 4.A1 in Appendix 4.A) for both all respondents and ZHC workers from the LFS, and can be used to check the representativeness of the CEP survey. In terms of overall representativeness, our survey fairs well with respect to age, qualifications and regional distribution. Our survey does however under sample those who did not have a job last week. Furthermore, the survey's representativeness of ZHC workers is generally

good, however one can see that the mean hourly wage is just under £2 per hour higher in our survey. The median wages however are more similar (the gap reduces to £0.64), which suggests that the LSE-CEP survey has a slightly fatter right-hand tail of the wage distribution as discussed in Section 4.4.2.

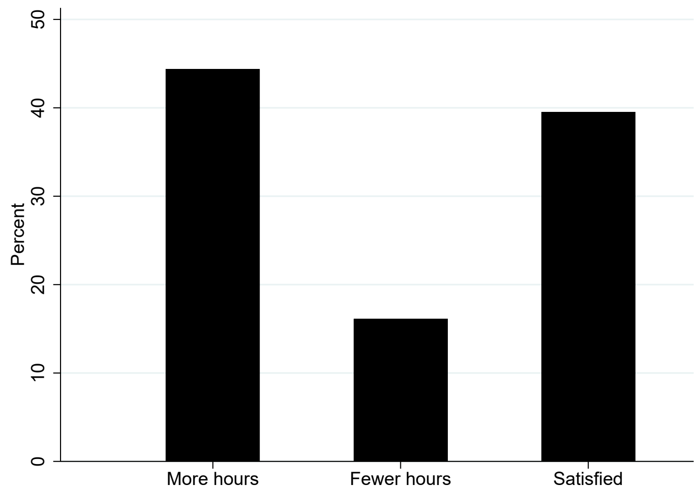
4.4.4 LSE-CEP Survey Results

In this subsection, we report a second set of results that emerged from the survey of employees on ZHCs, with a focus on workers preferences and employment conditions.

An important question is whether workers choose to be on ZHCs for the flexibility that they offer, or would instead like a job with a minimum number of guaranteed hours but could only find employment as ZHC workers. Our survey results suggest an almost even split between workers who are satisfied with their number of hours (40 percent) and workers who would rather work more hours (44 percent), while a remaining 16 percent would like to work fewer hours (Figure 4.4.4). Of those wanting to work more hours, when asked about the reason why there are unable to work more hours, 74 percent point to the lack of available work, followed by another 15 percent who are instead constrained by domestic commitments (Figure 4.4.5). As reported in Figure 4.4.6, domestic commitments are also the main reason brought about by people who would like to work fewer hours (38 percent), followed by the desire to spend more time on leisure and other unpaid activities (26 percent) or other types of work (14 percent), impediments due to illness or disability (10 percent) and study commitments (7 percent). In addition to the number of hours worked, the pattern of those hours may also be a relevant dimension of workers' satisfaction with their jobs. As with the desired number of hours, there appears to be an almost even split between respondents who would like to have a more regular pattern of hours (45 percent) and those who are satisfied with their current pattern of hours (43 percent), with the remaining 12 percent wanting a less regular schedule (Figure 4.4.7).

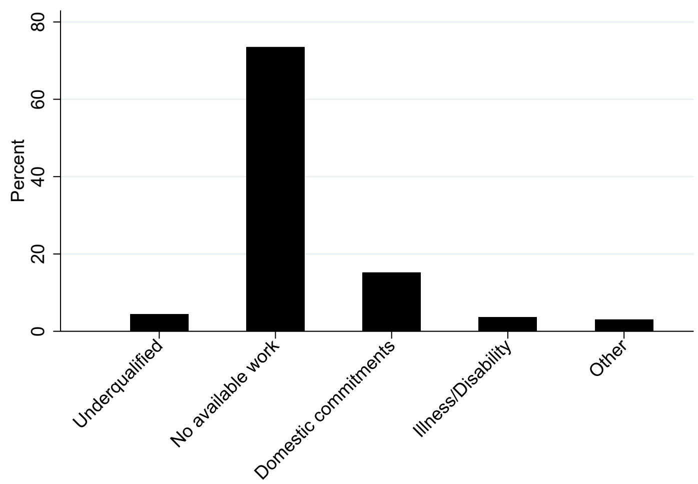
The survey responses regarding desired hours and work time patterns are suggestive of an almost even dichotomy between workers who are happy with the amount of work that they do, and workers who would like to work more but are unable to. We further investigate this issue by asking ZHC workers what are the reasons for their being on a ZHC (Figure 4.4.8). In line with our previous findings, the two main reasons that stand out are the inability to find employment in a job with a guaranteed number of hours (28 percent) and the flexibility to perform other activities (28 percent). Less prominent reasons are - in order of relevance - better remuneration than other available jobs (20 percent), complementing pay from other jobs (14 percent) and earning while studying (7

Figure 4.4.4: Desired Hours for Workers on ZHC



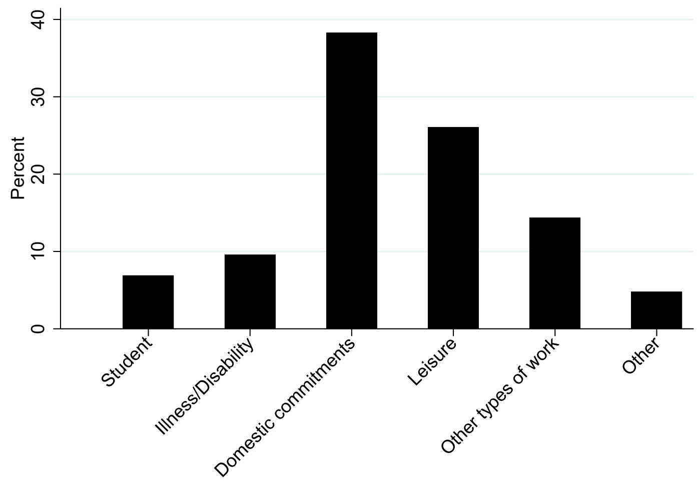
Notes: The graph shows the distribution of responses to the question "Would you have preferred to work more or fewer hours last week in your zero hours contract or on-call job at that wage rate? Or were you satisfied with the number of hours you worked?".
Source: LSE-CEP survey.

Figure 4.4.5: Reason for not Working More Hours (Workers on ZHC)



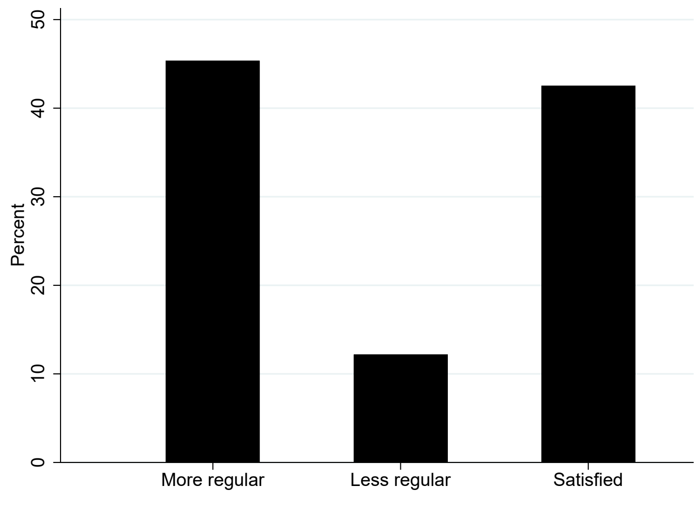
Notes: The graph shows the distribution of responses to the question "Why were you NOT able to work more last week?".
Source: LSE-CEP survey.

Figure 4.4.6: REASON FOR NOT WORKING FEWER HOURS (WORKERS ON ZHC)



Notes: The graph shows the distribution of responses to the question "Why would you want to work fewer hours?".
Source: LSE-CEP survey.

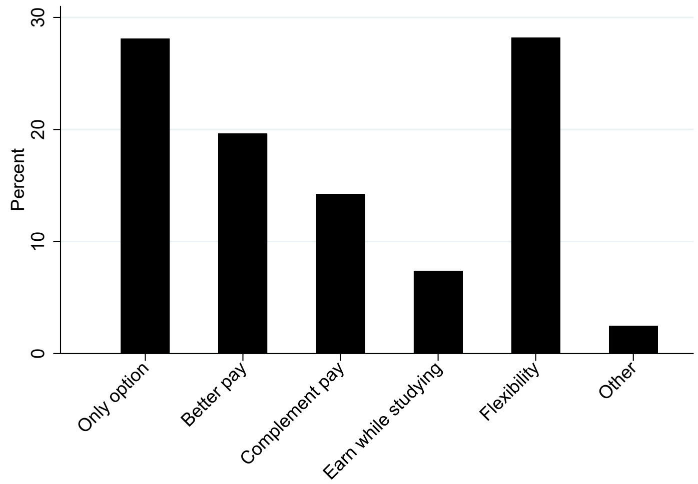
Figure 4.4.7: DESIRED PATTERN OF HOURS FOR WORKERS ON ZHC



Notes: The graph shows the distribution of responses to the question "Would you have preferred to work a pattern of more regular hours last week on your zero hours contract or on-call job at that wage rate? Or were you satisfied with the pattern of hours you worked?".
Source: LSE-CEP survey.

percent). Overall, 51 percent of respondents state that they are either satisfied or very satisfied with their ZHC job, 28 percent are neither satisfied nor dissatisfied, and the remaining 21 percent are dissatisfied or very dissatisfied (Figure 4.4.9).

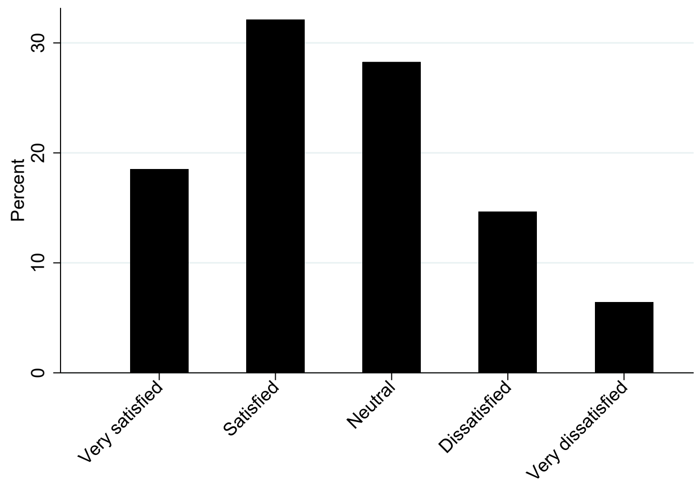
Figure 4.4.8: Main Reason for Being on ZHC



Notes: The graph shows the distribution of responses to the question "Which is the most important reason why you work on a zero hours contract or on-call job?".
Source: LSE-CEP survey.

Finally, we are interested in whether ZHC workers receive training and what type of training they would find most useful. According to our survey results, 55 percent of ZHC workers had received some form of training in the past year. As illustrated in column (1) of Table 4.4.6, the most common types of training are - in order of importance - safety training (56 percent), skills training (54 percent), quality training (30 percent), and professional and legal training (22 percent). Training was paid for by employers, contractors, customers or someone else in 72 percent of cases, by the respondent in 16 percent of cases and free for the remainder 12 percent (Table 4.4.7). We also asked all ZHC respondents what type of training they would find useful for their future job prospects (column (2) of Table 4.4.6): skills training stands out as 50 percent of respondents indicate is as useful, followed by safety training (27 percent) and other types of training (all deemed useful by approximately 23 percent of respondents). It therefore seems that, when offered, training meets individual requirements.

Figure 4.4.9: Job Satisfaction of Workers on ZHC



Notes: The graph shows the distribution of responses to the question "How satisfied are you with working on a zero hours contract or on-call job?".
Source: LSE-CEP survey.

Table 4.4.6: Training of Workers on ZHC

	Received last year (1)	Most useful (2)
Technical or technology training	0.18	0.23
Quality training	0.30	0.24
Skills training	0.54	0.50
Continuing education	0.13	0.20
Professional training and legal training	0.22	0.24
Managerial training	0.15	0.23
Safety training	0.56	0.27
Other	0.01	0.02
Observations	644	1,167

Notes: The table reports answers to the question "What type of training [did you receive last year]?" in column (1) and to the question "What type of training would you find most useful to improve your job prospects?" in column (2). The table reports the proportion of respondents who ticked each of the preset options.
Source: LSE-CEP survey.

Table 4.4.7: WHO PAYS FOR THE TRAINING OF WORKERS ON ZHC

	Who pays
Me or a family member	0.16
A contractor or customer	0.11
My employer	0.59
Someone else	0.02
No one, it was free	0.12
Observations	644

Notes: The table reports answers to the question "Who paid for the cost of the training?". The table reports the proportion of respondents who ticked each of the preset options.
Source: LSE-CEP survey.

4.5 Zero Hours Contracts and Minimum Wages

4.5.1 Conceptual Framework

As documented in the previous sections, a large fraction of workers on ZHCs are paid the minimum wage. An interesting question that is relevant for policy is to assess whether labor market policies such as minimum wage upratings are responsible for the increased diffusion of ZHCs, or – conversely – the latter are a consequence of factors that have little to do with labor market institutions. In the first case we should see that a raise of the minimum wage increases the utilization of ZHCs. In second case, we should see no effect of the minimum wage on ZHC usage. The rationale for a causal effect of minimum wage policies on ZHC utilization is that ZHCs can help firms buffer the wage cost shock due to the minimum wage increase by allowing them not to commit to a minimum number of hours. At the same time, though, the burden of insecurity would be transferred from firms onto risk-averse employees, potentially worsening the employment conditions of individual workers.

In this section, we exploit a large minimum wage increase recently implemented in the UK – the National Living Wage introduction – to shed light on the causal effect of minimum wage policies on the incidence of ZHCs. We do so in the context of the English adult social care sector, which previous research has demonstrated to be highly vulnerable to minimum wage increases (Machin et al. (2003); Machin and Wilson (2004); Giupponi and Machin (2018)) and which can therefore provide a good testing ground for the effects of minimum wage policies.

Whilst there is a sample selection issue of studying care workers, and associated questions of generalizability to the UK workforce more widely, looking at the adult social care sector allows us to have good quality data on hourly wages and contractual arrangements (which are necessary to answer well the question that we ask). Also, the fact that flexible work arrangements are already largely in use in this sector means that – if the NLW has an impact on ZHC utilization – this is a sector in which we can see it. Moreover, the estimates are relevant for other low-pay, ZHC-intense sectors, like hospitality and retail, which are those we care about the most when studying the economic effects of minimum wage floors.

4.5.2 The Introduction of the National Living Wage

The first UK national minimum wage policy dates back to April 1999, when the National Minimum Wage (NMW) was first introduced. At that time, a minimum hourly wage of £3.60 for workers aged 22 and over, and a lower rate of £3.00 for workers aged between 18 and 21 were established. Additional rates have been introduced in subsequent years, so that as of October 2015 the NMW rates were as follows: an adult minimum rate of £6.70 for workers aged 21 and over, a youth development rate of £5.30 for those aged 18-20, a youth minimum of £3.87 for 16-17 year olds and an apprentice rate of £3.30.

On July 8^{th} 2015, the newly elected Conservative Party government called an emergency budget, in which the Chancellor George Osborne announced the introduction of the National Living Wage (NLW). This unexpected intervention changed the structure of minimum wages by introducing a new minimum wage rate of £7.20 an hour for workers aged 25 or above starting from April 1^{st} 2016, while leaving the minimum wage rates for younger workers unchanged.[11] Five minimum wage rates are now in operation in the UK: the NLW for workers aged 25 and over, the NMW for 21-24 year olds, the youth development rate for 18-20 year olds, the young worker rate for 16 and 17 year old, and the apprentice minimum wage.[12]

The NLW introduction was an unexpected and radical policy intervention. Firstly, it came from a political party that had traditionally been hostile to minimum wages, especially at the time of the NMW introduction in April 1999. Secondly, the NLW introduction generated a wage change much larger than recent uprates, namely an increase of 10.8 percent at the time of announcement in July 2015 and of 7.5 percent at the time of implementation on April 1^{st} 2016. Most importantly for our analysis, the unexpected and

[11] Additionally, the NLW was set to achieve 60 percent of median earnings by 2020, which - at the time of the announcement - was forecasted to be £9.00 by the UK Office for Budget Responsibility.

[12] See Giupponi and Machin (2018) for a comprehensive discussion of minimum wages in the UK and for an empirical analysis of the wage and employment consequences of this significant change in the structure of minimum wages.

sizable wage shock generated by the NLW introduction provides a unique "experiment" to study the consequences of the minimum wage increase and the wage cost shock it induced on employers' use of ZHCs.

4.5.3 The Adult Social Care Sector

The impact of the NLW introduction on ZHC utilization is studied in the context of workers and firms in the English adult social care sector. Specifically, we will consider adult social care providers operating in the residential care home industry and the domiciliary care industry. Residential care refers to the provision of accommodation and personal care to adults in a communal residential center, which may or may not provide nursing facilities. Members of staff in residential care homes are predominantly care assistants, who provide 24 hour supervision, meals and help with personal care needs. Domiciliary care – also referred to as home care – is a social care service provided to people who live in their own houses and require assistance with personal care routines, household tasks such as cleaning and cooking, or any other activities they may need to live independently. Domiciliary care assistants typically work individually, and are often contracted on flexible working hours or ZHCs since domiciliary care work tends to be organized into short and fragmented home visits.

The choice of focusing on the adult social care sector is motivated by various reasons. Firstly, the sector is highly vulnerable to minimum wages changes, as it has many low-paid workers. Of these, the vast majority are older than 25, making the setting especially suited to analyzing the NLW introduction. Secondly, the sector is close to what can be considered a competitive labor market, as it consists of a large number of relatively small firms providing a rather homogeneous service, and it is very labor intensive and not unionized. Thirdly, residents' fees are regulated and paid for by local authorities, making it difficult for firms to pass higher costs onto prices. For all these reasons, a minimum wage change is likely to have a substantial impact on total costs and on economic outcomes of workers and firms in this sector, which therefore provides a useful testing ground for analyzing the impact of minimum wage policies. In other words, the high vulnerability to the minimum wage increases the likelihood of finding large effects from wage shocks. Finally, the incidence of ZHCs is high - particularly in the domiciliary care industry - making this setting especially suited to studying the impact of the NLW on ZHCs.

4.5.4 Data Sources

The main data source that is used to analyze the effect of the NLW introduction on ZHC utilization is the National Minimum Dataset for Social Care (NMDS-SC).[13] This is an online system administered by Skills for Care and funded by the UK Department of Health that collects information on the adult social care workforce in England. Social care providers can use NMDS-SC to record and manage information about their workers, such as payroll data, training and development, job roles, qualifications and basic demographics. By having an account and regularly updating it, providers are given access to a set of tools to visualize and analyze their data, submit applications for training and development funds, compare their employment and pay structure with those of other providers locally, regionally or nationally, access publications about the social care sector and other e-learning resources for free, and directly share their data and returns with authorities such as the Care Quality Commission and the NHS. No fee is charged to use NMDS-SC. However, in order to benefit of certain facilities, providers must update their account at least once per year.

The dataset is a panel of matched employer-employee data. For each provider, we have information on the industry and main service provided, service capacity and utilization, number of staff employed, geographic location and system update dates. For workers, we have information on demographics (gender, age and nationality), job characteristics (job role, contract type and qualifications), contracted weekly hours, hourly pay and update date of the hourly pay rate. We have access to the snapshot of the NMDS-SC online system at monthly frequency from March 2015 to March 2017, each snapshot including all providers in the system at that date.

A second data source is the Care Quality Commission (CQC) registry.[14] The registry contains a complete record of all active English care providers regulated by CQC at monthly frequency. It provides information on the activity status of providers and therefore allows us to identify when homes shut down and when new homes enter into the market.

4.5.5 Sample Design

Around 22,000 providers are registered with NMDS-SC as of March 2016. Of these, approximately 10,000 are residential care homes with or without nursing, and 3,800 are domiciliary care agencies. We match the sample of residential care homes and domicil-

[13] NMDS-SC (2013); NMDS-SC (2014).

[14] The CQC is the independent regulator of health and adult social care in England. It is responsible for setting standards of care and for monitoring, inspecting and rating adult social care providers, to make sure that they meet fundamental standards of quality and safety.

iary care agencies with the CQC registry of active locations from March 2015 to March 2017, from which we can obtain information on whether a firm is active or closed in a given month. Our sample comprises care homes that meet the following three criteria: *(i)* being active from March 2015 through to March 2017 according to the CQC registry, *(ii)* having a record on NMDS-SC for all those months and *(iii)* having updated their NMDS-SC account at least once after March 2016.[15] This selection leaves us with a balanced panel of 4,680 firms that are active in March 2016 and remain open until March 2017.[16]

4.5.6 Descriptive Statistics

Table 4.5.1 reports descriptive statistics for all firms in the balanced sample, and for care homes and domiciliary care agencies separately, as of March 2016. The adult social care sector is characterized by relatively low hourly pay (£7.57 per hour on average) and a large fraction of workers are aged 25 and over (88 percent on average), which are indicative of a high vulnerability to minimum wage increases in general and to the NLW introduction in particular.

The statistics reported in Table 4.5.1 also show that the care home sector is characterized by medium-sized establishments employing on average 45 employees. Domiciliary care agencies have a larger pool of employees as compared to care homes (66 vs 39 employees on average), and a remarkably higher proportion of ZHC workers (38 vs 5 percent) that translates into lower average weekly hours (16 vs 29 hours). Moreover, the proportion of workers on other flexible work arrangements such as temporary, bank or agency contracts, is almost twice as large in the domiciliary care sector (14 vs 8 percent). These differences most likely stem from the very nature of domiciliary care work, which tends to be organized into short and fragmented home visits to customers, so that domiciliary care assistants are often contracted on flexible working hours.

Apart from substantial differences in the types of working arrangements, the two sectors

[15] In order to avoid introducing sample selection driven by unobservable worker and firm characteristics correlated with the timing and frequency of updating, we do not condition our sample on a specific update date and only require that a firm update its records once in the twelve months after April 1^{st} 2016. Approximately 90 percent of NMDS-SC users update within a year.

[16] In our sample we have a total of 3,599 care homes and 1,081 domiciliary care agencies. According to the 2017 report on the care home market of the Competition and Markets Authority (2017), there are approximately 9,500 care homes in England. This implies that our sample represents approximately 38 percent of the market for care homes. According to a 2016 report of the United Kingdom Home Care Association (2016), the total number of registered locations providing domiciliary care in England was 8,500 in March 2016. This implies that our sample represents approximately 13 percent of the market of domiciliary care agencies.

Table 4.5.1: NMDS-SC Summary Statistics

	All firms		Care homes		Domiciliary care	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Number of employees	45.22	46.26	38.99	31.16	65.97	74.00
Proportion under 25	0.12	0.09	0.12	0.09	0.12	0.09
Hourly wage	7.57	1.09	7.53	1.11	7.67	1.01
Weekly hours	25.61	8.90	28.56	5.17	15.75	11.31
Weekly earnings	189.42	79.01	212.80	54.35	111.59	96.54
Hourly wage carer	7.10	0.93	7.01	0.97	7.43	0.68
Weekly hours carer	24.49	10.30	27.98	6.25	12.41	12.25
Prop. on ZHC	0.12	0.23	0.05	0.10	0.38	0.33
Prop. on permanent contract	0.88	0.17	0.90	0.11	0.82	0.27
Prop. on temporary contract	0.02	0.08	0.02	0.04	0.05	0.15
Prop. on bank contract	0.06	0.10	0.06	0.08	0.05	0.13
Prop. on agency contract	0.01	0.08	0.00	0.02	0.04	0.16
Female	0.85	0.13	0.84	0.13	0.87	0.11
Age	42.60	4.63	42.71	4.53	42.21	4.92
Prop. carer	0.61	0.19	0.56	0.16	0.75	0.23
Prop. with nursing qualification	0.03	0.06	0.04	0.07	0.00	0.01
Occupancy rate	0.77	0.33	0.92	0.14	0.27	0.30
Proportion paid below NLW	0.48	0.34	0.52	0.32	0.34	0.36
Observations	4,680		3,599		1,081	

Notes: The table reports the mean and standard deviation of a set of firm-level variables for the balanced sample of firms used in the analysis. The statistics refer to March 2016, and are shown for the full sample, and for the sample of care homes and domiciliary care agencies separately.
Source: NMDS-SC.

have an almost identical gender and age composition and similar wage rates. The main occupation in both sectors is care assistant and only a very small share of the workforce holds a nursing qualification. All these characteristics confirm that the adult social care sector is a pertinent context to the studying of the effects of the NLW introduction on wages and contractual arrangements.

4.5.7 NMDS-SC Representativeness

We check the representativeness of the NMDS-SC data using data from the Labour Force Survey (LFS). Table 4.A3 in Appendix 4.A reports the mean and standard deviation for a set of individual-level characteristics for care workers in the LFS.[17] The table also reports the same characteristics for care workers at the firm level in NMDS-SC. Demographic variables relating to gender, age and region line up very closely. The hourly wage rate and number of weekly hours worked are slightly higher in the LFS data, while the pro-

[17] We select employees with standard occupation classification (SOC2010) marked as "care workers" in the LFS. LFS data refer to 2015Q4 and 2016Q1. NMDS-SC data refer to March 2016.

portion of workers on ZHC is slightly lower. The discrepancy in average weekly hours in LFS and NMDS-SC is most likely due to the fact that the variable in LFS refers to actual hours worked, while in NMDS-SC to contractual hours, which – for ZHC workers – are equal to zero and therefore pull down the mean. The larger fraction of workers on ZHCs in NMDS-SC may be due to the fact that, in this dataset, we cannot account for multiple job holders, which tend to be more frequent in ZHC jobs. All in all, the statistics appear to line up quite satisfactorily, mostly showing a consistent pattern across sources.

4.5.8 Empirical Strategy

This section explores whether the minimum wage increase due to the NLW introduction had an impact on the share of workers on ZHCs. By tilting the composition of the workforce towards contracts without a guaranteed number of hours, employers can easily adjust employment at the intensive margin, either on top of or in substitution to adjustments along the extensive margin. Consistent with previous work (Giupponi and Machin (2018)), we will show that the NLW did not have a significant impact on employment, suggesting that any substitution toward contracts with flexible working arrangements is to be interpreted as an adjustment at the intensive margin.

The empirical strategy is based on a difference-in-differences methodology in which we exploit between-firm variation in the pre-NLW proportion of workers that would be affected by the minimum wage increase, in order to identify the effect of the minimum wage hike on ZHC utilization. The regression specification reads as follows:

$$\Delta^q Y_{j,t} = \alpha_{1,t} + \beta_{1,t} \cdot MIN_{j,Mar2016} + X'_{j,Mar2016} \cdot \gamma_{1,t} + \xi_{j,t} \tag{4.1}$$

where $\Delta^q Y_{j,t}$ is the quarter-on-quarter change in the proportion of workers on a ZHC in firm j between quarter t and quarter $t-1$; $MIN_{j,Mar2016}$ is the proportion of low-paid workers in firm j as of March 2016; X is a vector of pre-NLW firm-level characteristics measured in March 2016, including the proportion of female workers, the average age, the proportion working as care assistants, the proportion with nursing qualification, the occupancy rate and a set of local authority districts fixed effects; ξ is a disturbance term.[18, 19] The subscript t indicates the quarter relative to March 2016, which is normalized to take value $t = 0$. The variable $MIN_{j,Mar2016}$ is constructed as the proportion of workers that in March 2016 were paid below the age-specific minimum wage rate that would be

[18] Data on the gender and age composition, and on the occupancy rate is missing for some firms. Such missing information is controlled for via a set of dummy variables.

[19] There is a total of 325 local authority districts in our sample and of 326 local authority districts in England. They split England into 326 areas of local governance.

in place as of April 2016. In other words, the variable provides a measure of the NLW bite at firm level.

The coefficients $\beta_{1,t}$ for $t = -4, ..., 0$ are treatment leads and provide an easy way to test whether there is any correlation between ZHC utilization and the proportion of low-paid workers prior to the NLW introduction. In other words, the leads allow to test whether there were divergent trends in ZHC utilization between firms more and less exposed to the minimum wage increase before the policy change. This is equivalent to testing for the parallel trends assumption in a traditional difference-in-differences setting.

To document the evolution of the relationship between the low-paid proportion and ZHC growth in the post-reform quarters, we measure the outcome variable $\Delta^q Y_{j,t}$ as the long difference between March 2016 and, respectively, June 2016, September 2016, December 2016 and March 2017. This is equivalent to estimating the cumulative effect of the reform over post-reform quarters, i.e. the sum $\sum_{t=1}^{k} \beta_{1,t}$ for $k = 1, ..., 4$.

The empirical strategy rests on the assumption that firms with the highest potential to be affected by the NLW introduction were indeed those that experienced larger wage growth in the quarters following the policy change, as a consequence of the NLW introduction. Firstly, we provide evidence that this is indeed the case. Secondly, we show that the between-firm correlation between the proportion of pre-NLW low-paid workers and wage growth is entirely due to the minimum wage change. To this end, we estimate a regression specification similar to model 4.1, using quarter-on-quarter wage growth as outcome variable. The regression specification reads as follows:

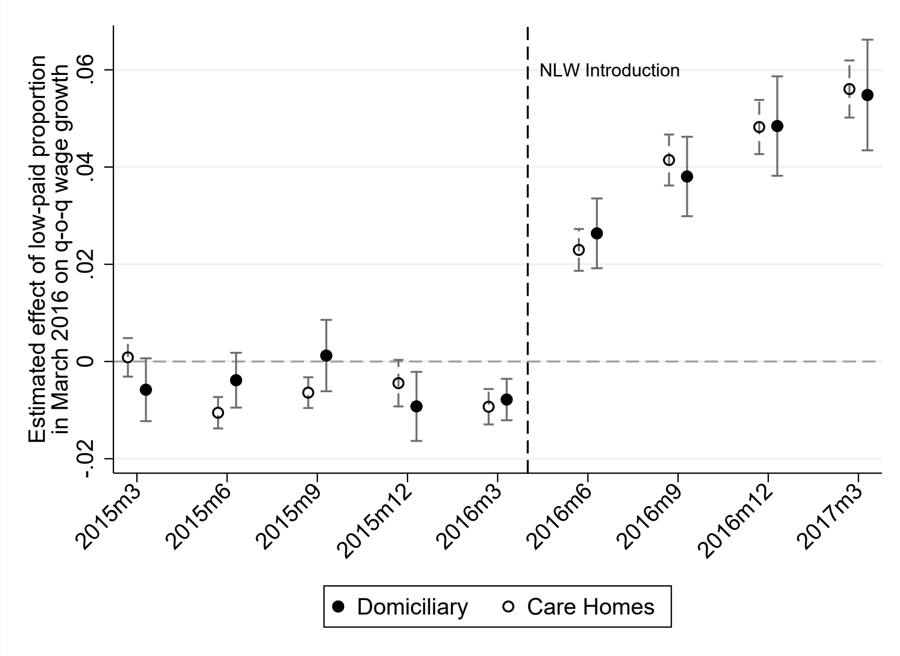
$$\Delta^q \ln W_{j,t} = \alpha_{2,t} + \beta_{2,t} \cdot MIN_{j,Mar2016} + X'_{j,Mar2016} \cdot \gamma_{2,t} + \eta_{j,t} \tag{4.2}$$

where $\Delta^q \ln W_{j,t}$ is the quarter-on-quarter change in the logarithm of the average hourly wage in firm j between quarter t and quarter $t-1$; $MIN_{j,Mar2016}$ is the proportion of low-paid workers in firm j in March 2016; X is the set of above listed covariates and η a disturbance term. Analogously to what discussed for model 4.1, the coefficients $\beta_{2,t}$ for $t = -4, ..., 0$ are treatment leads that allow to test the exogeneity of the minimum wage increase. For post-NLW quarters, we measure hourly wage growth ($\Delta^q \ln W_{j,t}$) between March 2016 and, respectively, June 2016, September 2016, December 2016 and March 2017.

4.5.9 Main Results

Figure 4.5.1 reports the coefficients $\beta_{2,t}$ for $t = -4, ..., 0$ and the cumulated sum $\sum_{t=1}^{k} \beta_{2,t}$ for $k = 1, ..., 4$, from estimating model 4.2 on the balanced panel of firms that are active throughout all months between March 2015 and March 2017. The dots indicate the estimated coefficients and the capped vertical bars report 95 percent confidence intervals based on robust standard errors. The specification allows for heterogeneity in the $\beta_{2,t}$ coefficients between care homes (hollow circles) and domiciliary care agencies (black circles) and includes the full set of controls. The results provide compelling evidence of the causal effect of the minimum wage change on hourly wage growth: whilst no systematic correlation between the low-paid proportion and quarter-on-quarter wage growth can be detected prior to the NLW introduction, a statistically significant correlation emerges from the first quarter following the minimum wage increase.

Figure 4.5.1: Effect of Initial Low-paid Proportion on Wage Growth by Sector



Notes: For the quarters before the NLW introduction, the graph reports the estimated coefficients $\hat{\beta}_{2,t}$ from model 4.2 for care homes and domiciliary care agencies. After the NLW introduction, the graph reports the estimated sum $\sum_{t=1}^{k} \hat{\beta_{2,t}}$ for $k = 1, ..., 4$. The sample is a balanced panel of adult social care providers active between March 2015 and March 2017. The vertical bars indicate 95 percent confidence intervals based on robust standard errors. Control variables included in the underlying regression are the initial proportion female, proportion with nursing qualification, proportion of care assistants, average age (all workers), occupancy rate and local authority district dummies. When data on firm-level covariates is missing, such missing information is controlled for via a set of dummy variables.
Source: NMDS-SC.

In order to ease the interpretation of the results, Table 4.5.2 reports the estimates of

Table 4.5.2: WAGE EQUATIONS

Change in log average hourly wage

March 2016 to March 2017

	(1)	(2)	(3)	(4)
Initial low-paid proportion	0.053***	0.054***	0.056***	0.056***
	(0.002)	(0.003)	(0.003)	(0.003)
Initial low-paid proportion x Domiciliary		-0.001		-0.001
		(0.006)		(0.006)
Observations	4,680	4,680	4,680	4,680
Controls	No	No	Yes	Yes
F-stat	519.52	280.43	410.41	203.22
Mean of dep. var.:				
All firms	0.041			
Care homes	0.043			
Domiciliary care	0.036			

Notes: The table reports the estimated coefficient $\hat{\beta}_3$ from model 4.3. The sample is a balanced panel of adult social care providers active between March 2015 and March 2017. Robust standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the initial proportion female, proportion with nursing qualification, proportion of care assistants, average age (all workers), occupancy rate and local authority district dummies. When data on firm-level covariates is missing, such missing information is controlled for via a set of dummy variables.
Source: NMDS-SC.

the cumulated sum $\sum_{t=1}^{k} \beta_{2,t}$ for $k = 4$. This is equivalent to estimating the following specification:

$$\Delta \ln W_{j,t} = \alpha_3 + \beta_3 \cdot MIN_{j,Mar2016} + X'_{j,Mar2016} \cdot \gamma_3 + \nu_{j,t} \tag{4.3}$$

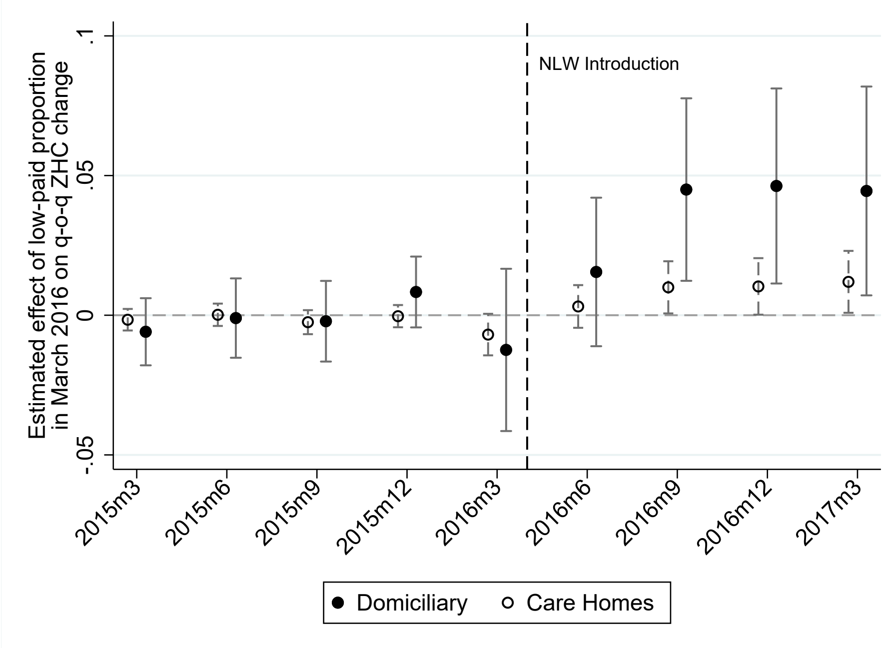
where $\Delta \ln W_{j,t}$ is the change in the natural logarithm of the average hourly wage in firm j between March 2016 and March 2017; all other variables are defined as above and ν is a disturbance term. The parameter β_3 captures the relationship between the proportion of low-paid workers and the average hourly wage growth in the 12 months after the NLW introduction.

The specifications in columns (1) and (3) of Table 4.5.2 report the estimated coefficient β_3 for the pooled sample of care homes and domiciliary care agencies, while those in columns (2) and (4) allow β_3 to vary across the two sectors. The regression models in columns (3) and (4) include the above-listed firm-level controls. In all cases there is significant evidence of larger wage increases in firms with more low-wage workers in the pre-NLW period, as measured by the March 2016 proportion of low-wage workers. According to the estimate in column (3), a one standard deviation increase in the proportion of low-paid workers (corresponding to a 34 percentage point change as reported in Table 4.5.1) implies a 1.9 percentage-point faster wage growth on a baseline of 4 percent, indicating a strong and significant relationship between our measure of the NLW bite ($MIN_{j,Mar2016}$) and wage growth after the policy change. According to the estimates in columns (2) and (4), there is no differential relationship between the initial proportion of low-paid workers and wage growth in the domiciliary care and care home sector.

We now consider whether the wage cost shock induced by the NLW introduction had consequences on ZHC utilization by firms. Figure 4.5.2 probes the relationship between the low-paid proportion in March 2016 and growth in ZHC utilization by reporting the coefficients $\beta_{1,t}$ for $t = -4, ..., 0$ and the cumulated sum $\sum_{t=1}^{k} \beta_{1,t}$ for $k = 1, ..., 4$, from estimating model 4.1 on the balanced panel of firms that are active throughout all months between March 2015 and March 2017. Similar to Figure 4.5.1, the dots indicate the estimated coefficients and the capped vertical bars report 95 percent confidence intervals based on robust standard errors. The specification allows for heterogeneity in the $\beta_{1,t}$ coefficients between care homes (hollow circles) and domiciliary care agencies (black circles) and includes the full set of controls. The graph shows no differential growth in ZHC utilization prior to the introduction of the NLW across firms more or less exposed to the minimum wage increase. After the policy change, a positive relationship between our measure of the NLW bite and ZHC utilization emerges in both sectors, with a larger effect size in the domiciliary care one. Starting from the second quarter after March 2016 coefficients are statistically significant and persistent over time. The overall dynamic of the effect gives strength to a causal interpretation of the impact of the minimum wage hike on ZHC utilization.

Table 4.5.3 reports the regression coefficient β_3 from estimating model 4.3 using the change in the share of ZHC workers between March 2016 and March 2017 ($\Delta Y_{j,t}$) as outcome variable. Estimates in columns (1) and (3) refer to the pooled sample of care homes and domiciliary care agencies, while those in columns (2) and (4) allow β_3 to vary across the two sectors. The regression models in columns (3) and (4) include firm-level controls. The coefficient estimate reported in column (3) indicates that a one standard deviation increase in the proportion of low-paid workers is associated with a statistically significant 0.5 percentage-point faster growth in ZHC utilization. When β_3 is allowed to vary across care home and domiciliary care sectors (columns (2) and (4)), the effect increases by a factor of more than three in the domiciliary care sector. According to the results in column (4), a one standard deviation increase in the proportion of workers paid below the minimum is associated with a 0.4 percentage point larger increase in ZHC utilization from a baseline of 0.6 in the care home sector, and a 1.5 percentage point larger increase in ZHC utilization from a baseline of 6 percentage points in the domiciliary care

Figure 4.5.2: Effect of Initial Low-paid Proportion on Proportion of Employees on ZHC by Sector



Notes: For the quarters before the NLW introduction, the graph reports the estimated coefficients $\hat{\beta}_{1,t}$ from model 4.1 for care homes and domiciliary care agencies. After the NLW introduction, the graph reports the estimated sum $\sum_{t=1}^{k} \widehat{\beta_{1,t}}$ for $k = 1, ..., 4$. The sample is a balanced panel of adult social care providers active between March 2015 and March 2017. The vertical bars indicate 95 percent confidence intervals based on robust standard errors. Control variables included in the underlying regression are the initial proportion female, proportion with nursing qualification, proportion of care assistants, average age (all workers), occupancy rate and local authority district dummies. When data on firm-level covariates is missing, such missing information is controlled for via a set of dummy variables.
Source: NMDS-SC.

Table 4.5.3: Zero Hours Contracts Equations

Change in proportion of employees on ZHCs

March 2016 to March 2017

	(1)	(2)	(3)	(4)	(5)	(6)
Initial low-paid prop	0.001	0.006*	0.014**	0.012**		
	(0.006)	(0.004)	(0.007)	(0.006)		
Initial low-paid prop x Domic		0.039**		0.033*		
		(0.019)		(0.019)		
Change in log avg wage					0.257**	0.219**
					(0.126)	(0.101)
Change in log avg wage x Domic						0.596*
						(0.350)
Observations	4,680	4,680	4,680	4,680	4,680	4,680
Controls	No	No	Yes	Yes	Yes	Yes
Mean of dep. var.:						
All firms	0.019					
Care homes	0.006					
Domiciliary care	0.061					

Notes: The table reports the estimated reduced-form coefficient $\hat{\beta}_3$ from model 4.3 in columns (1)-(4), and the estimated IV coefficient $\hat{\beta}_4$ from model 4.4 in columns (5)-(6), using the change in the share of workers on ZHC as outcome variable. The sample is a balanced panel of adult social care providers active between March 2015 and March 2017. Robust standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the initial proportion female, proportion with nursing qualification, proportion of care assistants, average age (all workers), occupancy rate and local authority district dummies. When data on firm-level covariates is missing, such missing information is controlled for via a set of dummy variables.
Source: NMDS-SC.

sector. We take this evidence as suggestive of an increase in the share of contracts with no minimum guaranteed hours in response to the minimum wage increase, more so in a context - such as that of domiciliary care agencies - in which work tends to be organized into short and fragmented tasks.[20]

An interesting question to ask is whether the increased share of ZHCs is due to the conversion of previously non-ZHC positions into ZHC ones, the creation of new ZHC jobs or the displacement of workers on non-ZHC positions. For the first option to be true, we would need to observe no employment effects of the NLW introduction, for the second positive employment effects and for the third negative employment effects. We investigate this mechanism in Table 4.A4 in Appendix 4.A, where we report estimates of the coefficient β_3 of model 4.3, using the change in the logarithm of employment headcount between March 2016 and March 2017 as outcome variable. Our results do not point to significant

[20]It is worth noting that, relative to the baseline, the effect size is larger for more exposed care homes, though this is due entirely to the slower baseline growth rate.

employment effects twelve months after the NLW introduction, thus suggesting that new ZHC jobs replaced non-ZHC positions.

We also investigate whether the NLW introduction had an impact on the utilization of other flexible contractual arrangements: temporary contracts, bank work and temporary agency contracts.[21] Regression estimates of model 4.3 are reported in columns (1) to (4) of the various panels of Table 4.A5 in Appendix 4.A. For temporary contracts of all types, estimates are of limited magnitude and statistically insignificant.

4.5.10 Estimating the Effect of Wages on ZHC Utilization

The analysis illustrated in the previous subsection provides reduced-form evidence of the causal effect on the NLW introduction on the increased utilization of ZHCs. In this section, we are interested in estimating the effect of the wage cost shock induced by the NLW introduction on ZHC utilization, i.e. a parameter that can potentially be generalized to other policy-relevant settings.

The empirical strategy is based on the estimation of the following structural-form model:

$$\Delta Y_{j,t} = \alpha_4 + \beta_4 \cdot \Delta \ln W_{j,t} + X'_{j,Mar2016} \cdot \gamma_4 + \theta_{j,t} \tag{4.4}$$

where $\Delta Y_{j,t}$ is the change in the share of workers employed with a zero hours contract between March 2016 and March 2017; $\Delta \ln W_{j,t}$ is the change in the natural logarithm of the average wage in firm j between March 2016 and March 2017; X is a vector of above-listed pre-NLW firm-level characteristics and local authority districts fixed effects; θ is a disturbance term. The parameter β_4 measures the semi-elasticity of ZHC utilization to the wage rate.

Due to the potential endogeneity of $\Delta \ln W_{j,t}$, we estimate equation 4.4 via a two-stage least squares approach and instrument the change in the logarithm of the average wage $\Delta \ln W_{j,t}$ with $MIN_{j,Mar2016}$. Model 4.3 can therefore be considered as the first stage of the instrumental variable model. The estimates reported in Table 4.5.2 prove the relevance of $MIN_{j,Mar2016}$ as instrument for $\Delta \ln W_{j,t}$. Moreover, the patterns illustrated in

[21] We report here the formal definitions of these three contractual arrangements, as defined by NMDS-SC. *Temporary contract*: the worker is employed for a limited duration, normally either on a fixed term contract or for a fixed task, or on a spell of casual or seasonal employment as a "temp". *Bank worker*: the worker is retained by the organisation as a whole, but deployed on a casual or short term basis. *Temporary agency work*: the worker is supplied by an outside employment agency/bureau; this category includes staff employed by NHS professionals, and workers supplied on contract e.g. by outside catering and cleaning companies.

Figures 4.5.1 and 4.5.2 combined provide compelling evidence in favour of the exogeneity of the instrument and of the exclusion restriction.

Estimates of the coefficient β_4 are reported in columns (5) and (6) of Table 4.5.3, where column (5) is based on the pooled sample, while column (6) allows the coefficient β_4 to vary between care homes and domiciliary care agencies. The estimate in column (5) points to a positive and significant wage semi-elasticity of 0.26, whereby a 4.1 percent increase in hourly wages (the average in the sample) leads to a 1.1 percentage point faster growth in ZHC utilization on a baseline of 1.9 percentage points. Once we allow the parameter to vary across the two industries, the effect becomes significantly larger in the domiciliary care sector, and smaller for the care home sector. According to the estimates in column (6), a 4.1 percent increase in wages (the average in the sample) leads to a 3.3 percentage point faster growth on a baseline of 6.1 percentage points in the domiciliary care sector. In the care home sector, a similar wage increase leads to a 0.9 percentage point faster growth in ZHC utilization, on a baseline of 0.6 percentage points.[22] Thus, it seems that one consequence of care sector employers paying higher wages to their staff is a raised likelihood of also placing them on a zero hours contract. This is especially true of domiciliary care employers.

4.5.11 Using LFS to Further Probe the Results for Low Paid Workers

Finally, we test whether a change in the proportion of ZHC utilization for care workers, and workers in other low paying industries, following the introduction of the NLW is also visible in the national statistics data. Figure 4.5.3 presents the evolution of the proportion of care workers on ZHCs around the introduction of the NLW using data from the LFS, for the period from 2014 to 2017. As can be seen, in the quarter following the introduction there is an increase in the proportion of ZHCs. The first two columns of Table 4.5.4 present an empirical counterpart to the graph from the following estimating equation:

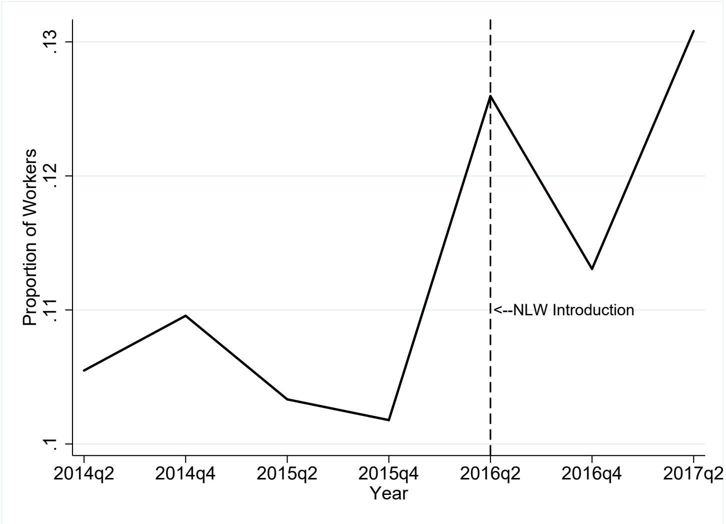
$$ZHC_{i,t} = \alpha_5 + \beta_5 \cdot PostNLW_t + X'_{i,t} \cdot \gamma_5 + u_{i,t} \tag{4.5}$$

where ZHC is a binary indicator of ZHC status for worker i in period t; $PostNLW$ is a dummy taking value one after March 2016; X is a vector of individual-level controls including age, education, and dummies for gender, white ethnicity, British nationality, working in the public sector and regional location; u is a disturbance term.[23]

[22] Estimates of model 4.4 using the share of other forms of flexible contractual arrangements as outcome variable are reported in the various panels of Table 4.A5 in Appendix 4.A.

[23] Twelve region dummies were included in total.

Figure 4.5.3: Proportion of Care Workers on ZHC (LFS)



Notes: The graph presents the evolution of the proportion of care workers on ZHCs from April 2014 to April 2017. The dashed line marks the introduction of the NLW at the start of 2^{nd} quarter in 2016. **Source:** LFS.

The results shown in the first two columns of Table 4.5.4 demonstrate that, following the NLW introduction, the proportion of workers employed on ZHCs in the social care sector increased. In the column (2) specification including controls, it rose by 1 percentage point, or a sizable 24 percent of the pre-NLW mean.[24] Furthermore, this positive association appears generalizable to other lowing paying industries. Columns (3) and (4) of Table 4.5.4 present results for estimates of equation 4.5 using a sample of all workers employed in low paying industries.[25] As can be seen, the results are almost identical to those for the social care industry. Table 4.A6 in Appendix 4.A breaks down the results into all 13 low paying industries and as can be seen all industries (aside from security) have a positive β_5 coefficient (albeit with varying magnitudes and degrees of significance). Given the evidence outlined earlier in this section using the NMDS-SC data, we feel there is substantive evidence to suggest that the increase in ZHC utilization in the social care industry and in low paying industries in general in the national statistics is due to the NLW introduction.

[24] A regression using only care workers (i.e. based on occupation rather than industry) yields a similar result, with a coefficient of 0.018 and a standard error of 0.007, representing a 17 percent increase on the pre-NLW mean.

[25] The low paying industries used are those in the UK's Low Pay Commission list, which can be found in Low Pay Comission (2017), and are listed in Table 4.A6 in Appendix 4.A.

Table 4.5.4: Zero Hours Contracts Equations (LFS Sample)

Probability of being on a ZHC

	Social care		Low-pay industries	
	(1)	(2)	(3)	(4)
Post NLW	0.011***	0.010***	0.008***	0.010***
	(0.003)	(0.003)	(0.001)	(0.001)
Observations	25,191	25,191	91,362	91,362
Controls	No	Yes	No	Yes
Pre-NLW mean of dep. var.	0.042	0.042	0.041	0.041

Notes: The table reports the estimated reduced-form coefficient $\hat{\beta}_5$ from model 4.5. The sample for the first two columns is workers employed in the social care industry, and for the second pair of columns is workers employed in low-pay industries (defined in Low Pay Comission (2017)). The samples contain 4 pre-NLW quarters (2014-2015 quarter 2 and quarter 4) and 3 post-NLW quarters (2016 quarter 2 and quarter 4, and 2017 quarter 2). Controls include age, education, gender, a dummy for white ethnicity, a dummy for British nationality, a dummy for working in the public sector and twelve regional dummies. Robust standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1.
Source: NMDS-SC.

4.6 Conclusion

This paper offers new evidence on the rise and nature of alternative work arrangements, with a specific focus on ZHCs in the context of the UK labor market. Combining both secondary and newly collected survey data, we provide a comprehensive assessment of the nature of ZHCs, which had been so far only very limitedly studied. The survey data allow us to empirically document the characteristics of workers engaged in ZHCs and to better understand the trade-off between flexibility and insecure, low pay that is inherent in this type of work arrangement.

Furthermore, we investigate whether minimum wage policies have a role in the increased utilization of ZHCs by firms. We do so by leveraging a novel matched employer employee dataset of English adult social care providers and credible identifying variation stemming from the NLW introduction in the UK labor market.

The analysis finds that many workers on ZHCs are relatively low paid, with a large proportion being paid at or slightly above the minimum wage. Such relatively low pay, coupled with limited and fragmented hours, implies high levels of earnings insecurity for workers whose only option is to work on this type of arrangement. Indeed, a stark dichotomy emerges between workers who value the flexibility provided by ZHC jobs, and workers who would rather work more and more regular hours and therefore appear to be engaged in ZHCs out of necessity rather than choice.

The analysis reveals that minimum wage policies appear to have had some bearing on the increased utilization of ZHCs. Specifically, in the context of the English adult social care sector, we find that the NLW introduction led to a larger incidence of ZHCs. The increase is more highly pronounced in the domiciliary care sector, a sector in which work has traditionally been organized around fragmented hours. This suggests that firms exploit the flexibility of ZHCs in order to buffer the wage cost shock induced by the minimum wage increase. It remains to be understood whether these effects will stabilize or grow larger in the longer run – an issue we intend to study in due course. Similarly, the issue of whether there should be a higher minimum wage for ZHC workers (as suggested in the 2017 Taylor Review of Modern Working Practices) is a research question that needs economic evidence to better inform its viability as a future option for labor market policy.[26] In particular, our evidence suggests that a domiciliary worker paid the NMW experienced both an increase of 7.5 percent in their wages and 6.1 percent in their probability of being on a ZHC as a result of the NLW introduction, and such a trade-off may have important welfare implications for workers, both in their current employment and for their future career trajectories.

[26] Taylor (2017).

Appendix

4.A Additional Tables

Table 4.A1: Sample of Survey Respondents of LSE-CEP Survey

	Mean	S.D.
Female	0.53	0.50
Age	40.93	13.04
Age 18-24	0.14	0.35
Age 25-34	0.21	0.41
Age 35-44	0.22	0.41
Age 45-54	0.25	0.43
Age 55-65	0.19	0.39
No qualifications	0.04	0.19
Some GCSE/O levels	0.12	0.32
5 or more GCSE/O levels	0.13	0.34
Trade/technical/vocational training	0.12	0.33
A levels	0.22	0.41
Bachelor's degree	0.26	0.44
Master's degree	0.09	0.28
Doctorate degree	0.02	0.12
North East	0.05	0.22
North West	0.11	0.32
Yorkshire and Humberside	0.09	0.29
East Midlands	0.08	0.27
West Midlands	0.09	0.29
Eastern England	0.07	0.26
London	0.12	0.33
South East	0.15	0.35
South West	0.08	0.27
Wales	0.05	0.22
Scotland	0.08	0.27
Northern Ireland	0.02	0.14
Employed by government	0.17	0.38
Employed by private company	0.49	0.50
Employed by non-profit organization	0.07	0.26
Self-employed, with or without employees	0.11	0.32
Working in the family business	0.01	0.11
Only work last week was filling out surveys	0.03	0.17
Did not have a job last week	0.12	0.32
Observations	18,831	

Notes: The table reports the mean and standard deviation of a set of individual characteristics for the full sample of respondents to the LSE-CEP Survey of Self-Employment and Alternative Work Arrangements.
Source: LSE-CEP survey.

Table 4.A2: CEP-LSE Survey Representativeness based on LFS 2017

	All individuals		ZHC workers	
	Mean	S.D.	Mean	S.D.
Female	0.52	0.50	0.60	0.49
Age	42.78	13.34	37.85	14.91
Age 18-24	0.11	0.32	0.28	0.45
Age 25-34	0.19	0.40	0.19	0.39
Age 35-44	0.22	0.41	0.16	0.37
Age 45-54	0.24	0.43	0.18	0.38
Age 55-65	0.24	0.43	0.19	0.39
No Qualifications	0.08	0.26	0.06	0.24
GCSE/O levels	0.20	0.40	0.22	0.41
Trade/Technical/Other	0.09	0.28	0.10	0.30
A Levels	0.23	0.42	0.28	0.45
Bachelor's Degree	0.30	0.46	0.23	0.42
Master's Degree	0.05	0.21	0.03	0.17
Doctorate Degree	0.01	0.10	0.00	0.06
North East	0.04	0.20	0.05	0.22
North West	0.11	0.31	0.09	0.29
Yorkshire The Humber	0.09	0.28	0.08	0.28
East Midlands	0.07	0.26	0.08	0.27
West Midlands	0.09	0.28	0.08	0.26
East of England	0.09	0.29	0.09	0.29
London	0.11	0.32	0.12	0.32
South East	0.13	0.34	0.15	0.35
South West	0.09	0.29	0.11	0.32
Wales	0.04	0.21	0.01	0.11
Scotland	0.08	0.27	0.08	0.27
Northern Ireland	0.05	0.21	0.05	0.23
Employed by Public Sector	0.17	0.38	0.16	0.36
Employed by Private Sector	0.58	0.49	0.84	0.37
Self-employed, with or without employees	0.11	0.31	0.09	0.29
Does not have a job	0.24	0.43	0.00	0.00
Hourly Wage	14.82	11.42	9.70	7.12
Hourly Wage (median)	11.55		8.0	
Observations	108,983		1,686	

Notes: The table reports summary statistics of individual level characteristics for all working age respondents and ZHC workers. Wage data only appears in two waves of the LFS, thus wage statistics are based off approximately one third of the number of observations.
Source: LFS.

Table 4.A3: NMDS-SC Survey Representativeness (Care Workers)

	LFS		NMDS-SC	
	Mean	S.D.	Mean	S.D.
	(1)	(2)	(3)	(4)
Prop. female	0.85	0.36	0.85	0.13
Age	42.62	13.58	42.60	4.63
Hourly rate	7.91	1.50	7.10	0.93
Weekly hours	28.38	16.14	24.49	10.30
Proportion on ZHC	0.11	0.31	0.12	0.23
North East	0.07	0.25	0.05	0.23
North West	0.13	0.34	0.13	0.34
Yorkshire and Humberside	0.12	0.32	0.10	0.31
East Midlands	0.08	0.28	0.09	0.28
West Midlands	0.11	0.31	0.12	0.33
East England	0.12	0.32	0.13	0.34
London	0.09	0.28	0.06	0.24
South East	0.15	0.36	0.15	0.36
South West	0.13	0.34	0.15	0.36
Observations	2,025		4,680	

Notes: The table reports the mean and standard deviation for a set of individual-level characteristics for care workers in the LFS (columns (1) and (2)). The table also reports the mean and standard deviation for the same set of characteristics at the firm level in NMDS-SC (columns (3) and (4)). The LFS data refer to 2015Q4 and 2016Q1, and the NMDS-SC data to March 2016. The ZHC indicator only appears in April-June and October-December quarters of the LFS. Thus the proportion of ZHC reported in column (1) is based on 2015Q4 data only. Wage data only appears in two waves of the LFS, thus wage statistics in columns (1) and (2) are based off approximately one fifth of the number of observations.
Source: LFS and NMDS-SC.

Table 4.A4: Employment Equations

Change in log number of employees

March 2016 to March 2017

	(1)	(2)	(3)	(4)
Initial low-paid proportion	-0.000	-0.010	-0.001	-0.009
	(0.011)	(0.011)	(0.014)	(0.013)
Initial low-paid proportion x Domiciliary		0.036		0.024
		(0.032)		(0.033)
Observations	4,680	4,680	4,680	4,680
Controls	No	No	Yes	Yes
F-stat	519.52	280.43	410.41	203.22
Mean of dep. var.:				
All firms	0.013			
Care homes	0.013			
Domiciliary care	0.012			

Notes: The table reports the estimated reduced-form coefficient $\hat{\beta}_3$ from model 4.3, using the change in log headcount employment as outcome variable. The sample is a balanced panel of adult social care providers active between March 2015 and March 2017. Robust standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the initial proportion female, proportion with nursing qualification, proportion of care assistants, average age (all workers), occupancy rate and local authority district dummies. When data on firm-level covariates is missing, such missing information is controlled for via a set of dummy variables.
Source: NMDS-SC.

Table 4.A5: Employment Contract Equations

Change in proportion of employees by contract type between March 2016 and March 2017

Panel A - Temporary contract

	(1)	(2)	(3)	(4)	(5)	(6)
Initial low-paid prop	-0.002	-0.003	-0.002	-0.000		
	(0.003)	(0.002)	(0.003)	(0.002)		
Initial low-paid prop x Domic		-0.003		-0.001		
		(0.010)		(0.010)		
Change in log avg wage					-0.038	-0.008
					(0.060)	(0.046)
Change in log avg wage x Domic						-0.129
						(0.167)
Observations	4,680	4,680	4,680	4,680	4,680	4,680
Controls	No	No	Yes	Yes	Yes	Yes
Mean of dep. var.:						
All firms	-0.002					
Care homes	-0.001					
Domiciliary care	-0.005					

Panel B - Bank

	(1)	(2)	(3)	(4)	(5)	(6)
Initial low-paid prop	0.002	-0.001	0.002	-0.001		
	(0.003)	(0.003)	(0.003)	(0.003)		
Initial low-paid prop x Domic		0.008		0.011		
		(0.006)		(0.007)		
Change in log avg wage					0.037	-0.024
					(0.056)	(0.063)
Change in log avg wage x Domic						0.193
						(0.118)
Observations	4,680	4,680	4,680	4,680	4,680	4,680
Controls	No	No	Yes	Yes	Yes	Yes
Mean of dep. var.:						
All firms	-0.004					
Care homes	-0.004					
Domiciliary care	-0.005					

Table 4.A5 Continued: Employment Contract Equations

Panel C - Agency contract

	(1)	(2)	(3)	(4)	(5)	(6)
Initial low-paid prop	0.001	-0.001*	0.001	0.000		
	(0.002)	(0.001)	(0.002)	(0.002)		
Initial low-paid prop x Domic		0.000		0.001		
		(0.007)		(0.008)		
Change in log avg wage					0.017	0.001
					(0.040)	(0.027)
Change in log avg wage x Domic						0.023
						(0.137)
Observations	4,680	4,680	4,680	4,680	4,680	4,680
Controls	No	No	Yes	Yes	Yes	Yes
Mean of dep. var.:						
All firms	-0.002					
Care homes	-0.000					
Domiciliary care	-0.009					

Notes: The table reports the estimated reduced-form coefficient $\hat{\beta}_3$ from model 4.3 in columns (1)-(4), and the estimated IV coefficient $\hat{\beta}_4$ from model 4.4 in columns (5)-(6), using the change in the share of workers on a given contract as outcome variable. The sample is a balanced panel of adult social care providers active between March 2015 and March 2017. Robust standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the initial proportion female, proportion with nursing qualification, proportion of care assistants, average age (all workers), occupancy rate and local authority district dummies. When data on firm-level covariates is missing, such missing information is controlled for via a set of dummy variables. *Temporary contract*: the worker is employed for a limited duration, normally either on a fixed term contract or for a fixed task, or on a spell of casual or seasonal employment as a "temp". *Bank worker*: the worker is retained by the organisation as a whole, but deployed on a casual or short term basis. *Temporary agency work*: the worker is supplied by an outside employment agency/bureau; this category includes staff employed by NHS professionals, and workers supplied on contract e.g. by outside catering and cleaning companies.
Source: NMDS-SC.

Table 4.A6: Zero Hour Contracts Equation, Low Pay Industries (LFS Sample)

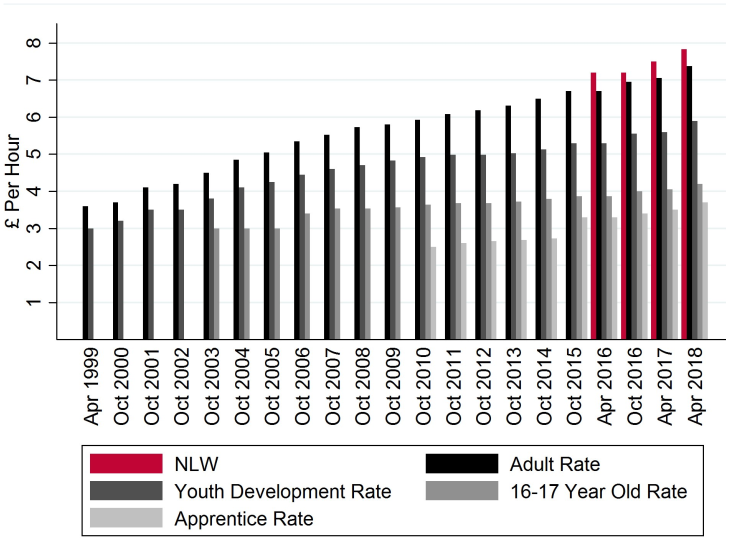
Probability of being on a ZHC

	Retail		Hospitality		Social care	
	(1)	(2)	(3)	(4)	(5)	(6)
Post NLW	0.001	0.002	0.0118**	0.014**	0.011***	0.010***
	(0.002)	(0.002)	(0.006)	(0.006)	(0.003)	(0.003)
Observations	27,058	27,058	12,446	12,446	25,191	25,191
Controls	No	Yes	No	Yes	No	Yes
Pre-NLW mean of dep. var.:	0.017	0.017	0.102	0.102	0.042	0.042
	Employment agency		Cleaning and maintenance		Leisure, travel and sport	
	(7)	(8)	(9)	(10)	(11)	(12)
Post NLW	0.013	0.013	0.013***	0.014***	0.024**	0.025**
	(0.013)	(0.013)	(0.004)	(0.004)	(0.011)	(0.010)
Observations	1,701	1,701	5,729	5,729	3,541	3,541
Controls	No	Yes	No	Yes	No	Yes
Pre-NLW mean of dep. var.:	0.072	0.072	0.019	0.019	0.099	0.099
	Food processing		Wholesale of food		Childcare	
	(13)	(14)	(15)	(16)	(17)	(18)
Post NLW	0.011*	0.013**	0.003	0.004	0.006	0.006
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Observations	2,885	2,885	1,915	1,915	3,246	3,246
Controls	No	Yes	No	Yes	No	Yes
Pre-NLW mean of dep. var.:	0.025	0.025	0.010	0.010	0.031	0.031
	Agriculture		Security		Textiles	
	(19)	(20)	(21)	(22)	(23)	(24)
Post NLW	0.001	0.001	-0.024	-0.019	0.018**	0.019**
	(0.003)	(0.004)	(0.019)	(0.019)	(0.008)	(0.008)
Observations	3,084	3,084	1,057	1,057	996	996
Controls	No	Yes	No	Yes	No	Yes
Pre-NLW mean of dep. var.:	0.010	0.010	0.115	0.115	0.009	0.009
	Hairdressing		Pooled			
	(25)	(26)	(27)	(28)		
Post NLW	0.010*	0.010**	0.008***	0.010***		
	(0.005)	(0.005)	(0.001)	(0.001)		
Observations	2,513	2,513	91,362	91,362		
Controls	No	Yes	No	Yes		
Pre-NLW mean of dep. var.:	0.013	0.013	0.041	0.041		

Notes: The table reports the estimated reduced-form coefficient $\hat{\beta}_5$ from model 4.5, using different Low Paying Industry samples, as defined in Low Pay Comission (2017). The samples contain 4 pre-NLW quarters (2014-2015 quarter 2 and quarter 4) and 3 post-NLW quarters (2016 quarter 2 and quarter 4, and 2017 quarter 2). Controls include age, education, gender, a dummy for white ethnicity, a dummy for British nationality, a dummy for working in the public sector and twelve regional dummies. Robust standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1.
Source: LFS.

4.B Additional Figures

Figure 4.B1: Minimum Wage Rates in the UK between 1999 and 2018



Notes: The graph reports the various minimum wage rates in the UK between 1999 and 2018. The apprentice rate applies to apprentices. The 16-17 year-old rate to workers aged 16 and 17. The youth development rate to workers aged 18-20. The adult rate applied to workers aged 21 and over until March 2016. From April 2016, the adult rate applies to workers aged 21-24 and the NLW to those aged 25 and over.
Source: Low Pay Commission.

4.C LSE-CEP Survey of Self-employment and Alternative Work Arrangements: Survey Questionnaire

R1 What is the highest degree or level of school you have completed?

- ○ No qualifications
- ○ Some GCSE/O levels.
- ○ 5 or more GCSE/O levels
- ○ Trade/technical/vocational training
- ○ A levels
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctorate degree

R2 Are you?

- ○ Male
- ○ Female

R3 What is your age? [ALLOW INTEGER NUMBERS BETWEEN 15 AND 99]

____

R4 Which region do you usually live in?

- ○ North East
- ○ North West
- ○ Yorkshire and Humberside
- ○ East Midlands
- ○ West Midlands
- ○ Eastern England
- ○ London
- ○ South East
- ○ South West
- ○ Wales
- ○ Scotland

- Northern Ireland

S1 On your main job last week, were you employed by government, by a private company, a nonprofit organization, or were you self-employed or working in the family business? Or were you not working at all last week?

- Employed by government GO TO S2
- Employed by private for-profit company GO TO S2
- Employed by nonprofit organization including tax exempt and charitable organizations GO TO S2
- Self-employed, with or without employees GO TO S3
- Working in the family business GO TO S3
- Only work last week was filling out surveys SCREENS OUT
- Did not have a job last week SCREENS OUT

S2 Many people work in self-employment, on either a part-time or full-time basis, doing things such as working on construction jobs, selling goods or services in their businesses, or working through a digital platform or intermediary, such as Uber, Upwork, Deliveroo or Avon. Last week, were you working or self-employed as an independent contractor, an independent consultant, or freelance worker? That is, someone who obtains customers on their own to provide a product or service.

- Yes
- No

S3 Last week, were you on a zero hours contract? Zero hours contracts are also known as casual contracts or "on call" work. Under such contracts, people agree to be available for work as and when required, but have no guaranteed hours or times of work.

- Yes GO TO QUESTION Q1
- No GO TO QUESTION D1

Q1 In your employment as a zero hours contract or on-call worker last week, did you have more than one employer or contract? Please consider only jobs on zero hours contracts or on-call jobs when answering this question.

- Yes
- No

Q2 Last week, did you do any paid work as self-employed or on employment contracts other than zero hours contracts or on-call jobs?

- Yes
- No

Q3 In your zero hours contract or on-call job, how many hours did you work last week? Please, consider only hours you are paid for.
Please enter: __________ hours last week

Q4 In your zero hours contract or on-call job, how many hours do you work on average in a week? Please, consider only hours you are paid for.
Please enter: __________ hours on average in a week

Q5 On how many (different) days per week do you usually work?
Please enter: __________ days per week

Q6 How much did you earn per hour in your zero hours contract or on-call job last week? Please, consider only hours you are paid for.
Please enter earnings: £__________ per hour

Q7 Did you do any hours of unpaid work in your zero hours contract or on-call job last week? E.g. travel time from one customer to another.

- Yes
- No

IF Q7 = Yes
Q7a How many hours of unpaid work did you do in your zero hours contract or on-call job last week?
Please enter: __________ hours of unpaid work last week

Q8 Would you have preferred to work more or fewer hours last week in your zero hours contract or on-call job at that wage rate? Or were you satisfied with the number of hours you worked?

- More hours last week
- Fewer hours last week
- Satisfied with number of hours

IF Q8 = More hours last week
Q8a Why were you not able to work more last week?

- I am not qualified for the available work
- There isn't enough available work
- I have domestic commitments that prevent me from working more
- I am ill or disabled

- Other

IF Q8 = Fewer hours last week
Q8b Why would you want to work fewer hours?

- I am a student
- I am ill or disabled and do not feel I can take on more hours
- I have domestic commitments that prevent me from working more
- I want to spend more time on leisure or other unpaid activities
- I want to do other types of work
- Other

Q9 Would you have preferred to work a pattern of more regular hours last week on your zero hours contract or on-call job at that wage rate? Or were you satisfied with the pattern of hours you worked?

- More regular hours last week
- Less regular hours last week
- Satisfied with pattern of hours

Q10 How satisfied are you with working on a zero hours contract or on-call job?

- Very satisfied
- Satisfied
- Neither satisfied not dissatisfied
- Dissatisfied
- Very dissatisfied

Q11 Which of the following are reasons why you work on a zero hours contract or on-call job? Tick all that apply.

- [ ] Could not find employment in a job with a guaranteed number of hours
- [ ] Pay is better than other available jobs
- [ ] To complement pay from other jobs
- [ ] To earn money while going to school
- [ ] Gives me flexibility to perform other activities
- [ ] Other

Q11a Which is the most important reason why you work on a zero hours contract or on-call job?

- Could not find employment in a job with a guaranteed number of hours
- Pay is better than other available jobs
- To complement pay from other jobs
- To earn money while going to school
- Gives me flexibility to perform other activities
- Other

IF Q11a = Could not find employment in a job with a guaranteed number of hours
Q11b Please indicate which of the following reasons contributed to you not finding employment in a job with a guaranteed number of hours:

- Lack of jobs near where I live
- I faced discrimination
- I am overqualified for the available jobs
- I am underqualified for the available jobs
- Other

Q12 For how long have you been working on a zero hours contract or on-call job?

- Less than one month
- 1 - 6 months
- 7 - 12 months
- 1 - 2 years
- 3 - 4 years
- 5 years or more

Q13 How much longer do you expect to remain in your zero hours contract or on-call job?

- Less than one month
- 1 - 6 months
- 7 - 12 months
- One year or more

Q14 Have you received any work-related training in the last year?

- ○ Yes SKIP TO Q14a
- ○ No SKIP TO Q14c

Q14a What type of training? (Mark all that apply) [LIST IN RANDOM ORDER, BUT OTHER IS LAST]

- ☐ Technical or technology training
- ☐ Quality training
- ☐ Skills training
- ☐ Continuing education
- ☐ Professional training and legal training
- ☐ Managerial training
- ☐ Safety training
- ☐ Other (please specify: ________)

Q14b Who paid for the cost of the training?

- ○ Me or a family member
- ○ A contractor or customer
- ○ My employer
- ○ Someone else
- ○ No one, it was free

Q14c What type of training would you find most useful to improve your job prospects? (Mark all that apply) [LIST IN RANDOM ORDER, BUT OTHER IS LAST]

- ☐ Technical or technology training
- ☐ Quality training
- ☐ Skills training
- ☐ Continuing education
- ☐ Professional training and legal training
- ☐ Managerial training
- ☐ Safety training
- ☐ Other (please specify: ________)

Q15 In your job on a zero hours contract or on-call job, what kind of work do you do, that is, what is your occupation? (For example: plumber, typist, farmer)
Please enter your occupation: ___________

Q15a What are your usual activities or duties at this job? (For example: typing, keeping account books, filing, selling cars, operating printing press, laying brick)
Please enter your usual activities or duties: ___________

Q15b What kind of business or industry are you in at this job?

- ○ (A) Agriculture, Forestry and Fishing
- ○ (B) Mining and Quarrying
- ○ (C) Manufacturing
- ○ (D) Electricity, Gas, Steam and Air Conditioning Supply
- ○ (E) Water Supply, Sewerage, Waste Management and Remediation Activities
- ○ (F) Construction
- ○ (G) Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles
- ○ (H) Transportation and Storage
- ○ (I) Accommodation and Food Service Activities
- ○ (J) Information and Communication
- ○ (K) Financial and Insurance Activities
- ○ (L) Real Estate Activities
- ○ (M) Professional, Scientific and Technical Activities
- ○ (N) Administrative and Support Service Activities
- ○ (O) Public Administration and Defense, Compulsory Social Security
- ○ (P) Education
- ○ (Q) Human Health and Social Work Activities
- ○ (R) Arts, Entertainment and Recreation
- ○ (S) Other Service Activities
- ○ (T) Activities of Households as Employers of Domestic Personnel, Undifferentiated Goods and Services Producing Activities of Households for Own Use
- ○ (U) Activities of Extraterritorial Organizations and Bodies
- ○ Other (please specify: ___________)

Q15c In your zero hours contract or on-call job, what is the main company you work for?
Please specify name: ___________

D1 Which country were you born in?
Please specify: ___________

D2 What is your nationality?
Please specify: ___________

D3 Which category or categories below best describe your ethnic group? (Mark all that apply)

- ☐ White
- ☐ Mixed / Multiple ethnic group
- ☐ Asian / Asian British
- ☐ Black / African / Caribbean / Black British
- ☐ Chinese
- ☐ Arab
- ☐ Other (please specify: ___________)

D4 How many years of working experience have you got?

- ○ Less than one year
- ○ 1 - 3 years
- ○ 3 - 5 years
- ○ 5 years or more

D5 Are you now married, widowed, divorced, separated or never married?

- ○ Married
- ○ Widowed
- ○ Divorced
- ○ Separated
- ○ Never Married
- ○ Other (please specify: ___________)

D6 How many children do you have?

- ○ 0

- 1
- 2
- 3 or more

D7 Which category represents your total individual income (before taxes) during the past 12 months? This should include money from all jobs, net income from a business or farm, and any rent, pensions, dividends, interest, social security payments or other money income you received.

- Less than £5,000
- £5,000 to 9,999
- £10,000 to 19,999
- £20,000 to 39,999
- £40,000 to 69,999
- £70,000 or more

D8 Which category represents total income (before taxes) of your household during the past 12 months? This should include money from all jobs, net income from a business or farm, and any rent, pensions, dividends, interest, social security payments or other money income that all members of your household received, including you.

- Less than £5,000
- £5,000 to 9,999
- £10,000 to 19,999
- £20,000 to 39,999
- £40,000 to 69,999
- £70,000 or more

D9 Do you use services such as Uber, TaskRabbit, Airbnb or Deliveroo?

- Yes
- No

D10 Could you tell us how interesting or uninteresting you found the questions in this survey?

- Very interesting
- Interesting
- Neither interesting nor uninteresting
- Uninteresting
- Very uninteresting

5

Willing to pay for security: a discrete choice experiment to analyse labour supply preferences

Abstract

This paper investigates whether labour supply preferences are responsible for the rise in atypical work arrangements in the UK and US. By employing vignettes in a survey the author estimates the distribution for willingness-to-pay over various job attributes. The list of attributes includes distinguishing factors of typical and atypical work, such as security, work-related benefits, flexibility, autonomy and tax. The results suggest that the majority of workers prefer characteristics associated with traditional employee-employer relationships, and this holds for the sub-sample of those in atypical work. Additionally, preferences across the UK and US are very similar, despite differences in labour market regulations. Ceteris paribus, the author finds that the changing nature of work is likely to have significant negative welfare implications for many workers.

5.1 Introduction

A number of developed economies have experienced an increase in the proportion of workers involved in atypical work arrangements (Boeri et al., 2020; Adams et al., 2020). These include, though are not limited to, arrangements such as short and zero hours contracts, gig and HIT (human intelligence task) work, and freelancing. In the United Kingdom, the proportion in self-employment has risen by 25% over the past two decades, and as shown by figure 5.1.1, this increase is entirely driven by those without employees[1]. The proportion of workers on zero hour contracts (ZHCs)[2] has increased from 200,000 to almost a million over the same time period. The United States has experienced similar trends, with Katz and Krueger (2019b) finding almost a 20% rise in the proportion of workers engaged in alternative work arrangements between 2005 and 2015.

The welfare effects associated with this trend will depend on the underlying drivers. Income and wages for atypical work arrangements are on average lower than traditional employment relations in the UK, and ZHC workers experienced a greater drop in wages and weaker recovery following the onset of the Great Recession (see figures 5.1.2a and5.1.2b). Similarly in the US, Katz and Krueger (2019a) find that even after conditioning on personal characteristics and occupation dummies workers in atypical work arrangements have lower weekly earnings. Atypical work arrangements are additionally generally not afforded certain non-pecuniary benefits such as job security and holiday and sick pay. However, they are more likely to enjoy other benefits such as flexibility, autonomy and a favourable tax structure. This indicates two possible mechanisms, one where labour demand conditions for traditional employees are weak, thus pushing workers into accepting more precarious working conditions with lower wages, and another where workers are choosing to trade in pay and security for more flexible and autonomous working arrangements. This paper investigates the extent to which the latter matters, and seeks to answer whether labour supply preferences for particular job attributes could be an underlying factor driving the rise in atypical employment.

Eliciting labour supply preferences is challenging. Realised choice data lacks detailed information on both the chosen job and the available alternatives resulting in identification issues. To overcome this I exploit the trade-off between typical and atypical job attributes in a discrete job choice experiment using vignettes in a novel representative survey. I estimate preferences and willingness-to-pay (WTP) distributions for a variety of job attributes which often distinguish typical from atypical work arrangements. The survey setting allows the collection of individual-level characteristics including detailed

[1]This encompasses freelancers, gig and HIT workers and crowd workers.

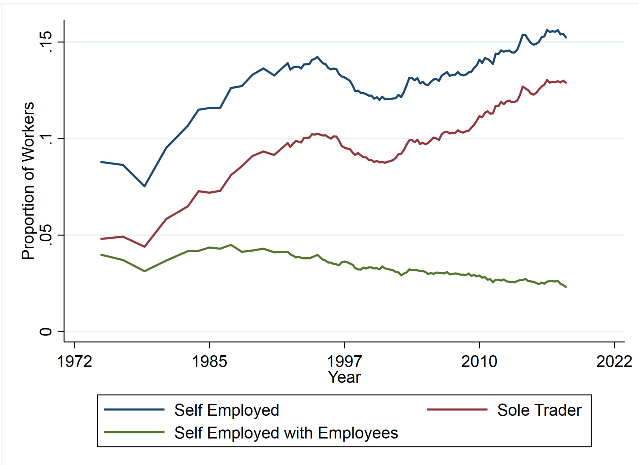
[2]ZHCs are an employment contract under which a worker is not guaranteed any hours and is only paid for work carried out. For a full discussion of ZHCs see Datta et al. (2019)

demographics and preferences such as risk aversion. This additional information in conjunction with the distributional estimation allows for a careful treatment of individual heterogeneity.

Using a mixed logit model I find that workers in both the UK and US value security and traditional employment benefits such as holiday and sick pay far more than hours and location flexibility, autonomy and advantageous tax treatment. Estimates are very similar across the two countries which is unexpected given differences in labour market institutions. While a small proportion of workers place a substantial value on flexibility, an even smaller proportion place a lower value on security. Thus, little evidence is found that backs the hypothesis that worker preferences have contributed to the increase of atypical work arrangements. On the contrary, the evidence suggests that approximately half of workers in atypical roles would prefer more traditional work arrangements. The results are robust to a variety of specifications, unaffected by hypothetical bias, and little evidence of inattention is found.

The remainder of this paper is structured as follows. Section 5.2 gives an overview of the existing literature on the topic. Section 5.3 describes the survey design and data, and section 5.4 motivates and describes the vignette methodology used. Section 5.5 outlines the empirical framework. Section 5.6 reports the results and compares them to a simple calibrated model of search, and section 5.7 closes with some concluding remarks.

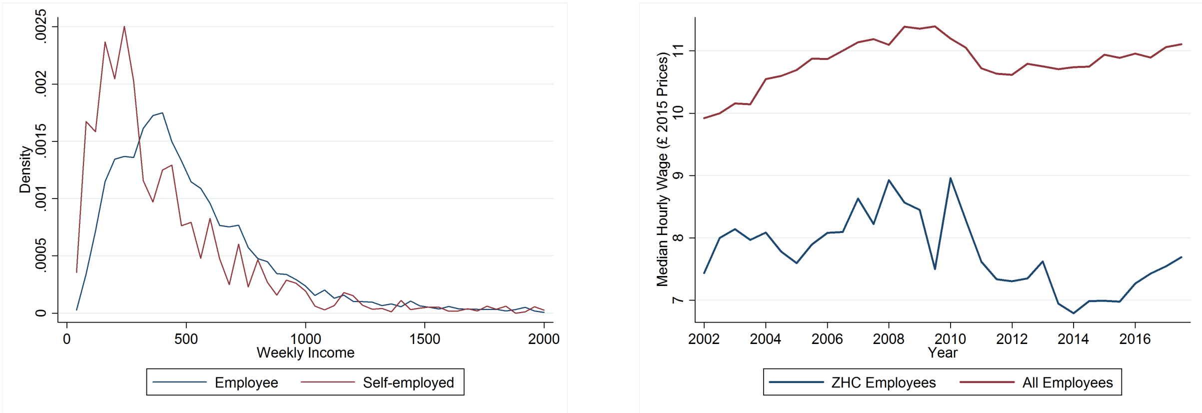
Figure 5.1.1: Self Employment Proportions: 1975 -2018



Notes: The graph shows the proportion of self-employed workers in the UK between 1975 and 2018.
Source: Labour Force Survey (LFS)

Figure 5.1.2: Atypical vs Typical Income and Wages

(a) Employee vs Self-Employed Income: 2016 (b) Employee Wages, All vs ZHC: 2002 -2018



Notes: The left hand panel shows the cross sectional distribution of weekly income for employees and self employed in the UK. The right hand panel shows the time series of the median hourly wage in 2015 prices for ZHC employees and all employees in the UK.
Source: Family Resource Survey and LFS

5.2 Related Literature

Analysis of atypical work arrangements and their impacts to workers is not a new topic. A branch of early literature from the 1990s characterised such arrangements as offering lower wages with less security and benefits, and little scope for human capital accumulation (Rodgers and Rodgers, 1989; M. Beard and R. Edwards, 1995; Nollen, 1996; Kalleberg, 2000). However, even at that time the heterogeneity in the market was highlighted (Büchtemann and Quack, 1989).

The emergence of atypical work arrangements has been attributed to a variety of causes including weak demand conditions, regulation, demographic changes, technological change and preferences. In the early literature Cordova (1986) highlights the importance of the slow down in economic growth that occurred in the 1980s, while more recently Katz and Krueger (2017) find that US workers who experience unemployment spells are more likely (7 to 17%) to be involved in a form of atypical work arrangement. Kalleberg (2000) argues that technological improvements in information and communication systems additionally made it easier for firms to arrange temporary workers, and this is further exemplified by the emergence of recent online “gig” platforms. Parts of the early literature also highlight the importance of labour market regulation in driving increases in atypical work (Lee, 1996; Capelli et al., 1997). Recent causal evidence from Datta et al. (2019) confirms this as a contributing factor, finding that the introduction of the National Living Wage (which represented a 7.5% increase in the wage floor) increased care homes and domiciliary care agencies use of ZHCs.

A small body of recent literature exists that looks to estimate worker preferences over job characteristics and fringe benefits, and it is these studies that this paper is most comparable to. Mas and Pallais (2017) employ a discrete choice experiment during the hiring period for a call centre in the US. They estimate the WTP distribution for flexibility attributes for jobs, including flexibility of hours and work location, and find that hours flexibility is not valued by the majority of workers, though there is a long right tail who are price inelastic for flexibility. Both Eriksson and Kristensen (2014) and Wiswall and Zafar (2018) use a similar vignette method as used in this study. While a focus in both papers is placed more so on preferences over job packages and other characteristics such as bonuses and health insurance, some attributes of the atypical-typical trade-off are considered, such as flexibility. Eriksson and Kristensen (2014) in particular find that among five different job amenities (such as bonuses and on the job training) that flexibility is the most valued.

This paper contributes to the above literature along a number of dimensions. Firstly, it uses an experimental design which allows the distributions of preferences to be backed out for arguably the most important distinguishing characteristics of typical and atypical work arrangements. The existing literature tends to focus predominantly on flexibility, this paper however allows for a more complete understanding of labour supply decisions into atypical jobs. Secondly, as the experiment employs vignettes in a survey setting, it allows for other individual level preferences to be elicited, such as risk aversion, as well as other individual level characteristics. As a result this offers itself to deeper heterogeneity analysis. Finally, it uses representative samples of both the UK and US population, and thus can be generalised to make inferences about the labour supply decisions for workers in the UK and US, while also lending itself to make cross country comparisons.

5.3 Survey Design and Data

Data was collected using an internet based survey launched in July 2018 on the Prolific Academic platform, targeted at a panel of working-age UK and US respondents. The Labour Choice Survey (LCS) was approximately 15 minutes long and contained questions on demographics, instruments for measuring preferences relating to risk and time, a short cognitive ability test and a fictitious discrete job choice experiment based on vignettes. Respondents were paid £4.55 ($5.81) for completing the survey, equivalent to £18.20 ($23.26) per hour. This rate is far higher than what is often paid on online platforms[3] and is equivalent to the 68th percentile of income in the UK and the 63th in the US. This

[3] Adams et al. (2018) estimate the median hourly wage on Mechanical Turk is only $2 per hour.

may help mitigate selection issues which could arise from a lower payment rate. Prior to taking the survey to the field, a small pilot survey was run on a different platform and respondents were asked to give feedback concerning the clarity of the questions and no issues were raised.

5.3.1 Preferences

Two preference parameters which might be correlated with job choice decisions, and in particular self-employment decisions, are risk aversion and time discounting. Self-employment is often characterised by short-term contract work which offers less security than traditional employment. It is thus hypothesised that individuals with lower levels of risk aversion may be more likely to select into self-employment and therefore present with lower WTP for job security characteristics. Additionally, newly formed companies or sole traders can face a number of months or years as the business develops till they see meaningful returns. The self-employed may therefore be represented more by individuals with a lower discount factor.

In order to elicit preferences on both risk aversion and discounting I employ part of the preference survey module from Falk et al. (2016). For both preferences a hypothetical choice experiment is used which is analogous to the more commonly used revealed preference approach.

For both preferences the streamlined quantitative questions are used due to time restrictions, though as noted by Falk et al. (2016), this has a minimal impact on the explanatory power of the module. For both risk and discounting, five interdependent hypothetical choice experiments are asked following a "staircase" procedure.[4] Risk preferences are elicited with a choice between a lottery and a sure payment, while discounting preferences are elicited with a choice between a payment today and a payment in 12 months. Figures 5.B.1 and 5.B.2 in section 5.B present example quantitative questions for risk and discounting preferences respectively.

5.3.2 Cognitive Ability Test

There appears no a priori reason why cognitive ability should be linked to labour choice decisions, and estimates from the US indicates that there is no relationship between job preferences and cognitive ability (Mas and Pallais, 2017). However, to test this on a UK

[4]For illustrations of the staircases please see Appendix E and F in Falk et al. (2016).

based sample I also include a short cognitive test.

I use a highly streamlined version of the Wonderlic Personnel Test. The full test consists of 50 multiple choice questions to be answered in 12 minutes. Due to time constraints I reduce this to 6 questions to be answered in 90 seconds. The questions cover logic, maths and literacy, and are of varying difficulty in order to create separation of scores.

5.3.3 Descriptive Statistics and Representativeness of Sample

Table 5.3.1 presents descriptive statistics from the LCS, and where possible, the corresponding statistics from the UK's Quarterly Labour Force Survey (QLFS) and the US's Current Population Survey (CPS) in order to assess the representativeness of the respondents.

There is an even spread of men and women in the survey[5] as well as an even spread across ages. In the UK (US) 67% (53%) are cohabiting with some form of partner and 52% (41%) have children. All these figures line up relatively well with the QLFS and CPS statistics, though our UK sample has marginally less people with children (to the tune of 8 percentage points). Measures for the preference parameters are very similar across the two countries. The samples are on average risk averse, requiring an £82.95 ($89.06) certainty equivalent to induce indifference to a £300 ($300) 50/50 lottery, and they have a discount factor of 0.66 (0.64), which is inline with similar estimates (Dohmen et al., 2010).

Respondents possess a variety of education levels and approximately 50% have an undergraduate degree or higher in both countries. The education level proportions are generally similar to the national data, though in the US the LCS survey has under-sampled those with a lower level of education.

As everyone in the sample is by definition in some form of employment (respondents on Prolific Academic are paid to respond to surveys) I restrict analysis in the national data to only those who are active in the labour force. 69% (62%) of the LCS sample earn the bulk of their earnings through a traditional employment relationship while the remaining

[5] Seventeen respondents identified as transsexual or non-binary in total, all others identified as either male or female.

Table 5.3.1: Descriptive Statistics

	UK				US			
	LCS Mean	LCS StdDev	QLFS Mean	QLFS StdDev	LCS Mean	LCS StdDev	CPS Mean	CPS StdDev
Demographics								
Female	0.53	0.50	0.49	0.50	0.53	0.50	0.48	0.50
Age	42.01	13.40	42.61	12.48	39.38	13.18	41.88	13.30
Married, cohabiting	0.67	0.47	0.71	0.46	0.53	0.50	0.55	0.50
Has children	0.52	0.50	0.60	0.49	0.41	0.49		
Preferences								
Certainty Equivalent to 50/50 (£/$)300 lottery	82.96	47.79			89.06	53.18		
Discount Factor	0.66	0.17			0.64	0.18		
Education								
Less Than High School	0.20	0.40	0.24	0.43	0.01	0.10	0.06	0.24
High School	0.20	0.40	0.23	0.42	0.09	0.29	0.27	0.44
Technical, Vocational, Some College	0.09	0.29	0.08	0.27	0.38	0.49	0.29	0.45
Batcherlor's Degree or higher	0.50	0.50	0.43	0.50	0.52	0.50	0.38	0.48
Woderlic Test Score /6 (IQ)	1.55	1.27			1.68	1.33		
Work								
Employee	0.69	0.46	0.85	0.35	0.62	0.49	0.90	0.30
Self-employed	0.31	0.46	0.15	0.35	0.38	0.49	0.10	0.30
Employee Hourly Rate (£/$)	14.10	8.62	14.75	9.59	23.02	16.39	24.28	15.65
Self Employment Hourly Rate (£/$)	14.56	11.84			24.05	25.56		
Gig Work Hourly Rate (£/$)	5.55	5.54			8.12	10.62		
N	2,013		42,116		1,871		55,102	

Notes: The table reports the mean and standard deviation of a set of individual level characteristics for the UK and US samples from the Labour Choice Survey, the UK Labour Force Survey and the US Current Population Survey.

31% (38%) through self-employment channels, such as freelancing, gig work and running a business. There is around 16 (28) percentage points more individuals who are classified as self-employed in the LCS sample in comparison to the national data, though this is unsurprising given the platform being used is likely to draw in more gig and HIT workers. That said the mean employee hourly rate of £14.10 ($23.02) in the LCS is almost identical to the national data. The mean hourly rate from self-employment is very similar to the employment hourly rate though has a larger standard deviation in both the US and UK. The gig hourly rates (£5.55 and $10.62) are considerably lower however, and in the UK's case, below the National Living Wage (£7.83).

Overall the LCS samples match the national data well, and based on the aforementioned observables the LCS sample is generally representative of the entire population.

5.4 Vignettes

5.4.1 Motivation

The use of realised choice data to elicit preferences has a number of shortcomings. Firstly, detailed job data (beyond wages) for a sample of the labour force is not easily available. Secondly, even if the aforementioned data was available, it would not be possible to view the alternatives within an individual's choice set, and thus deducing a ranking would not be possible. Finally, within this data there would undoubtedly be correlation between observable and unobservable job characteristics, thus biasing the results.[6] The use of vignettes are able to overcome these shortcomings hence their recent surge in use for eliciting preferences (Eriksson and Kristensen, 2014; Wiswall and Zafar, 2018; Maestas et al., 2018; Adams and Andrew, 2019; Ameriks et al., 2020; Dhingra and Machin, 2020) In using an experimental approach with vignettes these shortcomings can be overcome. By offering respondents a repeated set of choices between jobs which have had specific attributes manipulated so as to create a trade-off, preferences can be identified. Furthermore, by making it explicit that the jobs only differ on the observables there is no possibility of an omitted variable bias. The use of vignettes also allows one to mix characteristics of atypical and typical work arrangements easily to disentangle preferences over each attribute, which would otherwise not be possible.

The only drawback of using vignettes comes from the potential presence of a "hypothetical bias"[7] which has been widely noted in the contingent valuation literature (Loomis, 2011). However, the contingent valuation approach is very different to that used in this paper. The contingent valuation literature generally concerns public goods and environmental valuations (e.g. oil spills); this is fundamentally different to the question asked here, as markets for such goods do not actually exist (see Portney (1994) and Loomis (2011)). Thus decision making and choices are likely to be highly arbitrary for such

[6]For a formal derivation of this omitted variable bias see Wiswall and Zafar (2018).

[7]The biasing of estimates as the experiment is based on a hypothetical setting.

problems. For the markets of interest here (i.e. labour markets), agents will have taken previous consideration to their employment choices, as well as have real life reference points. Indeed, Eriksson and Kristensen (2014) argue that relative valuations between non-pecuniary job benefits should not be affected by a hypothetical bias. Furthermore, this is supported by empirical evidence. Mas and Pallais (2017) run both a field experiment in the employment process for a call centre, as well as a hypothetical choice experiment in the Understanding America Study (UAS) survey, and find that the results between the two approaches are very similar. They conclude that a well designed survey-based choice experiment can elicit responses close to actual market choices, and that the survey has additional advantages as questions can be posed that would not be appropriate in a job application. Nevertheless, as outlined in section 5.4.4 certain ex-ante and ex-post measures are taken to mitigate any possible bias.

5.4.2 Attributes and Values

Jobs are described by seven attributes- wage, longevity, holiday and sick pay eligibility, flexibility of work hours, flexibility to work from home, ability to choose tasks performed on-the-job and tax implications. These characteristics have been chosen as they are likely to reflect differences between traditional and atypical working arrangements. Though they are unlikely to offer a complete description of typical versus atypical jobs, they were chosen for their importance and tractability. Caussade et al. (2005) find that the more attributes varied in a discrete choice setting, the greater the detriment to the ability to choose. Therefore in each vignette only three of the characteristics are varied between the two jobs and the remaining four are held constant so as to reduce cognitive burden.

Atypical jobs are often likely to be characterised by some job attributes which individuals may find preferable. The ability to choose hours and place of work are non-pecuniary benefits which describe many atypical employment relationships. ZHCs, for example, should in theory allow workers the opportunity to turn down work if they so wish.[8] Similarly many online freelancing platforms function without any expectation of a self-employed worker even meeting their clients, and thus working from home is common. Additionally,

[8]It is questionable however, whether all ZHC roles afford workers this ability in practice (Wakeling, 2014).

Table 5.4.1: Vignette Attributes and Values

Attribute	Values
Wages	£8.50, £10, £11.50, £13, £14.50, £16, £17.50 \$12, \$14.16, \$16.33, \$18.50, \$20.66, \$22.83, \$25
Holiday & Sick Pay	28 days paid annual leave and 16 weeks paid occupational sick leave (or pro rata if part time), No holiday pay and no sick pay
Longevity	1 month, 1 year, Permanent
Ability to choose hours	Freely choose how many hours and when you work them, 40 hours a week 9am-5pm
Ability to work from home	Can work from home all the time, Can work from home 50% of the time, Can not work from home
Ability to choose which tasks you do on the job	May freely decide which tasks are done on the job relevant to the occupation Must perform all tasks dictated by the company
Tax Implications	Declare taxes as self-employed and thus can deduct relevant expenses, Taxed as a traditional employees and thus may not deduct relevant expensese

Notes: The table reports the possible values each attribute may take in the discrete choice experiment.

self-employed workers are afforded far greater autonomy over the tasks they perform. They have the ability to either turn down jobs or parts of jobs they do not wish to perform, or even sub-contract them out. Finally, self-employed workers are able to declare taxes through their yearly self-assessment in which they may deduct certain expenses from their tax liability. These include work related travel, use of home as office space, equipment, communication connections (e.g. internet and phone) and utility bills.

Conversely atypical jobs are often likely to be characterised by contractual obligations that differ from the usual “permanent” employment relationship, this is certainly the case with freelancing and other forms of self-employment. The longevity attribute thus considers this, while also acting as a proxy for job security. Furthermore, atypical work arrangements, in particular self-employment, offer no holiday or sick pay as is mandatory in the UK in an employment role[9]. The trade-off between these benefits and costs is what the vignettes attempts to exploit to estimate WTP for various attributes.

[9]There are no similar federal mandatory rulings in the US, however more than half of employees do get some coverage.

Table 5.4.1 presents each job attribute and the various values which each attribute can take. Hourly wages range from £8.50 (\$12) to £17.50 (\$25), in gaps of £1.50 (\$2.16). The option for holiday and sick pay is chosen as 28 days paid annual leave is mandatory in the UK and the median occupational sick pay in the UK is 16 weeks (Unison, 2017).

5.4.3 Job Attributes and Institutions in the US & UK Labour Markets

In order to get comparable results across the two countries the experiments for both samples are identical aside from the currency and hourly wages as outlined in table 5.4.1. It is important to note however that the institutional arrangements for some of these attributes are different in the US than to the UK, and furthermore the interpretation of some attribute values may be different.

Only around 34% of employment relationships in the US are afforded some type of "just cause" protection in their contracts (Verkerke, 2009). This means the remaining 66% of employees are subject to the "at-will" standard of employment law, where an employer can dismiss an employee without notice, and without having to present a reason for termination. This is fundamentally different to the UK where workers are protected by statutory minimum notice periods, unfair dismissal legislation, and redundancy pay rights. These rights are usually less binding in short fixed term contracts as they require minimum work periods. As a result, a "Permanent" job in the UK is likely to have a different interpretation to the same job in the US, and thus one would expect a lower WTP for a permanent job in the US than the UK.

As mentioned above, full time workers in the UK must receive at least 28 days paid annual leave per year (including public holidays), while in the US there is no statutory minimum. Despite there being no legislative requirement, around 77% of American employees do receive some paid leave, though survey data suggests that it is much less than the UK, with the average private sector employee receiving only 16 days paid leave per year (Ray et al., 2013). Similarly, in the UK workers are entitled to Statutory Sick Pay (£92.05 per week) for up to 28 weeks paid by your employer, though survey data suggests that three quarters are covered by occupational sick pay schemes. In the first year of employment the median worker receives 16 weeks coverage, and this increases to a full years coverage after 5 years. In the US at a federal level there is no statutory sick pay, though some states have passed legislation on paid sick leave. According to the BLS the average private sector employee has 8 days of paid sick leave available to them in their first year, while federal employees are eligible for 13 paid sick days per year. Given the wide difference in the status quo of these two job attributes in the two countries, this could induce some behavioural differences as per the endowment effect (Kahneman et al., 1991).

5.4.4 The Questions

In order to personalise the question, the individual's forename is inserted into the start of the introductory text. Furthermore, respondents are advised that jobs are identical in every possible way except for those characteristics highlighted in the vignette. As outlined above, this part of the question is key for identification and ensuring the analysis is causal. Though hypothetical bias is unlikley to be an issue in this setting as already discussed, two recommendations to address hypothetical bias are utilised. Firstly, Carson and Groves (2007) recommend that the survey design must have the potential to affect future utility to ensure incentive compatibility. Indeed, there is evidence that bias reduces in contingent valuation exercises where the probability of a real economic commitment increase (Landry and List, 2007; Mitani and Flores, 2014). As a result the question is framed so that respondents may "have their say" and that the results may inform policy making in the future. Secondly, after each vignette a follow up question asks the respondent for the certainty of their response on a scale of 0-100. Estimation can then be performed on just those with high certainty levels (e.g. 70 and above). A similar technique has previously been used in the contingent valuation literature for public goods, where respondents responding affirmative for some sort of provision are recoded as "no" if their certainty measure if less than a specific cutoff (Blumenschein et al., 2008, 2001). Figures 5.B.3 and 5.B.4 in section 5.B show an example introduction and question from the hypothetical discrete choice experiment.

5.4.5 Choice of Vignettes

In each scenario the wage plus two other characteristics are varied across the two jobs while the remaining characteristics are held constant. Assuming preferences over attributes are independent, there are 3276 possible unique vignettes which could be presented. This number reduces to 468 if we consider vignettes with the same varied non-wage characteristics and the same difference in wage (Δ_{wage}) across the two jobs as duplicates.

106 vignettes were chosen by a randomisation program that had to fulfil a number of requirements. In particular:

- Each attribute was given an equal number of occurrences of being varied, weighted by the possible number of values that attribute could take.
- Of the six possible Δ_{wage}'s, each should appear a minimum of 13 times in total across the 106 vignettes.
- Each Δ_{wage} should appear at least four times for each varied characteristic, ensuring a full possible range of trade-offs for each attribute.
- No more than 15% (16) of vignettes should have responses which a priori appear strictly dominated.

The chosen 106 vignettes were then grouped into 6 sets according to which attributes were varied, and respondents were randomly presented with one of the vignettes from each set.

5.5 Model and Empirical Framework

In this section I present the canonical random utility model used in discrete choice settings, and apply it to the context of job choices and then show how WTP can be calculated based off estimates of this model.

5.5.1 The Canonical Random Utility Model and Mixed Logit Estimation

Let $i = 1, ..., I$ index individuals, $j = 1, ..., J$ jobs and $a = 1, ..., A$ attributes. Individual i maximizes utility from job j, $U_{ij} \in \mathbb{R}$ with

$$U_{ij} = u_i(X_j) + \epsilon_{ij} \tag{5.1}$$

where a job X_j is simply a vector of A attributes $X_j = [X_{j1}, ..., X_{jA}]$. $u_i(X_j)$ represents the individual specific utility over the given job characteristics and $\epsilon_{ij} \in \mathbb{R}$ is an individual-job specific error term.

An individual i chooses job j out of choice set $\mathscr{J}$ if it results in the highest possible utility. Formally j is chosen if $\forall\ j' \neq j\ \ \in \mathscr{J}$, $U_{ij} > U_{ij'}$. ϵ_{ij} is treated as random, assuming linear sub utility we thus know that the probability individual i chooses job j is

$$P_{ij} = Pr(\epsilon_{ij'} - \epsilon_{ij}\ < (X_j - X_{j'})'\beta_i)\ \forall j' \neq j\ \in \mathscr{J} \tag{5.2}$$

By imposing some assumption on the distribution on the individual-job specific error term we get some of the most commonly used discrete choice models. In particular, if we assume that ϵ_{ij} is distributed i.i.d. Type I extreme value and restrict $\beta_i = \beta\ \forall i$ we obtain the conditional logit model:

$$P_{ij} = \frac{exp(X_j'\beta)}{\sum_{j\in\mathscr{J}} exp(X_{j'}'\beta)} \tag{5.3}$$

While the conditional logit model was a workhorse for estimation of discrete choice models for a period it has two key limitations. Firstly, it assumes preferences are homogeneous across agents which is not ideal for investigating labour supply decisions across a varied populace. Secondly the model presents with an independence of irrelevant alternatives (IIA) property:

$$\frac{P_{ij}}{P_{ik}} = \frac{exp(X_j'\beta)/\sum_{j'\in\mathscr{J}} exp(X_{j'}'\beta)}{exp(X_k'\beta)/\sum_{j'\in\mathscr{J}} exp(X_{j'}'\beta)} = \frac{exp(X_j'\beta)}{exp(X_k'\beta)} \tag{5.4}$$

which implies that any changes to the choice set $\mathscr{J}$ (except to jobs j and k) should have no effect on the ratio of the probabilities of choosing job j or k. This would evidently be problematic in a scenario of job choice where options in a choice set could grow or change, with jobs which are highly substitutable for one another.

It is possible however to overcome both of these limitations. In particular, if we allow heterogeneity in preferences (i.e. in β_i), then conditional on a specific β_i equation (5.3) becomes:

$$P_{ij}(\beta_i) = \frac{exp(X_j'\beta_i)}{\sum_{j\in\mathscr{J}} exp(X_{j'}'\beta_i)} \tag{5.5}$$

To back out the unconditional probability one simply integrates (5.6) over the distribution of β_i which, if we assume a parametric form, depends on some parameters θ:

$$P_{ij} = \int \frac{exp(X_j'\beta_i)}{\sum_{j\in\mathscr{J}} exp(X_{j'}'\beta_i)} f(\beta|\theta)d\beta \tag{5.6}$$

and thus we allow decision makers to have different preferences, and the IIA property no longer holds allowing general patterns of substitution between alternatives. This is the mixed logit model from Revelt and Train (1998) and can be estimated via simulated maximum likelihood.

This model is highly useful for the setting being studied, in particular it does not impose a representative agent requirement and allows for a distribution of preferences which are not related to observable characteristics. Furthermore, it relaxes any assumptions of income maximisation and allows agents' utility to be driven by other non-pecuniary benefits which are often important in job choice. Note that the above can also extend X_j to X_{ji} so that it contains not only job characteristics but also observable demographic characteristics interacted with job characteristics. This would allow the estimated parameters of the distribution to vary across subsets of the population, which is highly desirable for analysing job choice preferences. For example, it may be the case that the sub sample of individuals with a lower level of personal assets may have a higher mean preference for job security. Arguably the key limitation of this model is the requirement of specifying a distribution f for preferences β, typically a normal or lognormal distribution is assumed.

5.5.2 Willingness To Pay

To simplify the interpretation of the β_i estimates, and to further give them greater economic meaning it is usual to transform the estimates into a WTP. This transformation is relatively straight forward. If we take (5.1) and substitute in a linear sub utility function we have:

$$U_{ij} = \beta_{i0}X_{j0} + \beta_{i1}X_{j1} + ... + \beta_{iA}X_{jA} + \epsilon_{ij} \tag{5.7}$$

where X_{j0} is the wage for job j and the remaining variables represent other job characteristics. If the wage coefficient is fixed (i.e. not randomly distributed) and we differentiate equation (5.7) and set it equal to zero we get:

$$dU_{ij} = \beta_0 dX_{j0} + \beta_{i1}dX_{j1} + ... + \beta_{iA}dX_{jA} + d\epsilon_{ij} = 0 \tag{5.8}$$

Assuming that only the wage (X_{j0}) and another variable, e.g. job security (X_{js}), vary we have:

$$\begin{aligned} \beta_0 dX_{j0} &= -\beta_{is}dX_{js} \;\Leftrightarrow \\ \frac{-\beta_{is}}{\beta_0} &= \frac{dX_{j0}}{dX_{js}}|_{dU_{ij}=0} \Leftrightarrow \\ WTP_{is} &= -\frac{\beta_{is}}{\beta_0} \end{aligned} \tag{5.9}$$

The interpretation of this is clear: the WTP of individual i for a change in job security measures how much the wage must be changed to ensure that utility remains constant. Such an interpretation is highly useful, as it effectively places a monetary value on different job characteristics and can thus be informative on job choice decision making.

As the coefficient to the wage variable is assumed fixed, this implies that a variable's

WTP is distributed the same as the variables's preference coefficient, though scaled by the inverse of the wage coefficient. Furthermore, choosing to fix the wage coefficient is convenient for two reasons. Firstly, if all coefficients are allowed to vary then, as noted in Revelt and Train (1998), identification is difficult. Secondly, the ratio of two normally distributed variables does not have well defined moments and the ratio of a normal and log-normal distribution can result in a highly skewed WTP distribution.

One drawback of this approach however is the assumption that preferences over wages do not vary in the population. While convenient, if this restriction doesn't hold, then variation in preferences to the wage may be incorrectly interpreted as a variation in WTP. A possible workaround developed by Train and Weeks (2005) involves a redefining of the model into what they call WTP space (in contrast to preference space). If we define the WTP coefficient for variable s, $\gamma_{is} = \frac{\beta_{is}}{\beta_{i0}}$ then equation (5.7) becomes:

$$U_{ij} = \beta_{i0}X_{j0} + \beta_{i0}\gamma_{i1}X_{j1} + ... + \beta_{i0}\gamma_{iA}X_{jA} + \epsilon_{ij} \tag{5.10}$$

Obviously equations (5.7) and (5.10) are equivalent, however the key difference is estimating according to equation (5.10) will mean assuming a distribution for WTP rather than preferences. Train and Weeks (2005) find that models estimated in preference space fit the data better, but result in larger (and sometimes unrealistic) means and standard deviations for the WTP distribution. Thus, while estimates in preference space will be used as a baseline, as recommended by Hole and Kolstad (2012) estimates in WTP space will be used for sensitivity analysis.

5.6 Results

5.6.1 Baseline Results

Columns 1 and 4 of table 5.6.1 presents the baseline estimates for the UK and US respectively, of the mixed logit model discussed in section 5.5, where the wage parameter is assumed fixed, and all other variables are assumed to be distributed normally. Parameters associated with contract longevity (permanent and one year) are compared against a baseline of one month, holiday and sick pay against no such benefits, flexible hours against a standard 9am-5pm arrangement, ability to work from home (both 100% and 50% of the time) against a requirement of always working in the office, workplace autonomy against a baseline of a dictatorial set up, and being taxed as self-employed against a traditional employee taxation arrangement. In both countries all mean estimates are highly significant and positive aside from that for the attribute associated with being taxed as self-employed, which is negative. For similar parameters, the estimates appear sensible. In particular, the mean preference for a permanent contract is larger than that for a one year contract, and the preference to work from home 100% of the time is larger than the 50% counterpart.

The mean estimates are suggestive that individuals highly value security. Both permanent and one year contracts compared to a baseline of one month have the highest coefficients (2.88 and 1.92 respectively in the UK and 2.40 and 1.78 in the US), eligibility for holiday and sick pay follows second in the UK (1.89) though in the US is almost identical to working from home 100% (1.596 and 1.623 respectively). Various forms of flexibility are highly valued, though not to the same extent as security. Within the set of flexibility parameters, working from home 100% of the time has the largest coefficient (1.36 in the UK) while flexible hours and working from home 50% of the time have similar mean preference estimates (0.76 and 0.88 respectively in the UK and 0.79 and 0.99 in the US). Workplace autonomy (through choosing tasks) remains valued though relatively less so (0.574 in the UK and 0.561 in the US).

The only surprising mean estimate is that for declaring taxes as a self-employed worker (-0.25 in the UK and -0.12 in the US), which given the ability to declare certain expenses, one would expect to be positive. However the negative sign can be explained by two possibilities. One is that a large number of respondents have not filled out self-employed tax returns before, and thus have limited knowledge of the potential value. A second possibility is that filling out self-employed tax returns can be cumbersome and time consuming, and in some cases may require the help (and therefore expense) of an accountant. This is especially the case when compared to the effortless PAYE system that almost all

Table 5.6.1: Mixed Logit Estimates

	UK (£)			US ($)		
	(1) Preference space	(2) Preference space (WTP)	(3) WTP Space (%)	(4) Preference Space	(5) Preference Space (WTP)	(6) WTP Space (%)
Mean						
Wage	0.321***			0.244***		
	(0.00988)			(0.00746)		
Permanent	2.881***	8.99***	55.4***	2.401***	9.84***	44.1***
	(0.115)	(0.277)	(1.73)	(0.103)	(0.330)	(1.29)
One Year	1.916***	5.98***	37.7***	1.780***	7.30***	32.0***
	(0.0797)	(0.197)	(1.25)	(0.0790)	(0.254)	(1.06)
Holiday & Sick Pay	1.890***	5.90***	35.2***	1.596***	6.54***	27.3***
	(0.0776)	(0.189)	(1.02)	(0.0700)	(0.230)	(0.897)
Flexible Hours	0.763***	2.38***	14.9***	0.789***	3.23***	14.2***
	(0.0606)	(0.177)	(0.943)	(0.0621)	(0.236)	(0.905)
Work Home- 100%	1.355***	4.23***	22.6***	1.623***	6.66***	25.6***
	(0.0707)	(0.193)	(1.16)	(0.0777)	(0.269)	(1.17)
Work Home- 50%	0.883***	2.75***	14.0***	0.985***	4.04***	14.3***
	(0.0603)	(0.177)	(1.05)	(0.0655)	(0.245)	(1.04)
Choose Tasks	0.574***	1.79***	11.2***	0.561***	2.30***	10.7***
	(0.0517)	(0.154)	(0.89)	(0.0537)	(0.212)	(.860)
Self-Employed Tax	-0.250***	-0.78***	-2.61***	-0.122**	-0.50**	-0.49
	(0.0526)	(0.164)	(1.00)	(0.0524)	(0.215)	(0.883)
SD						
Permanent	1.525***	4.76***	22.2***	1.424***	5.84***	20.9***
	(0.148)	(0.416)	(3.33)	(0.136)	(0.503)	(2.00)
One Year	0.701***	2.19***	14.3***	0.672***	2.76***	13.3***
	(0.154)	(0.463)	(3.14)	(0.146)	(0.574)	(1.67)
Holiday & Sick Pay	1.009***	3.15***	16.6***	0.838***	3.43***	10.1***
	(0.133)	(0.387)	(2.62)	(0.128)	(0.492)	(2.28)
Flexible Hours	1.037***	3.23***	11.6***	1.036***	4.25***	13.5***
	(0.116)	(0.334)	(2.79)	(0.122)	(0.464)	(1.80)
Work Home- 100%	0.382*	1.19**	6.53*	0.309	1.26	7.45***
	(0.197)	(0.606)	(3.52)	(0.274)	(1.12)	(2.84)
Work Home- 50%	0.0273	0.09	2.83	0.340**	1.39**	4.27*
	(0.158)	(0.494)	(2.55)	(0.169)	(0.680)	(2.30)
Choose Tasks	0.441***	1.38***	9.14***	0.359**	1.47**	5.95***
	(0.167)	(0.511)	(2.04)	(0.178)	(0.719)	(2.11)
Self-Employed Tax	0.561***	1.75***	8.61***	0.485***	1.99***	8.57***
	(0.161)	(0.486)	(2.88)	(0.154)	(0.613)	(2.16)
N	24336	24336	24336	22652	22652	22652
Log-Likelihood	-5870.39		-5771.21	-5448.46		-5359.42
AIC	11774.77		11578.42	10930.91		10754.84
BIC	11912.47		11724.22	11067.39		10899.35

Notes: The table reports the results from the mixed logit estimates for the UK and US samples, standard errors are reported in parentheses, P-value: *** p<0.01, ** p<0.05, * p<0.1. Columns (1) and (4) report preference estimates estimated in preference space, columns (2) and (5) report WTP estimates measured in currency estimated in preference space and columns (3) and (6) report WTP estimates measured in % estimated in WTP space.

employees experience. This in turn could mean that an attribute of declaring taxes as self-employed may actually result in disutility at the mean. It is useful to note however that 33% of individuals in the UK and 40% in the US do have a positive valuation of self-employed taxation as demonstrated by figure 5.B.5 and table 5.6.3.

All estimates for the standard deviations are significantly different from zero except for the work from home attribute, though it is significant at the 10% level for the 100% of the time variation in the UK and significant at the 5% level for the 50% variation in the US. This demonstrates the importance of allowing for a distribution in preferences for job attributes, as there is evidently heterogeneity across the sample.

A striking feature of these results is the similarity in both ranking and effect size across the two countries. The wage parameter is larger in the UK, which in turn means that WTPs will be different, however this is unsurprising given the sterling to dollar exchange rate[10].

For a clearer interpretation of the aforementioned results, I additionally calculate the relevant WTPs for each parameter, and these are located in columns 2 and 5 of table 5.6.1. These are simply the empirical counterparts to equation 5.9, and offer an easy interpretation to the estimated results: for a change in a job characteristic, how much would an individual need to pay (or be paid) to maintain the same level of utility. Columns 3 and 6 report the WTP reported in % terms of the wage rate, and is estimated in WTP space. It is worth noting that the specification estimated in WTP space performs better on all three measures of fit.

What is striking about these results is the value which agents place on parameters associated with job security in both countries. On average an individual in the UK (US) is willing to give up approximately 55% (44.1%) of their hourly earnings to secure a permanent contract or 37.7% (32.0%) for a one year contract, against a baseline of a one month contract. As outlined in section 5.4.3, labour market regulation is very different between the UK and US, and one would assume that a permanent contract would be

[10]The exchange rate was in the region of £1=$1.31 during the time of the survey

worth considerably more in the UK, and while that is somewhat true, a permanent contract is still highly valued in the US. Given the size of the permanent estimate, there was concern that the parameter could be picking up respondents expectations of career development in jobs with permanent contracts, despite being instructed that jobs are identical aside from the characteristics highlighted. This would obviously bias up the results for the permanent contract. However, given the one year contract has a sizeable WTP estimate as well, it appears unlikely this is the case. Though estimating a slightly different parameter, the results bear some similarity to Mas and Pallais (2017)'s finding that workers would be willing to take a \$6 per hour pay cut for a job that gave 40 hours per week over one that only offered 20 hours per week.

Second to contract length, holiday and sick pay has the largest WTP at almost 35.2% (27.3%) of hourly wages at the mean. Holiday pay entitlement in the UK gives workers 28 days paid annual leave per year (if full time), and a number of companies do not deduct bank holidays from this amount. The NHS for example, the UK's largest employer, gives in total 37 days paid holiday for staff tenured over 5 years. A back of the envelope calculation using the estimate from column 2 in table 5.6.1 implies that someone on an hourly rate of £15 an hour gains an additional £2.50 an hour from holiday pay.[11] Thus such a high WTP for holiday and sick pay must mean that either agents place a very high value on the insurance against sickness, or they systematically overestimate the attribute's value. If the latter of these issues is the case, as 69% of our UK sample are employees and recipients of this benefit, we may be seeing a form of the endowment effect within these estimates.[12] Thus, as agents may interpret it as "giving up" holiday and sick pay, the estimate could actually be interpreted as a willingness to accept (WTA), and the endowment effect could in turn be resulting in this over-valuation.[13] A similar anomaly could in fact be happening with the estimates for contract longevity if a large portion of respondents are accustomed to longer contracts.

Holiday and sickness coverage in the US is on average less and this could explain why

[11] 37 days paid holiday per year equates to 7.4 working weeks and thus 45 weeks of remaining work. $\frac{7.4}{45} \approx 16.5\%$. $16.5\% *$ £15 $\approx$ £2.50.

[12] The endowment effect is the observation that agents place greater value on goods they own.

[13] In particular, the difference between the WTA and WTP would be equal to the bias induced by the endowment effect. For a more complete description please refer to Kahneman et al. (1991).

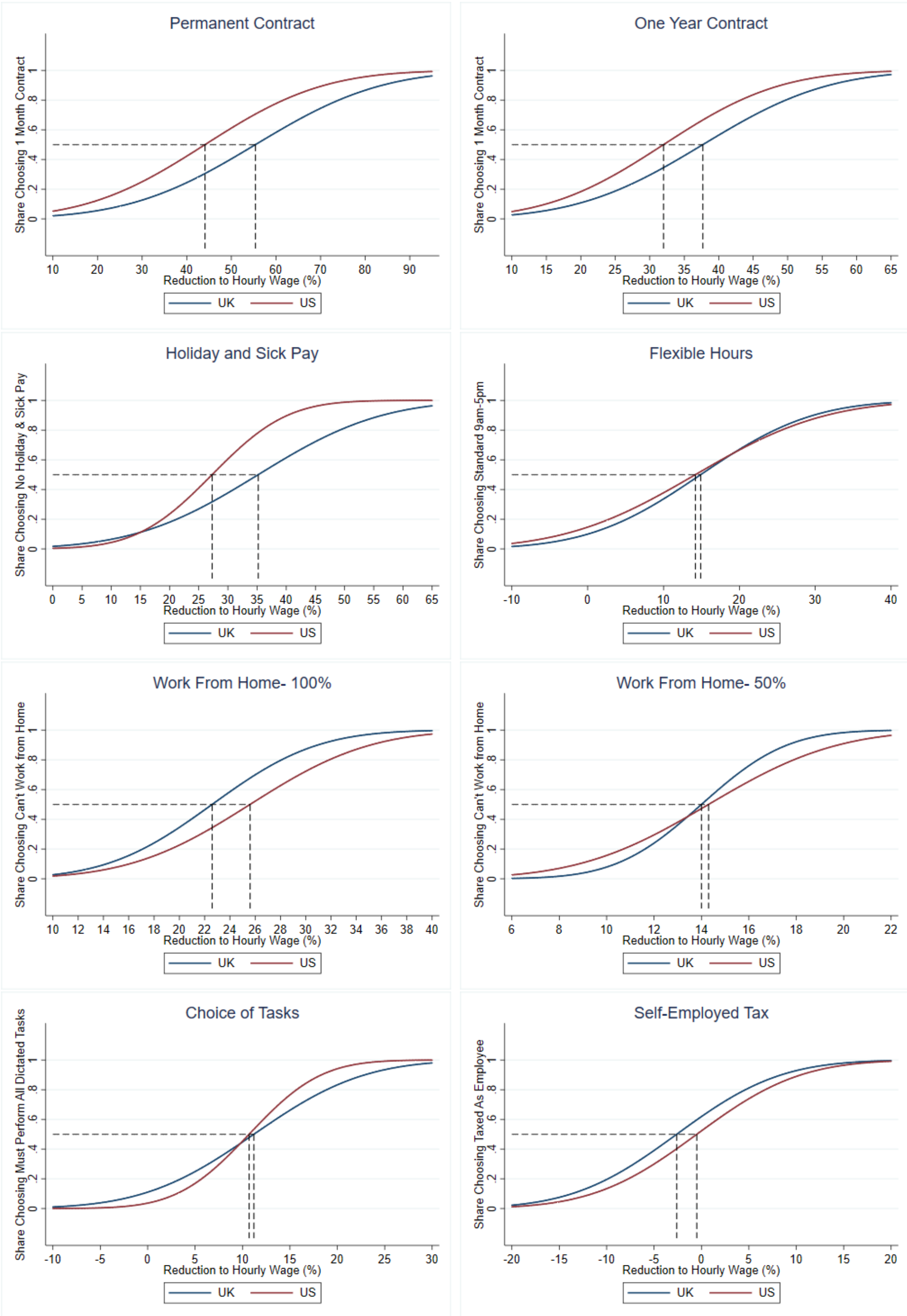
the WTP estimate (when estimated in %) is around 25% lower in the US. That said, the estimated WTP for holiday and sick pay in the US is still large. While an endowment effect could be biasing up the results for the US sample, one would expect it to be smaller than the UK as there is a smaller proportion of employees (7 percentage points less) and, as discussed in section 5.4.3, both coverage and depth of this benefit is less. One alternative explanation, aside from a high valuation of sickness insurance, is that in the US there is no statutory law concerning unpaid leave from work aside for sickness and caring responsibilities. Therefore the benefit of 28 days paid annual leave may be valued not just for the paid leave, but also for the guarantee of time off work around national holidays. However, without more information, it is difficult to conclusively say what may be driving the surprisingly large estimates for holiday and sick pay.

WTP estimates for flexibility are also considerable. At the mean agents are willing to give up around 22.6% (25.6%) of their hourly wage to be able to work from home, and 14.0% (14.3%) 50% of the time. Similarly at the mean agents are willing to give up 14.9% (14.2%) of their hourly wage to be able to choose their work hours. Workplace autonomy appears to be valued slightly less, though is still significant at approximately 11.2% (10.7%) on average.

While analysis of the means is informative, one benefit of the methodology used is the full picture offered of the distribution of WTPs. Figure 5.6.1 presents CDFs of WTPs estimated in % terms for each attribute against their baseline state in both countries, with a marker at the median. As one can see from the CDFs, WTPs for job attributes are very similar across the two countries, and in fact for the job attributes where there are no major institutional differences (i.e. flexible hours, choice of tasks and work from home) the distributions look almost identical. In the cases of contract length and holiday and sick pay, the distributions do show some difference, however the differences are generally smaller than expected given the large regulatory differences across the two economies.

As already noted, aside from declaring taxes as self-employed, most attributes have a very small proportion of individuals that would require a wage premia to induce indifference. The permanent attribute while having a large mean, also has a large standard deviation

Figure 5.6.1: CDFs of WTPs, Estimated in WTP Space



Notes: The graphs report the CDFs of WTPs for each job attribute for the UK and US samples, estimated in % terms in WTP space. The dashed line marks the median on each graph.

resulting in a wide distribution of WTP. One fifth of people would be willing to pay more than 70% in the UK, and 60% in the US, of their hourly wage for a permanent rather than a one month contract. It is worthwhile to note that these WTPs have been fitted to a normal distribution, and as the support is unbounded, the tails should be treated with some caution.

There is a small proportion of individuals willing to pay highly for flexibility. In the UK a fifth of individuals are willing to forgo 28% of their hourly wage or more, to be able to work from home all the time and the equivalent figure for the US is 32%. In both the US and the UK around a fifth of people are willing to pay 25% of their hourly wage for flexible hours. These figures however, are still dwarfed by the WTP for security related traditional employment attributes, even at the bottom end of the distribution. In the UK only around 10% of individuals, and in the US only about 25% of individuals, would be willing to forgo a permanent contract in exchange for avoiding a 30% pay reduction.

Overall, while there is clearly a small proportion of individuals willing to pay highly for flexibility, autonomy and a self-employed tax structure, there are even less willing to give up security. The evidence thus far is suggestive that preferences for flexibility, autonomy and tax benefits are unlikely to be driving the changes in work patterns seen in the aggregate data.

5.6.2 Contract Length and Theory

As discussed in section 5.6.1 respondents across both countries placed the largest value on more secure jobs, as measured by contract length, and the estimates for these were at first glance surprisingly high. In order to see how well the results align with theory, I calibrate a simple search model to see how well the estimates line up.

Let δ be the seperation rate, λ the offer rate, r the interest rate, w the wage, z the unemployment benefit, U the value of being unemployed and V the value of being employed.

The value of being employed is

$$rV = w + \delta(U - V) \tag{5.11}$$

and the value of being unemployed

$$rU = z + \lambda(V - U) \tag{5.12}$$

With some manipulation and letting $\rho = \frac{z}{w}$ be the replacement ratio, $r \approx 0$ and noting in the steady state $\frac{\delta}{\lambda+\delta} = u$ where u is the unemployment rate, one can show the elasticity of the wage to the seperation rate is

$$\frac{d\ lnw}{d\ ln\delta} = (1 - \rho)u \tag{5.13}$$

If one sets $w =$ £14.10 which is the mean hourly wage in the UK sample, and assuming 35 weekly hours, the weekly income is £507.50. In the UK Jobseekers Allowance (unemployment insurance) is equal to £73.10 per week, and thus $\rho = 0.144$. Furthermore current data from the ONS states that $u = 0.04$.

This implies

$$\frac{d\ lnw}{d\ ln\delta} = 0.03424. \tag{5.14}$$

If we assume time is monthly, then a one month contract implies $\delta^{month} = 1$, and in expectation a one year contract implies $\delta^{year} = 0.083$. Therefore, switching from a one year to a one month contract implies an 11 times increase in δ, and by equation 5.14 this would require a 37.4% increase in the wage. This calibrated figure aligns almost exactly with the estimate from column 3 in table 5.6.1 for the one year contract, offering assurance that the estimates are within a theoretically sensible range.

5.6.3 Employees vs Self-Employed

It is unsurprising that at the mean individuals value attributes which are associated with traditional working arrangements more so than flexibility, autonomy and tax benefits.

Until recently this was the arrangement for almost all workers in the UK economy, and currently around 62% of the workforce are in full time employee-employer relationships. In the US this figure is slightly higher at 67%. Two key questions in ascertaining whether the rise in atypical work arrangements is predominantly demand or supply side driven are:

- Do those in atypical work arrangements have different preferences to those in traditional employment relationships?
- If they do, is this difference large enough to make them value atypical work more than traditional working arrangements?

Before turning to a greater breakdown of heterogeneity I will seek to answer these two questions. Table 5.A.1 in section 5.A presents an extension of the normally distributed model estimated in WTP space,[14] with interaction effects at the mean for those whose earnings predominantly come from various forms of self-employment.[15] For both countries all interaction effects except those for holiday and sick pay and tax are statistically significant and all are in the direction one would expect to see when workers sort into types of employment relationships based on their preferences. In particular, the self-employed have a lower preference for security and higher preferences for flexibility, workplace autonomy and self-employment tax structure. At the mean self-employed agents are willing to pay £2.40 ($3.05) less per hour for a permanent contract than employees. Their WTP for parameters generally associated with atypical work attributes is between £0.56 ($0.63) to £2.12 ($3.20) higher than employees. It is noteworthy that even self-employed individuals appear indifferent to being able to declare taxes as self-employed at the mean. This suggests that filling out tax returns and maintaining sole-trader accounts is costly. These results confirm the fact that those in atypical working relationships have a comparatively greater preference for these working arrangements than those in traditional relationships.

For ease of exposition, table 5.6.2 presents the mean WTPs estimated in WTP space in the US and UK for three samples: all respondents, the employed and the self-employed.

[14] This is estimated in WTP space rather than preference space given the marginally better fit WTP space estimates give, as detailed in section 5.6.5.

[15] The standard deviation of the distributions is assumed to remain constant between the employed and self-employed for computational reasons, thus the interaction effect simply represents a shifting of the distribution.

Table 5.6.2: WTP Employed vs Self-Employed

Parameter	WTP(£)			WTP($)		
	All	Employed	Self-Employed	All	Employed	Self-Employed
Typical						
Permanent	8.97	9.69	7.29	9.92	11.13	8.09
OneYear	6.03	6.54	5.07	7.26	7.88	6.31
Holiday & Sick Pay	5.71	5.90	5.90	6.44	6.56	6.56
Atypical						
Flexible Hours	2.26	2.05	3.12	3.06	2.08	5.17
Work Home-100%	3.56	3.02	5.14	5.87	5.95	8.15
Work Home-50%	2.18	1.87	2.94	3.26	3.07	4.24
Choose Tasks	1.57	1.40	2.28	2.20	1.79	2.58
Self-Employed Tax	-0.53	-0.67	-0.11	-0.29	-0.55	-0.55
Typical	14.68	15.59	13.19	16.36	17.69	14.65
Atypical	6.86	5.80	10.43	10.84	8.26	15.35

Notes: The table reports the mean WTP estimates estimated in WTP space for all respondents, employed respondents and self-employed respondents separately.

It is clear from these estimates that while self-employed individuals have comparatively greater preferences for atypical employment, they still value security very highly. In the UK the self-employed value a permanent contract more than any other attribute by a sizeable margin (£1.39). In the US a permanent contract is the second most valued attribute by the self-employed, with the ability to work from home all the time only marginally more valued ($0.06). In both countries the self employed have a greater preference for both a one year contract and holiday and sick pay more so than any of the atypical attributes excluding working from home 100%.

The last two rows of table 5.6.2 show a simple summation of the atypical and typical parameters.[16] Based on these job attributes it appears at the mean, that even self-employed individuals prefer typical over atypical work arrangements in the UK. This is suggestive that, for more than half of the self-employed in the UK,[17] working in an atypical working arrangement is not preferred to typical work, and thus their choice of work arrangement is unlikely going to be supply-side driven. The proportion in the US is just below half but still sizeable (47%). This implies that the increase in atypical jobs may have important

[16]For the typical summation "one year" is excluded and for atypical "work home-50%" is excluded.

[17]The actual figure is 68%, which can be calculated by simply summing the 6 normally distributed random variables, and looking at the share below £0.

negative welfare implications for workers, and may represent a form of redistribution from workers to firms. As the self-employed do have a comparatively greater preference for atypical work, it may be the case that when presented with weak traditional employment opportunities, they are the first to sort into atypical work, though further work is required to confirm this.

One caveat to this analysis is that it relies on the attributes used in the vignettes to be the most valued by agents when considering job choices, and furthermore, that they are representative of a specific working arrangement. Given the attribute values were based on the statutory rules and average workplace arrangement in the UK this implies this analysis may be more suited to the UK setting. The only other attribute which may have a sizeable value and could be an important distinguishing factor of a typical work arrangement is the opportunity for on the job training. This however is likely to have a positive WTP (evidence from Eriksson and Kristensen (2014) confirms this) and thus would further compound the valuation of a typical work arrangement against an atypical one. There are obviously circumstances where traditional employees may get more flexibility to work from home (for example computer programmers) and there are circumstances where those who are self-employed may be relatively secure if they have over time built up a base of regular customers. However, contract longevity, holiday and sick pay, flexibility, autonomy and tax implications appear a priori to be the most important distinguishing factors on average for different working arrangements.

5.6.4 Additional Heterogeneity Analysis

Table 5.A.2 located in section 5.A presents the results of the mixed logit model estimated in WTP space with the full set of interactions, so as to analyse heterogeneity at the mean along a number of dimensions.[18] Women in both the US and UK are found to have a higher WTP for holiday and sick pay (£0.96 and $1.11), while in the UK they have a stronger preference for contract security and in the US a weaker one. These results in the UK indicate that women have a stronger preference for security in general, though no similar conclusion can be drawn in the US. Women are also found to value hours

[18]As before, interactions only shift the distribution, maintaining the same standard deviation.

flexibility more so in the UK than their male counterparts, and this may go some way in explaining why more women in the UK are in ZHC positions than men (approximately 3% of women have ZHCs while around 2.3% of men do).

Risk averse agents are identified by those whose certainty equivalent to the 50/50 £300 lottery is less than £150. Unsurprisingly, risk averse agents are seen to value security more than their risk neutral and risk loving counterparts. On average risk averse agents are willing to pay an extra £2.42 (\$2.68) per hour for a permanent contract and £1.58 (\$2.26) for a one year contract. This is suggestive that less risk averse agents sort into self-employment. Young individuals (defined by those whose age falls below the mean age of the sample) value a permanent contract by around £1.23 more per hour in the UK (though no significant difference in the US) and individuals with children place a considerable amount more (£3.08 and \$1.41) on a permanent contract, demonstrative that a regular cash flow is highly important for these individuals. In the US both women and those with children place a greater value on working from home all the time (\$1.32 and \$1.04 respectively). This suggests an interaction between these two may contribute to the gender pay gap in the US.

A question is asked in the survey concerning respondents' ability to pay for an unexpected cost shock. Based on the response to this, a dummy variable was created to mark individuals who would not be able to weather a £500 cost shock through either self-insurance or informal insurance (e.g. borrowing from a family member). I find no significant interaction effects for this marker, nor for those who scored above average on the IQ test (aside from flexible hours in the US). Agents in the sample who are more patient in the US, have a stronger preference for security while in the UK there is no discernible pattern, with patient agents preferring both security and flexibility attributes, however the effect sizes are generally small.

5.6.5 Robustness

One drawback of assuming that preferences are normally distributed is that the distribution spans from $-\infty$ to $+\infty$. This implies that some individuals will place a negative value on some preferences which one would assume should always be positive, and that a small proportion of individuals would have either implausibly high or low preferences for certain attributes.

Analysis of the distributions for preference estimates in columns 1 and 4 of table 5.6.1 (see figure 5.B.5 in section 5.B) reveals even preferences which one would assume are strictly preferred by all individuals (e.g. holiday and sick pay) have some share of people who negatively value the parameter, as a result of the distribution which the parameters are fitted to. Table 5.6.3 gives the proportion of preferences below zero when fitted to a normal distribution. Aside from method of taxation, flexible hours and choosing tasks, all preferences have a share below 0 of less than 5%. As a result, to test for sensitivity to the chosen distribution, column 2 of tables 5.A.3 and 5.A.4 located in section 5.A presents the natural logarithm of the coefficients when fitting all preferences with a share below 0 at less than 5%, to a log-normal distribution, and column 3 presents the transformed results so they are comparable to the baseline specification, which is located in column 1.

Table 5.6.3: Share of Preferences Below Zero

Parameter	Share Below Zero (UK)	Share Below Zero (US)
Permanent	2.94%	4.59%
One Year	0.31%	0.40%
Hoiday & Sick pay	3.05%	2.84%
Flexible Hours	23.08%	22.3%
Work Home-100%	0%	0%
Work Home- 50%	0%	0.19%
Choose Tasks	9.66%	5.91%
Self-Employed Tax	67.2%	59.9%

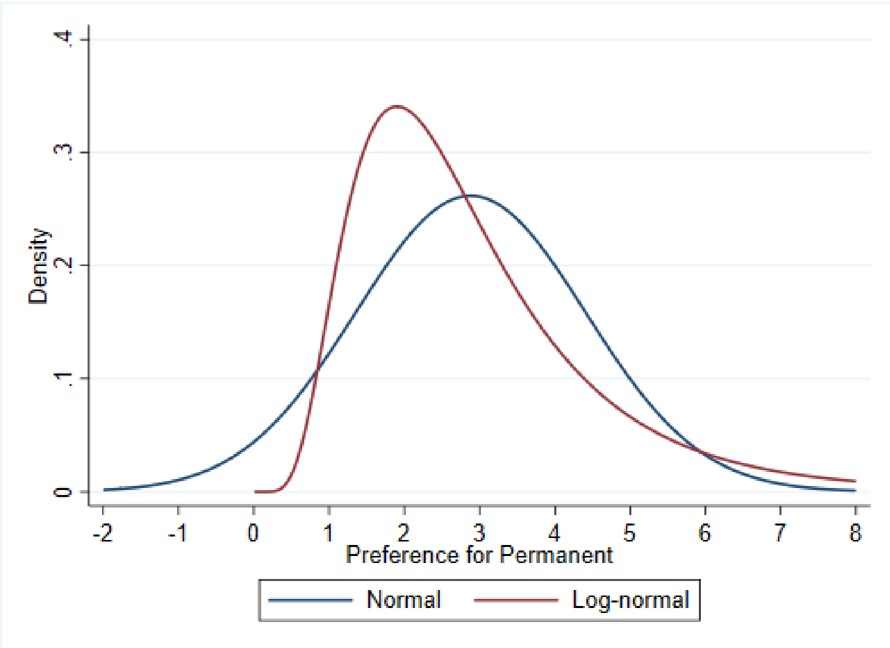
Notes: The table reports the share of preferences that are below zero for each job attribute for the UK and US samples, estimated in preference space.

As can be seen, when comparing columns 1 and 3, there is little qualitative difference at the mean and for the standard deviation between the normal and log-normal specifications.[19] Additionally, the normal distribution performs better on both the Akaike and

[19] One would a priori assume flexible hours would dominate its 9am-5pm counterpart (and similarly

Bayesian Information Criteria, as well as having a larger log-likelihood, thus fitting the data better.

Figure 5.6.2: Normal vs Log-Normal Preference Distribution for Permanent



Notes: The graph reports the PDF for the preference parameter for the UK when estimated in preference space, fitted to a normal distribution and log-normal distribution.

One drawback of fitting the preferences to a log-normal distribution is the resulting thicker right hand tail. Figure 5.6.2 presents the distributions for the permanent preference parameter when it is assumed to be normal and log-normal. As can be seen, the log-normal distribution predicts a greater share of the population to be located in the right hand side tail, at potentially implausible estimates (the mean WTP for the permanent parameter is already very high as seen in section 5.6.1). Thus whether a normal or log-normal distribution is assumed, the tails should be treated with caution.

Column 4 of tables 5.A.3 and 5.A.4 presents the results for the specification which only includes vignette responses where individuals give a follow up certainty score of 70 or higher. As mentioned in section 5.4.4, if any hypothetical bias does exist, this may serve

for workplace autonomy) unless some agents have a preference for a type of commitment device. Thus, a specification was also estimated which imposed flexible hours and tasks to be distributed log-normally. This caused little variation in the parameter estimates, except for flexible hours and tasks, which saw their standard deviation increase by an implausibly high manner resulting in an absurdly thick right tail. It is thus assumed that forcing those parameters to only be positive distributed results in a misspecification issue.

in reducing it. As can be seen, all estimated mean coefficients increase in absolute size (the only exception is self-employed tax in the US) and similarly, the estimated standard deviations are marginally larger for some parameters. The estimated standard deviations for a few parameters become insignificant, this could point to a more concentrated distribution for those with higher levels of certainty, however this could also be due to a loss of power from the drop in sample size. It is important to note that the relative effect sizes are not fundamentally different from the baseline specification. The relative effect sizes (which are effectively WTPs) are more important for interpreting the estimates, and as it stands, the preference ordering remains generally unchanged [20]. This is demonstrated in tables 5.A.5 and 5.A.6 which present the counterpart WTP estimates to tables 5.A.3 and 5.A.4, as well as additional columns estimated in WTP space rather than preference space in terms of both currency and %.

The results estimated in WTP space rather than preference space are generally similar to the baseline and have little qualitative difference, though notably the standard deviation estimates are moderately smaller for the permanent contract and flexible hours in both countries. Thus in line with what Train and Weeks (2005) find, the estimates in WTP space are arguably more realistic (e.g. for permanent contracts), as the smaller standard deviation makes extremely high WTP estimates less likely. Conversely to what Train and Weeks (2005) find, the model in WTP space also performs better on all three measures of fit.

It is clear from tables 5.A.5 and 5.A.6 there is little variation across specification, demonstrating the lack of sensitivity to distributional assumptions, certainty of responses and space of estimation, thus offering strong credibility to the results.

One final aspect to consider is the issue of inattention biasing the results. Humans have been found to be inattentive in a vast number of economic areas including calculating tax, purchasing services, durable, and non-durable goods, and when making investment decisions (Gabaix, 2019; DellaVigna, 2009). The setting of labour market decisions is unlikely to be an exception, and this may be of particular concern given the hypothetical

[20] Ability to choose tasks increases to marginally preferred to flexible hours in the UK and holiday and sick pay becomes marginally more preferred to work from home 100% in the US

setting of the experiment. To quantify the extent that the sample was inattentive two seperate measures are calculated. Firstly, respondents were asked a simple attention question part way through the survey.[21] Secondly, of the 106 vignettes described in section 5.4, 8 had strictly dominating options. In both the UK and US only 1% of the sample answered the attention question incorrectly, and only 4% of responses chose a strictly dominated job. Assuming inattentive respondents made a choice with equal probability across jobs, this would mean that the inattention rate was 8%. This rate is low and unlikely to cause consequences for the interpretation of the results.

5.7 Conclusion

This paper contributes to the literature concerning the rise in atypical work arrangements, with a focus on the UK and the US, two economies which have seen a rise in atypical work arrangements. A key question addressed is whether this rise may be due to labour supply preferences for job attributes typically associated with atypical work. Using data from a novel survey employing vignettes in a discrete job choice experiment, I estimate the full distributions of the WTP for job security, entitlement to holiday and sick pay, hours and location flexibility, autonomy and how income is taxed. The results suggest supply side factors are unlikely going to be a cause of the rise in atypical work arrangements.

I find that attributes typically associated with traditional employee-employer relationships are by far the most valued. At the mean individuals are willing to give up approximately 50% of their hourly wage for a permanent contract against a one month contract in the UK and US, and a calibrated search model suggests the estimates align well with theory. After contract length the second highest valued job attribute in both countries is holiday and sick pay with WTPs of 35.2% and 27.3% of ones hourly wage.

Mean hourly WTPs for location and hour flexibility are substantial but considerably smaller (22.6% and 14.9% respectively in the UK and 25.6% and 14.2% in the US), and hourly WTP for autonomy is smaller still (11.2% in the UK and 10.7% in the US). The

[21] "What is 20-13?"

only attribute with a negative valuation is the ability to declare taxes as self-employed.

Heterogeneity analysis reveals evidence of sorting. In particular at the mean, self-employed individuals have a comparatively greater preference for atypical job attributes in comparison to their employed counterparts. However, self-employed individuals still value attributes associated with typical employee-employer relationships in general more than flexibility and autonomy. Additional heterogeneity analysis presents suggestive evidence that the gender gap observed for those on ZHCs in the UK may be partly due to a greater preference for hour flexibility by females.

The results in this paper contribute to the discussion around policy design for atypical labour markets. At first glance the results give credence to certain policy recommendations outlined in the UK government commissioned report "Good work: the Taylor review of modern working practices" (Taylor, 2017). In particular, those policies aimed at securing workers in precarious employment relationships rights closer to employees and security in the number of hours they work. However, labour supply preferences are of course only half the story. It is vital analysis be performed on the demand side so that a well rounded welfare assessment could be made on the impact of those policies. Some analysis in this vein does exist (Datta et al. (2019)), though it is limited to a specific policy response, concerning the UK's National Living Wage. If it is found that firms are benefiting from the rise in atypical work arrangements, this could be indicative of a redistribution of welfare from workers to firms, and representative of a weakening in the position for labour.

Appendix

5.A Additional Tables

Table 5.A.1: WTP Heterogeneity by Working Arrangement

	UK (£)	US ($)
Mean		
Permanent	9.69***	11.13***
	(0.313)	(0.422)
One Year	6.54***	7.88***
	(0.214)	(0.310)
Holiday & Sick Pay	5.90***	6.56***
	(0.196)	(0.275)
Hours	2.05***	2.08***
	(0.199)	(0.277)
Work Home-100%	3.02***	4.95***
	(0.215)	(0.321)
Work Home-50%	1.87***	3.07***
	(0.199)	(0.291)
Choose Tasks	1.40***	1.79***
	(0.174)	(0.243)
Self-Employed Tax	-0.67***	-0.55**

	(0.188)	(0.251)
Self-Employed X Permanent	-2.40***	-3.05***
	(0.452)	(0.627)
Self-Employed X OneYear	-1.47***	-1.57***
	(0.375)	(0.509)
Self-Employed X Holiday & Sick Pay	-0.57	-0.14
	(0.353)	(0.452)
Self-Employed X Hours	1.07***	3.09***
	(0.374)	(0.465)
Self-Employed X Work Home-100%	2.12***	3.20***
	(0.402)	(0.565)
Self-Employed X Work Home-50%	1.07***	1.17**
	(0.368)	(0.477)
Self-Employed X Choose Tasks	0.88***	0.79**
	(0.325)	(0.398)
Self-Employed X Self-Employed Tax	0.56*	0.63
	(0.322)	(0.412)
SD		
Permanent	3.52***	5.18***
	(0.303)	(0.463)
One Year	1.54***	3.19***
	(0.447)	(0.434)
Holiday & Sick Pay	3.08***	3.48***
	(0.296)	(0.375)
Hours	2.87***	3.80***
	(0.302)	(0.437)
Work Home-100%	0.72	2.03***
	(0.444)	(0.573)
Work Home-50%	0.52	1.44***
	(0.358)	(0.482)
Choose Tasks	1.26***	0.24
	(0.343)	(0.602)

Self-Employed Tax	0.53	1.45***
	(0.544)	(0.569)
N	24336	22652
Log-Likelihood	-5748.55	-5329.71

Notes: The table reports WTP estimates from the mixed logit estimation in preference space, with interaction effects between the mean of the job attribute and whether the respondent was self-employed, against a baseline of being an employee.

Table 5.A.2: Mixed Logit with Full Set of Interactions

		WTP (£)	WTP ($)
Mean			
	Permanent	5.264***	7.961***
		(0.784)	(1.094)
	OneYear	3.501***	5.722***
		(0.670)	(0.905)
	Holiday & Sick Pay	3.158***	4.025***
		(0.588)	(0.737)
	Flexible Hours	2.162***	1.081
		(0.655)	(0.826)
	Work Home-100%	3.438***	3.503***
		(0.661)	(0.904)
	Work Home-50%	1.883***	3.561***
		(0.593)	(0.818)
	Choose Tasks	1.502***	1.081
		(0.483)	(0.687)
	Self-Employed Tax	0.136	-0.334
		(0.531)	(0.743)
Female	Permanent	0.331	-1.057*
		(0.443)	(0.594)
	OneYear	0.822**	-1.485***
		(0.352)	(0.487)
	Holiday & Sick Pay	0.960***	1.113***
		(0.329)	(0.425)
	Flexible Hours	0.822**	0.192
		(0.334)	(0.430)
	Work Home-100%	0.370	1.039**
		(0.333)	(0.524)
	Work Home-50%	0.0758	-0.261
		(0.320)	(0.454)
	Choose Tasks	0.0987	0.277
		(0.281)	(0.390)
	Self-Employed Tax	-0.813***	-0.0575
		(0.291)	(0.393)

Risk Averse	Permanent	2.421***	2.676***
		(0.650)	(0.775)
	OneYear	1.580***	2.262***
		(0.567)	(0.684)
	Holiday & Sick Pay	1.325***	0.195
		(0.474)	(0.562)
	Flexible Hours	-0.463	1.350**
		(0.578)	(0.624)
	Work Home-100%	-0.885	0.564
		(0.564)	(0.686)
	Work Home-50%	0.0640	-0.458
		(0.480)	(0.623)
	Choose Tasks	0.225	0.865
		(0.399)	(0.540)
	Self-Employed Tax	-0.291	0.0637
		(0.440)	(0.567)
Young	Permanent	1.230**	0.220
		(0.511)	(0.656)
	OneYear	0.435	0.371
		(0.384)	(0.544)
	Holiday & Sick Pay	0.686**	1.011**
		(0.348)	(0.477)
	Flexible Hours	-0.495	-0.483
		(0.348)	(0.488)
	Work Home-100%	-0.109	-0.628
		(0.357)	(0.565)
	Work Home-50%	-0.205	-0.430
		(0.341)	(0.491)
	Choose Tasks	-0.486	-0.292
		(0.301)	(0.425)
	Self-Employed Tax	0.284	0.274
		(0.297)	(0.444)
Has Child	Permanent	3.083***	1.414**
		(0.495)	(0.659)
	OneYear	1.496***	0.155
		(0.398)	(0.528)

	Holiday & Sick Pay	0.326	1.056**
		(0.341)	(0.467)
	Flexible Hours	-0.412	-0.410
		(0.355)	(0.469)
	Work Home-100%	0.0321	1.317**
		(0.356)	(0.563)
	Work Home-50%	0.0529	0.767
		(0.350)	(0.482)
	Choose Tasks	-0.542*	-0.0887
		(0.296)	(0.417)
	Self-Employed Tax	-0.374	-1.038**
		(0.312)	(0.432)
Self –Employed	Permanent	-2.013	-3.055
		(0.542)	(0.605)
	OneYear	-1.538	-1.442
		(0.373)	(0.497)
	Holiday & Sick Pay	-0.411	0.0607
		(0.343)	(0.448)
	Flexible Hours	0.908	2.802
		(0.355)	(0.463)
	Work Home-100%	1.999	2.967
		(0.373)	(0.545)
	Work Home-50%	1.226	1.017
		(0.364)	(0.481)
	Choose Tasks	0.456	0.763
		(0.333)	(0.405)
	Self-Employed Tax	0.796	0.535
		(0.303)	(0.404)
Self-insurance	Permanent	-0.564	0.203
		(0.472)	(0.574)
	OneYear	-0.0402	-0.0753
		(0.374)	(0.477)
	Holiday & Sick Pay	0.313	0.216
		(0.348)	(0.424)
	Flexible Hours	-0.254	-0.247
		(0.351)	(0.434)
	Work Home-100%	-0.574	0.558

		(0.364)	(0.524)
	Work Home-50%	-0.171	0.436
		(0.349)	(0.447)
	Choose Tasks	0.0383	-0.0913
		(0.288)	(0.394)
	Self-Employed Tax	0.377	-0.145
		(0.309)	(0.393)
Patient	Permanent	0.722	1.542***
		(0.440)	(0.571)
	OneYear	0.751**	1.244***
		(0.354)	(0.482)
	Holiday & Sick Pay	0.676**	0.673
		(0.339)	(0.421)
	Flexible Hours	0.846**	0.215
		(0.339)	(0.431)
	Work Home-100%	1.121***	-0.0792
		(0.340)	(0.519)
	Work Home-50%	0.283	-0.355
		(0.325)	(0.453)
	Choose Tasks	0.198	0.402
		(0.290)	(0.398)
	Self-Employed Tax	-0.579**	0.624
		(0.295)	(0.397)
High IQ	Permanent	-0.682	-0.827
		(0.504)	(0.644)
	OneYear	-0.296	-0.0547
		(0.438)	(0.529)
	Holiday & Sick Pay	0.551	0.447
		(0.386)	(0.461)
	Flexible Hours	0.235	1.166**
		(0.396)	(0.506)
	Work Home-100%	-0.605	0.212
		(0.408)	(0.581)
	Work Home-50%	-0.561	-0.159
		(0.361)	(0.495)
	Choose Tasks	0.498	-0.197
		(0.323)	(0.431)

	Self-Employed Tax	-0.148	-0.611
		(0.333)	(0.440)
SD			
	Permanent	3.808***	4.702***
		(0.298)	(0.436)
	One Year	1.817***	3.174***
		(0.286)	(0.357)
	Holiday & Sick Pay	3.133***	3.134***
		(0.233)	(0.388)
	Flexible Hours	3.072***	3.581***
		(0.237)	(0.362)
	Work Home-100%	1.117***	2.082***
		(0.315)	(0.606)
	Work Home-50%	1.107***	0.107
		(0.273)	(0.548)
	Choose Tasks	0.985***	0.803*
		(0.278)	(0.467)
	Self-Employed Tax	0.277	1.173**
		(0.318)	(0.555)
N		24336	22652
Log-Likelihood		-5659.22	-5272.12

Notes: The table reports WTP estimates from the mixed logit estimation in preference space, with interaction effects between the mean of the job attribute and a selection of individual level characteristics. Standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1

Table 5.A.3: Mixed Logit Preference Estimates- UK

	(1) Normal	(2) LogNormal	(3) Transformed Log Normal	(4) Normal-Certainty≥70
Mean				
Wage	0.321***	0.313***	0.313***	0.395***
	(0.00988)	(0.00923)	(0.00923)	(0.0137)
Permanent	2.881***	0.928***	2.916***	3.686***
	(0.115)	(0.0378)	(0.140)	(0.161)
OneYear	1.916***	0.580***	1.874***	2.438***
	(0.0797)	(0.0430)	(0.076)	(0.108)
Holiday & Sick Pay	1.890***	0.480***	1.917***	2.225***
	(0.0776)	0.0444)	(0.095)	(0.104)
Flexible Hours	0.763***	0.751***	0.751***	0.888***
	(0.0606)	(0.0595)	(0.0595)	(0.0765)
Work Home-100%	1.355***	0.243***	1.336***	1.633***
	(0.0707)	(0.0692)	(0.069)	(0.0899)
Work Home-50%	0.883***	-0.137**	0.873***	1.005***
	(0.0603)	(0.0678)	(0.059)	(0.0750)
Choose Tasks	0.574***	0.566***	0.566***	0.728***
	(0.0517)	(0.0509)	(0.0509)	(0.0670)
Self-Employed Tax	-0.250***	-0.245***	-0.245***	-0.341***
	(0.0526)	(0.0512)	(0.0512)	(0.0685)
SD				
Permanent	1.525***	0.534***	1.674***	1.739***
	(0.148)	(0.0599)	(0.273)	(0.177)
OneYear	0.701***	0.310***	0.595***	0.477
	(0.154)	(0.0706)	(0.1482)	(0.326)
Holiday & Sick Pay	1.009***	0.584***	1.221***	1.223***
	(0.133)	(0.0836)	(0.247)	(0.167)
Flexible Hours	1.037***	0.997***	0.997***	1.182***
	(0.116)	(0.112)	(0.112)	(0.142)
Work Home-100%	0.382*	0.307*	0.4202	0.0562
	(0.197)	(0.181)	(0.265)	(0.235)
Work Home-50%	0.0273	0.0374	0.0327	0.0138
	(0.158)	(0.179)	(0.156)	(0.191)
Choose Tasks	0.441***	0.448***	0.448***	0.540***
	(0.167)	(0.156)	(0.156)	(0.167)
Self-Employed Tax	0.561***	0.473**	0.473**	0.692***
	(0.161)	(0.189)	(0.189)	(0.185)
N	24336	24336		18818
Log-Likelihood	-5870.39	-5875.20		-3941.87
AIC	11774.77	11784.39		7917.747
BIC	11912.47	11922.08		8051.071

Notes: The table reports the mixed logit preference estimates for the UK in preference space. Column (1) fits the preferences to a normal distribution, (2) to a log-normal distribution, (3) reports the transformed log-normal estimates and (4) the normally fitted estimates conditioning only on those respondents who reported greater certainty than 70%.Standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1

Table 5.A.4: Mixed Logit Preference Estimates- US

	(1) Normal	(2) LogNormal	(3) Transformed Log Normal	(4) Normal-Certainty≥70
Mean				
Wage	0.244***	0.240***	0.240***	0.292***
	(0.00746)	(0.00703)	(0.00703)	(0.010)
Permanent	2.401***	0.728***	2.44***	3.091***
	(0.103)	(0.0447)	(0.122)	(0.148)
One Year	1.780***	0.492***	1.750***	2.249***
	(0.0790)	(0.0492)	(0.078)	(0.111)
Holiday & Sick Pay	1.596***	0.316***	1.623***	1.923***
	(0.0700)	(0.0542)	(0.082)	(0.0953)
Flexible Hours	0.789***	0.771***	0.771***	0.876***
	(0.0621)	(0.0608)	(0.0608)	(0.0726)
Work Home-100%	1.623***	0.436***	1.622***	1.892***
	(0.0777)	(0.0537)	(0.078)	(0.103)
Work Home-50%	0.985***	-0.0411	0.970***	1.108***
	(0.0655)	(0.0726)	(0.063)	(0.0821)
Choose Tasks	0.561***	0.552***	0.552***	0.690***
	(0.0537)	(0.0533)	(0.0533)	(0.0649)
Self-Employed Tax	-0.122**	-0.129**	-0.129**	-0.0646
	(0.0524)	(0.0510)	(0.0510)	(0.0638)
SD				
Permanent	1.424***	0.576***	1.533***	1.826***
	(0.136)	(0.0662)	(0.255)	(0.172)
One Year	0.672***	0.368***	0.665***	0.914***
	(0.146)	(0.0683)	(0.1379)	(0.175)
Holiday & Sick Pay	0.838***	0.580***	1.028***	1.026***
	(0.128)	(0.0963)	(0.231)	(0.169)
Flexible Hours	1.036***	1.024***	1.024***	0.891***
	(0.122)	(0.121)	(0.121)	(0.157)
Work Home-100%	0.309	0.308***	0.5112***	0.688***
	(0.274)	(0.0844)	(0.150)	(0.182)
Work Home-50%	0.340**	0.144	0.1404	0.346
	(0.169)	(0.280)	(0.277)	(0.234)
Choose Tasks	0.359**	0.401**	0.401**	0.148
	(0.178)	(0.161)	(0.161)	(0.335)
Self-Employed Tax	0.485***	0.316	0.316	0.327
	(0.154)	(0.259)	(0.259)	(0.284)
Log-Likelihood	-5448.46	-5453.04		-3898.82
AIC	10930.91	10940.08		7831.64
BIC	11067.39	11076.55		7964.49

Notes: The table reports the mixed logit preference estimates for the US in preference space. Column (1) fits the preferences to a normal distribution, (2) to a log-normal distribution, (3) reports the transformed log-normal estimates and (4) the normally fitted estimates conditioning only on those respondents who reported greater certainty than 70%. Standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1

Table 5.A.5: WTP Estimates UK

Parameter	(1) Normal	(2) Log-Normal	(3) Normal-Certainty ≥70	(4) Normal-WTP Space	(5) Normal-WTP Space(%)
	WTP (£/%)				
Mean					
Permanent	8.99	9.31	9.34	8.97	55.4
One Year	5.98	5.99	6.18	6.03	37.7
Holiday & Sick Pay	5.90	6.12	5.64	5.71	35.2
Flexible Hours	2.38	2.40	2.25	2.26	14.9
Work Home-100%	4.23	4.27	4.14	3.56	22.6
Work Home-50%	2.75	2.79	2.55	2.18	14.0
Choose Tasks	1.79	1.80	1.84	1.57	11.2
Self-Employed Tax	-0.78	-0.78	-0.86	-0.53	-2.61
SD					
Permanent	4.76	5.35	4.40	3.65	22.2
One Year	2.19	1.90	1.21^{+}	1.99	14.3
Holiday & Sick Pay	3.15	3.90	3.10	2.68	16.6
Flexible Hours	3.23	3.19	2.99	1.98	11.6
Work Home-100%	1.19	0.98^{+}	0.14^{+}	1.38	6.53
Work Home-50%	0.09^{+}	0.12^{+}	0.03^{+}	0.86	2.83^{+}
Choose Tasks	1.38	1.43	1.37	1.31	9.13
Self-Employed Tax	1.75	1.51	1.75	1.52	8.61
Information Criteria					
Log-Likelihood	-5870.39	-5875.20	-3941.87	-5792.42	-5771.21
AIC	11774.77	11784.39	7917.74	11620.85	11578.42
BIC	11912.47	11922.08	8051.07	11766.64	11724.22

Notes: The table reports the mixed logit WTP estimates for the UK. Column (1) fits the preferences to a normal distribution in preference space, (2) fits the preferences to a log-normal distribution in preference space, (3) reports the normally fitted estimates in preference space conditioning only on those respondents who reported greater certainty than 70 (4) fits the WTPs to a normal distribution and (5) fits the WTPs to a normal distribution in % terms.

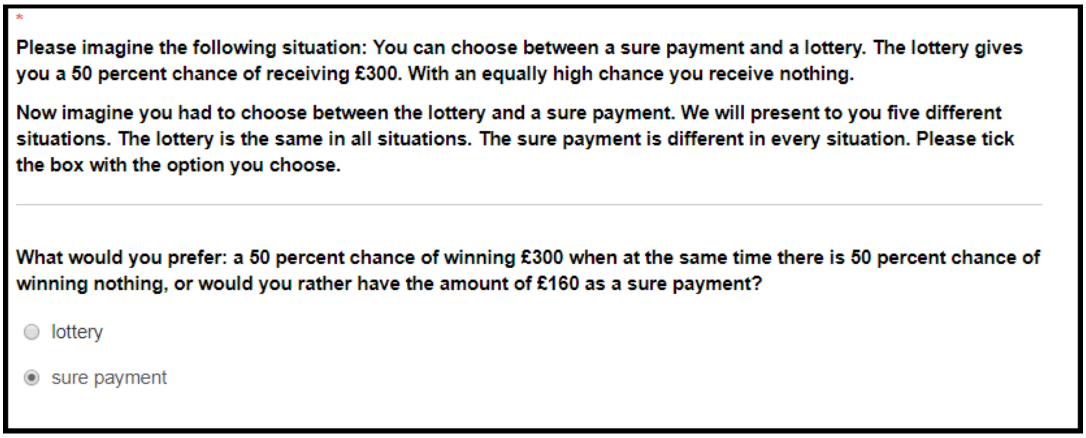
Table 5.A.6: WTP Estimates US

	WTP ($/%)				
	(1)	(2)	(3)	(4)	(5)
Parameter	Normal	Log-Normal	Normal-Certainty $\geq$70	Normal-WTP Space	Normal-WTP Space(%)
Mean					
Permanent	9.84	10.21	10.58	9.92	44.1
One Year	7.30	7.31	7.70	7.26	32.0
Holiday & Sick Pay	6.54	6.78	6.58	6.44	27.3
Flexible Hours	3.23	3.22	3.00	3.06	14.2
Work Home-100%	6.66	6.77	6.48	5.87	25.6
Work Home-50%	4.04	4.05	3.80	3.26	14.3
Choose Tasks	2.30	2.31	2.36	2.20	10.7
Self-Employed Tax	-0.50	-0.54	-0.22^{+}	-0.29^{+}	-0.49^{+}
SD					
Permanent	5.84	6.40	6.25	5.25	20.9
One Year	2.76	2.78	3.13	3.10	13.3
Holiday & Sick Pay	3.43	4.29	3.51	3.62	10.1
Flexible Hours	4.25	4.28	3.05	3.14	13.5
Work Home-100%	1.26	2.13	2.36	1.60	7.45
Work Home-50%	1.39	0.59^{+}	1.18^{+}	0.98^{+}	4.27
Choose Tasks	1.47	1.67	0.51^{+}	1.51	5.95
Self-Employed Tax	1.99	1.32^{+}	1.12^{+}	2.20	8.57
Information Criteria					
Log-Likelihood	-5444.12	-5504.19	-3889.02	-5402.11	-5359.42
AIC	10922.23	11026.38	7812.03	10840.22	10754.84
BIC	11058.71	11098.63	7944.87	10984.72	10899.35

Notes: The table reports the mixed logit WTP estimates for the UK. Column (1) fits the preferences to a normal distribution in preference space, (2) fits the preferences to a log-normal distribution in preference space, (3) reports the normally fitted estimates in preference space conditioning only on those respondents who reported greater certainty than 70 (4) fits the WTPs to a normal distribution and (5) fits the WTPs to a normal distribution in % terms.

5.B Additional Figures

Figure 5.B.1: Example Risk Question



*

Please imagine the following situation: You can choose between a sure payment and a lottery. The lottery gives you a 50 percent chance of receiving £300. With an equally high chance you receive nothing.

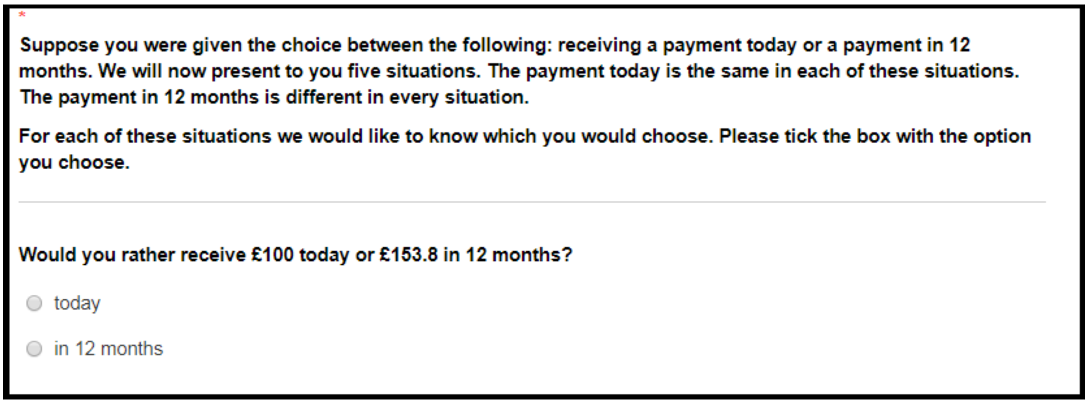
Now imagine you had to choose between the lottery and a sure payment. We will present to you five different situations. The lottery is the same in all situations. The sure payment is different in every situation. Please tick the box with the option you choose.

What would you prefer: a 50 percent chance of winning £300 when at the same time there is 50 percent chance of winning nothing, or would you rather have the amount of £160 as a sure payment?

- lottery
- sure payment

Notes: The figure reports an example question from the survey used to elicit risk aversion.

Figure 5.B.2: Example Discounting Question



*

Suppose you were given the choice between the following: receiving a payment today or a payment in 12 months. We will now present to you five situations. The payment today is the same in each of these situations. The payment in 12 months is different in every situation.

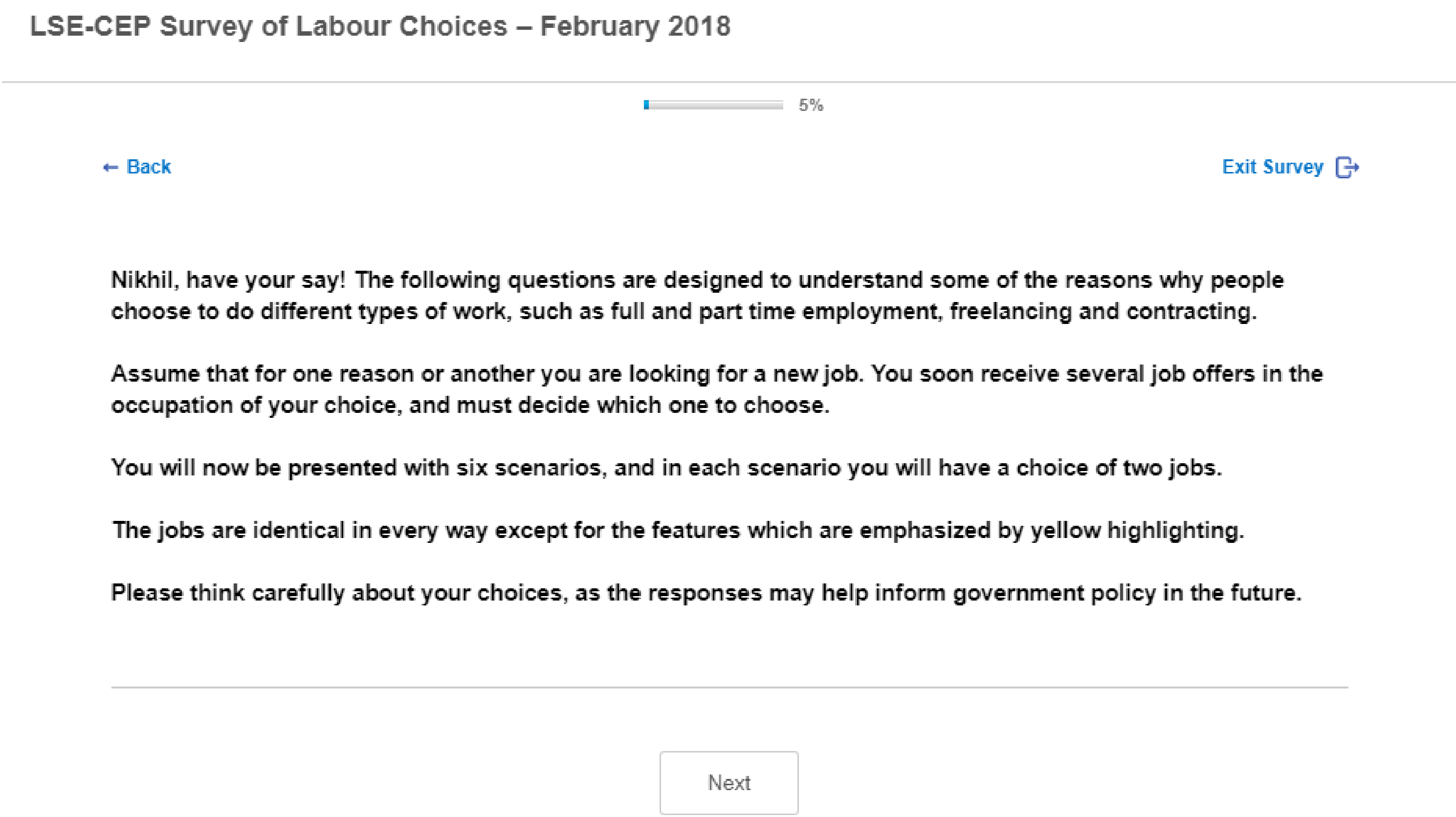
For each of these situations we would like to know which you would choose. Please tick the box with the option you choose.

Would you rather receive £100 today or £153.8 in 12 months?

- today
- in 12 months

Notes: The figure reports an example question from the survey used to the respondents discount factor.

Figure 5.B.3: Vignette Introduction


LSE-CEP Survey of Labour Choices – February 2018

5%

← Back

Exit Survey

Nikhil, have your say! The following questions are designed to understand some of the reasons why people choose to do different types of work, such as full and part time employment, freelancing and contracting.

Assume that for one reason or another you are looking for a new job. You soon receive several job offers in the occupation of your choice, and must decide which one to choose.

You will now be presented with six scenarios, and in each scenario you will have a choice of two jobs.

The jobs are identical in every way except for the features which are emphasized by yellow highlighting.

Please think carefully about your choices, as the responses may help inform government policy in the future.

Next

Notes: The figure reports the text in the introduction to the discrete choice question in the survey.

Figure 5.B.4: Example Choice Question

LSE-CEP Survey of Labour Choices – February 2018

11%

← Back   Questions marked with a * are required   Exit Survey

The jobs are identical in every way except for the features which are emphasized by yellow highlighting.

Which job do you prefer A or B? Please mark the corresponding circle.

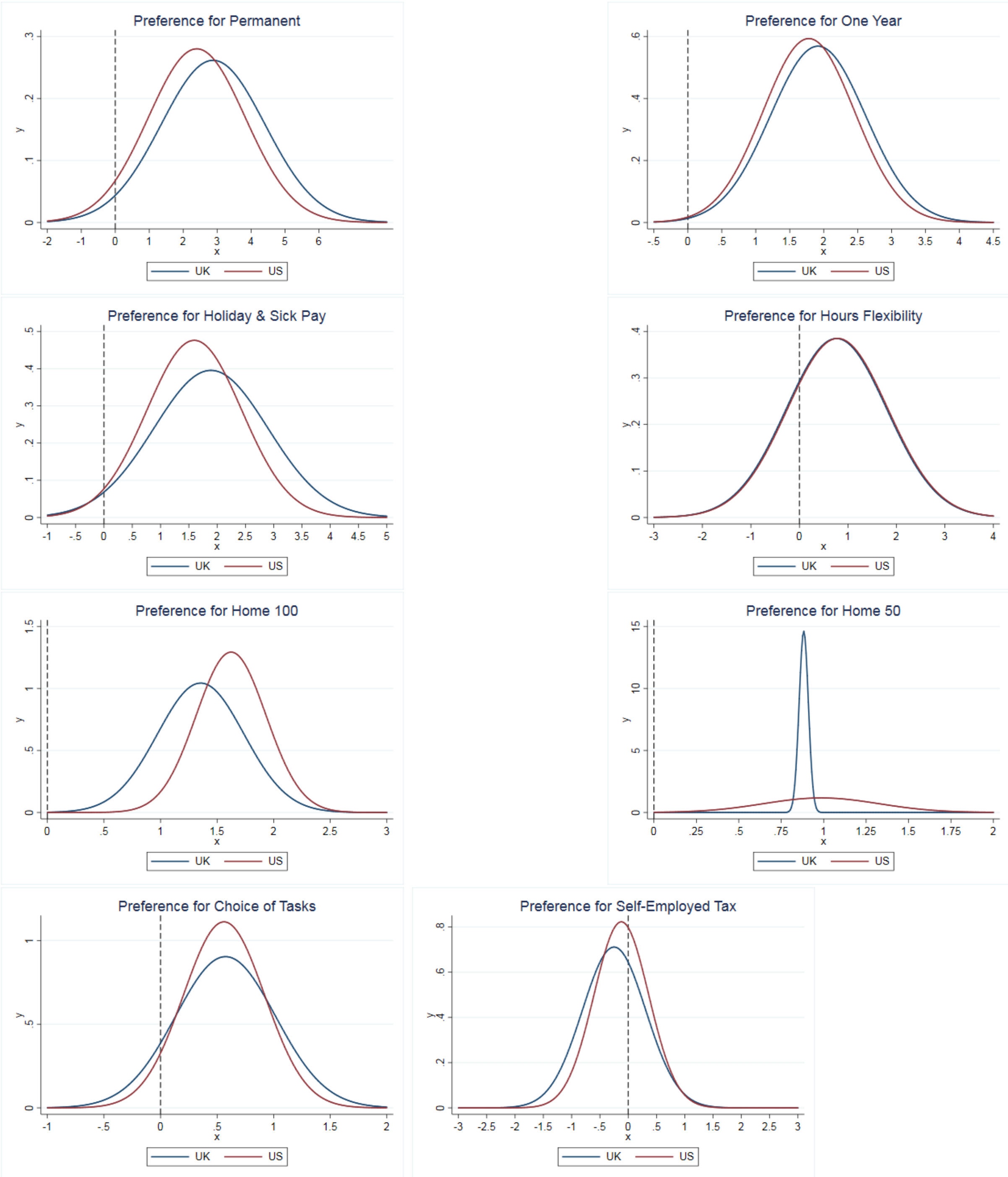
Job A   Job B

*

	Job A		Job B
Hourly wage before tax:	£16.00		£8.50
Holiday & sick pay:	28 days paid annual leave and 16 weeks paid occupational sick leave (or pro rata if part time)		28 days paid annual leave and 16 weeks paid occupational sick leave (or pro rata if part time)
Longevity:	The job is for 1 month		The job is permanent
Ability to choose hours:	You may freely decide how many hours you work a week, and when you do them		You may freely decide how many hours you work a week, and when you do them
Ability to work from home:	You may not work from home		You have the option to work from home 50% of the time
Ability to choose which tasks you do on the job:	You may freely decide which tasks you do on the job relevant to your occupation		You may freely decide which tasks you do on the job relevant to your occupation
Tax Implications:	You declare taxes as self-employed and thus can deduct relevant expenses		You declare taxes as self-employed and thus can deduct relevant expenses

Notes: The figure reports an example discrete choice vignette from the survey.

Figure 5.B.5: Distribution of Preferences



Notes: The graphs report the PDF for the distribution of preferences over job attributes estimated in preference space, the UK and US sample.

6 Conclusion

This thesis studies the role of monopsony power, minimum wages and atypical work arrangements in modern labour markets in developed economies. It provides evidence on the existence, extent and causes of monopsony power, and documents the role that wage floors can have in correcting low wages created by monopsonistic power, without negatively affecting aggregate employment outcomes. It also shows that wage floors can, in certain circumstances, change the contractual relationships between workers and firms, and that ceteris paribus workers prefer traditional employer-employee relations.

Chapter two presents estimates of labour supply elasticity to the individual firm and the implied wage-markdowns based of these estimates. Furthermore, it shows that workers have a strong distaste for commuting and this distaste for commuting is likely to be responsible for approximately one third of the estimated wage markdown.

Chapter three explores the consequence of age-wage discontinuities in a company's wage profile, coupled with the introduction of a living wage. It shows that prior to living-wage treatment there are positive labour supply responses at the age discontinuity, but a fall in hours at the discontinuity following treatment. However, there is no evidence of the living wage introduction affecting aggregate hours. This suggests that firms redistributed hours within firms by age, depending on differential eligibility to be paid the Living Wage.

Chapter four documents the evolving nature of atypical work arrangements in the UK and places a strong focus on ZHCs. The chapter uses data from a novel survey to describe the role of ZHCs in the UK labour market. It additionally explores the interaction with minimum wages, and shows that the introduction of the NLW in 2016 in the UK results in an increase in the use of ZHCs.

Chapter five utilises a discrete choice experiment in a novel survey of US and UK workers to estimate willingness-to-pays for job attributes typically associated with traditional employer-employee contracts and more atypical contractual relations. The results suggest that the majority of workers prefer characteristics associated with traditional relations and this holds even for the subset of workers in atypical work.

Overall, this thesis provides evidence on wage determination, minimum wages, and atypical work arrangements and their roles in a modern developed labour market. It shows that labour markets for low paid workers exhibit strong monopsony power, that minimum wages can go some way in remedying this issue, but in certain circumstances minimum wages can cause growth in atypical work arrangements, and workers have a strong preference for traditional employer-employee relations.

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