Impacts of a Higher Than Mandated Minimum Wage: The UK Living Wage

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Contents

Executive Summary

This study addresses the impacts of a higher than mandated minimum wage, with a focus on "Living Wages". Analysis of higher than mandated minimum wage rates can provide an indication of the likely impact of further uprating of statutory minimum wage rates. We study the impact of a higher than mandated wage floor for a UK based services firm with hundreds of establishments across the UK and a large BAME workforce.

Utilising a state-of-the-art estimator which treats the variation in treatment timing with due caution we examine how a firm responds to the Living Wage Foundation's (LWF) Living Wage (LW). The Living Wage Foundation's Living Wage is calculated based on a basket of goods and services for London and the rest of the UK, and is considerably higher than the mandated National Living Wage (NLW).

Exposure to the LW increases wages for entry-level workers by approximately 7% against a counterfactual of untreated workers in similar establishments. The LW introduction increased an establishment's average wage bill by approximately 1.5%. LW exposure reduced the within-establishment BAME wage-gap by almost 50%, from 7 to 3.5 percentage points.

There is no negative impact of LW exposure on a variety of employment measures: this includes the number of positions, headcount employment, hours and the BAME employment gap. If anything, there is weak evidence of positive employment effects at the establishment level consistent with monopsony models of the labour market.

Firms responded to the LW by altering their employment composition, increasing the ratio of entry-level workers to supervisors. This finding is the opposite to what is expected in a model of perfect competition, where wage increases for one type of labour input would typically result in a relative decrease of that labour input in the employment composition. This result can be explained by monopsony power in the labour market and weak substitutability between entry-level workers and supervisors. In particular, a positive labour supply response dominates the negative demand response, resulting in an increase in the skill composition ratio of entry-level to skilled workers.

The LW resulted in a coarser within-establishment wage structure. An exposed establishment reduces the number of pay points on its pay scale by 2-2.5 on average, and there is evidence that there are spill-overs of this onto non-minimum wage jobs. This result is likely to be indicative of compression of the within establishment wage variation and means wage variation will be less able to replicate variation in productivity across workers. There is no negative impact of the LW on the rate that workers get promoted in treated establishments, and this holds when we look at just entry-level workers who are more highly exposed.

The findings suggest that overall impacts of exposure to the higher than mandated Living Wage Foundation's Living Wage appear promising. Wages for minimum-wage jobs rise substantially, and there are no obvious negative impacts on employment or promotions. While the results are suggestive that a higher minimum wage can have positive welfare effects, these results should be viewed as a first step. In particular, as the results are estimated using data from a single firm, policy makers should exercise caution regarding generalisability.

Introduction

Stagnating wage growth and the decoupling of wages from productivity have made minimum wages a popular and necessary policy instrument in recent years in both the UK and abroad. In the UK the past decade saw a traditionally anti minimum-wage party introduce a new wage band to the National Minimum Wage (NMW), coined the National Living Wage (NLW), which represented a more than 10% increase in the wage floor for over 25s at the point of announcement. The NLW has since been extended to cover all those over the age of 23, and the UK government has set a commitment for the NLW to reach two-thirds of median earnings by 2024 for those aged 21 and over.

The name given to the new wage band introduced in 2016 was not by coincidence. The concept of "living wages", a wage floor calculated to meet some minimum standards of living based on a basket of consumption goods rather than based on a percentage of the average wage rate, had been gaining traction amongst campaign groups, policy makers and in the media for some time prior to that. In the UK the Living Wage Foundation (LWF), a charity and campaign group, along with the Resolution Foundation, an independent think tank, calculate living wage rates for London and the rest of the UK.[1] The LWF has accredited thousands of employers in the UK including major corporations such as Nestlé, KPMG and Ikea as well as local government institutions. In the US many cities have passed living-wage ordinances (Dube and Lindner, 2021; Sosnaud, 2016) and Massachusetts Institute of Technology run an online living wage calculator for different US geographies (Glasmeier, 2020). The emergence of discussions concerning living wages (and more recently, "living hours") has been in part due to the rise of households experiencing in-work poverty. Calculations from the Joseph Rowntree Foundation suggest that, as of 2020, 56% of those experiencing poverty were from in-work households, a

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

figure 19 percentage points higher than 20 years previous, while the overall UK poverty rate has remained unchanged (JRF, 2020). Their estimates also consistently suggest that all BAME groups experience greater poverty levels than their white counterparts in the UK.

UK based studies to date have focused on ex-post evaluations of nationally mandated minimum wage introductions or upratings to assess the impacts, typically focusing on wages and employment. This paper deviates from this literature along two dimensions. First, it studies exposure to a "living wage" which is set at a level considerably higher than the nationally mandated minimum based upon a basket of goods calculation. It therefore gives evidence as to how firms may react to a minimum wage closer to a true "Living Wage". Second, due to the richness of the dataset that is used, it can look at a range of possible margins of adjustment. This includes wages, extensive and intensive margins of employment, heterogeneity of these by ethnicity, skill composition, rates of promotions and the structure of wages within establishments.

Special access to a novel dataset containing complete HR records for a large single company with many establishments, provides a unique opportunity to test the impacts of a higher minimum wage on a firm that is relatively representative of its industry. This is possible because many of the establishments in this company have become required to pay a higher than mandated minimum wage due to contractual agreements requiring them to pay the Living Wage Foundation's minimum wage rates. Not only does this allow estimation of the likely impact of a higher minimum wage rate, but because a large proportion of the company's workforce are from Black, Asian and Minority Ethnic (BAME) backgrounds it also enables an assessment of whether and how higher minimum wages impact BAME wage and employment gaps.

The Company and the Setting

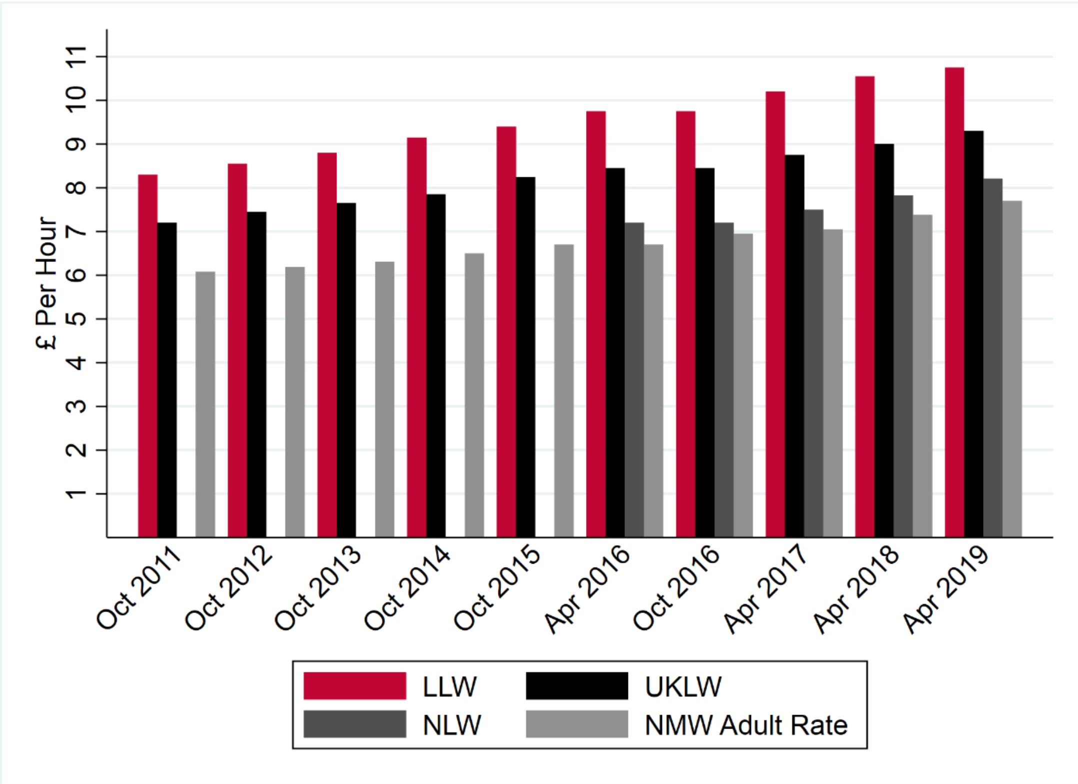
To study the impact of a "true" Living Wage based on a basket of goods and services and is higher than the nationally mandated minimum, we utilise a novel dataset which contains the complete HR data for The Company for the period of 2011 – 2019 in conjunction with staggered establishment level Living Wage exposure. The following section details the experimental setting which we utilise to study the impact. A large proportion of The Company's workforce are BAME and therefore the setting also lends itself to studying heterogenous impacts of a high Living Wage along the ethnicity dimension.

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 true "living wage". Each year the LW is calculated utilising price data from a representative basket of goods and services and is published for London (LLW) and the rest of the UK (UKLW). The LLW rate has typically been approximately 30-35% higher than the official statutory National Minimum Wage (NMW) or National Living Wage (NLW), while the UKLW has been about 15-20% higher as can be seen by Figure 1.

The Living Wage is voluntary and not nationally mandated, unlike the National Minimum Wage or National Living Wage. Once an organisation signs up to become "Living Wage" employers, it can achieve accredited status following audits. As of July 2020, the LWF lists 6,562 accredited employers and included in this list are 107 local government units[2]. When public bodies achieve accreditation, their contractors are additionally required to pay the LLW or UKLW (depending on location).

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

Figure 1 Living Wage Rates



Notes: 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).

The Company operates in the service sector and a large portion of its turnover is from government procurement contracts, for council services. The council services they provide are not typical natural monopolies, and other private firms compete in the same local markets. As The Company has many procurement contracts with local councils and additionally 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 and this induces considerable variation in treatment over time. 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[3]. As Figure 2 shows, this setting gives a large amount of variation in Living Wage treatment for establishments run by The Company. Over the period for which we have HR data approximately 140 establishments went from being untreated to treated, while run by The Company, and by the end of our sample period this made up just under half of all establishments. Such variation lends itself to a multiple period difference-in-difference analysis, which is detailed more in the methodology section.

Figure 2 - 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.

[3] Correct as of July 2019.

The setting combined with the data from the Company's payroll allows a novel analysis of how firms react to a "true" Living Wage based on a basket of goods calculation. As all the establishments in our analysis are operated by the same company using the same structure of operations and management, but with establishment level autonomy over finances[4], employment, workforce composition and promotions, we can see a true counterfactual, when comparing treated and untreated establishments. It is additionally worth noting, given the quality of the dataset we are able to study a number of margins. These include the impact on wages, the BAME wage gap, extensive and intensive employment changes, the BAME employment gap, skills composition, promotions and the structure of pay scales.

Descriptive Statistics

The mean hourly wage across all positions has not fundamentally changed over the seven-year period, and in 2018 was £12.37 per hour, which is approximately 25% lower than the average hourly wage for the UK in 2018. Over the same period the NMW/NLW has increased by 28%, the UKLW by 25%, and the median wage by 15%. This negligible change in mean hourly wage for The Company likely reflects compositional changes within the total workforce, in particular the growth of non-London establishments which pay lower rates than their London counterparts. The average wage for entry level workers has seen an increase of around 25% and in 2018 stood at £9.48. Managers weekly earnings are on average 2 -3 times higher than entry level workers, though some of this is driven by the fact that there is a large number of part time workers, around two thirds of employees are on ZHCs (Zero Hours Contracts). The number of unique pay bands has decreased over time for both all employees and just for entry level workers. Three fifths of staff are female and one fifth are BAME (Black,

[4] Discussions with the director of HR suggest there is no cross-subsidisation of finances between exposed and un-exposed establishments. Additionally, exposure to the Living Wage does not come with any other changes to the financial arrangements with the local council; and as the firm is a local services provider there is no scope to move production between establishments.

Asian and minority ethnic), and the average age of staff has varied between 33 and 38, which is lower than the national average mean which stands at 43.

Table presents summary statistics on the workforce employed by The Company for years 2011, 2015 and 2018 at the establishment level. As can be seen the size of The Company increased a lot during our sample period, with its number of establishments increasing from 85 in 2011 to to 328 in 2018. This expansion has seen an increase in the number of non-London establishments. In 2011 almost 90% of establishments were based in London, by 2018 this figure had dropped to 50%. Over time the average size of an establishment has decreased, but in 2018 each establishment is still sizeable, on average employing approximately 50 people. The table reports data on both the number of employees and the number of positions. Employees are equivalent to a headcount of workers, while positions are specific job roles with an associated wage. The difference in these two figures demonstrates that some individuals are working in more than one position within an establishment. Approximately half of the positions on average in each establishment are entry-level positions, and there are on average 4-5 entry level workers to each manager within each establishment. Entry-level jobs are an internal descriptor for The Company, and all entry-level jobs are paid the same rate within an establishment. They are essentially low skilled jobs which do not require previous experience or qualifications. Roles with this classification would typically be considered "minimum wage" jobs in the UK. In treated establishments they are paid the Living Wage rate, and in untreated establishments they are paid below this rate.

The mean hourly wage across all positions has not fundamentally changed over the seven-year period, and in 2018 was £12.37 per hour, which is approximately 25% lower than the average hourly wage for the UK in 2018[5]. Over the same period the NMW/NLW has increased by 28%, the UKLW by 25%, and the median wage by 15%. This negligible change in mean hourly wage for The Company likely reflects compositional changes within the total workforce, in particular the growth of non-London establishments which pay lower rates than

[5] This stood at £16.71 as calculated using the Annual Survey of Hours and Earnings.

their London counterparts. The average wage for entry level workers has seen an increase of around 25% and in 2018 stood at £9.48. Managers weekly earnings are on average 2 -3 times higher than entry level workers, though some of this is driven by the fact that there is a large number of part time workers, around two thirds of employees are on ZHCs (Zero Hours Contracts). The number of unique pay bands has decreased over time for both all employees and just for entry level workers. Three fifths of staff are female and one fifth are BAME (Black, Asian and minority ethnic), and the average age of staff has varied between 33 and 38, which is lower than the national average mean which stands at 43.[6]

[6] As per the LFS, 2018.

Table 1 – Establishment Level Summary Statistics

	2011		2015		2018	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
<u>*Establishment level variables*</u>						
No. Employees	59.64	39.74	54.61	46.87	47.70	44.78
No. Positions	65.78	44.28	62.52	54.87	55.44	52.50
No. Entry Level Positions	32.26	23.65	28.58	24.86	27.02	25.22
Ratio Entry Level – Managers	4.46	2.27	4.23	2.73	4.75	3.38
Hourly Wage	12.20	2.42	12.53	2.50	12.37	2.47
Hourly Wage – Entry Level	7.68	1.09	8.40	1.27	9.48	1.23
Weekly Hours	19.53	6.35	17.76	6.41	17.01	6.59
Weekly Earnings	207.57	79.32	200.99	99.32	206.63	113.08
Weekly Earnings – Entry Level	189.03	65.81	156.97	74.76	156.84	77.60
Weekly Earnings – Managers	435.26	95.37	425.17	114.18	434.96	128.56
No. Pay Bands	22.31	10.41	19.78	12.74	17.17	11.74
No. Pay Bands – Entry Level	9.01	4.89	6.78	4.30	5.93	4.55
Prop. Zero-Hours Contracts (ZHC)	0.68	0.20	0.66	0.26	0.63	0.25
Female	0.58	0.15	0.58	0.17	0.61	0.18
BAME	0.29	0.19	0.26	0.20	0.20	0.19
Age	33.51	3.83	35.87	5.53	37.63	6.90
London	0.89	0.31	0.71	0.46	0.49	0.50
Number of Establishments	85		190		328	

Note: The table reports the mean and standard deviation of a set of establishment-level variables for the sample of establishments used in the analysis for three separate years. Statistics are reported from 1st June of the associated year. All monetary statistics are in nominal terms. Hourly wages are calculated at the position level, earnings are calculated at the employee level.

Table 2 presents descriptive statistics for workers at The Company for the year 2019 with breakdowns for BAME and non-BAME workers. About one fifth of the workforce are classified as BAME, which indicates we should have the statistical power to examine heterogenous effects of the Living Wage along a BAME dimension. The breakdown suggests that BAME workers in The Company on average have a very similar wage to non-BAME workers, and entry level BAME workers earn about £0.79 per hour more. This is likely driven by the fact that more BAME workers are located in London, which has a higher wage level to reflect local price levels. BAME workers work on average fewer hours, are 8pp more likely to be on a ZHC, and are more highly represented in entry-level (unskilled) roles.

Table 2 – Worker Level Summary Statistics, BAME vs Non-BAME

	Non-BAME		**BAME**		**Total**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Number of Positions	12087		4123		18185	
Hourly Wage	12.97	5.80	13.12	5.13	12.97	5.64
Hourly Wage – Entry	9.06	1.65	9.86	0.97	9.25	1.54
Weekly Hours	12.42	15.44	10.32	14.54	11.87	15.13
Weekly Earnings - Entry	153.57	224.79	108.28	139.52	115.21	137.45
ZHC	0.72		0.80		0.73	
Female	0.62		0.58		0.61	
Entry-level Employee	0.45		0.53		0.47	

Note: The table reports the mean and standard deviation of a set of worker-level variables for June 2018. The Total column includes BAME, non-BAME and those who did not provide their ethnicity.

Table 3 presents differences in descriptive statistics for worker level means between The Company and workers in the LFS working within the same industry (4 digit SIC code) with breakdowns for London and non-London. Differences in descriptive statistics rather than the raw values are presented for confidentiality purposes. As can be seen the firm's workforce is relatively representative of the industry. The Company employs marginally more women, and this is more pronounced in London, has almost identical age values, and similar levels of skill composition to the rest of the industry, especially outside of London. The Company pays slightly higher wages, however this is likely partly due to Living Wage treatment.

Table 3 - Representativeness Of Workforce, March 2019

	The Company – LFS		
	Total	London	Non-London
Female	0.07	0.14	0.04
Age	0.7	1.4	-0.1
Entry-Level	0.06	0.12	0.06
Hourly Rate (£)	2.14	0.33	1.84

Note: The table reports the difference in the mean for particular worker level variables for The Company's workforce against workers in the same industry within the LFS, for 2019, with breakdowns for London and non-London. Differences in descriptive statistics are presented rather than the raw statistics for confidentiality reasons. Entry-level occupations are defined according to The Company's internal occupation classification.

The Causal Impact of the Living Wage

To estimate the causal impact of the Living Wage on a variety of outcomes, including wages, the BAME wage gap, skill composition, coarseness of the wage structure, promotions, employment and hours, and the BAME employment gap, we employ a difference-in-difference estimator which treats the multiple treatment timing (i.e. the differential timing introduction of the Living Wage) of the setting with due caution. The intuition of identifying the causal impact of the Living Wage introduction on outcomes is as follows. When an establishment receives treatment (i.e. has to pay the Living Wage) we observe its differential growth rates in outcomes such as wages and employment, when compared to untreated establishments within our dataset within the same company. A key assumption underlying this intuition is that establishments experience similar wage growth in the absence of treatment, and this assumption can be tested by testing if there are differential pre-trends prior to treatment.

There has been a recent interest in the workings of difference-in-difference and event study estimators, especially when there is variation in treatment timing or heterogenous treatment effects (for example see Sun and Abraham (2021), Callaway and Sant'Anna (2021), Goodman-Bacon (2021) 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, 2021), biased estimates of treatment effects when the control group contains treated units when dynamic treatment effects are present (Goodman-Bacon, 2021), the structure of weights assigned across treatment cohorts when estimating dynamic treatment effects (Sun and Abraham, 2021) and the structure of weights across dynamic treatment effects when estimating a single treatment effect (Borusyak and Jaravel, 2017). As we have variation in treatment timing (i.e. when establishments begin to pay the Living Wage) one may be particularly concerned about ensuring there is a clear definition of which groups are used as “treatment” establishments, and which are used as “control” establishments. Additionally there may be heterogenous effects due to differences in the Living Wage relative to the minimum wage over time and geography. Therefore, it is prudent to utilise an estimator robust against these issues. We attempt to overcome these issues by implementing an estimator utilised in Datta and Machin (2021) which is based on the estimator developed by Sun and Abraham (2021).

The estimator in practice is a staggered difference-in-differences (or event study) estimator, which estimates the effects for each treatment cohort, where a treatment cohort is defined by a group of establishments receiving treatment at the same time. The control group for each treatment cohort are those who will not be treated for at least two years, or have already been treated at least two years previously. The final point estimates are then a weighted average across these treatment cohorts, where the weights are calculated according to the number of treated establishments in each treatment cohort. For a full exposition of the methodology, see the Appendix.

Results

Wages

Figure graphically reports event study coefficients for log mean wages of all workers, entry level workers, and non-entry level workers as the dependent variable. As can be seen in all instances 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 a sharp, statistically significant rise in wages for all workers and entry level workers which is roughly consistent throughout the year following treatment, when compared to non-treated establishments. Wages on average for non-entry level workers (where the Living Wage is non-binding) experience a very slight decrease following treatment, though this is on the bounds of significance.

Figure 3 – The Living Wage and Wages

Notes: The graph reports the estimate~~ds~~ coefficient $\widehat{v_g}$ from model (4) without controls. 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. The specification for all workers contains a control for the proportion of entry level workers. Source (Datta and Machin, 2021).

The average long run impacts are reported in Table and

Table As can be seen, the introduction of the Living Wage increases the wages for all workers within an establishment on average by 1.5%, and for entry level workers by 6.6%, and both estimates are highly significant. Column (3) of Table 5 presents results with the inclusion of an interaction of Living Wage treatment with whether establishments were based in London. This interaction allows us to explore heterogenous effects for London against the rest of the

UK. As can be seen, there is no statistical difference on the impact of treatment across this dimension of geographical space. This is driven by the fact that despite the Living Wage is higher in London than the rest of the UK, wages for The Company were higher in London than the rest of the UK in the absence of treatment. This is a common approach used by firms to address differences in local price levels. Wages for non-entry level workers fall on average by 0.9%, though given the detailed knowledge we know about wages within establishments, this impact is likely due to compositional changes of the non-entry level workforce. Specifically, as non-entry level workers make up a large array of hierarchical positions, it could be driven by changes to the composition of non-entry level jobs within each establishment. All estimates are unaffected by the inclusion of controls.

Table 4 - Wage Equations, all workers

Dep. Var.: Log wages

	D-in-D		Event Study
	(1)	(2)	(3)
LW_{it}	0.014***	0.015***	
	(0.003)	(0.04)	
LW_{it} x Quarter			
-4			.001
			(.002)
-3			.005*
			(.003)
-2			.004*
			(.002)
-1			.002
			(.001)
0			.016***
			(.003)
1			.019***
			(.004)
2			.017***
			(.004)
3			.015***
			(.005)
Controls	No	Yes	Yes
Observations	17,879	17,879	17,879

Notes: The table reports the estimated coefficients $\widehat{v_g}$ and $\hat{v}$ from models (4) and (6) of the Appendix. The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

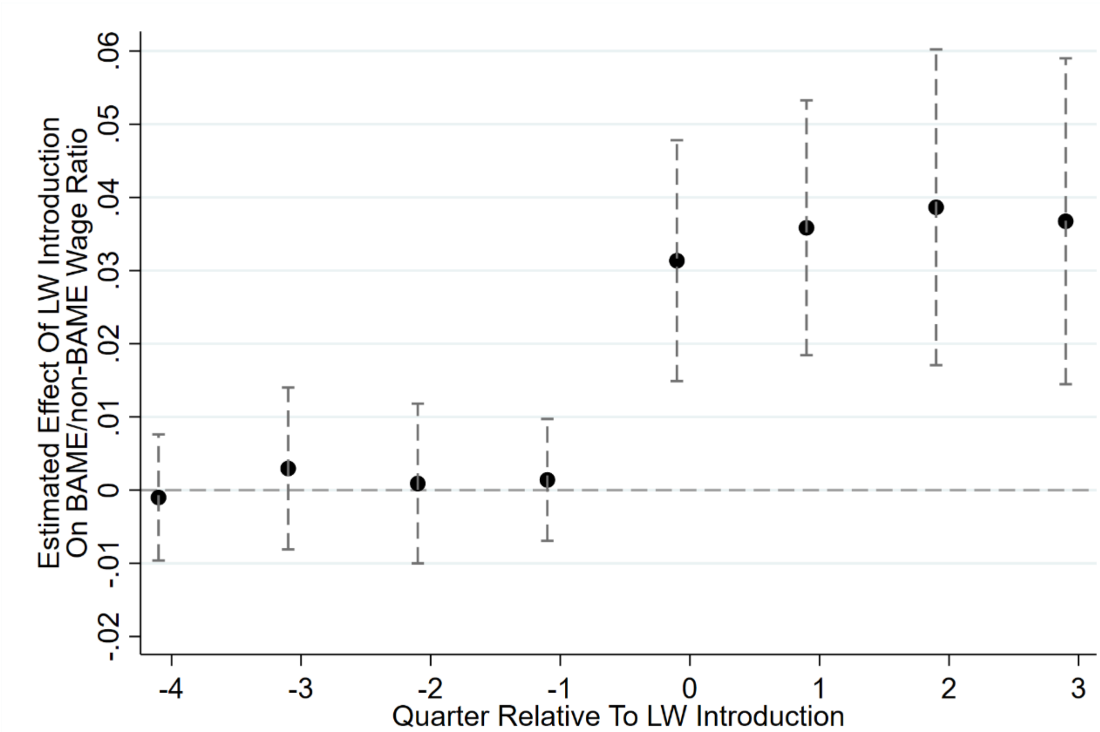
Table 5 - Wage Equations, by worker type

Dep. Var.: Log wages

	Entry Level Workers			Non-Entry Level Workers	
Variable	D-in-D	Event Study	D-in-D	D-in-D	Event Study
	(1)	(2)	(3)	(4)	(5)
LW_{it}	0.066***		0.063***	-0.009**	
	(0.004)		(0.011)	(0.004)	
LW_{it} x London			0.010		
			(0.013)		
LW_{it} x Quarter					
-4		-.001			.003
		(.002)			(.002)
-3		-.002			.009**
		(.003)			(.004)
-2		.004			.004
		(.002)			(.003)
-1		.002			.002
		(.001)			(.002)
0		.062***			-.005
		(.004)			(.003)
1		.067***			-.002
		(.005)			(.005)
2		.067***			-.007
		(.005)			(.006)
3		.067***			-.009
		(.006)			(.006)
Controls	Yes	Yes		Yes	Yes
Observations	17,879	17,879	17,879	17,879	17,879

Notes: The table reports the estimated coefficients $\widehat{v_g}$ and $\hat{v}$ from models (4) and (6) of the Appendix. The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

Figure 4 – The Living Wage and the BAME Wage Gap



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. 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. Mean of dependent variable = 0.92.

Figure 4 graphically represents the point estimates with the BAME wage gap as the dependent variable along with 95% confidence intervals. The introduction of the Living Wage reduced the BAME-non-BAME wage ratio by a steady 3.5pp, which is almost 50% of the existing gap within each establishment. The results suggest that the Living Wage had a strong, meaningful impact on closing part of the BAME wage gap, and this appears to be driven by the fact that a larger proportion of BAME workers were in entry-level positions. Figures A1 and A2 in the appendix show breakdowns for London and the rest of the UK. Impacts across both areas of the UK seem on average the same, though the point estimates for non-London areas are noisier. Table 6 reports the counterpart coefficients as well as the results from the long run estimates.

Table 6 - Wage Equations, BAME wage gap

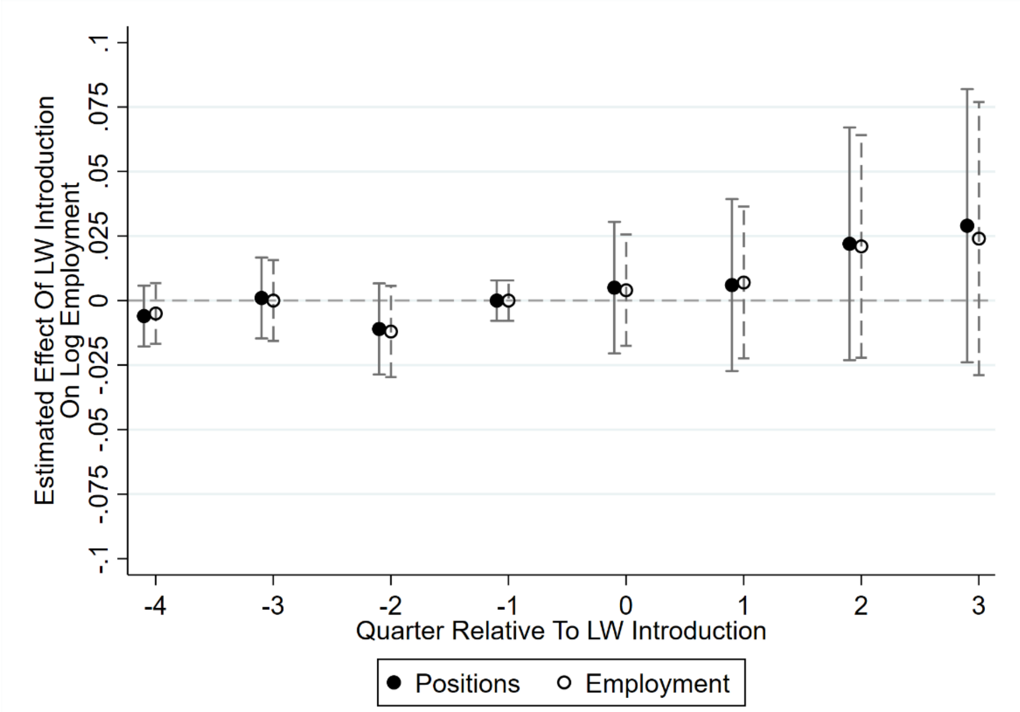
Dep. Var.: Wage BAME/Wage non-BAME

	D-in-D		Event Study
	(1)	(2)	(3)
LW_{it}	0.033***	0.032***	
	(0.010)	(0.010)	
LW_{it} x Quarter			
-4			-0.001
			(.004)
-3			0.003
			(.005)
-2			-0.001
			(.005)
-1			0.001
			(.004)
0			.031***
			(.008)
1			.036***
			(.008)
2			.039***
			(.011)
3			.037***
			(.011)
Controls	No	Yes	Yes
Observations	17,879	17,879	17,879

Notes: The table reports the estimated coefficients $\widehat{v_g}$ and $\hat{v}$ from models (4) and (6) of the Appendix. The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

Employment

Figure 5 – The Living Wage and Employment



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. 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. Source (Datta and Machin, 2022).

Table 7 reports estimates from specifications for various measures of log employment (positions, headcount employment and casual hours). We find no long run impacts on employment at both the extensive and intensive margin. Although all point estimates are not statistically significant from 0, all are positive. The dynamic impact plots in figure 5 suggest weak evidence of increases in both positions and headcount employment as a result of the Living Wage which is consistent with a model of monopsony power in the labour market.

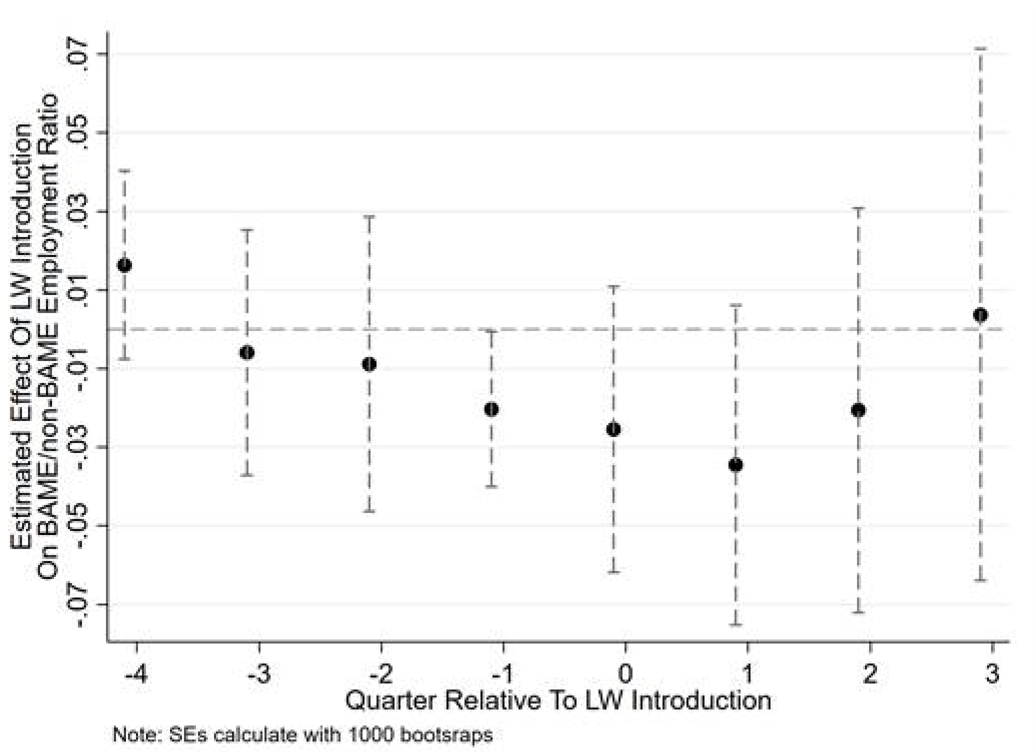
Table 7 – Employment Equations

Dep. Var.: Log Positions, Log Employment, Log Casual Hours

	Positions		Employment		Casual Hours	
	(1)	(2)	(3)	(4)	(5)	(6)
LW_{it}	0.021	0.009	0.019	0.007	0.036	0.005
	(0.19)	(0.017)	(0.019)	(0.017)	(0.072)	(0.066)
Controls	No	Yes	No	Yes	No	Yes
Observations	17,879	17,879	17,879	17,879	17,879	17,879

Notes: The table reports the estimated coefficients $\widehat{v_g}$ and $\hat{v}$ from models (4) and (6). The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

Figure 6 – The Living Wage and the BAME Employment Gap



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. 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.

Figure 6 graphically reports estimates from a specification with the establishment level ratio of BAME to non-BAME employment as the dependent variable. All point estimates are not statistically different from zero, suggesting there are no clear patterns of impact of the Living Wage on the BAME employment ratio. Table 8 reports the counterpart estimates along with the long run effect estimates. The long run estimates corroborate the assessment that the Living Wage had no effects on the BAME employment ratio.

Table 8 - Employment Equations, BAME employment gap

Dep. Var.: Wage BAME/Wage non-BAME Employment

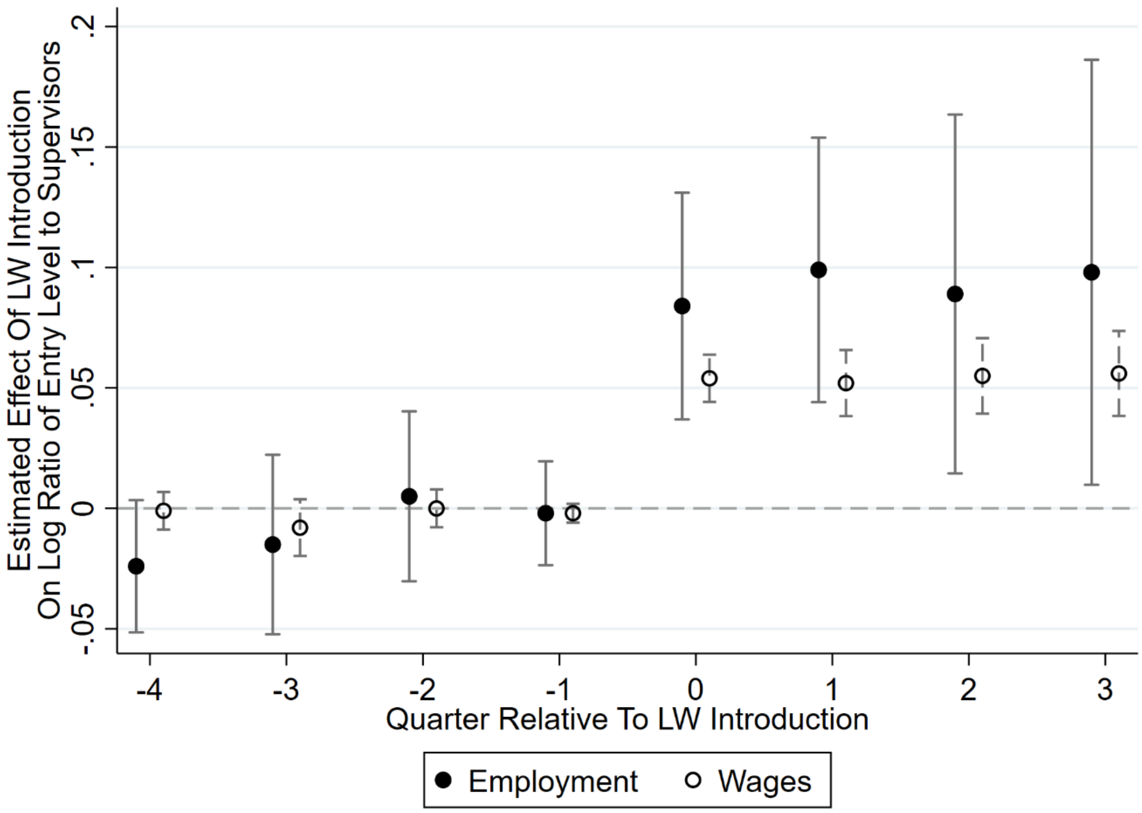
	D-in-D		Event Study
	(1)	(2)	(3)
LW_{it}	-0.015	-0.013	
	(0.019)	(0.020)	
LW_{it} x Quarter			
-4			0.016
			(0.012)
-3			-0.006
			(0.016)
-2			-0.009
			(0.019)
-1			-0.020**
			(0.010)
0			-0.025
			(0.019)
1			-0.035*
			(0.021)
2			-0.021
			(0.026)
3			0.004
			(0.035)
Controls	No	Yes	Yes
Observations	17,879	17,879	17,879

Notes: The table reports the estimated coefficients $\widehat{v_g}$ and $\hat{v}$ from models (4) and (6) of the Appendix. The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

Skill Composition

Figure 7 plots the coefficients from specifications looking at the ratio of log wages and log employment for unskilled to skilled workers as the dependent variables, where unskilled workers are those in entry-level jobs, and skilled workers are those in supervisory and managerial positions. Both see a sizeable positive consistent increase following the adoption of the Living Wage. As before the hypothesis of parallel pre-trends between treated and untreated centres cannot be rejected. Table 9 reports counterpart point estimates. The results suggest that the Living Wage introduction increased unskilled wages relative to skilled wages by 5.9%(or percentage points) while the employment composition of unskilled workers to skilled workers increased by 8.2%(or percentage points). These results are consistent with the firm having monopsony power in the labour market, and weak substitutability in production between different skill levels. The results are suggestive that as employment of the less skilled group increased, employment of the skilled group reduced, assuming total employment is unchanged. That said figure 5 is suggestive of weak total employment increases.

Figure 7 – The Living Wage and Skill Composition



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. 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. Source (Datta and Machin, 2022).

Table 9- Skill Composition Equations

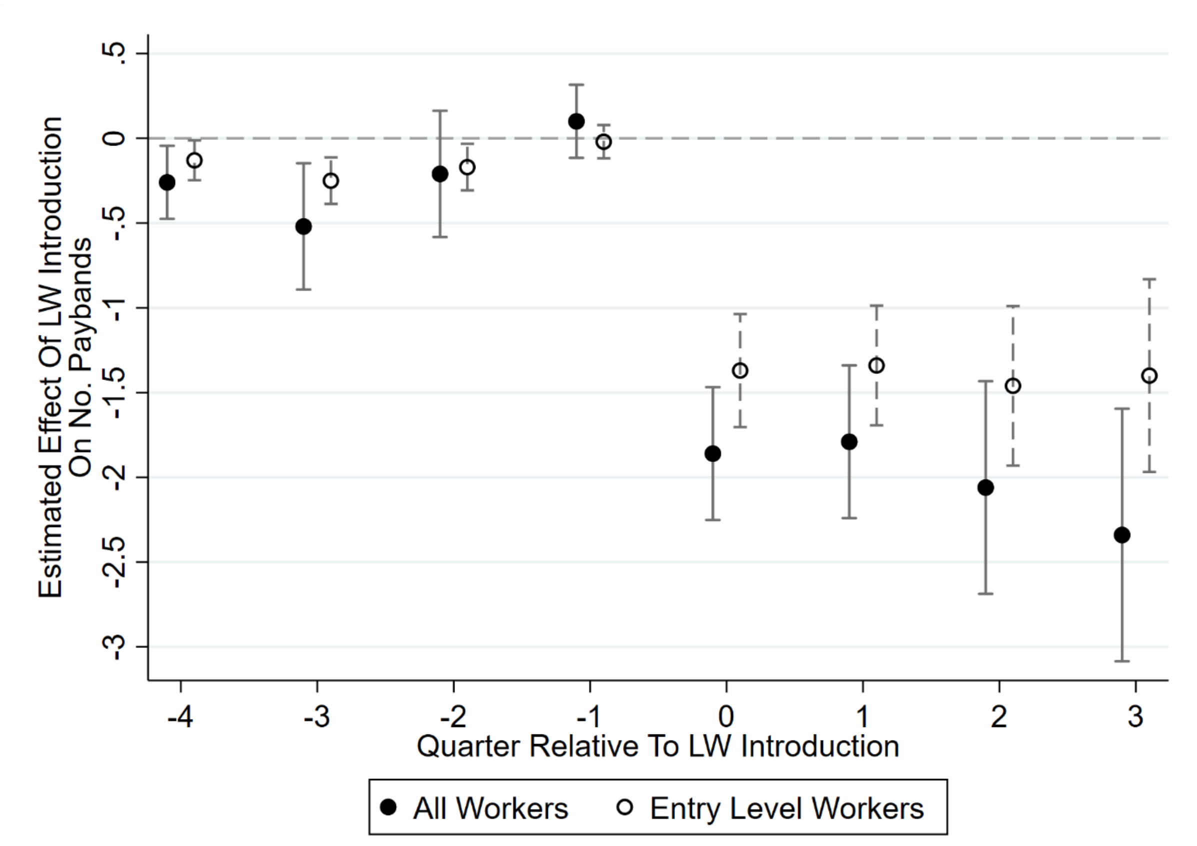
Dep. Var.: Log Ratio of Entry Level Workers to Supervisors and Managers – Positions and Wages

	Positions		Wages	
	D-in-D	Event Study	D-in-D	Event Study
	(1)	(2)	(3)	(4)
LW_{it}	0.082***		0.059***	
	(0.031)		(0.007)	
LW_{it} x Quarter				
-4		-.024		-.001
		(.016)		(.004)
-3		-.016		-.007
		(.021)		(.006)
-2		.002		0
		(.021)		(.005)
-1		0		-.002
		(.012)		(.003)
0		.07***		.055***
		(.023)		(.007)
1		.081***		.054***
		(.028)		(.009)
2		.069**		.057***
		(.034)		(.009)
3		.081**		.058***
		(.039)		(.009)
Controls	Yes	Yes	Yes	Yes
Observations	17,879	17,879	17,879	17,879

Notes: The table reports the estimated coefficients $\widehat{v_g}$ and $\hat{v}$ from models (4) and (6) of the Appendix. The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

Coarseness of Wage Structure

Figure 8 - The Living Wage and the Number of Paybands



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. 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. Source (Datta and Machin, 2022).

Error! Reference source not found. graphically reports the estimates from a specification using the number of unique pay points within an establishment for all workers and entry-level workers as the dependent variable respectively. Unique pay points relate to the degree of wage dispersion within The Company as well as the hierarchical structure of job roles. The larger the number of unique pay points, the more easily an establishment should be able to match the dispersion of relatively productivities of workers. As in the case of wages there is an absence of any obvious differing pre-trends (though there appear quarter specific minor deviations), and immediately following the adoption of the Living Wage there is a sharp and consistent reduction in the number of pay points. Estimates in Table 10 present the counterpart point estimates. They suggest that establishments exposed to the Living Wage reduced the number of unique pay rates by approximately 1.25 for entry level workers, and closer to 2 for all workers over the year following exposure. It is interesting to note here that not only entry level workers' wages were directly affected by the Living Wage, but affected establishments changed the pay structure for non-entry level workers as well, as shown by the difference between the estimates in columns (1) and (3), and (2) and (4) in Table 10. As before estimates are robust to the inclusion of controls.

Table 10 – The Living Wage and the Number of Paybands, by worker type

Dep. Var.: No. Unique Pay Rates

	All Workers		Entry Level Workers	
	D-in-D	Event Study	D-in-D	Event Study
	(1)	(2)	(3)	(4)
LW_{it}	-1.82***		-1.29***	
	(0.260)		(0.18)	
LW_{it} x Quarter				
-4		-0.27**		-0.13*
		(0.12)		(0.07)
-3		-0.54***		-0.26***
		(0.18)		(0.09)
-2		-0.23		-0.18*
		(0.17)		(0.10)
-1		.09		-0.02
		(0.09)		(0.06)
0		-1.91***		-1.41***
		(0.26)		(0.2)
1		-1.86***		-1.40***
		(0.28)		(0.21)
2		-2.12***		-1.51***
		(0.34)		(0.24)
3		-2.41***		-1.44***
		(0.39)		(0.27)
Controls	Yes	Yes	Yes	Yes
Observations	17,879	17,879	17,879	17,879

Notes: The table reports the estimated coefficients $\widehat{v_g}$ and $\hat{v}$ from models (4) and (6) of the Appendix. The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

Promotions

Table similarly reports estimates of specifications of log promotions for all workers and entry level workers while figure 9 shows the graphical plots. As The Company operates a hierarchical structure of job roles, we define a promotion as moving up the hierarchy within an establishment (e.g. from entry-level to supervisor), which is always associated with an hourly pay increase and thus moving up along the pay points within The Company. As was the case with employment, we find no impact on the promotion rate in centres exposed to the Living Wage.

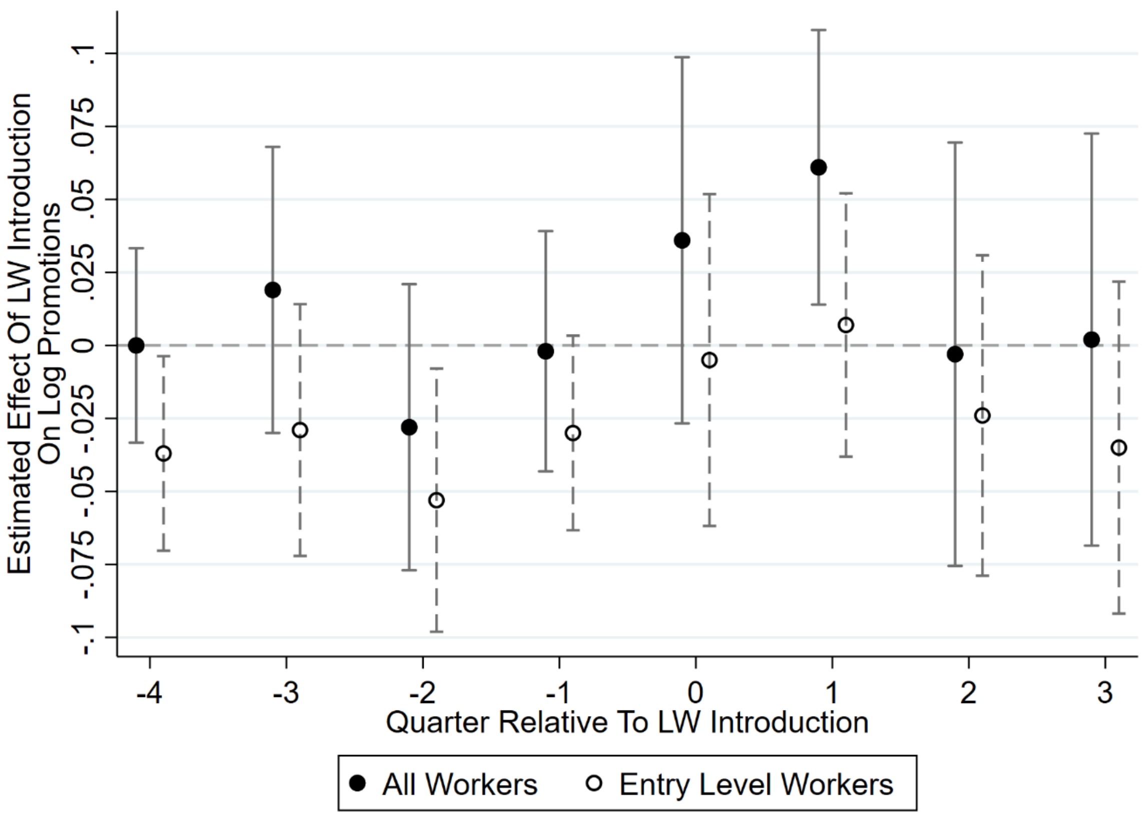
Table 11 – The Living Wage and Promotions, by worker type

Dep. Var.: Log Promotions

	All Workers		Entry Level Workers	
	(1)	(2)	(3)	(4)
LW_{it}	0.028	0.024	0.015	0.013
	(0.024)	(0.024)	(0.021)	(0.023)
Controls	No	Yes	No	Yes
Observations	17,879	17,879	17,879	17,879

Notes: The table reports the estimated coefficient $\hat{\upsilon}$ from model (6). The sample is a panel of establishments run by The Company active between January 2011 and April 2019. Bootstrapped standard errors are reported in parentheses. P-value: *** p<0.01, ** p<0.05, * p<0.1. Control variables are the proportion female, proportion BAME and mean age.

Figure 9 – The Living Wage and Promotions



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. 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. Source (Datta and Machin, 2022).

Discussion

The results from the previous section indicate a generally positive impact of the Living Wage on workers. Wages for the most highly exposed saw very sizeable increases, while the evidence suggests that a higher wage floor can go some way in reducing the within-establishment BAME wage gap. Impacts on employment were negligible, and examination of the dynamic treatment effects suggest that impacts could be positive. Furthermore, the changes in skill composition for affected establishments indicate that entry-level workers saw their relative numbers *increase* in response to the adoption of the Living Wage.

These results are likely a strong indication of the presence of monopsony power in the labour market. In a perfectly competitive setting, we would expect an increase in the relative wage to result in a decrease in the relative employment composition assuming there is some substitutability between skill types. However, we can see that a positive labour supply response is dominating the demand response, resulting in an increase in the skill composition of unskilled to skilled workers.

Overall, we see minimal negative effects, as even intensive margin employment adjustments for highly exposed workers (those on causal, zero-hours contracts where hours adjustment is frictionless) were non-existent. This is the first study to also examine progression effects for minimum wage workers, by examining the impact on promotions for exposed establishments. It is reassuring to see no obvious impacts on the rate of promotions for workers in exposed establishments. We do however see a reduction in the number of unique pay points within exposed firms, and this reduction has spill over impacts to non-minimum wage jobs. This result is likely to be indicative of a compression of the within establishment wage variation, and an increasing coarseness of pay-scales. This latter finding likely means that wage variation will be less able to replicate variation in productivity across workers. Furthermore, as the minimum wage increases, it may well become the going rate for a much larger proportion of workers.

Conclusion

This study investigated the impacts of a true "Living Wage" as calculated by a basket of goods, significantly higher than the mandated minimum wage. It utilizes a bespoke dataset for a firm with hundreds of establishments across the UK, which were at different times exposed to the LWF's Living Wage, to examine the impact of a wage floor much higher than the mandated minimum. We show that exposure to the LWF's Living Wage resulted in considerable wage increases for entry-level workers, helped reduce the within-establishment BAME-wage gap by almost 50%, or 3.5 pp. We find no negative impacts on extensive or intensive measures of employment, despite the firm employing many ZHC workers and would thus easily be able to adjust hours. We find the firm changes the skill composition by increasing the ratio of entry-level workers to supervisors and managers, which is consistent with monopsony power in the labour market and weak substitutability between different skill groups in production. Results also suggest that establishments respond to the Living Wage by reducing the number of pay points along their pay scale, and this has spillovers to positions unaffected by the Living Wage.

The results from this study are promising. They suggest that a higher minimum wage has aggregate benefits for BAME workers, with minimal employment losses. Furthermore, the results also suggest that firms are likely able to cope with “true” Living Wages as measured by a basket of goods and services, and that these can have a sizeable impact on wages for workers. This ability to cope appears at first glance to be due to monopsony power still existing in low pay sections of the labour market. The study is therefore the first piece of evidence which suggests a minimum wage at the level of a living wage may induce positive welfare benefits to workers, without leading to unintended consequences related to employment or progression. That said this study should be seen as a first step in this direction given some caveats. In particular, as the estimation strategy exploits just a single firm being treated with the LWF’s Living Wage, the results are absent of general equilibrium effects. Additionally, as the study is based on the experience of a single firm one must be cautious with generalisability, as there are likely heterogeneities across firms in their structure, productivity and extent of monopsony power.

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Appendix - Methodology

Borrowing notation from Sun and Abraham (2021), let Y_{it} denote some outcome for unit i at time t with treatment status $D_{it} \in \{0,1\} : D_{it} = 1$ if i is treated in period t and $D_{it} = 0$ otherwise, where treatment is absorbing, and therefore $D_{is} \leq D_{it}$ for some time periods $s < t$. A unit's treatment path can therefore be characterised by $E_i = \min\{t : D_{it} = 1\}$, and where we let $E_i = \infty$ if the unit is never treated. Units can therefore be categorized into disjoint cohorts $e \in \{t_{min}, \dots, t_{max}, \infty\}$, where units in cohort e are first treated at the same time $\{i : E_i = e\}$. Y_{it}^{e} is the potential outcome in period t when unit i is first treated at time e and Y_{it}^{∞} is the potential outcome at time t if unit i never receives treatment. A cohort-specific average treatment effect on the treated l periods from treatment is thus:

$$CATT_{e,l} = E\left[Y_{i,e+l} - Y_{i,e+l}^{\infty} \,\middle|\, E_i = e\right] \tag{1}$$

This notation permits treatment effect heterogeneity across cohorts (i.e. establishments treated with the Living Wage at the same time), which in this setting may be important as the bite of the living wage may change over time. We are then interested in some weighted average of (1), 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 both the average dynamic effects (which allows an analysis of the pre-trends) and the average "long-term" impacts. The "long term" impact in this setting is the average impact of Living Wage treatment for an establishment within The Company across all time periods, against the counterfactual of not having to pay the Living Wage.

For analysing the average dynamic effects, we focus on the weighted average similar to that proposed in Sun and Abraham (2021)

$$v_g = \frac{1}{|g|} \sum_{l \in g} \sum_{e} CATT_{e,l} \Pr\{E_i = e \mid E_i \in l\} \tag{2}$$

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

In practice (2) is estimated using the following methodology:

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

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{l \neq -1,-12} \delta_{e,l} \, LW_{i,t+l} + \beta' X_{it} + \varepsilon_{it} \tag{3}$$

Where α_i is the establishment fixed effect, λ_t is a year-month fixed effect, $LW_{i,t}$ is a dummy variable which represents whether an establishment pays the Living Wage and X_{it} 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), we normalise the dynamic effects to two periods, -1 and -12, to deal with the underidentification issues they raise.

2. We estimate the weights $\Pr\{E_i = e \mid E_i \in l]\}$ using sample shares of each cohort in the relevant relative period l.

3. We 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

$$\widehat{v_g} = \frac{1}{3} \sum_{l \in g} \sum_{e} \hat{\delta}_{e,l} \, \widehat{\Pr}\{E_i = e \mid E_i \in l]\} \tag{4}$$

For analysing the average long-term impacts, the methodology is very similar except that specification (3) in step 1 is replaced with the typical difference-in-difference estimator

$$Y_{i,t} = \alpha_i + \lambda_t + \bar{\delta}_e LW_{it} + \beta' X_{it} + \varepsilon_{it} \tag{5}$$

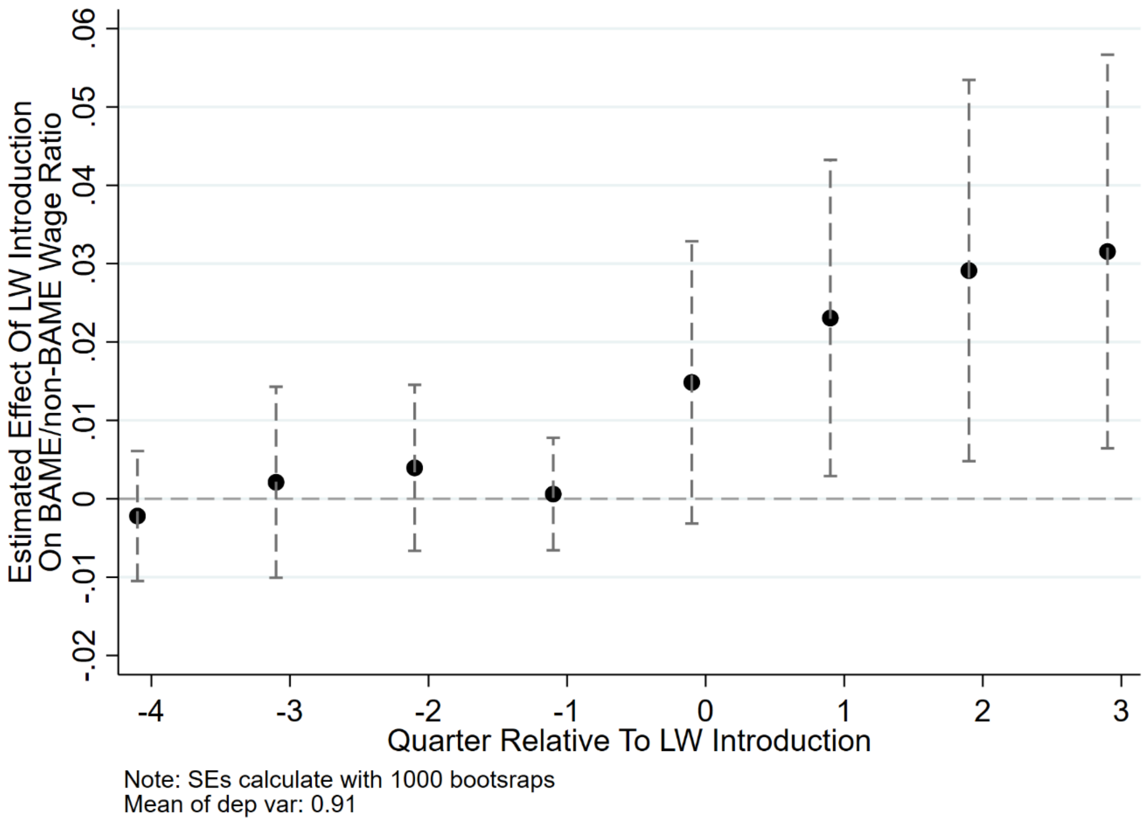
the weights in step 2 are simply replaced with the cohort share weights $\Pr\{E_i = e\}$ and the aggregation in step 3 is such that

$$\hat{v} = \sum_e \hat{\hat{\delta}}_e \, \widehat{\Pr}\{E_i = e\} \tag{6}$$

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, 2021). 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 applied econometrics literature (Borusyak and Jaravel, 2017).

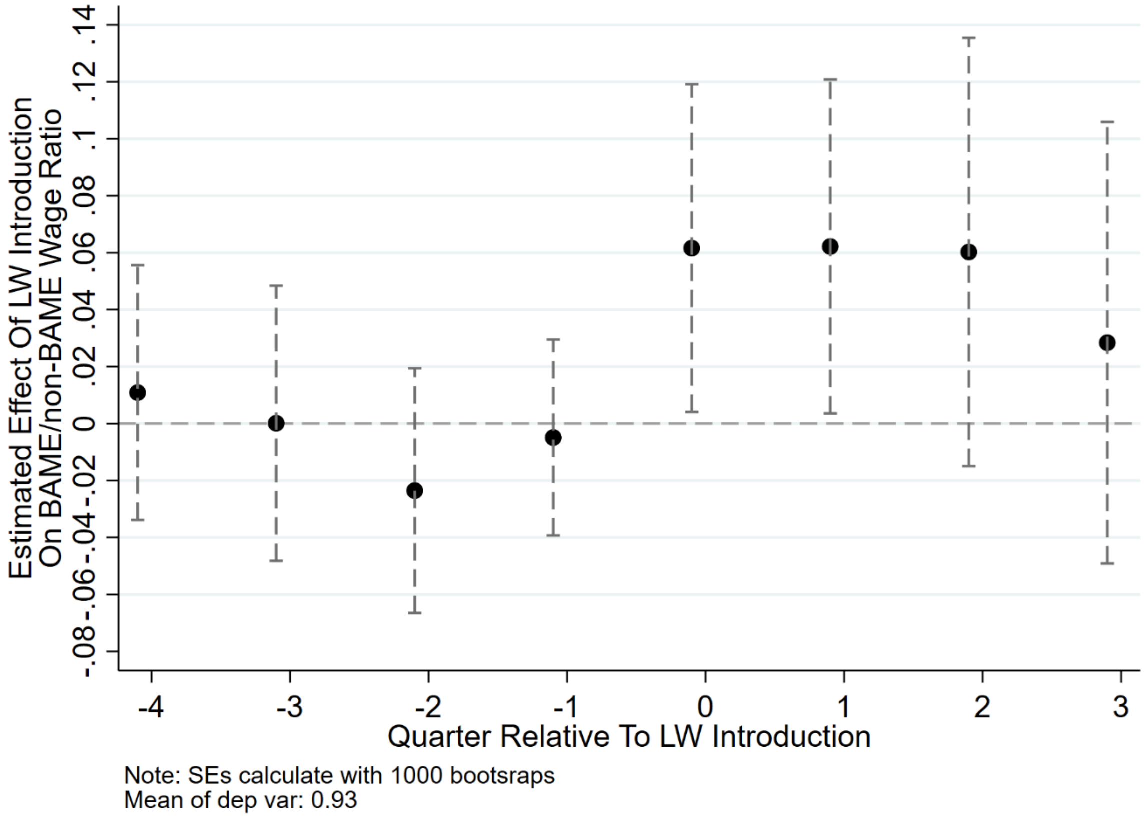
Appendix – Additional Figures

Figure A1 - The Living Wage and the BAME Wage Gap, London



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. The sample is a panel of establishments run by The Company active between January 2011 and April 2019 based in London. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors.

Figure A2 – The Living Wage and the BAME Wage Gap, Outside of London



Notes: The graph reports the estimated coefficient $\widehat{v_g}$ from model (4) of the Appendix without controls. The sample is a panel of establishments run by The Company active between January 2011 and April 2019 based outside of London. The vertical bars indicate 95% confidence intervals based on bootstrapped standard errors.