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DISCUSSION PAPER SERIES

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ABSTRACT

Are Estimates of Non-Standard Employment Wage Penalties Robust to Different Wage Measures? The Case of Zero Hours Contracts in the UK*

A range of evidence suggests that non-standard jobs, including fixed-term and other temporary jobs such as casual jobs, pay lower wages than more standard, permanent jobs, even after controlling for differences in worker and job characteristics. A recent literature suggests this is also the case for zero hours contracts (ZHCs), a growing form of non-standard employment in several developed countries, including the UK. These studies typically rely on derived wage variables – derived from survey responses to questions on earnings and hours data – which are prone to various forms of measurement error, some of which may be correlated with employment contract. Many relevant surveys, however, also include stated-rate hourly wage questions which, although also likely measured with error, are not subject to the same measurement issues. This suggests potential for sensitivity in non-standard employment wage penalty estimates depending on the wage measure used. Using the example of ZHCs in the UK, we first use derived wages to replicate the ballpark conditional ZHC wage penalty typical of existing studies. We then show that there is no conditional ZHC wage penalty, on average, when using the stated-rate hourly wage measure. This also holds for other non-standard employment types, including casual and fixed-term employment. Further, whereas the derived wage measure suggests, in line with existing literature, that the ZHC wage penalty is largest at the bottom of the wage distribution, we show the opposite to be the case when using the stated-rate wage measure. We discuss implications for policy, our understanding of labour market behaviour, and also for the wider literature on non-standard work wage penalties.

JEL Classification: J21, J48, M55

Keywords: zero hours contracts, casual jobs, non-standard employment, precarious employment, atypical employment, wages

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1. Introduction

Across a range of developed economies there have been substantial increases in the share of workers in what can be described as non-standard employment arrangements. While the specific form of these contractual arrangements is heavily dependent on country-specific institutional and legal frameworks, a common feature is a reduction in job security often combined with greater hours variability. This has given rise to a range of concerns regarding potential negative effects on worker outcomes, with the effect on wages being a focus of both researchers and policy makers (e.g. OECD, 2015; Taylor et al., 2017; Lass and Wooden, 2019). This is a critical point. If the characteristics of non-standard employment contracts are broadly undesirable then they should generate compensating wage differentials or other offsetting desirable characteristics (Rosen, 1986). For example, workers for whom short-term variability in hours and even earnings generates disutility should receive higher wages in compensation. Similar arguments follow in terms of the expectation of greater job insecurity on wages (Abowd and Ashenfelter, 1981). A lack of wage compensation, or even the existence of wage penalties, would make it more likely that these changes in contractual arrangements reflect a decline in worker welfare, suggesting a role for policy intervention. In practice, a typical finding in the international literature is that non-standard jobs, including fixed-term and other temporary jobs such as casual jobs, appear to pay lower wages than permanent jobs, even after controlling for differences in observable (and in some cases time-invariant unobservable) worker and job characteristics (e.g. Booth et al., 2002; Hagen, 2002; Forde and Slater, 2005; Mertens et al., 2007; Jahn and Pozzoli, 2013).

Recently, the UK has witnessed a rise in a specific form of non-standard employment, zero hours contracts (ZHCs), that exhibit both job insecurity and short-term hours variability (Datta et al., 2019; Farina et al., 2020). Again, as with other forms of non-standard employment, this has led to concerns about worker outcomes including wages. At first glance the evidence with respect to wages appears strong. Several recent studies have shown that wages are lower in ZHC jobs than in other types of jobs in the UK, with estimated unconditional hourly wage penalties typically between 30% and 50%, which remain large (in the order of 5% to 9%) even after conditioning on observable job and worker characteristics (Adams and Prassl, 2018; Clarke and Cominetti, 2019; Datta et al., 2019; Gardiner, 2016; Koumenta and Williams, 2019; TUC, 2014). No studies report a ZHC wage premium or the absence of a ZHC wage penalty. In addition, Gardiner (2016) shows that the pay penalty appears to be larger towards the bottom of the wage distribution, where concerns over declines in job quality are most acute. Where studies in the wider non-standard employment literature examine wage effects across the distribution, they also tend to find larger wage penalties towards the bottom of the wage distribution and smaller wage penalties, or in some cases a wage premium, at the top (e.g. Mertens et al., 2007; Lass and Wooden, 2019).

This wage penalty literature, including that for ZHCs, typically relies upon wage information that is derived from survey responses to questions on earnings and hours data, and these are particularly prone to measurement error (for examples of such studies see Booth et al., 2002; Hagen, 2002; Forde and Slater, 2005; Mertens et al., 2007; Lass and Wooden, 2019; for a discussion of measurement error in derived hourly wages, and its econometric consequences, see Bound et al., 1994).[1] If this measurement error is uncorrelated with employment contract then, although it may lead to imprecise estimates of contractual wage penalties, it will not bias estimates. This seems probable for some sources of measurement error in derived wages but not others. For example, rounding in reported hours and earnings is likely uncorrelated with employment contract. However, there are other sources of measurement error that may be correlated with contractual status. One concern is if reported periods for earnings and hours do not match. A symptom of this is that wage distributions using derived measures have been found to be wider than those using alternative wage measures, e.g. as reported by employers, and with many implausible values (Ormerod and Ritchie, 2007). This may be more problematic for workers, such as those in non-standard employment, whose hours and earnings may vary considerably from week to week. Another potential concern with reported hours in this context is the scope for differential inclusion of unpaid hours by survey respondents under different contracts. Previous research suggests that unpaid hours are widespread among ZHC workers (Datta et al, 2019). Importantly, and as we argue further, both could lead to consequential bias in estimates of contractual wage penalties.

An alternative to this kind of derived hourly wage measure exists in many of the surveys used to date in the wage penalty literature.[2] These surveys all include stated-rate hourly wage questions for workers paid an hourly rate. Naturally, these stated-rate measures are also susceptible to measurement error, e.g. related to rounding, but arguably do not suffer from the same potential mismatch between hours and earnings periods, or inclusion of unpaid hours. Furthermore, these two wage measures capture slightly different things, both of which are potentially interesting. The stated-rate measures the on-paper hourly wage rate (as would be reported by the employer), whereas the derived hourly wage may measure something closer to the in-practice hourly wage, accounting for any unpaid hours worked that survey respondents include in their total hours responses. If workers on non-standard

[1] Jahn and Pozzoli (2013), which uses administrative data for Germany, is an exception, although the wage variable is still derived and refers to the daily wage rather than the hourly wage.
[2] Including, for the UK, the Labour Force Survey (LFS), the British Household Panel Survey, and Understanding Society, and internationally, the German Socio-Economic Panel, and the US Current Population Survey.

contracts disproportionately include unpaid hours in their hours responses – consider, for example, domiciliary care workers on ZHCs paid for appointment time but not travel time in between appointments – then there are measurement differences between the two wage variables that are correlated with contract type, suggesting potential for sensitivity in wage penalty estimates depending on the wage measure used. The two measures may diverge in another respect, too; whereas a stated-rate measure will typically capture only the basic rate, a derived wage measure will capture any above-basic earnings due to overtime or shift premiums. If such premiums are more likely (or larger) for standard, permanent workers than for those on non-standard contracts – and ZHC workers, in particular, seem unlikely to work overtime that attracts a wage premium given the lack of contracted hours – then there is further scope for sensitivity in non-standard employment wage penalty estimates according to the wage measure used.

At first glance, then, it seems surprising that stated-rate measures have not been used alongside derived wage measures in the non-standard employment wage penalty literature, including the ZHC wage penalty literature. This leads to questions about the robustness of this literature's conclusions. One likely contributing factor is the trade-off in terms of reduced sample coverage; stated-rate wage measures tend to cover far fewer survey respondents than derived wage measures because not all workers are paid an (or know their) hourly rate. This likely reduces their usefulness for estimating the wage differential experienced by fixed-term workers, for example, some of whom might be paid on a monthly/annual salary basis. But for ZHCs, and potentially other variable-hours contract types such as casual and short-hours contracts, this may be a moot point because almost all such workers will be paid on an hourly basis and will likely be familiar with their hourly rate. Furthermore, because non-ZHC hourly-paid jobs (and the workers who hold them) are likely to be closer to ZHC jobs in terms of observable and unobservable job and worker characteristics than non-ZHC jobs paid an annual salary, estimation on a sample restricted to hourly-paid workers may have advantages in terms of the internal validity of ZHC wage penalty estimates.

Using UK LFS data this paper estimates ZHC wage differentials using both derived and, for the first time, stated-rate wage measures. Using derived wages we replicate the ballpark conditional ZHC wage penalty typical of existing studies. We then show, in contrast, that there is no conditional ZHC wage penalty, on average, when using the stated-rate hourly wage measure. In an extension, we exploit the longitudinal structure of the LFS to show this is also the case in individual fixed effects models which provide additional control for time-invariant unobserved heterogeneity of workers. Furthermore, whereas the derived wage measure suggests, in line with existing literature, that the ZHC wage penalty is largest at the bottom of the wage distribution, we show the opposite to be the case when using the stated-rate wage measure in quantile regression analysis. These conclusions hold when estimated on a common sample; the sensitivity reflects differences in measurement of wages rather than differences in sample. The takeaway message is that the size, nature and even existence of any ZHC (and other non-standard employment) wage penalty in the UK appears highly sensitive to how wages are measured. The implied conjecture is that this might also be the case for some other estimates of non-standard employment wage penalties in the wider literature.

2. Data

In the UK, ZHCs have been defined as employment contracts where the employer does not guarantee the individual any work and the individual is not obliged to accept any work offered (e.g. DBIS, 2013). This makes them comparable to a range of employment arrangements in other countries, including ZHCs in Finland, 'If and When' contracts in Ireland, some causal work in Australia, and others (see Datta et al., 2019; O'Sullivan, 2019). In practice, not all ZHCs appear to offer the right to turn down work without penalty – so called 'one-sided flexibility' (CIPD, 2015; Low Pay Commission, 2018). Recent (but pre-covid-19) estimates suggest that three percent of those in employment, or 974,000 workers, were employed under a ZHC in their main job in the UK in October-December 2019 (ONS, 2020).

Our main data source, following earlier studies of the ZHC wage penalty, is the UK LFS. We restrict our attention to those aged 16+, in employment (excluding the self-employed), and we pool over the period from 2015-2018.[3] The LFS collects data from households for five consecutive quarters, with a fifth of the sample replaced each quarter. The LFS is used primarily as a cross-sectional data set in applied research (the Quarterly Labour Force Survey, or QLFS). Because it has a rotating panel structure, however, it can also be used as a longitudinal data set (the Longitudinal Labour Force Survey, or LLFS). For most of the analysis here we use the QLFS as it offers a larger sample and includes a wider selection of relevant variables (e.g. on other non-standard employment contracts). Unlike existing studies of the ZHC wage penalty, however, we complement our analysis of the QLFS with analysis of LLFS which provides an opportunity to difference out individual time-invariant unobservables. Given that questions on earnings, wages and contract type are not asked in every wave and every quarter, as we discuss below, when using the LLFS we are limited to quarter 2 (Q2) and quarter 4 (Q4) entry cohorts from 2015-2017, with just two observations (wave 1 and wave 5) for each individual in the relevant balanced panels. The resulting sample size is small, covering just 1,540

[3] We include proxy responses throughout but our key conclusions are robust to their omission.

individuals drawn from four cohorts.[4] Because this is pushing at the limits of the data, conclusions from the LLFS analysis are treated as tentative.

The UK LFS contains two hourly wage measures (for a discussion see Ormerod and Ritchie, 2007). The first is an hourly pay variable (HOURPAY) derived from gross weekly earnings in the respondent's main job (in the last pay period) divided by the total number of (usual) weekly hours of work, including (usual) hours of paid overtime (but not unpaid overtime), in the main job. Note that weekly earnings in the last period is itself a derived variable, as respondents are asked how much they were paid the last time and, subsequently, what period the payment covered (If the pay period is monthly, for example, this must be converted into a weekly equivalent). Also note the scope for mismatch between the pay period (linked to the most recent occasion the respondent was paid) and the hours (their usual hours). This is addressed by a contingency; for respondents who say their pay varies from one period to the next – highly likely for many ZHC and some other non-standard contract workers – HOURPAY uses usual pay (converted to weekly) in place of pay in the last period. But even the concept of usual pay, let alone its accurate reporting, seems problematical for many ZHC and other variable-hours workers. As a result, this is likely to be a noisy measure of wages, and particularly so for ZHC workers. It is unclear, however, whether this form of measurement error (rather than simply its variance) is correlated with ZHC (or any other contract) status. Also potentially concerning in the context of estimating the ZHC wage penalty is inclusion of unpaid hours in total usual hours by survey respondents in a manner that could be correlated with contract type. While it seems possible that workers in standard, permanent jobs disproportionately include unpaid hours, it seems more likely that workers in non-standard jobs do so, in which case estimated non-standard employment wage penalties may be exaggerated. Unpaid hours appear to be common among ZHC workers in the UK, with Datta et al. (2019) citing survey evidence that 30% of ZHC workers regularly work unpaid hours, on average eight hours per week. Note that earnings information is only collected in wave 1 and wave 5 for each respondent. That aside, however, the measure has good coverage, given that earnings and hours data are observed for almost all those in employment in the relevant waves. As a result, HOURPAY is available for roughly two fifths of the QLFS employed sample in any one quarter.

The alternative measure (HRRATE) is a directly reported hourly wage rate.[5] Ormerod and Ritchie (2007) compare the merits of the two LFS wage measures, and although HRRATE is also subject to some forms of measurement error (e.g. rounding), omits any above-basic pay premiums, and is only

[4] No data are provided for the 2015Q4 entry cohort or for wave 5 of the 2016Q2 cohort.
[5] The question is as follows: *What is your (basic) hourly rate?*

returned for those workers who previously answer yes to the question whether they are paid on an hourly basis, it is the preferred LFS-based wage measure of the ONS when estimating the extent of low-pay. A key argument for this is that reduced coverage relative to HOURPAY is not as salient an issue towards the bottom of the wage distribution because most low-pay workers are paid on an hourly basis. The same is true for workers on ZHCs (along with their most similar counterparts in standard, permanent employment); for our QLFS sample, 83% of those who report being on a ZHC also report their hourly wage rate. Crucially for our purposes, the scope for hours and earnings mismatch and for inconsistent inclusion of unpaid hours in HOURPAY is absent for HRRATE. Despite this, however, we do not prefer one measure to the other here. Rather, we view HOURPAY and HRRATE as complementary measures – one that seeks to measure the on-paper hourly wage and one that seeks to measure hourly pay – which may lead to different conclusions about the ZHC wage penalty (and those for other forms of non-standard employment). In the following discussion for the sake of clarity we refer to these two sources of wage data as hourly pay and the hourly wage rate, respectively.[6] Note that, like HOURPAY, the relevant questions for HRRATE are only asked to LFS respondents in employment in waves 1 and 5. Throughout the paper both wage variables are measured in real rather than nominal terms (£2017Q2).

Information on ZHCs is collected in the LFS via a question (FLEX10) which asks respondents if they are employed on a flexible hours contract in their main job. Respondents are able to choose up to three options, with ZHCs one of these.[7] We treat an individual as being employed on a ZHC if they choose ZHC for any of the three options. Note that until January 2020, FLEX10 was only asked every other quarter, specifically in April-June (Q2) and October-December (Q4), so our QLFS and LLFS samples are restricted to these quarters only. A second question (JOBTYP) collects information on whether the main job was permanent or temporary. We define a 'temporary job' dummy equal to 1 if respondents report being in a temporary job, and 0 otherwise. Those answering 'temporary' are asked a follow up question (JBTP10).[8] We use this to disaggregate temporary employment into its component types, constructing one dummy for each of the five types.[9] Finally, those who report being in permanent employment are asked whether they are employed through an employment agency,

[6] Following the LFS documentation and, specifically, the Labour Force Survey User Guide – Volume 3: Details of LFS variables relative to the years 2015-2018, observations with hourly pay >£100 (HOURPAY) are treated as missing.
[7] The question is worded as follows: *Some people have special working hours arrangements that vary daily or weekly. In your (main) job is your agreed working arrangement any of the following…1 flexitime (flexible working hours), 2 an annualised hours contract, 3 term-time working, 4 job sharing, 5 a nine-day fortnight, 6 a four-and-a-half day week, 7 zero hours contract, 8 on-call working, or 9 none of these?*
[8] The first question is worded as follows: *Leaving aside your own personal intentions and circumstances, was your job... 1 a permanent job, 2 or was there some way that it was not permanent?* The follow-up question is: *In what way was the job not permanent, was it... 1 working for an employment agency, 2 casual type of work, 3 seasonal work, 4 done under contract for a fixed period or for a fixed task, 5 or was there some other way that it was not permanent?*
[9] Note that respondents can choose more than one option (up to five), so these dummies overlap.

from which we define an additional dummy for ‘permanent agency’ employment. Note that ZHC is not an option in JBTP10. Although ZHCs can effectively be severed at any time as the employer is not obliged to offer the individual any work, they are not treated as a form of temporary employment by the ONS. Indeed most ZHC workers (65% in our QLFS sample) report being in permanent employment in the LFS.

Naturally, measurement error in ZHC status is an additional concern for estimating ZHC wage effects. Farina et al. (2020) discusses a range of measurement issues. These include a shift-work check in the LFS questionnaire in Q2 from 2004-2013 where respondents who say they were on shift work are not asked FLEX10, suggesting the possibility of under-reporting of ZHC status prior to 2013. The most important ZHC measurement issue, however, concerns the likely lack of respondent awareness of ZHCs prior to intense media coverage in 2013. Farina et al. (2020) show that growing public awareness of ZHCs can account for between one quarter and two thirds of the very rapid growth in reported ZHC numbers in the LFS over 2013/14, but suggest that there is no clear association beyond 2014. Both random noise and systematic under-reporting of the ZHC dummy variable will lead to attenuation bias in the estimated ZHC pay penalty, with the magnitude of the bias depending on the extent of misclassification. Further, if unreported ZHCs are drawn disproportionately from lower-wage (higher-wage) ZHCs, there may be an additional positive (negative) bias on the estimated ZHC coefficient in the wage regression. Together this motivates our choice to focus on the period of 2015-2018 i.e. *after* the public-awareness induced growth in reported ZHC prevalence over 2013/14 and after the shift-work check is removed.[10]

INSERT FIGURE 1

As a starting point for investigating these issues Figure 1 presents kernel density plots of the distributions of each wage variable for our QLFS sample, separately for ZHC and non-ZHC workers. Focusing first on derived hourly pay, the distribution for ZHC workers clearly sits to the left of the distribution for non-ZHC workers, with a range of higher wage rates with little support for ZHC workers. The gap between the ZHC and non-ZHC mean wage (the unconditional ZHC pay penalty) is £5.40 (see also Table A1 in the Appendix), consistent with the estimate from Datta et al. (2019). Given the coverage of the derived measure, this comparison is made over almost all workers in the relevant quarters and waves. In contrast, the wage distributions for ZHC and non-ZHC workers appear more similar when stated-rate hourly wages are used, with the difference in means (the unconditional ZHC pay penalty) just £1.30. The sample for this comparison is much smaller because

[10] Our key conclusions are also robust to narrowing this time window.

many non-ZHC workers (and a minority of ZHC workers) do not report an hourly wage rate. Whether from differences in sample or differences in measurement, however, it is immediately apparent that the choice of wage measure is likely to be consequential for estimating the ZHC wage penalty.

Appendix Table A1 provides descriptive statistics by ZHC status for our baseline QLFS sample on wages (both measures), the prevalence of other atypical contractual forms, and a long list of socio-demographic and job characteristics used as controls in our regression analysis. ZHC workers tend to have characteristics that are associated with lower wages, e.g. they are disproportionately concentrated among younger age groups, women, black and other minority ethnic groups, and non-graduates. As a result, unconditional wage gap estimates do not compare like with like, and this motivates the regression approach set out in the following section. Also note the higher reported prevalence of other atypical contract forms among ZHC workers: ZHC workers disproportionately describe themselves as being in temporary employment (although this is still a minority), in particular temporary agency, casual or temporary other employment. Also note the concentration of ZHCs in particular industrial sectors and occupational groups, most notably the distribution, hotels and restaurants and other services sectors, and personal service and elementary occupations.

3. Estimation

Our benchmark regression model is the following which estimates, by OLS, the ZHC wage differential conditioned on a wide range of observable worker and job characteristics:

$$\ln(wage)_i = \beta_0 + \beta_1 ZHC_i + \boldsymbol{X'_{1i}\beta_2} + \boldsymbol{X'_{2i}\beta_3} + \beta_4 TEMP_i + \boldsymbol{X'_{3i}\beta_5} + \varepsilon_i \qquad (1)$$

where the dependent variable is the log of hourly pay or the hourly wage for individual i. ZHC is a binary indicator taking value 1 if workers report to be on a ZHC in their main job, and 0 otherwise. $\boldsymbol{X_{1i}}$ denotes the set of individual characteristics observed for worker *i*, as listed in Table A1, and including dummy variables for quarter/year. $\boldsymbol{X_{2i}}$ denotes the set of job characteristics for worker *i* (excluding dummies for contract form), as listed in Table A1. $TEMP_i$ is a binary dummy for being employed on any form of temporary contract. $\boldsymbol{X_{3i}}$ is a set of other atypical working arrangement dummies including casual, seasonal, fixed-term, temporary agency, permanent agency, and other temporary. We start by estimating (1) excluding $\boldsymbol{X_{1i}}$, $\boldsymbol{X_{2i}}$, $TEMP_i$ and $\boldsymbol{X_{3i}}$ and then introduce the controls step by step. (When $\boldsymbol{X_{3i}}$ is included we drop $TEMP_i$.) In each case the parameter β_1 gives the estimated wage differential between ZHC and non-ZHC workers. Initially we allow the estimation samples to vary according to wage measure used. We then impose a common sample.

We then extend the estimation in three directions. First, to explore whether ZHC wage penalties are heterogeneous, and whether any such heterogeneity is sensitive to the particular wage measure employed, we repeat estimation of (1), including all controls but excluding $TEMP_i$, for a wide range of subsamples including by age group, gender, education, occupation and industry. No existing studies of the ZHC wage penalty have examined how wage effects vary across these different groups.

Second, following Gardiner (2016) in the ZHC literature, and numerous studies in the wider non-standard employment wage penalty literature (e.g. Mertens et al., 2007; Lass and Wooden, 2019), we estimate quantile regression versions of (1) to assess the nature of the ZHC wage penalty at several different points along the wage distribution for each wage variable, and the sensitivity of these estimated distributional effects to the wage measure used. If wage penalties vary across the distribution then the estimates provided by Equation (1) – estimates at the mean – will only give part of the picture, and may under- or overestimate wage penalties at different points in the distribution. To date, most concern around ZHC wage penalties (and wage penalties for other non-standard employment contracts) has focussed on low-pay workers, both because existing evidence from quantile regressions typically points to larger wage penalties at the bottom of the wage distribution (e.g. Gardiner (2016) in the case of ZHCs), and because concerns about growing precariousness, poverty and economic hardship are most acute for low-pay workers. But while these types of contracts are concentrated amongst low-paid workers, they can also be found in higher-paid occupations, where they might more readily reflect a trade-off between flexibility and pay on the part of the worker. Specifically, we use quantile regression to estimate distributional analogues of (1) at the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles for each wage measure. Because most studies of the relationship between non-standard employment and wages at different points in the wage distribution have used conditional quantile regression (CQR) methods, as developed by Koenker and Bassett (1978), we do the same here.[11] However, because the resulting estimates are difficult to interpret and difficult to compare across studies with different sets of control variables, we also report unconditional quantile regression (UQR) estimates, following Lass and Wooden (2019), which do not suffer from these drawbacks (see Firpo et al., 2009).[12] In each case the full set of controls, as in Column (4) of Tables 1-3, is included in the model.

[11] Although it is not clear, this also appears to be the case for Gardiner (2016) – the only existing quantile regression study of the ZHC wage penalty.

[12] In CQR, the quantiles of the distribution are conditioned on the covariates, rather than simply being defined by the unconditional distribution of the outcome variable. Adapting an example from Lass and Wooden (2019): If we investigate the ZHC wage differential at the 10th percentile of the wage distribution and additionally control for educational level, the resulting coefficient for ZHC work measures the average wage differential between ZHC and other workers at the 10th percentile of the separate wage distributions for each educational level. As workers at the 10th percentile of the wage distribution for graduates can be expected to have a much higher wage than workers at the 10th

Finally, we exploit the LLFS over the same period to estimate an individual fixed effects version of (1) for each wage variable. Even when conditioning on the extensive set of observable controls included in (1), non-random sorting of workers into employment contracts, which may bias our OLS estimates of β_1, remains possible. If less productive workers sort into ZHCs, for example, ZHC wage penalties will be overestimated. To the extent that any such unobserved differences in productivity are time-invariant, however, fixed effects estimation will difference them out. Despite this advantage, no existing study of the ZHC wage penalty takes this approach – perhaps reflecting the paucity of the LLFS data for this purpose – although it is quite common in the wider non-standard employment wage penalty literature (e.g. Booth et al., 2002; Lass and Wooden, 2019). Note that in this particular case there are also some disadvantages of the fixed effects approach, including possible exacerbation of any attenuation bias due to measurement error in the ZHC dummy, the smaller sample size in the LLFS compared to the QLFS[13], and the reduced set of observed job characteristics available in the LLFS compared to the QLFS. In the latter respect, the most notable omission from the LLFS is the set of variables denoting temporary job type; we observe only whether the respondent is on a ZHC and in a temporary or permanent job, so the fixed effects regressions include $TEMP_i$ but exclude $\boldsymbol{X_{3i}}$. Combined, these disadvantages mean we focus primarily on the OLS estimates of (1), treating the fixed effects estimates mainly as a check on the robustness of our key conclusions.

4. Results

4.1 Baseline OLS estimates and their sensitivity

Table 1 presents OLS estimates of (1), estimated on our QLFS sample pooling over 2015-2018, using the hourly pay measure. The first column excludes controls from (1), so provides the estimated unconditional ZHC pay penalty, averaged over this period, in percentage terms. This unconditional estimate is very large, at 46%, but similar to estimates reported using earlier QLFS data (Gardiner, 2016) or QLFS data for 2016Q4 (Adams and Prassl, 2018).

INSERT TABLE 1

Including standard demographic characteristics as controls, along with regional and year/quarter dummies (column 2), reduces this by a half. This reflects the fact that workers in ZHC jobs have a

percentile of the distribution for workers with no qualifications, the resulting averaged coefficient is difficult to interpret. Adding further covariates complicates this further, and makes comparison across studies with different covariates difficult.

[13] Table A2 in the Appendix shows that the QLFS and LLFS samples are similar in many respects (e.g. mean wages according to both measures) but differ in some others, with the LLFS sample more concentrated in the middle of the age distribution, more frequently reporting children in the household, and with some minor differences in ethnic composition, education levels, job tenure, sectoral, occupational and regional distribution.

range of characteristics that are themselves associated with lower wages (e.g. they are more likely to be young). Column (3) adds a range of controls for job characteristics which again has a sizeable impact on the pay penalty, reducing it to 4.5%. This is smaller than the nearest equivalent estimate of Adams and Prassl (2018) for 2016Q4 (9%), who control for industry, occupation and part-time status but not for tenure and temporary employment. Note that the estimated ZHC wage penalty is also smaller than the 7.4% wage penalty for temporary employment. This model is very close to the models of Gardiner (2016) and Clarke and Comineti (2019), who estimate ZHC wage penalties of 6.6% (for 2011-2016) and 5% (for 2018) respectively, and temporary employment wage penalties of 5.5% and 6% respectively. One implication is that ZHCs are not out of line with other non-standard employment contracts in terms of wages, at least once observable job and worker characteristics are conditioned upon.

We further explore the ZHC wage penalty compared to those for other atypical employment types in column (4), which splits temporary jobs into the different contract types and includes the permanent agency dummy. Note that adding these other contract types makes no difference to the estimated ZHC wage penalty. Again, we see that the ZHC wage penalty is not out of line with wage penalties for other non-standard contract forms, all of which, with the exception of temporary agency work, are estimated to be larger than 4.5%, with the wage penalty for seasonal employment estimated to be three times as large, at 13.9%.

Table 2 repeats this exercise using the directly-reported hourly-wage measure. Note the smaller sample in this case given the lower coverage of this measure.[14] Column (1) shows the unconditional wage penalty is much smaller when comparing ZHC workers to those in other hourly-paid jobs, at 12.5%. These other hourly-paid jobs (and the workers who hold them) are likely to be more similar to ZHC jobs in terms of both observable and unobservable characteristics, which although advantageous for estimating the ZHC wage penalty other things being equal, makes the estimated ZHC wage penalty in column (1) more difficult to interpret as an unconditional wage penalty because, in effect, the sample selection already conditions on worker and job characteristics to the extent that they are correlated with hourly-paid status.

INSERT TABLE 2

[14] Rather than estimating on all available observations in our sample, to facilitate comparison of estimates using the different wage measures on a common sample (in Table 3), we restrict the sample for Table 2 to those observations for which both HRRATE and HOURPAY are specified. This reduces the sample for Table 2 by approximately 5%, with estimates highly robust to this step.

Again, the estimated wage penalty falls once controls are included for worker (column 2) and job (column 3) characteristics, in the latter case to 1.2%, on the borderline of statistical significance at conventional levels. This is considerably smaller than all existing estimates from the nearest-equivalent models in the studies cited above. Also note the contrast in the estimated wage penalty for temporary employment when comparing hourly pay (a wage penalty of 7.5%) with the hourly wage rate (a wage premium of 2.2%). Adding other contract types to the model in column (4) slightly reduces the estimated ZHC wage penalty to 0.9%, which now falls below conventional levels of statistical significance. Similarly, there is no statistically significant wage penalty or premium for casual, seasonal or other temporary work. We estimate wage premiums for permanent agency, temporary agency and fixed-term jobs, however, of 3.8%, 5.9% and 5.3% respectively. The bottom line, when using this alternative wage measure, is that there is no ZHC wage penalty at the mean – nor is there a wage penalty for fixed-term, casual or seasonal work – when we condition on worker and job characteristics and other atypical contractual forms which overlap with ZHC status. This calls into question the robustness of existing ZHC wage penalty estimates for the UK and, by implication, perhaps other non-standard employment wage penalty estimates in the wider literature.

There are two potential explanations for the difference in the conditional ZHC wage penalty estimates when comparing the two wage measures. First, the wage rate regressions are estimated on a selected sample compared to the hourly pay sample. Almost all (95%) of those who report their hourly wage rate also report earnings and hours information from which the hourly pay measure is derived. But only a third of those for whom we observe hourly pay also report their hourly wage rate. We test whether this explains the difference in estimated ZHC wage penalties by re-estimating Equation (1) on the hourly wage rate sample but using hourly pay as the dependent variable. Table 3 presents the results. Although the unconditional ZHC wage penalty is smaller than in Table 1 – we are now comparing ZHC jobs with more similar non-ZHC jobs than in Table 1 – once we condition on observable worker and job characteristics there is only a small difference between the Table 1 and Table 3 estimates of the ZHC wage penalty (4.5% compared to 3.9%). The implication is that the contrast in the estimated ZHC wage penalties across the two measures of wages does not reflect sample selection.

INSERT TABLE 3

The second potential explanation for the contrast is differences in what is measured by the two wage measures, including but not limited to measurement error in hourly pay from mismatch between hours and earnings and from heterogeneous inclusion of unpaid hours. Figure 2a shows the distributions for the common sample, again by ZHC status. Clearly the hourly pay distribution is more dispersed than the hourly wage rate distribution, in particular with a heavier left tail. The mode, median and mean wage is also lower for this measure once we restrict to the common sample. If this left shift in the wage distribution is uncorrelated with ZHC status it may reduce the precision of our estimates but will not impart bias. Figure 2b, however, shows that the left shift in the wage distribution when comparing the two measures is particularly pronounced among ZHC workers. In other words, there are disproportionately more low-paid ZHC workers than non-ZHC workers using hourly pay when compared to hourly rate. Although various forms of skewed mismatch between earnings and hours responses that are correlated with ZHC status seem possible, our conjecture is that this most likely reflects disproportionate inclusion of unpaid hours in paid hours responses by ZHC workers, i.e. that ZHC workers disproportionately overestimate their hours of (paid) work compared to those employed under other contractual forms. For example, ZHCs are highly prevalent among domiciliary care workers, often paid only for time scheduled with clients and not for time travelling between appointments (Bessa et al., 2013). Differences between pay and basic wage relating to overtime and shift premiums, with ZHC workers less able than other workers to access such premiums, or their premiums being smaller, would suggest a right-shift in the hourly pay distribution compared to the hourly wage distribution (and particularly for non-ZHC workers), rather than the left-shift that we observe in the data.

INSERT FIGURE 2

The bottom line is that the sensitivity in ZHC wage penalty estimates demonstrated here is driven by measurement differences not by sample differences. The implication of this sensitivity is that earlier estimates of the ZHC wage penalty appear to have exaggerated the extent to which wages in ZHC jobs are lower, at least on paper, than those in observationally similar non-ZHC jobs for observationally similar workers. This is to the extent that we question whether there is any conditional ZHC wage penalty at all. There is an important caveat to this argument, however, which is that by better measuring hourly wages *on paper*, the stated-rate wage measure may *overestimate* the hourly wage rate of ZHC workers *in practice*. From this perspective the two sets of estimates are perhaps best interpretable as a range, with hourly pay potentially overestimating the ZHC wage penalty and the hourly wage rate potentially underestimating the ZHC wage penalty. Either way there are sufficient grounds to question the existence, and certainly the magnitude, of the estimated ZHC wage penalty presented in the existing literature, and by implication, the robustness of existing non-standard employment wage penalty estimates in the wider literature.

4.2 Heterogeneous effects, quantile regression, and fixed effects extensions

Although we find no statistically significant ZHC wage penalty on average when using the hourly wage rate measure, there may be ZHC wage penalties for particular demographic groups or job types when using this measure. Furthermore, the nature of any heterogeneity in ZHC wage effects may differ according to the two wage measures. To assess these questions we re-estimate (1) on the QLFS common sample split by demographic and job characteristics. Results are presented in Appendix Tables A3 and A4, for hourly pay and the hourly wage rate respectively. Table A3 suggests larger wage penalties, using the hourly pay measure, for 16-24s and 35-49s, for men than for women (for whom the ZHC wage penalty is not statistically significant), for middling levels of education compared to either extreme, for UK/British citizens compared to non-UK/British citizens, for jobs in the private sector compared to the public sector (for which there is no ZHC wage penalty), and concentrated in particular industries (notably restaurants/hotels where ZHC jobs are particularly prevalent, and transport) and occupations (notably managers, sales and customer service, process, plant and machine operatives, and elementary occupations).

Although estimated coefficients are typically smaller, this pattern of heterogeneous effects is also evident when using the hourly wage rate measure. In particular, there are statistically significant (although small) ZHC wage penalties for 35-49 year olds, those whose highest education level is secondary, those in the private sector, those in the restaurant and hotel sector, and those in managerial, sales and customer service, process, plant and machine operative, and elementary occupations. The main exception to this conclusion of robust patterns of heterogeneity is that when using the hourly wage rate measure, non-UK citizens experience a wage penalty and UK/British citizens do not.

INSERT TABLES 4 & 5

Tables 4 and 5 present CQR estimates of ZHC wage penalties at different points in the (conditional) wage distribution, for the hourly pay and hourly wage rate measures respectively. First consider hourly pay (Table 4). As reported by Gardiner (2016), we find that the ZHC hourly pay penalty is largest at the bottom of the wage distribution (Gardiner reports a wage penalty of 9.5% at the 20th percentile compared to our estimated wage penalties of 13.5% at the 10th percentile and 6.4% at the 25th percentile). The estimated wage penalty then falls monotonically as we move up the wage distribution, reaching zero at the 75th percentile, and becoming positive (a wage premium of 5.3%) at the 90th percentile. This pattern also holds for fixed-term employment (although no estimate is statistically significant at conventional levels) and for casual employment, consistent with Mertens et al. (2007) for Germany and Lass and Wooden (2019) for Australia, respectively, both of which use derived hourly pay as their wage measure.

When using the hourly wage rate, however, the pattern of estimated ZHC wage penalties across the distribution reverses, with the largest wage penalty (3.3%) at the 90th percentile and the smallest (a statistically insignificant 0.6%) at the 10th percentile. The absence of a ZHC wage penalty at the mean, using this measure, is complemented by the absence of a ZHC wage penalty towards the bottom of the wage distribution, where concerns over precariousness and its impacts have been most acute. Given that many ZHC workers and their close comparators towards the bottom of the wage distribution will be paid at or close to the National Minimum Wage (for <25s) or the National Living Wage (for >=25s), this is perhaps to be expected. But again it demonstrates the sensitivity of conclusions about ZHC wage penalties to the particular wage measure used. In this case the implications for the wider non-standard employment wage penalty literature are less clear. Although the monotonic pattern of wage penalties for casual employment disappears (in line with the zero estimate at the mean), we do not see a similar reversal for fixed-term employment, agency employment, seasonal employment or temporary other. Note, however, that we now see statistically significant wage premiums for fixed-term employment at all points in the distribution bar the 10th percentile.

This sensitivity in estimated ZHC wage penalties across the distribution is also demonstrated in the UQR estimates presented in Tables A5 (hourly pay) and A6 (hourly rate) in the Appendix. As in the CQR models, UQR estimates using hourly pay suggest ZHC wage penalties that are largest at the bottom of the wage distribution. There is no such pattern, however, when using the hourly wage rate, which again suggests *smaller* ZHC wage penalties towards the bottom of the wage distribution. As in the CQR models, the pattern (though not the magnitudes) of wage penalty estimates across the distribution for other forms of non-standard employment appears to be less sensitive to the wage measure used than is the case for ZHCs.

Finally, Table A7 in the Appendix presents individual fixed-effects estimates of the ZHC wage penalty using the LLFS sample common to both hourly pay and hourly wage rate measures. For comparison, the OLS equivalent estimates with the same sample (and reduced LLFS set of controls) are also presented. The OLS estimates in Columns 1 and 3 are consistent with those in Tables 2 and 3, despite the difference in sample and changes in the composition of the covariates, again showing sensitivity in the estimated ZHC wage penalty according to the wage measure employed (although in this case both estimates are smaller in magnitude and imprecisely estimated). The key point from Table A7, however, is that including individual fixed effects makes very little difference to estimated

ZHC coefficients, although again both coefficients are imprecisely estimated. For hourly pay, the fixed effects estimate of the ZHC wage penalty is (an imprecisely estimated) 5.4%; for the hourly wage rate it is 0.2%. We draw two conclusions from this. First, ZHC wage penalty estimates are sensitive to the wage measure employed in both OLS and fixed effects models. Second, once we condition on our long list of observable worker and job characteristics, and once we restrict to hourly-paid jobs for which HRRATE is returned, selection into ZHC jobs on worker time-invariant unobservable characteristics does not appear to be driving the estimated ZHC wage penalty (or its absence in the case of hourly wage rate estimates). Note, however, that estimated wage differentials for temporary employment appear more sensitive to the inclusion of individual fixed effects, to the extent that a small overall wage premium according to OLS hourly rate estimates becomes a small but non-significant wage penalty according to the fixed effect hourly rate estimates.

5. Discussion and Conclusion

All existing studies of the ZHC wage differential in the UK use a single cross-sectional data source (the LFS) and a single wage variable which is prone to measurement error (derived hourly pay). In doing so they consistently show large unconditional and conditional ZHC wage penalties. On the basis of this ZHC contracts might be viewed as being associated with lower worker welfare. In this paper we show that this conclusion is highly sensitive to issues of wage measurement, to the extent that we question whether there is any conditional ZHC wage penalty at all. Further, we show that conclusions about how ZHC wage penalties vary across the wage distribution are also highly sensitive to the wage measure used: hourly pay estimates suggest larger ZHC wage penalties at the bottom of the distribution; hourly rate estimates suggest the opposite. The nature, magnitude and even existence of wage penalty estimates for other forms of non-standard employment in the UK are also shown to be sensitive to the wage measure used. An implication is that the typical finding of non-standard wage penalties in the wider international literature, which also tends to use similar derived hourly pay measures, may also be similarly sensitive. A natural question is how robust are the conclusions of these studies be to the use of stated wage rates rather than derived hourly wages?

How do we interpret the possible absence of a ZHC wage differential, on average, from a theoretical perspective? Given the insecure and variable hours nature of ZHCs one might expect a wage *premium* – a compensating wage differential – in a competitive labour market. Mas and Pallais (2017), for example, find that workers tend to require a substantial wage premium to accept a schedule set by an employer at short notice. Our estimates showing wage premiums for other contingent forms of employment including fixed-term and agency jobs are consistent with compensating differentials for insecurity. On the other hand, because (at least some) ZHCs offer workers flexibility about when they work, one might expect a wage *penalty* if ZHC workers are prepared to pay for such flexibility by accepting lower wages (and Mas and Pallais (2017) suggest that some workers are indeed willing to pay for flexibility). One possible explanation for the zero ZHC wage penalty or premium is that these offsetting non-wage characteristics (and indeed any other ZHC-related non-wage characteristics) balance out in terms of the attractiveness of ZHC jobs overall. Alternatively, labour market frictions and/or a lack of alternative work for these workers may limit the extent to which ZHC workers, but not necessarily other contingent contract workers, are able to command a positive compensating wage differential; ZHC jobs are disproportionately concentrated among women, young workers and migrant workers, for example. It is also difficult to square ZHC wage penalties that exist only for men and not women (using either wage measure) with compensating wage differentials; we would need to argue that male ZHC workers are prepared to pay more for flexible hours than female ZHC workers on average, which seems unlikely. Perhaps more likely is that employers disproportionately use ZHCs to screen male workers (see Faccini, 2014), or that some employers view ZHC employment among men but not necessarily women as a negative productivity signal.

Efforts to improve our understanding of ZHCs are particularly timely given the range of policy interventions, from banning ZHCs to imposing a wage premium on non-guaranteed hours to imposing a right-to-convert for workers, currently being proposed in the mainstream of the UK debate (e.g. DBEIS, 2019; Labour Party, 2019; Taylor et al., 2017). Whilst we do not directly address these policy proposals here, the lack of any clear conditional wage penalty, where one had previously been widely reported, weakens one of the arguments for such intervention; ZHCs may be inferior jobs in numerous respects, but lower hourly wages may not be one of them. Having said that, even if there is no overall wage penalty for ZHC workers that does not suggest that low wages in these jobs are not a source of concern. The absence of a premium could still be interpreted as problematic if one expects compensating differentials to workers for their loss of job security and increased burden of working-hours volatility.

Of course, the sensitivity of the estimated ZHC wage penalty (and, indeed, other non-standard employment wage penalties) demonstrated here to the wage measure used, both at the mean and across the wage distribution, makes drawing any conclusions about labour market behaviour, or implications for policy, more difficult. ZHC wage penalties that are larger at the top of the wage distribution than at the bottom may appear more consistent with pay-flexibility trade-offs among workers with outside options, and less requiring of policy intervention, than wage penalties concentrated at the bottom of the distribution, but as things stand we cannot be confident regarding the nature of ZHC wage penalties across the distribution. Similarly, ZHC wage penalties at the mean may appear less consistent with compensating wage differentials, and more deserving of policy intervention, than the absence of any such penalty, but again we cannot be confident whether such a penalty exists or not. Again, because this sensitivity may also affect the wider non-standard employment wage penalty literature to some extent, some of what we think we know about labour markets in this respect, and some of what we advise policy makers regarding intervention, may also require reconsideration.

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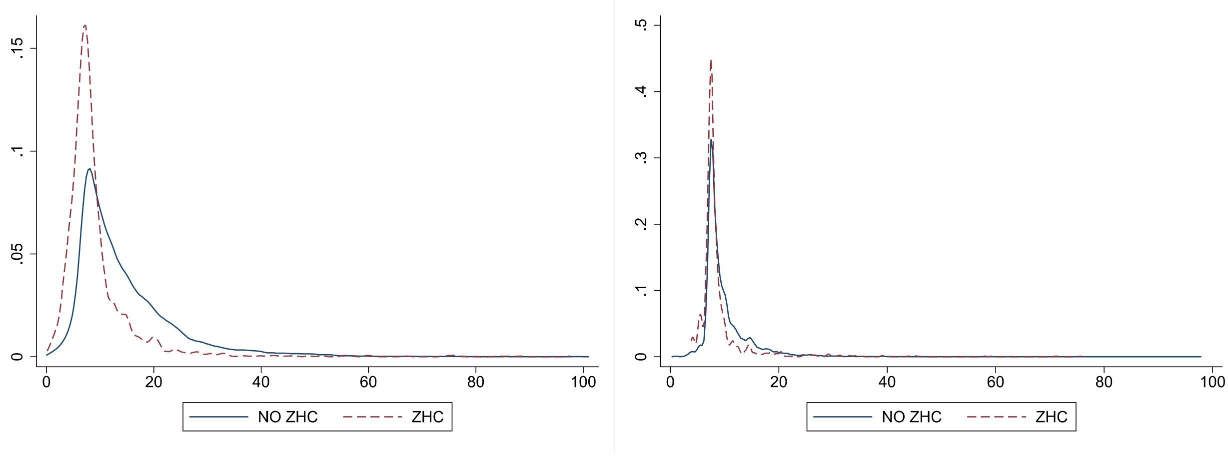
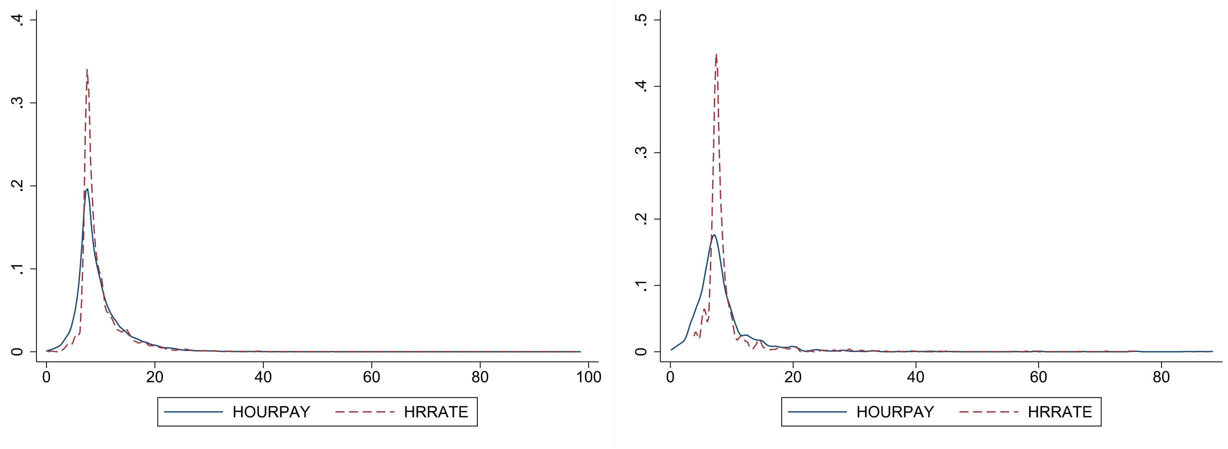
Figure 1: Distribution of Earnings by ZHC Status



Derived Hourly Pay **Reported Hourly Wage Rate**

Note: The figures give the distribution of hourly pay for people in employment, excluding self-employed, for workers on ZHCs (red/dotted line) and those not on ZHCs (blue/solid line). The figures are obtained using QLFS Q2 and Q4 data over the period 2015-2018. Hourly wages > £100 are treated as missing. Nobs = 81284 (derived hourly pay) and 26790 (hourly wage rate).

Fig 2 – Derived Hourly Pay vs Reported Hourly Wage Rate Distributions, by ZHC Status



2a: All in Employment **2b: ZHC Only**

Note: The figures give the distribution of hourly pay for all workers (2a) and for ZHC workers only (2b). The blue/solid line uses the derived hourly pay (HOURPAY) measure of hourly wage, and the red/dotted line uses the reported hourly wage rate (HRRATE) measure. The figures are obtained using QLFS Q2 and Q4 data over the period 2015-2018. Hourly wages > £100 are treated as missing. Nobs = 26790 (Fig 2a) and 1531 (Fig 2b).

Table 1: OLS Wage Regression, QLFS 2015-2018, Log Hourly Pay

	(1)	(2)	(3)	(4)
ZHC	**-0.460***** **(0.013)**	**-0.232***** **(0.013)**	**-0.045***** **(0.012)**	**-0.045***** **(0.013)**
Temporary Job			**-0.074***** **(0.009)**	
Permanent Agency Work				0.009 (0.013)
Temporary Contract: Agency Work				**-0.027*** **(0.015)**
Temporary Contract: Casual				**-0.055**** **(0.022)**
Temporary Contract: Seasonal				**-0.139***** **(0.039)**
Temporary Contract: Fixed Term				**-0.054***** **(0.012)**
Temporary Contract: Other				**-0.117***** **(0.023)**
Demographic Characteristics	No	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes
Regional Dummies	No	Yes	Yes	Yes
Quarter Dummies	No	Yes	Yes	Yes
N	81,284	81,284	81,284	81,284
R-squared	0.014	0.322	0.459	0.459

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. The dependent variable is (log) hourly pay expressed in £2017Q2. Demographic characteristics are age, gender, marital status, binary indicators for the presence of children in the household, non-UK/British Citizenship, ethnic group, full-time student status, and highest qualification achieved. Job characteristics (Column 3) are temporary job, part-time job, public employment, tenure, occupation and industry indicators. Robust standard errors in parentheses.

Table 2: OLS Wage Regression, QLFS 2015-2018, Log Hourly Wage Rate

	(1)	(2)	(3)	(4)
ZHC	**-0.125***	**-0.071***	**-0.012***	-0.009
	(0.009)	**(0.008)**	**(0.007)**	(0.007)
Temporary Job			**0.022***	
			(0.007)	
Permanent Agency Work				**0.038***
				(0.011)
Temporary Contract: Agency Work				**0.059***
				(0.012)
Temporary Contract: Casual				0.000
				(0.011)
Temporary Contract: Seasonal				-0.013
				(0.017)
Temporary Contract: Fixed Term				**0.053***
				(0.015)
Temporary Contract: Other				-0.027
				(0.017)
Demographic Characteristics	No	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes
Regional Dummies	No	Yes	Yes	Yes
Quarter Dummies	No	Yes	Yes	Yes
N	26,790	26,790	26,790	26,790
R-squared	0.007	0.282	0.494	0.495

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. The dependent variable is (log) hourly wage rate expressed in £2017Q2. Demographic characteristics are age groups, gender, marital status, binary indicators for the presence of children in the household, non-UK/British Citizenship, ethnic group, full-time student status, and highest qualification achieved. Job characteristics (Column 3) are temporary job, part-time job, public employment, tenure, occupation and industry indicators. The estimation sample consists of LFS respondents in our pooled sample who reported information on both HOURPAY and HRRATE. Robust standard errors in parentheses.

Table 3: OLS Wage Regression, QLFS 2015-2018, Log Hourly Pay, Hourly-Wage-Rate Sample

	(1)	(2)	(3)	(4)
ZHC	**-0.178***** **(0.014)**	**-0.112***** **(0.014)**	**-0.040***** **(0.013)**	**-0.039***** **(0.013)**
Temporary Job			**-0.019*** **(0.011)**	
Permanent Agency Work				0.015 (0.018)
Temporary Contract: Agency Work				**0.048***** **(0.017)**
Temporary Contract: Casual				-0.034 (0.024)
Temporary Contract: Seasonal				**-0.075**** **(0.038)**
Temporary Contract: Fixed Term				0.007 (0.020)
Temporary Contract: Other				**-0.073***** **(0.023)**
Demographic Characteristics	No	Yes	Yes	Yes
Job Characteristics	No	No	Yes	Yes
Regional Dummies	No	Yes	Yes	Yes
Quarter Dummies	No	Yes	Yes	Yes
N	26,790	26,790	26,790	26,790
R-squared	0.009	0.197	0.333	0.334

Notes: Significance at the 10% level is represented by ∗, at the 5% level by **, and at the 1% level by ∗∗∗. The dependent variable is (log) hourly pay expressed in £2017Q2. Demographic characteristics are age groups, gender, marital status, binary indicators for the presence of children in the household, non-UK/British Citizenship, ethnic group, full-time student status, and highest qualification achieved. Job characteristics (Column 3) are temporary job, part-time job, public employment, tenure, occupation and industry indicators. The estimation sample consists of LFS respondents in our pooled sample who reported information on both HOURPAY and HRRATE. Robust standard errors in parentheses.

Table 4: Quantile Regression, QLFS 2015-2018, Log Hourly Pay

	(1)	(2)	(3)	(4)	(5)
	0.10	**0.25**	**0.50**	**0.75**	**0.90**
ZHC	**-0.130*****	**-0.064*****	**-0.036*****	-0.007	**0.053****
	(0.030)	**(0.013)**	**(0.010)**	(0.013)	**(0.021)**
Permanent Agency Work	-0.003	-0.006	0.007	**0.035***	**0.064*****
	(0.021)	(0.016)	(0.014)	**(0.019)**	**(0.021)**
Temp. Contract: Agency Work	**0.040***	0.008	0.012	**0.059*****	**0.076****
	(0.023)	(0.013)	(0.016)	**(0.022)**	**(0.033)**
Temporary Contract: Casual	**-0.159*****	**-0.074*****	-0.028	0.012	**0.069****
	(0.039)	**(0.025)**	(0.020)	(0.019)	**(0.030)**
Temporary Contract: Seasonal	**-0.229****	**-0.087***	0.009	0.000	-0.036
	(0.091)	**(0.052)**	(0.026)	(0.023)	(0.026)
Temporary Contract: Fixed Term	-0.046	-0.031	0.008	0.015	0.023
	(0.032)	(0.019)	(0.016)	(0.019)	(0.023)
Temporary Contract: Other	**-0.211*****	**-0.092****	**-0.046****	**-0.042****	-0.020
	(0.046)	**(0.037)**	**(0.022)**	**(0.021)**	(0.037)
Demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes
N	26,790	26,790	26,790	26,790	26,790

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. Conditional quantile regression. The dependent variable is (log) hourly pay expressed in £2017Q2. Demographic characteristics are age groups, gender, marital status, binary indicators for the presence of children in the household, non-UK/British Citizenship, ethnic group, full-time student status, and highest qualification achieved. Job characteristics are temporary job, part-time job, public employment, tenure, occupation and industry indicators. The estimation sample consists of LFS respondents in our pooled sample who reported information on both HOURPAY and HRRATE. Robust standard errors in parentheses.

Table 5: Quantile Regression, QLFS 2015-2018, Log Hourly Wage Rate

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	0.10	**0.25**	**0.50**	**0.75**	**0.90**
ZHC	-0.006	**-0.011****	**-0.021*****	**-0.026*****	**-0.033*****
	(0.004)	**(0.005)**	**(0.005)**	**(0.006)**	**(0.010)**
Permanent Agency Work	-0.001	0.004	0.009	**0.031****	**0.075*****
	(0.006)	(0.008)	(0.009)	**(0.016)**	**(0.020)**
Temp. Contract: Agency Work	0.008	0.011	**0.019***	**0.060*****	**0.099*****
	(0.006)	(0.007)	**(0.011)**	**(0.018)**	**(0.029)**
Temporary Contract: Casual	-0.011	-0.007	-0.010	-0.014	-0.002
	(0.011)	(0.009)	(0.010)	(0.009)	(0.017)
Temporary Contract: Seasonal	-0.010	-0.027	-0.006	**-0.027****	0.020
	(0.015)	(0.017)	(0.012)	**(0.012)**	(0.032)
Temporary Contract: Fixed Term	-0.001	**0.017***	**0.029*****	**0.051*****	**0.083*****
	(0.011)	**(0.010)**	**(0.010)**	**(0.014)**	**(0.025)**
Temporary Contract: Other	**-0.044*****	**-0.040*****	-0.014	0.017	0.023
	(0.012)	**(0.012)**	(0.013)	(0.014)	(0.022)
Demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes
N	26,790	26,790	26,790	26,790	26,790

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. Conditional quantile regression. The dependent variable is the (log) hourly wage rate expressed in £2017Q2. Demographic characteristics are age groups, gender, marital status, binary indicators for the presence of children in the household, non-UK/British Citizenship, ethnic group, full-time student status, and highest qualification achieved. Job characteristics are temporary job, part-time job, public employment, tenure, occupation and industry indicators. The estimation sample consists of LFS respondents in our pooled sample who reported information on both HOURPAY and HRRATE. Robust standard errors in parentheses.

Table A1: Descriptive Statistics by ZHC Status

	Employed not on a ZHC	Employed on a ZHC	
	Mean	**Mean**	**t-test for mean difference**
	(St. Dev.)	**(St. Dev.)**	
HOURPAY (2017£)	14.60	9.17	-662.81***
	(9.62)	(7.42)	
HRRATE (2017£)	10.03	8.76	-151.25***
	(8.95)	(4.95)	
Usual Work Hours	34.07	23.99	-1,079.85***
	(10.83)	(13.32)	
Perm Agency Contr.	0.015	0.053	355.98***
Temp.: Agency	0.008	0.085	903.56***
Temp.: Casual	0.007	0.134	1,559.76***
Temp.: Seasonal	0.003	0.024	460.93***
Temp.: Fixed Period	0.024	0.051	204.71***
Temp.: Other	0.006	0.081	976.54***
Age Group (16-24)	0.109	0.348	881.55***
Age Group (25-34)	0.238	0.190	-131.57***
Age Group (35-49)	0.352	0.205	-359.37***
Age Group (50-64)	0.275	0.208	-175.28***
Age Group (65+)	0.027	0.049	160.67***
Female	0.501	0.581	186.68***
Mar. Stat.: Divorced	0.075	0.063	-54.23***
Mar. Stat.: Married	0.511	0.314	-462.37***
Mar. Stat.: Other	0.016	0.018	13.64***
Mar. Stat.: Separated	0.025	0.031	38.22***
Mar. Stat.: Single	0.372	0.575	490.72***
Children (0-4)	0.159	0.122	-119.90***
Children (5-15)	0.282	0.265	-43.24***
Non UK/Brit. Citizen	0.128	0.178	174.04***
Ethnic: Asian	0.050	0.049	-4.77***
Ethnic: Black	0.027	0.060	235.07***
Ethnic: Chinese	0.005	0.004	-24.17***
Ethnic: Other	0.025	0.033	63.96***
Ethnic: White	0.893	0.854	-148.11***
Full-time Student	0.031	0.190	1,020.02***
Educ.: Degree/Equiv.	0.356	0.213	-350.69***
Educ.: Higher Educ.	0.098	0.100	9.57***
Educ.: GCE A level	0.224	0.298	205.82***
Educ.: GCSE A-C	0.196	0.235	115.10***
Educ.: Other	0.073	0.092	85.75***
Educ.: No Qualif.	0.053	0.062	46.29***
Part-Time	0.249	0.653	1,085.60***
Temporary Job	0.046	0.348	1,613.59***
Public Employment	0.273	0.160	-297.64***
Tenure:(0-11) months	0.162	0.382	691.42***
Tenure:(12-23) months	0.115	0.193	283.89***
Tenure: (24-35) months	0.089	0.103	59.76***
Tenure: (36-47) months	0.069	0.076	29.07***
Tenure: (48-59) months	0.055	0.054	-7.21***
Tenure: 60+ months	0.509	0.192	-745.40***
Occ.: Manager/Senior Off.	0.100	0.020	-313.10***
Occ.: Professional	0.224	0.072	-428.29***

Occ.: Associate Prof. & Tech.	0.144	0.058	-289.42***
Occ.: Admin. & Secretarial	0.122	0.061	-218.92***
Occ.: Skilled Trades	0.075	0.043	-140.20***
Occ.: Personal Service	0.092	0.254	642.28***
Occ.: Sales & Customer Serv.	0.084	0.081	-12.97***
Occ.: Process, Plant, Mach. Op.	0.058	0.076	86.64***
Occ.: Elementary	0.100	0.335	898.95***
Industry: Agri & Fish	0.006	0.004	-37.59***
Industry: Bank, Fin. & Insur.	0.163	0.106	-180.16***
Industry: Construction	0.049	0.018	-169.33***
Industry: Distrib., Hotels & Rest.	0.187	0.339	452.23***
Industry: Energy & Water	0.019	0.004	-125.83***
Industry: Manufacturing	0.104	0.048	-215.99***
Industry: Other Services	0.043	0.094	289.21***
Industry: Publ. Ad., Educ, Health	0.341	0.337	-11.13***
Industry: Transport & Comm.	0.088	0.051	-154.45***
Region: East Midlands	0.075	0.089	61.62***
Region: Eastern	0.097	0.079	-71.83***
Region: London	0.131	0.125	-22.93***
Region: North East	0.042	0.044	12.77***
Region: North West	0.112	0.105	-27.83***
Region: Northern Ireland	0.021	0.010	-91.50***
Region: Scotland	0.08	0.069	-45.50***
Region: South East	0.142	0.134	-27.84***
Region: South West	0.087	0.115	117.65***
Region: Wales	0.045	0.053	42.43***
Region: West Midlands	0.081	0.084	12.05***
Region: Yorkshire-Humber	0.086	0.094	30.64***
Observations	79,423	1,861	

Notes: Each entry reports the weighted mean/proportion and standard deviation (in parentheses) for the demographic and job characteristics, obtained by pooling the QLFS April-June and October-December surveys over to the period 2015-2018, for respondents reporting information on HOURPAY interviewed in Wave 1 and Wave 5. Column (1) refers to all individuals in employment, excluding self-employed, not on ZHCs. Column (2) refers to individuals in employment, excluding self-employed, on ZHCs. Column 3 reports the two-sample t-test on the equality of means. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. The number of observations for HRRATE is 25,259 (Column 1) and 1,531 (Column 2).

Table A2: Descriptive Statistics - QLFS sample vs LLFS

	(1)	(2)	(3)
	QLFS	LLFS	
	Mean (St. Dev.)	Mean (St. Dev.)	t-test for equality of means
HOURPAY (2017£)	9.71	9.63	0.809
	(5.22)	(5.02)	
HRRATE (2017£)	9.96	9.68	1.748*
	(8.77)	(4.25)	
Working Hours	28.98	28.71	1.176
	(12.10)	(11.74)	
ZHC	0.060	0.062	-0.443
Perm Agency Contr.	0.023	-	
Temp.: Agency	0.021	-	
Temp.: Casual	0.022	-	
Temp.: Seasonal	0.007	-	
Temp.: Fixed Period	0.024	-	
Temp.: Other	0.015	-	
Age Group (16-24)	0.182	0.166	2.193**
Age Group (25-34)	0.210	0.217	-0.903
Age Group (35-49)	0.293	0.317	-2.768***
Age Group (50-64)	0.278	0.280	-0.235
Age Group (65+)	0.038	0.021	4.818***
Female	0.573	0.579	-0.638
Marital Status: Divorced	0.090	0.097	-1.280
Marital Status: Married	0.424	0.426	-0.213
Marital Status: Other	0.024	0.024	0.000
Marital Status: Separated	0.031	0.025	1.827*
Marital Status: Single	0.431	0.428	0.319
Children (0-4)	0.141	0.307	-24.158***
Children (5-15)	0.286	0.453	-19.236***
Non-UK/British Citizenship	0.150	.	
Ethnic Group: Asian	0.048	0.063	-3.651***
Ethnic Group: Black	0.032	0.019	3.937***
Ethnic Group: Chinese	0.002	0.000	2.200**
Ethnic Group: Other	0.024	0.020	1.378
Ethnic Group: White	0.893	0.898	-0.853
Full-time Student	0.073	.	
Education: Degree or equiv.	0.158	0.154	0.577
Education: Higher Education	0.097	0.101	-0.711
Education: GCE A level	0.281	0.318	-4.301***
Education: GCSE A-C	0.269	0.265	0.474
Education: Other	0.113	0.105	1.329
Education: No Qualification	0.081	0.057	4.675***
Part-Time	0.449	0.469	-2.114**
Temporary Job	0.084	0.076	1.527
Public Employment	0.197	0.183	1.853*
Tenure: (0-11) months	0.222	0.167	7.025***
Tenure: (12-23) months	0.139	0.150	-1.664*
Tenure: (24-35) months	0.092	0.111	-3.429***
Tenure: (36-47) months	0.071	0.093	-4.437***
Tenure: (48-59) months	0.053	0.059	-1.392
Tenure: 60+ months	0.423	0.420	0.319
Occup: Managers & Senior Off.	0.032	0.032	0.000
Occup: Professional	0.081	0.070	2.136**
Occup.: Associate Prof. & Tech.	0.064	0.054	2.167**
Occup: Admin. & Secretarial	0.098	0.109	-1.932*
Occup: Skilled Trades	0.094	0.094	0.000
Occup: Personal Service	0.161	0.168	-0.999
Occup: Sales & Customer Serv.	0.154	0.166	-1.743*
Occup: Process, Plant, Mach. Op.	0.096	0.112	-2.825***
Occup: Elementary	0.220	0.194	3.312***
Industry: Agri & Fish	0.007	0.008	-0.634
Industry: Bank, Fin. & Insur.	0.090	0.090	0.000
Industry: Construction	0.037	0.035	0.556
Industry: Distrib., Hotels & Rest.	0.322	0.313	1.015
Industry: Energy & Water	0.014	0.015	-0.441
Industry: Manufacturing	0.107	0.102	0.853
Industry: Other Services	0.051	0.053	-0.480

Industry: Publ. Ad., Educ, Health	0.307	0.324	-1.934*
Industry: Transport & Comm.	0.065	0.060	1.067
Region: East Midlands	0.086	0.084	0.375
Region: Eastern	0.089	0.073	2.977***
Region: London	0.081	0.077	0.771
Region: North East	0.050	0.056	-1.444
Region: North West	0.117	0.114	0.491
Region: Northern Ireland	0.025	0.020	1.692*
Region: Scotland	0.090	0.090	0.000
Region: South East	0.114	0.137	-3.774***
Region: South West	0.106	0.118	-2.045
Region: Wales	0.054	0.048	1.411
Region: West Midlands	0.085	0.079	1.138
Region: Yorksh.-Humber	0.105	0.104	0.171
Observations	26,790	3,080	

Notes: Each entry reports the weighted mean and standard deviation (in parentheses) for the demographic and job characteristics, obtained using the QLFS (Column 1) and LLFS (Column 2) estimation samples from Table 3 and Table A7 respectively. Column 3 reports the two-sample t-test statistic on the equality of means. Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. The estimates refer to all individuals in employment, excluding self-employed.

Table A3: OLS Wage Regressions by Worker / Job Characteristics, QLFS 2015-2018, Log Hourly Pay, Hourly Wage Rate Sample

	(1)	(2)	(3)
	β	**s.e.**	**N**
PANEL 1: AGE			
16-24	**-0.061*** **	**0.023**	**4,109**
25-34	-0.029	0.024	5.138
35-49	**-0.058** **	**0.027**	**8,332**
50-64	-0.041	0.031	8,164
65+	0.103	0.082	1,047
PANEL 2: GENDER			
Male	**-0.082** **	**0.024**	10,788
Female	-0.014	0.016	16,002
PANEL 3: EDUCATION			
Degree	-0.021	0.040	4,122
Higher Education	-0.060	0.043	2,640
Secondary Education	**-0.040** **	**0.016**	**14,699**
Other Education	-0.061	0.050	3,055
No Education	0.036	0.042	2,274
PANEL 4: INDUSTRY			
Agri/Fish	-0.286**	0.115	174
Banking	-0.057	0.039	2,371
Construction	-0.017	0.080	964
Restaurants/Hotel	-0.093***	0.021	**8,325**
Energy	0.041	0.107	384
Manufacturing	0.012	0.065	2,861
Other Services	-0.001	0.045	1,356
Public Admin., Education and Health	0.011	0.024	8,629
Transport	-0.117*	0.068	1,726
PANEL 5: OCCUPATION			
Managers & Senior Off.	**-0.170*** **	**0.063**	**856**
Professional	0.036	0.054	2,259
Associate Professions & Tech.	-0.030	0.084	1,683
Admin. & Secretarial	0.005	0.074	2,739
Skilled Trades	-0.069	0.066	2,459
Personal Service	0.015	0.023	4,426
Sales & Costumer Service	**-0.081***	**0.048**	**4,025**
Process, Plant and Machine Op.	**-0.130*** **	**0.050**	**2,596**
Elementary	**-0.073*** **	**0.020**	**5,747**
PANEL 6: CITIZENSHIP			
UK/British	**-0.039*** **	**0.015**	**22,922**
Non-UK/British	-0.029	0.028	3,868
PANEL 7: SECTOR			
Private Sector	**-0.052*** **	**0.014**	**21,213**
Public Sector	0.037	0.044	5,577

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. The dependent variable is (log) hourly pay expressed in £2017Q2. Controls and sample (from which each subsample is drawn) are as in Table 3 Column 4. Robust standard errors in parentheses.

Table A4: OLS Wage Regressions by Worker / Job Characteristics, QLFS 2015-2018, Log Hourly Wage Rate

	(1)	(2)	(3)
	β	**s.e.**	**N**
PANEL 1: AGE			
16-24	-0.007	0.010	4,109
25-34	**-0.025****	**0.012**	**5.138**
35-49	**-0.043*****	**0.013**	**8,332**
50-64	-0.021	0.015	8,164
65+	**0.090****	**0.044**	**1,047**
PANEL 2: GENDER			
Male	**-0.021***	**0.012**	**10,788**
Female	-0.005	0.008	16,002
PANEL 3: EDUCATION			
Degree	0.008	0.021	4,122
Higher Education	-0.026	0.024	2,640
Secondary Education	**-0.013***	**0.007**	**14,699**
Other Education	-0.017	0.014	3,055
No Education	-0.004	0.015	2,274
PANEL 4: INDUSTRY			
Agri/Fish	-0.062	0.065	174
Banking	-0.009	0.024	2,371
Construction	0.034	0.080	964
Restaurants/Hotel	**-0.048*****	**0.007**	**8,325**
Energy	-0.053	0.122	384
Manufacturing	-0.002	0.051	2,861
Other Services	0.017	0.020	1,356
Public Admin., Education and Health	0.014	0.012	8,629
Transport	-0.050	0.032	1,726
PANEL 5: OCCUPATION			
Managers & Senior Off.	**-0.138*****	**0.045**	**856**
Professional	**0.089****	**0.044**	**2,259**
Associate Professions & Tech.	0.028	0.051	1,683
Admin. & Secretarial	0.015	0.026	2,739
Skilled Trades	-0.023	0.037	2,459
Personal Service	0.004	0.009	4,426
Sales & Costumer Service	**-0.035****	**0.016**	**4,025**
Process, Plant and Machine Op.	**-0.058****	**0.025**	**2,596**
Elementary	**-0.030*****	**0.008**	**5,747**
PANEL 6: CITIZENSHIP			
UK/British	-0.005	0.008	22,922
Non-UK/British	**-0.026****	**0.013**	**3,868**
PANEL 7: SECTOR			
Private Sector	**-0.017*****	**0.007**	**21,213**
Public Sector	0.034	0.021	5,577

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. The dependent variable is the (log) hourly wage rate expressed in £2017Q2. Controls and sample (from which each subsample is drawn) are as in Table 3 Column 4. Robust standard errors in parentheses.

Table A5: Unconditional Quantile Regression, QLFS 2015-2018, Log Hourly Pay

	(1)	(2)	(3)	(4)	(5)
	0.10	**0.25**	**0.50**	**0.75**	**0.90**
ZHC	**-0.138*** **	**-0.060*** **	**-0.026*** **	0.006	**0.038***
	(0.026)	(0.010)	(0.010)	(0.014)	(0.021)
Permanent Agency Work	0.008	-0.004	0.011	**0.056** **	0.050
	(0.030)	(0.014)	(0.016)	**(0.025)**	(0.036)
Temp. Contract: Agency Work	0.034	0.017	0.009	**0.065** **	**0.068***
	(0.030)	(0.014)	(0.016)	**(0.026)**	**(0.039)**
Temporary Contract: Casual	**-0.162*** **	**-0.039** **	-0.017	0.019	0.039
	(0.047)	**(0.016)**	(0.015)	(0.023)	(0.036)
Temporary Contract: Seasonal	**-0.171** **	**-0.048***	**-0.051** **	0.024	-0.010
	(0.079)	**(0.027)**	**(0.024)**	(0.033)	(0.039)
Temporary Contract: Fixed Term	0.031	0.016	-0.007	0.007	-0.006
	(0.031)	(0.013)	(0.014)	(0.025)	(0.042)
Temporary Contract: Other	**-0.134*** **	**-0.057*** **	**-0.047** **	**-0.061** **	-0.040
	(0.049)	**(0.018)**	**(0.019)**	**(0.025)**	(0.039)
Demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes
N	26,790	26,790	26,790	26,790	26,790

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. Estimates obtained using the rifhdreg command for Stata. The dependent variable is the (log) hourly pay expressed in £2017Q2. Controls and sample as for Table 3 Column 4. Robust standard errors in parentheses.

Table A6: Unconditional Quantile Regression, QLFS 2015-2018, Log Hourly Wage Rate

	(1)	(2)	(3)	(4)	(5)
	0.10	**0.25**	**0.50**	**0.75**	**0.90**
ZHC	**-0.017****	**-0.013*****	**-0.033*****	**-0.031*****	-0.008
	(0.008)	(0.004)	(0.006)	(0.010)	(0.014)
Permanent Agency Work	-0.000	-0.002	0.015	**0.033***	**0.089*****
	(0.009)	(0.006)	(0.011)	**(0.019)**	**(0.029)**
Temp. Contract: Agency Work	**0.023****	-0.003	0.006	**0.086*****	**0.144*****
	(0.009)	(0.006)	(0.011)	**(0.022)**	**(0.034)**
Temporary Contract: Casual	**-0.047*****	**-0.012***	0.010	**0.025***	0.035
	(0.014)	**(0.006)**	(0.009)	**(0.015)**	(0.023)
Temporary Contract: Seasonal	**-0.058****	-0.014	-0.010	-0.009	0.008
	(0.023)	(0.011)	(0.016)	(0.025)	(0.028)
Temporary Contract: Fixed Term	**0.023****	**0.015*****	0.015	0.021	**0.077****
	(0.009)	**(0.005)**	(0.010)	(0.019)	**(0.034)**
Temporary Contract: Other	**-0.037****	**-0.026*****	-0.012	-0.028	0.023
	(0.015)	**(0.008)**	(0.014)	(0.020)	(0.031)
Demographic Characteristics	Yes	Yes	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes	Yes	Yes
Regional Dummies	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes
N	26,790	26,790	26,790	26,790	26,790

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. Estimates obtained using the rifhdreg command for Stata. The dependent variable is the (log) hourly wage rate expressed in £2017Q2. Controls and sample as for Table 3 Column 4. Robust standard errors in parentheses.

Table A7: OLS and Fixed Effects Wage Regressions, LLFS 2015-2018, Log Hourly Pay & Log Hourly Wage Rate

	Derived Hourly Pay		Hourly Wage Rate	
	OLS (LLFS)	**Fixed Effects (LLFS)**	**OLS (LLFS)**	**Fixed Effects (LLFS)**
ZHC	-0.032	-0.054	-0.000	-0.002
	(0.043)	(0.054)	(0.025)	(0.017)
Temporary Job	-0.001	-0.052	**0.067*** **	-0.019
	(0.038)	(0.065)	**(0.024)**	(0.019)
Demographic Characteristics	Yes	Yes	Yes	Yes
Job Characteristics	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
Observations	3,080	3,080	3,080	3,080
R^2	0.317	-	0.517	-
R^2 - within	-	0.038	-	0.058
Number of identifiers	-	1,540	-	1,540

Notes: Significance at the 10% level is represented by *, at the 5% level by **, and at the 1% level by ***. The dependent variable for the first two columns is (log) derived hourly pay and for the second two columns is (log) reported hourly wage (HRRATE), both expressed in £2017Q2. Demographic characteristics are age groups, gender, marital status, binary indicators for the presence of children in the household, ethnic groups (Column 1 and 3), regional dummies (Column 1 and 3) and highest qualification achieved. Job characteristics are temporary job, part-time job, public employment, tenure, occupation and industry indicators. The estimates were obtained using the LLFS for all people observed in employment in both waves 1 and 5, excluding self-employed, for whom ZHC status and HOURPAY and HRRATE was non-missing, entering the LFS sample between 2015Q2 and 2017Q4. Robust standard errors in parentheses.