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Recent changes in British wage inequality: Evidence from firms and occupations*

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Abstract

Using a linked employer-employee dataset, we study the increasing trend in British wage inequality over the past two decades. The dispersion of wages within firms accounts for the majority of changes to wage variance. Approximately all of the contribution to inequality dynamics from firm-specific factors are absorbed by controlling for the changing occupational content of wages. The modest trend in between-firm wage inequality is explained by a combination of changes in between-occupation inequality and the occupational composition of firms and employment. These results are robust to using weekly, hourly or annual measures of employee pay.

Keywords: wage inequality, within-firm inequality, occupational wage premiums

JEL codes: D22, E24, J31

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1 Introduction

The long-term trend of rising wage inequality in Great Britain has been extensively documented (Hills et al., 2010; Machin, 2011; Belfield et al., 2017). As in the US and several other countries, the majority of this increase in Britain occurred in the 1980s, but stagnant real median wages in the past two decades have refocused attention on where the proceeds of growth are ending up. Although well-studied, some ambiguity remains over what principally drives changes in the wage distributions of labour markets such as Britain's. One explanation points towards pay setting practices and the increasingly generous remuneration of executives and senior managers (Piketty, 2013). Others have identified rising skill and occupational wage premiums, associated with skill-biased technological change (Katz & Murphy, 1992; Machin & van Reenen, 1998). Further explanations highlight changing institutions, with examples in Britain being the decline in unionisation (Card et al., 2004) and the introduction of a minimum wage in 1999 (Machin, 2011). One way to potentially disentangle these explanations is to ask how much have the differences between firms, relative to within, accounted for recent inequality trends. We answer this question for the last two decades in Great Britain.

Among full-time employees over eighty percent of the increase in the variance of log weekly wages between 1996 and 2005 occurred within firms. In the subsequent decade to 2015 overall inequality decreased, whereas the dispersion of average firm wages increased. For measures of annual or hourly wages we similarly find that within-firm inequality changes predominantly accounted for overall changes. Faggio et al. (2010) find that rising British wage inequality in the fifteen years prior to 1999 was almost entirely accounted for by an estimate of between-firm variance. A contribution of this paper is to extend their results, using the same survey data of wages and hours, but by instead matching a representative sample of employees to the majority of large firms. This provides us with a more robust sample of employer-employee linked jobs, as opposed to using some separate source to estimate firm average wages; Faggio et al. (2010) lacked data on the wages within firms. Mueller et al. (2016) also study British wage inequality from the firm's perspective. Using data on average pay at hierarchy levels in 880 firms, they find not only substantial within-firm inequality in the years 2004-13, but that this tended to increase as firms grew. They suggest that overall wage inequality trends could be related to an increasing concentration of employment in large firms.

Several recent studies have documented that trends in employee wage inequality and the dispersion of firm productivity or average wages tend to coincide (see among others for the US: Davis & Haltiwanger, 1991; Dunne et al., 2004; Barth et al., 2016; Song et al., 2016. For Sweden: Nordström Skans et al., 2009; Akerman et al., 2013. For West Germany: Card et al., 2013. For Brazil: Alvarez et al., 2016; Benguria, 2015; Helpman et al., 2017. See also the literature review by Card et al., 2016). At first look our results for Britain would appear to conflict with this wider literature. The data are a one percent random sample of employees, and so we limit attention to mostly large firms, representing approximately forty percent of all UK employment. The overall trends in wage inequality for this forty percent are not dissimilar to the whole economy. But Song et al. (2016) have demonstrated that the contribution of between-firm wage dispersion to overall changes is smaller among large US firms. Although

our results are robust to varying the sample selection and resulting average firm size, we can only cautiously compare them to those found elsewhere using more widely representative data.

These British data do however offer some clear advantages. They are generally considered to be accurate records from firms' payrolls (Nickell & Quintini, 2003), giving measures of annual and weekly earnings, and their constituent components, including hours worked. They also contain a detailed classification of occupations. We use this to ask how much of the estimated contribution to inequality changes from firm-specific differences can be accounted for by changes to the occupational content of wages. The answer is approximately all. Some combination of changes to between-occupation inequality and the sorting of occupations across firms accounts for the role of dispersion in firm-specific wages over the last two decades in Britain.

It is well-known that the polarisation of employment across occupations, the increase in shares of employment in high- and low-skilled occupations, accounts for a significant part of long-run wage inequality changes in the UK, US and elsewhere (Goos & Manning, 2007; Autor et al., 2008; Williams, 2013). Song et al. (2016) suggest that while skill-biased technological change could account for overall wage inequality increases and the polarisation of employment, across firms there has perhaps been greater specialisation and concentration of occupations, explaining some part of the rising dispersion in average firm wages. This theory has been largely untested due to a lack of comprehensive data covering long periods of employee wages, detailed occupations and firm identities. A notable exception is Weber-Handwerker & Spletzer (2016), who do make some progress on this for the US for 2000-11, finding that the changing composition of employment over occupations, as opposed to industry, accounts for almost half of between-establishment wage growth. They also specifically find that occupational concentration in firms, measured by Herfindahl indices, explains only a small part. In contrast, we also allow for changing occupational wage premiums as well as their composition over firms and employment, and as such we are able to account for approximately all of the change in firm-specific inequality throughout the wage distribution. We view this as suggestive evidence that the estimated importance of between-firm inequality found elsewhere could similarly represent an important role for the occupational transformation of firms and labour markets.

The remainder of the paper proceeds as follows: Section 2 describes the data, Section 3 presents the results from decompositions of wage variance over the last two decades in Britain, Section 4 describes the dynamics of inequality throughout the wage distribution, and Section 5 summarises. Further information is presented in the Online Appendix concerning the data, sample construction, mathematical details and additional results.

2 Data

The data we use are from the New Earnings Survey Panel Dataset (NESPD), 1975-2015, which is distributed under secure license access by the UK Data Service, with the permission of the data owners, the Office for National Statistics (ONS). It is a continuing sample of approximately one percent of all Pay As You Earn (PAYE) taxpayers in Britain, with the sample selected using the same last two digits of worker National Insurance numbers, covering up to 180,000 employee jobs per year.¹ A small number of jobs not registered for PAYE, which tend to be of very low pay, are not sampled. Employees who are not paid in the reference period are also excluded. These are both potential sources of composition bias in measuring inequality changes, which could vary over the economic cycle. But it is certainly an advantage that the dataset is a long-running panel, since we can expect many repeated observations of employer-employee matches.² The data are collected via a questionnaire issued to employers, who are required by law to respond and complete it with reference to payrolls. They return the gross weekly earnings and hours worked of employees, and their detailed components, as well as an employee's occupation and other information related to remuneration, such as pensions and collective agreements. The reference period for the survey is always a week in April. Gross annual earnings for the year to April have been recorded since 1999.

It is a significant advantage of these data that we can consider the robustness of results across different frequencies of pay. For example, the compositional differences in two jobs samples from the NESPD which contain either non-missing observations of weekly or annual wages could be large, given that for the latter individuals must have been with the same employer for at least twelve months. Related, the timing of bonus payments tends to be seasonal in Britain. Approximately half of all such payments economy-wide and over seventy percent in the financial and insurance activities sector occur in the 'bonus season' of December-March.³ This seasonal pattern is consistent across years. Therefore the measures of weekly and hourly wages in April will only capture a small part of this pay component. The fraction of total employee remuneration which is from bonus payments has been fairly constant at 6-7 percent over the last two decades, but in the financial and insurance activities sector this has fluctuated between 20 and 35 percent around the Great Recession. If bonus payments have significantly affected trends in the employee wage distribution, then we could expect our results to differ between using annual vs. weekly or hourly measures.

Information on employer size and industry classification was added to the NESPD from 1996 onwards by the ONS, using Her Majesty's Revenue and Customs' Inter-Departmental Business Register (IDBR), an administrative census of all UK registered companies. Only tiny businesses consisting of the self-employed are not found on the IDBR. The employer reporting unit observed in the NESPD is generally the enterprise or a local unit thereof. For

¹National Insurance numbers are issued to all individuals in the UK who have the right to work. For UK nationals these are typically issued when turning sixteen.

²We do not exploit this feature fully since in the current publicly available form of the dataset employers can only be robustly identified over time for 2002-2015.

³See ONS statistical bulletin: "Average weekly earnings, bonus payments in Great Britain: financial year ending 2016".

the vast majority of the data used in the analysis that follows the ‘firm’ is an enterprise.⁴ For a sub-period, 2002-15, the enterprise of all jobs is identified, and we use this as a robustness check of whether our less precise definition of a firm could qualitatively affect any main results. We can do this using the annual cross-section datasets of the Annual Survey of Hours and Earnings, from which the NESPD in later periods is derived. This earnings survey is considered to be unusually accurate, at least when compared with household based surveys (Nickell & Quintini, 2003). The NESPD has undergone minor methodological changes over its lifetime, but the principal aim of collecting detailed and precise information on hours, pay and occupations has remained consistent. In Online Appendix A we summarise the relevant changes, as well as providing greater detail than what follows on the construction of our analysis sub-samples and variables.

2.1 Creating a large firms sample of the NESPD

For sub-samples of the NESPD we include only those aged 16-64 and exclude jobs where pay in the reference week has been affected by absence or leave. For weekly wages and hours worked we use the reported values excluding overtime. We drop a tiny number of jobs with records of over a hundred hours worked in the reference week. Hourly rates of pay are derived from gross weekly pay and basic (usual) hours worked. From 1999 we drop less than half a percent of observations in each year whose hourly rate of pay is less than eighty percent of the applicable National Minimum Wage. When considering annual earnings we use only observations where the employee has been in the same job for at least a year. All monetary values are deflated to 1997 prices using the ONS’ Retail Price Index from April, to match the reference period of the NESPD.⁵ To analyse and estimate a within-firm component of wage dispersion we have to match sufficient numbers of employees to each observed firm. Hence we construct a large firms sample of the NESPD. We consider only jobs in each year at enterprises with 250 employees or more according to the IDBR.⁶ In the baseline sample we keep only full-time jobs, defined as working over thirty hours in a week before overtime, and in each year then keep firms for which there are ten or more job observations with non-missing values of pay and hours worked. This firm-based selection imposes a de facto minimum firm size of more than a thousand employees. We construct several other sub-samples, which are discussed in the results, where we vary the minimum number of job observations required per firm and add part-time workers.

Throughout the following analysis and results one can generally replace any reference to ‘firms’ with ‘large firms,’ or even ‘very large firms.’ This is clear when we compare the enterprise size distributions in 2013 of the UK population and the firms in our baseline NESPD sub-sample (Table A1). Over seventy percent of UK enterprises with at least 250 employees have less than a thousand employees. But in our baseline sample such firms are only five

⁴We are comfortable that the enterprise is a typical definition of the firm, as defined for UK government administrative purposes. IDBR definition: ‘An Enterprise can be defined as the smallest combination of legal units (generally based on VAT and/or PAYE records) that is an organisational unit producing goods or services, which benefits from a certain degree of autonomy in decision-making, especially for the allocation of its current resources. An enterprise carries out one or more activities at one or more locations. An enterprise may be a sole legal unit.’

⁵Accessed from the ONS website 25/05/2016.

⁶The cut-off between the definition of Small and Medium Enterprises (SMEs) and Large firms in the UK is typically at 250 employees.

percent of the total number. On the other hand, firms with more than two thousand employees are relatively over represented: the sample includes a similar number of firms with over five thousand employees as there are such UK enterprises.⁷ Though we cannot represent the whole firm size distribution of Britain, we can nonetheless claim to sample employees from practically all very large enterprises. As such we are able to study a significant fraction of jobs and wages: in 2013 the firms in our sample represented approximately forty percent of employee jobs.⁸

Given we study the dynamics of wage inequality, we briefly document how the baseline sample's firm size distribution has evolved over time, between 1997 and 2007 for example (Table A2). The share of firms with more than two thousand employees increased by over thirteen percentage points in this period, with the largest increase among those with five thousand or more. The share of employee observations in very large firms similarly increased. The true distribution of these firms was relatively unchanged over the period, according to their administrative IDBR enterprise level of employment. We believe this difference reflects a shift since 2004 in the employer reporting unit of the earnings survey towards more commonly being the enterprise, as opposed to the local unit.⁹ We also describe the sample's changing industrial make-up over the same ten years (Figure C1).¹⁰ The share of firms associated with the manufacturing sector decreases notably, while real estate and business services firms are increasingly represented. We observe similar trends in the represented labour shares of sectors, though in this case there is also a decline in the share of employees in public administration and defence.

An advantage of our data over those used in similar studies is the presence of employer descriptions of jobs and their assignment to a detailed occupational classification. Throughout, occupations refer to the International Standard Classification of Occupations 1988 (ISCO88), unless stated otherwise. Due to inconsistencies in source data classifications we only consider occupations for the sub-period 1996-2010. Comparing the incidence of major occupation groups in the sample over time, some occupations are less prevalent in 2007 than in 1997, with a large decrease for professionals (Table A3). At the same time the share of elementary occupations has increased by almost the same amount. This sample of large British firms, and a further sample of their employees, would appear to have some different characteristics over time. Partially this could reflect long-run trends of structural change in the labour market.

2.2 Describing wages in large firms and the NESPD

Since economy-wide trends in wages have been extensively documented elsewhere using the NESPD (e.g. Machin, 2011), here we focus on whether recent patterns among jobs in large

⁷Part of the non-sampling discrepancy is due to the NESPD being British as opposed to UK. In 2013 ONS data suggests there were thirty enterprises in Northern Ireland with over a thousand employees. Using enterprise identifiers from the ASHE to define firms in 2013, and otherwise the same criteria to construct the baseline large firms sample, gives us 598 enterprises with over five thousand employees.

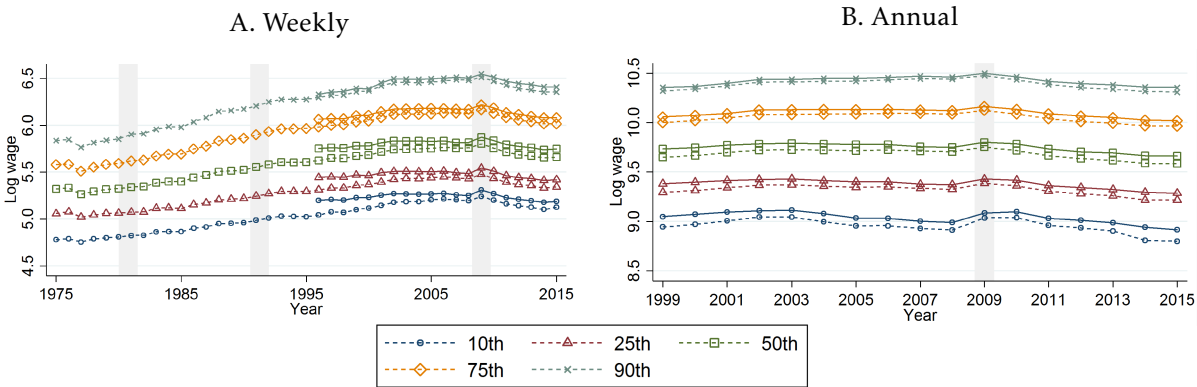
⁸According to the ONS Labour Market Statistics Workforce Jobs series, there were approximately 27.5 million employee jobs in Great Britain in 2013.

⁹This coincides with the replacement of the NESPD with the ASHE. Despite studying the documentation we cannot find any noteworthy reason for such a sizeable shift. As we show in what follows, we are confident that this does not qualitatively drive any of the main results.

¹⁰Throughout industry sectors refer to the Standard Industrial Classification (SIC) 2003.

firms have been notably different. Figure 1 compares selected percentiles of real log wages for full-time employees between our baseline sub-sample and the whole NESPD. Figure C2 similarly compares mean values. All measures of real wages were relatively stagnant during the 2000s. They have also seen a substantial decline since 2008, especially compared with the periods following other downturns. The variance of log weekly wages increased for the whole NESPD persistently from 1975 to 1995 (Figure 1A). The variance of wages in our baseline sample is somewhat lower than in the whole NESPD. This is due to a tighter distribution of wages above the median among those working in larger firms. Generally though the pattern of wages across the large firms distribution is similar to the whole NESPD: for example, both show a steep increase in hourly and weekly wages for top earners in the early 2000s, as well as a decline in variance at the onset of the Great Recession, driven by relatively higher earnings at the bottom. Figure 2A further demonstrates these changes by plotting weekly wages relative to 1996 for selected percentiles of the large firms sample.

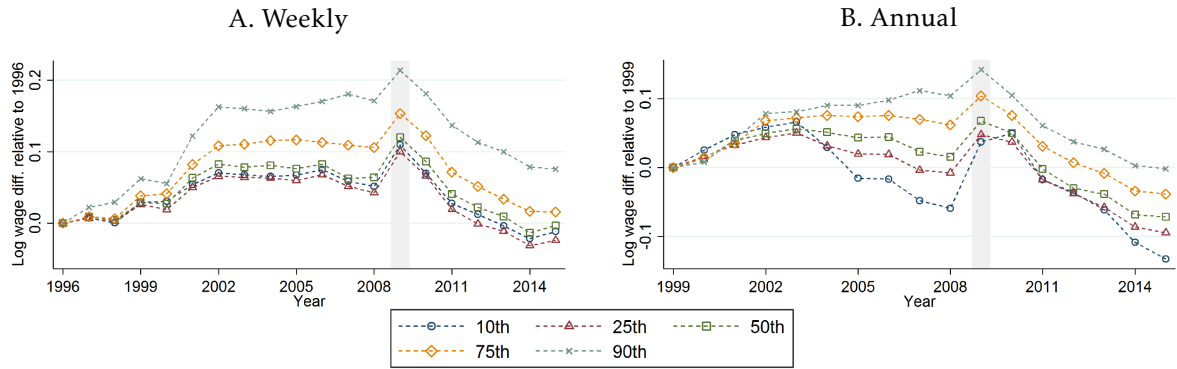
FIGURE 1: Percentiles of real log wages in large firms, full-time employees only, and comparison with the whole NESPD sample, 1975-2015



Note.- author calculations using the NESPD, age 16-64 and full-time employees only. ‘Weekly’ exclude overtime. ‘Annual’ are for employees with the firm at least one year. See the text for further details of sample construction. Shaded areas represent official UK recessions. Solid lines are the series for a large firm sub-sample of the NESPD.

The increase in the variance of log annual wages, which include all performance related payments, was more substantial between 1999 and 2007. As shown in Figures 1B and 2B, this is explained by real wages falling at the lower percentiles and only marginally rising at the median, while the ninetieth percentile increased consistently through this period. Much of the increase in variance during the preceding decade was reversed in 2008 by a relatively greater increase in log wages at the bottom. This large increase in real wages in 2008 partly reflects our choice of price deflator, which includes the slashing of mortgage interest costs during the financial crisis, as well as the well-understood cyclical composition bias in aggregate wage measures, which was large in the UK during the Great Recession (Elsby et al., 2016). These patterns and comparisons are similar when we consider all employees and not only those working full-time (Figures C3-C5).

FIGURE 2: Percentiles of real log wages in large firms, full-time employees only: differences relative to 1996/9



Note.- see Figure 1.

3 Wage inequality trends: the role of between-firm variance

To account for how much of the variance in employee wages is explained by differences in the average wages paid by firms, we use the decomposition of [Davis & Haltiwanger \(1991\)](#). The total variance of the natural logarithm of wages across a set of firms and their employees, V_e , can be decomposed into a within-firm component, V_{wf} , and the variance of average log wages between firms, V_{bf} . We estimate this decomposition as follows. Denoting the total number of firms in a given year by J , and the number of employees we observe in firm $j = 1, \dots, J$ by N_j , such that the total sample number of employees is $N = \sum_{j=1}^J N_j$, then we can write

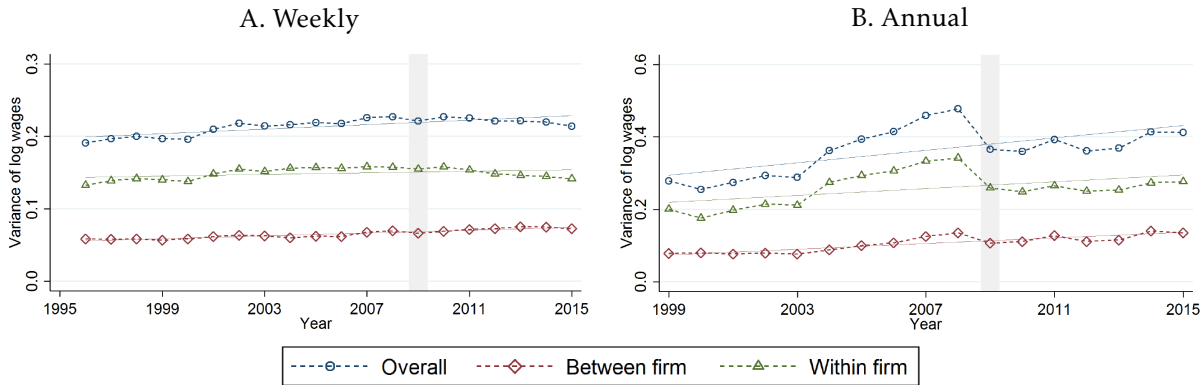
$$\underbrace{\frac{1}{N} \sum_{j=1}^J \sum_{i=1}^{N_j} (w_{ij} - \bar{w})^2}_{\text{Overall - } V_e} = \underbrace{\frac{1}{N} \sum_{j=1}^J \sum_{i=1}^{N_j} (w_{ij} - \bar{w}_j)^2}_{\text{Within-firm - } V_{wf}} + \underbrace{\sum_{j=1}^J \frac{N_j}{N} (\bar{w}_j - \bar{w})^2}_{\text{Between-firm - } V_{bf}}, \quad (1)$$

where w_{ij} , \bar{w} , and \bar{w}_j denote respectively the log wage of employee i in firm j , the sample mean of log wages, and the sample mean of log wages within firm j .¹¹ For convenience we leave implicit the dependence of j on i throughout the paper. The term capturing the between-firm component of wage dispersion weights by employment share the observed distance of a firm's estimated average wage to the overall average wage, such that larger firms have a potentially greater influence on wage dispersion than smaller firms. There are two potential choices for how to weight firms: by their shares of employee observations in the sample, or by their relative size as indicated by the IDBR recorded numbers of employees. Our preference throughout is the former, but we find the choice has no qualitative effect on results (see for example [Figure C6](#)).

¹¹Sampling errors in the measures of firm average wages (or hours) will generally induce a positive bias in between-firm variance estimates and their shares of the overall variance. We do not attempt to correct this, and instead rely on our analysis being focused on trends, since the size of this bias is unlikely to vary significantly over the period studied. The literature in this area, such as [Card et al. \(2013\)](#), also acknowledges the bias from sampling error, and similarly tends to ignore it, by arguing that trends are unlikely to be affected. Here we are especially reliant on any changes to the NESPD/ASHE sample frame or method not affecting the level of bias over time. We are confident that this is qualitatively the case, given our knowledge of the timing of any such changes, as discussed in [Online Appendix A](#).

Table 1 summarises the decomposition results discussed throughout this section. Since the data are not top-coded and a small sample, we exclude the top one percent of all earners from the variance calculations in this section. Throughout the remainder of the paper we mostly focus on weekly wages, as these are recorded in the data independently of an employer’s response for the hours worked of their employees. Further, this sample includes jobs which are less than a year old. These jobs would be excluded from an analysis of annual wages and their importance within the true wage distribution could vary over time. Figure 3 plots the estimated components of (1) for each year between 1996 and 2015 for full-time employees. Overall wage dispersion is increasing when measured over the entire sample period (column (9), Table 1). However there is an observable difference pre and post the 2008 financial crisis. The latter period experienced falling inequality, mostly accounted for by the decreasing variance of wages within firms, whilst at the same time between-firm inequality continued to increase. Prior to 2008, the increase in within-firm inequality explained the majority of the overall trend (over 80 percent: column (7), Table 1). The overall variance of log weekly wages mirrors closely the pattern of the within-firm component, as can be seen in Figure 3A. It is clear that the pre-2008 increase and the post-2008 decrease in inequality were driven mostly by the within-firm component in Britain (see also Figure C7A). A similar conclusion holds for annual wages in Figure 3B (see also Figure C9A). Just over forty percent of the long-run increase in annual wage inequality was accounted for by between-firm variation, compared, for example, with sixty percent found by Song et al. (2016) for jobs in large US firms. The decrease in wage dispersion during the financial crisis is also more pronounced in annual wages, and accounted for mostly within firms.

FIGURE 3: Within- and between-firm components of the variance in log employee wages, 1996-2015



Note.- author calculations using the NESPD, age 16-64 and full-time employees only. ‘Weekly’ exclude overtime. ‘Annual’ wages are for employees with the firm at least one year. The data is for all large firms in the NESPD who have at least ten full-time employee wage observations in that year. The top one percent of wage values in each year are excluded from calculations here. Shaded areas represent official UK recessions. Lines without markers are linear trends.

TABLE 1: Summary of decomposition results for the variance in real log employee wages

| | 1996/9* | | | 2005 | | | 2015 | | | Change 1996/9-2005 | | | Change 1996/9-2015 | | |
|-------------------------|--------------|--------------|--|--------------|--------------|--|--------------|--------------|--|--------------------|--------------|--------|--------------------|---------------|--------|
| | Level (1) | Share (2) | | Level (3) | Share (4) | | Level (5) | Share (6) | | Level (7) | Share (8) | | Level (9) | Share (10) | |
| Raw weekly wages: | 0.191 | | | 0.219 | | | 0.214 | | | 0.028 | | | 0.023 | | |
| Between: total | 0.058 | 0.305 | | 0.062 | 0.284 | | 0.072 | 0.339 | | 0.004 | | | 0.014 | | |
| Hourly wages bf | 0.074 | 0.387 | | 0.072 | 0.331 | | 0.083 | 0.389 | | -0.001 | | | 0.009 | | 0.002 |
| Usual hours bf | 0.005 | 0.029 | | 0.004 | 0.016 | | 0.004 | 0.016 | | -0.002 | | | -0.002 | | -0.012 |
| Covariance bf | -0.021 | -0.110 | | -0.014 | -0.063 | | -0.014 | -0.067 | | 0.007 | | | 0.007 | | 0.043 |
| Within: total | 0.133 | 0.695 | | 0.157 | 0.716 | | 0.141 | 0.661 | | 0.024 | | | 0.009 | | -0.034 |
| Hourly wages wf | 0.138 | 0.723 | | 0.161 | 0.734 | | 0.139 | 0.650 | | 0.023 | | | 0.001 | | -0.073 |
| Usual hours wf | 0.003 | 0.016 | | 0.006 | 0.027 | | 0.006 | 0.028 | | 0.003 | | | 0.003 | | 0.012 |
| Covariance wf | -0.008 | -0.044 | | -0.010 | -0.045 | | -0.003 | -0.016 | | -0.001 | | | -0.001 | | 0.027 |
| Unobs. weekly wages: | 0.082 | | | 0.090 | | | 0.090 | | | 0.008 | | | | | |
| Between | 0.024 | 0.277 | | 0.019 | 0.211 | | 0.019 | 0.211 | | -0.005 | | | | | |
| Within | 0.058 | 0.713 | | 0.071 | 0.789 | | 0.071 | 0.789 | | 0.013 | | 0.076 | | | |
| Raw annual earnings: | 0.279 | | | 0.393 | | | 0.412 | | | 0.115 | | | 0.133 | | |
| Between | 0.078 | 0.281 | | 0.010 | 0.254 | | 0.135 | 0.328 | | 0.022 | | | 0.057 | | |
| Within | 0.201 | 0.719 | | 0.293 | 0.746 | | 0.277 | 0.672 | | 0.093 | | 0.027 | 0.076 | | -0.047 |
| Unobs. annual earnings: | 0.202 | | | 0.303 | | | 0.303 | | | 0.101 | | | | | |
| Between | 0.039 | 0.189 | | 0.047 | 0.157 | | 0.047 | 0.157 | | 0.008 | | | | | |
| Within | 0.163 | 0.811 | | 0.256 | 0.843 | | 0.256 | 0.843 | | 0.093 | | 0.032 | | | |
| Raw weekly wages: | 0.574 | | | 0.629 | | | 0.601 | | | 0.055 | | | 0.027 | | |
| Between: total | 0.204 | 0.356 | | 0.204 | 0.325 | | 0.218 | 0.363 | | 0.000 | | | 0.014 | | |
| Hourly wages bf | 0.092 | 0.160 | | 0.090 | 0.143 | | 0.099 | 0.165 | | -0.002 | | | 0.007 | | 0.005 |
| Usual hours bf | 0.051 | 0.090 | | 0.050 | 0.080 | | 0.049 | 0.082 | | -0.001 | | | -0.002 | | -0.008 |
| Covariance bf | 0.061 | 0.106 | | 0.064 | 0.102 | | 0.070 | 0.116 | | 0.003 | | | 0.009 | | 0.010 |
| Within: total | 0.370 | 0.644 | | 0.424 | 0.675 | | 0.383 | 0.637 | | 0.055 | | | 0.013 | | -0.007 |
| Hourly wages wf | 0.169 | 0.295 | | 0.171 | 0.272 | | 0.139 | 0.231 | | 0.002 | | | -0.031 | | -0.064 |
| Usual hours wf | 0.133 | 0.232 | | 0.199 | 0.316 | | 0.188 | 0.312 | | 0.066 | | | 0.055 | | 0.081 |
| Covariance wf | 0.068 | 0.118 | | 0.055 | 0.087 | | 0.056 | 0.094 | | -0.013 | | -0.030 | -0.011 | | -0.024 |

* Weekly values refer to 1996, annual to 1999.

Note.- author calculations using the NESPD. See text for further description of the data sample and methods. *bf* and *wf* refer to the between- and within-firm components of the total variance. Unobserved wages control for 3-digit occupations. Relevant rows may not sum exactly due to rounding.

It is apparent that over the last two decades any short or medium-term inequality changes are not driven by the between-firm component. Overall wage inequality exhibits stronger co-movement with its within-firm component than the between, implying that the latter is less important in driving any overall changes. This result also holds when we consider three sub-samples, each consisting of approximately a third of the employee observations: the public sector, SIC 2003 sectors G-H (wholesale, retail, hotels, restaurants etc.), and the remainder of the private sector (Figure C7). Given we consider only full-time employees up to this point, unsurprisingly the results are qualitatively unchanged for hourly wage inequality (Figure C8). Where we can identify firms exactly at the enterprise level, using the ASHE datasets for 2002-15, results are also not qualitatively different (Figure C10).

The changes in weekly wage variance are small in magnitude compared with those measured for annual earnings. Two potential reasons for this difference are not plausible. First, employees with less than a year of tenure in jobs, not represented in the annual earnings decomposition, could have had increasingly similar wages. However, their sample weight is not large enough for this to be a plausible explanation, even if it were the case. Barth et al. (2016) find that ignoring job changers' wages in fact relatively dampens the measured change in US annual wage inequality. Second, though the share of bonuses in total pay was approximately constant over the period, there could have been increasing variance in these payments. If this were an important factor, we would expect to see greater increases at the top of the annual wage distribution when compared with the weekly, which we do not see in Figure 2. A third likely explanation, which we cannot precisely identify in this data, is that hours worked in jobs throughout the year have become more variable, especially in low-paying jobs. Although our sample of annual wages conditions on workers who are full-time in April, their hours could fluctuate over the year, including any overtime. Our view is that this explanation is the most likely.

For weekly measures we can also identify the determinants of actual wage inequality, as opposed to earnings, by further decomposing gross weekly wages into the components which account for the variance in log hourly wages, θ , log weekly hours worked, h , and their covariance:

$$V_{wf} = V_{wf}^{\theta} + V_{wf}^h + 2cov_{wf}(\theta, h), \quad (2)$$

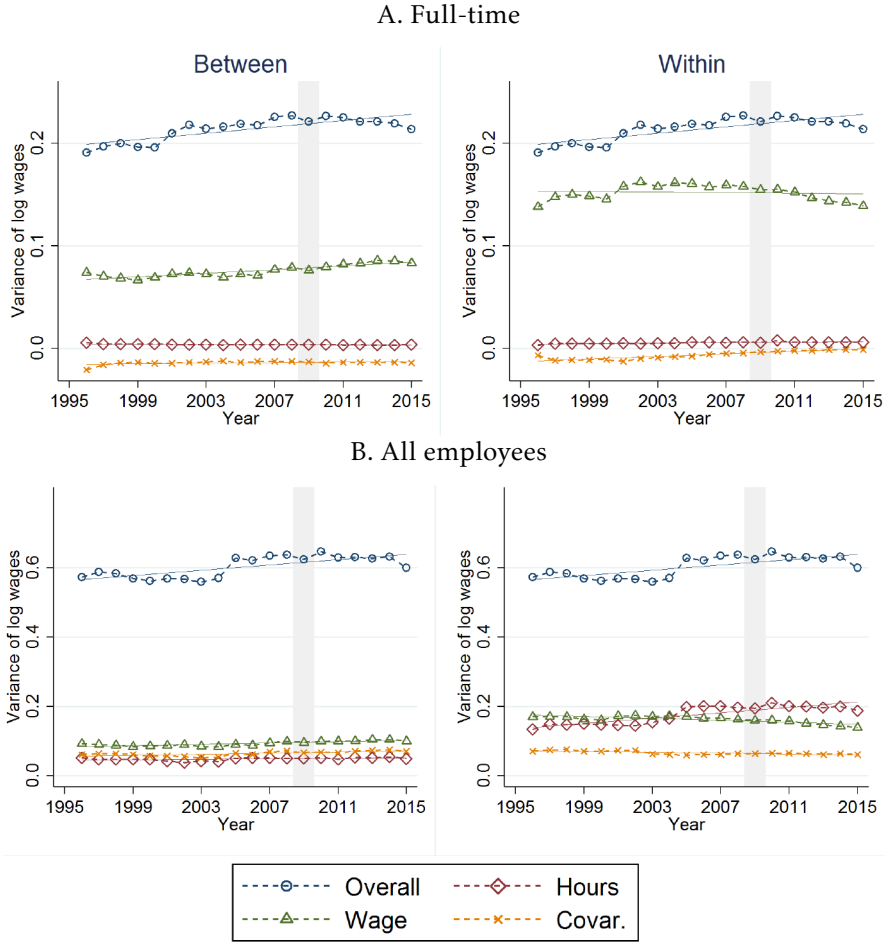
$$V_{bf} = V_{bf}^{\theta} + V_{bf}^h + 2cov_{bf}(\theta, h) \quad (3)$$

(see Online Appendix B.1 for exact definitions and derivations of these terms). The covariance terms are potentially large, since both individual and firm average wages and hours are known to be strongly correlated.

Figure 4 plots the decomposition described by (2)-(3) for weekly wages. Unlike other related studies, we can show explicitly that the variation in hours worked does not affect the decomposition results for full-time employees. Both between- and within-firm hours variance components together account for less than five percent of weekly wage variance throughout the period (column (2), (4), & (6), Table 1). This offers some support to results in other studies which cannot directly observe hours, but restrict their attention to full-time employees, such

as in Card et al. (2013). When we contrast this with a decomposition of weekly wage variance which includes those working part-time, changes in the variance of hours worked within firms most closely determine overall inequality changes: in the last two decades firms have been increasingly using a mix of part- and full-time employees. However, the sharp increase in wage variance among all employees in 2004-05 measured here coincides with a methodological shift in the survey, where more low-paid and part-time jobs without PAYE numbers were sampled. We discuss this further in the Online Appendix, but it is a good reason why we mostly focus on only full-time workers throughout the analysis here. In terms of levels, the combined hours components account for as much as forty percent of overall wage inequality. The covariance in hours and wages, both within and between firms, is also a significant part, accounting for as much as twenty percent, reflecting the tendency of part-time jobs to be more commonly low-wage.

FIGURE 4: Within- and between-firm, hourly rate and usual hours components of the variance in log weekly employee wages, 1996-2015



Note.- author calculations using the NESPD, age 16-64 only. Wages and hours exclude overtime. The top one percent of wage values in each year are excluded from calculations here. The data is for all large firms in the NESPD who have at least ten (full-time) employee observations in that year. The 'Covar.' series represent twice sample covariance terms. The 'Overall' series, in both left and right panels, is the total sample variance. As such, all other series across both panels sum within year to this total variance. See the text for further details of how the sample is constructed. Shaded areas represent official UK recessions. Lines without markers are linear trends.

3.1 Observed vs unobserved wage inequality

In Section 2 we described how the baseline sample has changed over time in terms of firm size, and the industry sectors and occupations represented. Further, we cannot be certain that the results are unaffected by changes in how much some characteristics of jobs are rewarded: for example, the recent rise in the London wage premium, which could potentially manifest as greater between-firm inequality.¹² To account for this, we regress log wages in each year of our sub-samples of the NESPD on employee characteristics, and then describe inequality in the resulting unobservable part: i.e. for each year, sample and measure of wages we estimate

$$w_{ij} = \mu + \beta' \mathbf{x}_{ij} + \underbrace{\alpha_j + \varepsilon_{ij}}_{\text{unobs.} - \psi_{ij}} , \quad (4)$$

where in each wage regression we include a minimum set of controls in the vector \mathbf{x}_{ij} for sex, age and its square, and the region of employment, and β is a vector of coefficients. What we call the unobservable part of wages is given by ψ_{ij} , and includes a firm-specific component α_j and the remaining heterogeneity in wages, which is left in the error term ε_{ij} . We use the estimated values of ψ_{ij} for each year to study how additional controls included in \mathbf{x}_{ij} , in particular for employee occupations, could allow us to more precisely determine the sources of wage inequality trends.¹³

At this point we acknowledge a limitation of our approach. What we call firm-specific effects are not comparable to the firm wage premiums identified by job-switching in [Card et al. \(2013\)](#) and [Song et al. \(2016\)](#) among others. Instead estimates $\hat{\alpha}_j$ should be interpreted as measuring the composition-adjusted differences of firm average wages from the overall employee sample mean, in each year. Their absolute levels and variance are surely biased upwards by not addressing unobservable worker heterogeneity and its distribution across firms. Several other studies in this literature have estimated firm premiums using variants of the two-way worker- and firm-fixed effects model of [Abowd et al. \(1999\)](#). However, as discussed at length by [Card et al. \(2016\)](#), estimates obtained from this model are prone to several sources of bias. We anticipate that these would be large using one percent samples of firm employees, making the interpretation of any results a significant challenge. For example, there is a well-known and typically substantial negative bias in small sample settings on the estimated correlation of worker- and firm-effects, with a coinciding positive bias on the variances of these individual effects. Our approach however has the advantage of allowing the sample and firm-specific effects to vary each year. It is also a tractable way to assess the combined roles of the changing observable composition of employment and wage premiums.

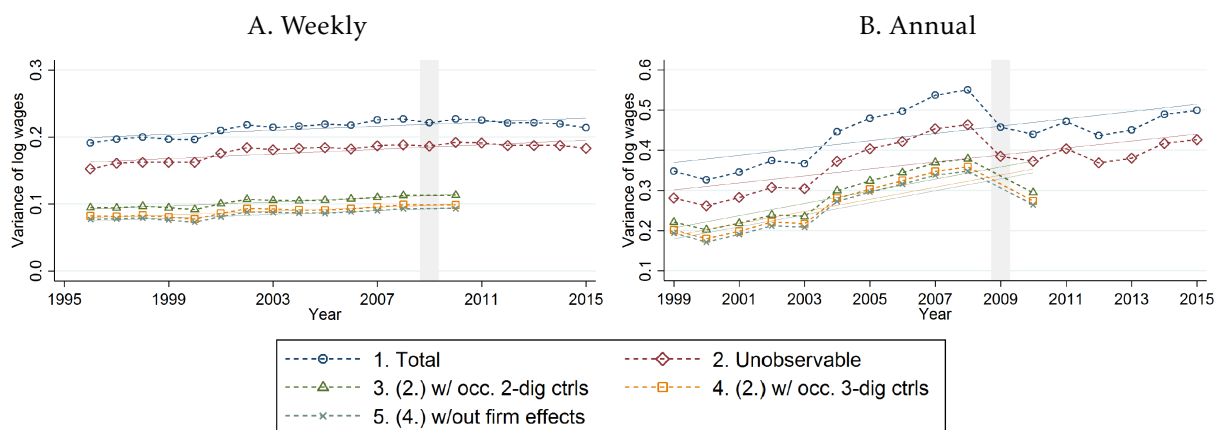
Figure 5 compares the total variance of log weekly and annual wages with the variance of the estimated values for their unobservable parts, using alternative specifications of the wage

¹²For example, ONS published results from the ASHE for the nominal median weekly pay of full-time employees show an increase between 1997 and 2007 of forty-five percent in London, compared with thirty-five percent in the North East.

¹³We do not have information on years of education, or some other explicit proxy for levels of human capital. The only way we can mitigate the resulting concern, that this missing information would be correlated with occupation controls, is by considering the robustness of any results whilst varying the detail of the occupational classification used.

regression described above: we compare $var(w_{ij})$ and $var(\hat{\psi}_{ij})$, with the difference between these values being the sum of variance in the estimated observable part of wage heterogeneity and twice its covariance with the firm-specific effects. For both measures of wages, the patterns over time appear to be mostly unaffected by the inclusion of controls in (4) for regions, age groups and gender (comparing series 2. with 1.). This implies that any dynamic changes in the overall composition of our baseline sample of the NESPD and/or wage premiums for these observable employee characteristics are insignificant. In other words, the changes in British wage inequality over this period are to some extent unobservable changes, occurring within sex, age groups and regions. However, adding controls for the occupational content of wages not only significantly explains a large part of the level, but also decreases the amount of the increase in wage inequality in the decade prior to the Great Recession which is accounted for by greater variance in unobservable heterogeneity (comparing series 3. and 4. with 1. and 2. in Figure 5, or column (7) in Table 1). This is increasingly the case when we control for a more detailed group of occupations. Changes in between-occupation inequality and the sorting of workers across occupations are important contributors to total changes in earnings inequality. We also show estimates of the residual variance, excluding firm effects from the estimated wage regressions. Though these are less robust, since they overestimate the role of occupations in the overall level, and potentially in the changes over time, the results show a similar pattern to those which include firm-specific effects.

FIGURE 5: Variance of estimated unobservable log employee wages, 1996-2015

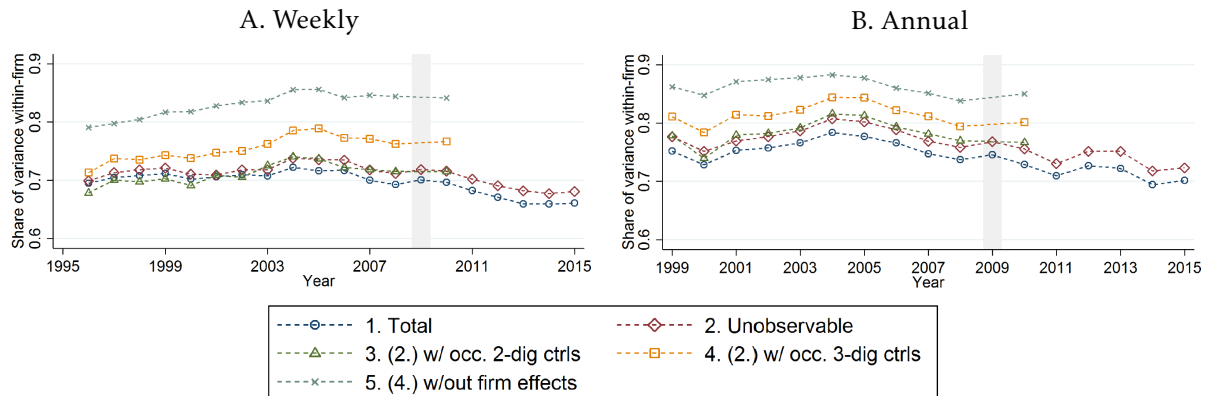


Note.- author calculations using the NESPD, age 16-64 and full-time employees only. ‘Weekly’ exclude overtime. ‘Annual’ are for employees with the firm at least one year. The top one percent of wage values in each year are excluded from calculations here. The data is for all firms in the NESPD who have at least ten full-time employee observations. ‘Total’ gives the total variance. All unobservable log wages are estimated using regressions with controls for sex, age, age squared and major regions. (2.)-(4.) include estimates of firm-specific effects, and respectively (3.) and (4.) add controls for ISCO 2- and 3-digit groups. (5.) is the variance of residuals from an estimation of the wage regression without firm-specific effects.

We can also account for the role of between-firm differences in unobservable wage inequality changes, by replacing the values and statistics for w with estimates $\hat{\psi}$ in (1). Figure 6 shows that by conditioning on 3-digit occupation groups the share in the overall variance level of the between-firm component, $var(\hat{\alpha}_j)$, is reduced on average from a third to a quarter for weekly wages, and from a quarter to a fifth for annual earnings (comparing series 4. with 1. and 2.). Unsurprisingly, a part of the difference in average wages across firms is accounted for by the types of workers they employ. More important for our focus on trends, the share of

unobservable wage variance which is within-firm, $var(\hat{\varepsilon}_{ij})$, is increasing over time, relative to the equivalent share of total wage variance, addressing the role of changing occupation-specific wage premiums and their composition in our sample. This suggests that measured changes in the actual between-firm component represent changes to between-occupation inequality and the distribution of occupations across firms.

FIGURE 6: Share of within-firm component in the variance of estimated unobservable log employee wages, 1996-2015



Note.- see Figure 5.

4 Inequality changes throughout the wage distribution

In analysing the dynamics and components of an aggregate measure of wage inequality we could be neglecting a more complex evolution of the cross-sectional wage distribution. To determine the role of firms in changes across and within the distribution of wages, we employ a graphical method popularised by [Juhn et al. \(1993\)](#), and subsequently adapted by [Song et al. \(2016\)](#) and [Benguria \(2015\)](#) among others. Simply we can write employee log wages as

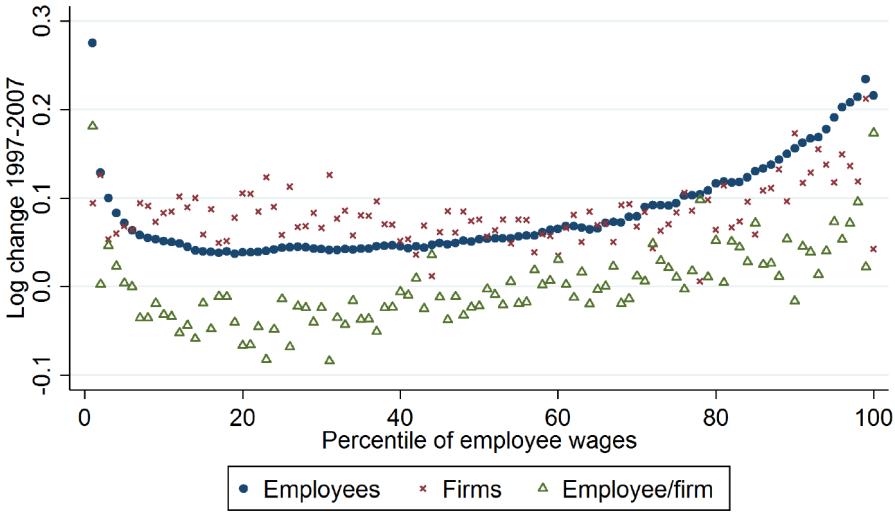
$$\underbrace{w_{ij}}_{\text{Employees}} = \underbrace{\bar{w}_j}_{\text{Firms}} + \underbrace{[w_{ij} - \bar{w}_j]}_{\text{Employee/firm}} . \quad (5)$$

We then compute estimates of the averages of each term in (5) within each percentile bin of the employee wage distribution in every year. By considering the resulting differences across percentiles and between years, we can then account for the role of firm average wages, as opposed to the relative difference between employees' wages and their firms' averages, in driving wage inequality changes. We also report a heuristic measure of what moves the wage distribution, which captures the share of the variance across percentiles in average wage changes accounted for by covariance with changes in the 'Employee/firm' (within-firm) component:

$$\gamma = \frac{cov(\Delta\{\bar{w}_{ij} - \bar{w}_j\}_p, \Delta\bar{w}_p)}{var(\Delta\bar{w}_p)} , \quad (6)$$

where $\Delta\bar{w}_p$ gives the change between two periods in the sample average log employee wage in percentile bin p .

FIGURE 7: Change 1997-2007 in the average real log weekly wage by percentile of employees, and the contribution from firms



Note.- author calculations using NESPD, age 16-64, full-time employees only. Weekly exclude overtime. The data is for all firms in the NESPD who have at least ten full-time employee observations. The ‘Employees’ values are computed by taking the average log real wages of employees within each percentile, increasingly ordered by the level of wages in each year, and taking the difference between years. The ‘Firms’ values are computed by taking the average across workers, in each percentile, of the average log wages of the firms they work for, in each year, and then taking the difference across years. The ‘Employees/Firms’ values are the residual difference between these other two lots: equivalently, the average across workers, in each percentile, of the log difference in employee wages from their firms’ average value, in each year, and taking the difference across years. $\gamma = 0.68$.

4.1 Actual employee wages

Figure 7 represents this graphical decomposition for the change in real log weekly wages between 1997 and 2007, using the baseline sub-sample of full-time employees. The relatively smooth ‘Employees’ series plots the change in the average log wage of workers in each percentile between the two years. To avoid confusion, these are unlikely to be the same individuals: this is a comparison of annual cross-sections. Each percentile is decomposed using around four to five hundred job observations in each year. A positive slope across percentiles indicates that in some portion of the wage distribution inequality has increased. For example, wages at the median increased by 5 log points (5%) over this period, but by 10 points (11%) at the seventy-fifth percentile, and 20 points (22%) at the ninety-fifth. Representing the evolution of wage inequality in this way shows that small changes in the time series of overall log wage variance can belie starker inequality dynamics. For instance, here we see that inequality fell among the very lowest earners, potentially due to the introduction of the National Minimum Wage in 1999. By construction, the average level of the ‘Firms’ components across percentiles is the same as that for ‘Employees’, and the ‘Employee/firm’ component is centred about zero. For the graphical analysis it is the slopes of these series across the percentiles which concern us. The firms component contributes somewhat to the rise in wage inequality at the top of the wage distribution, but the employee/firm component also contributes, increasing across the percentiles from the twentieth onwards. This is consistent with results for the US in Song et al. (2016), that among large firms the between-firm component appears to not be wholly driving wage dynamics. However, in Great Britain for this period, for smaller firms than what are considered large in Song et al. (2016), the firms component is weaker. The within-firm change

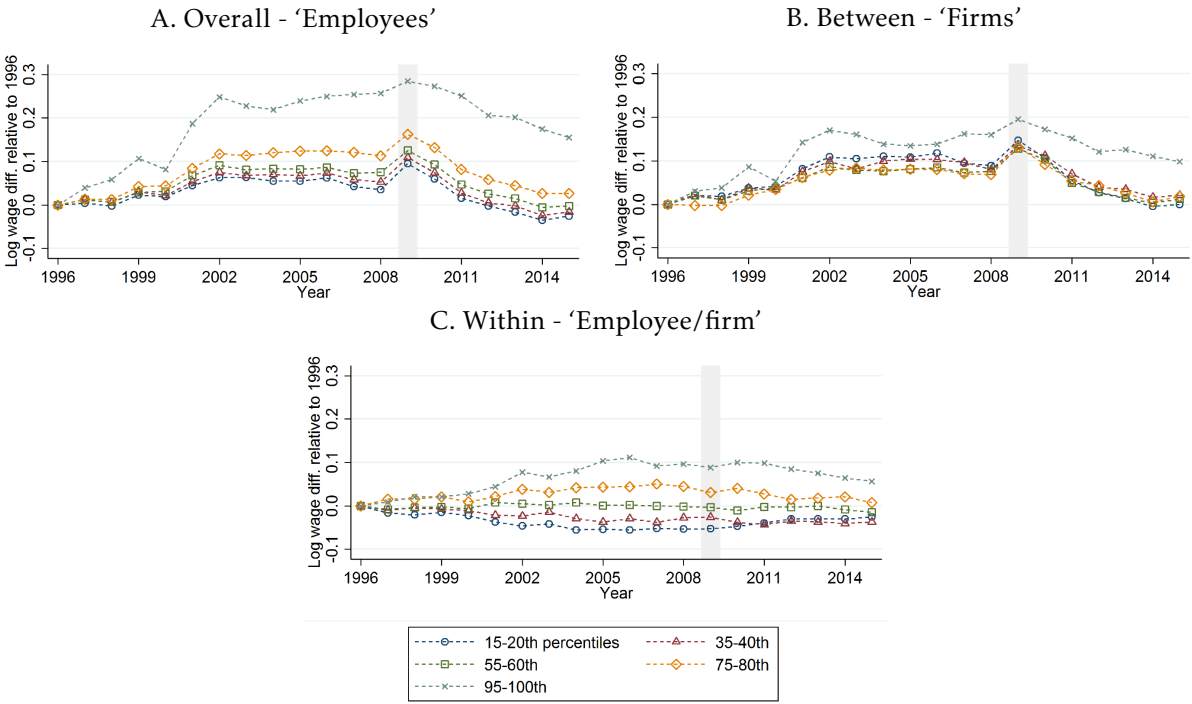
accounts for over two-thirds of the overall movement at percentiles across the distribution: $\gamma = 0.68$.

For this graphical decomposition we retain the top one percent of earners in the sample. The very top of the income and wage distribution has drawn significant attention recently, especially in the US (see [Piketty, 2013](#); [Song et al., 2016](#)). Although based on a small sample of these top earners in Britain, we can see from [Figure 7](#) that average weekly wages in the top one percent for 1997-2007 did not experience greater relative increases than those in the top decile. However, over eighty percent of the log wage increase for the top one percent occurred within firms, notably higher than for all other percentiles besides the bottom one percent.

Before progressing further, we also represent the change in inequality since the Great Recession, for 2008-2015, in the same way ([Figure C11](#)). We demonstrate here that our results are unaffected if we instead use the administrative definition of an enterprise from the ASHE datasets to define firms. Real wages decreased across the whole distribution since the financial crisis, but inequality also fell. However, there is no suggestion in the data that this can be accounted for by changes in the differences in average wages between firms. In fact, the within-firm component more than explains the changes across the distribution: $\gamma > 1$.

We consider how consistent these results are across the whole time period. Still focusing on full-time weekly wages, [Figure 8](#) plots the changes for selected ventiles of the employee weekly wage distribution relative to 1996. The average wages paid by firms can account for some of the relatively greater increase in the top five percent of employee wages in the early 2000s. But dispersion within firms explains most of the overall inequality dynamics over the last two decades.

FIGURE 8: Average real log weekly wage of employees in selected ventiles, relative to 1996, and contributions from firms



Note.- see [Figure 7](#).

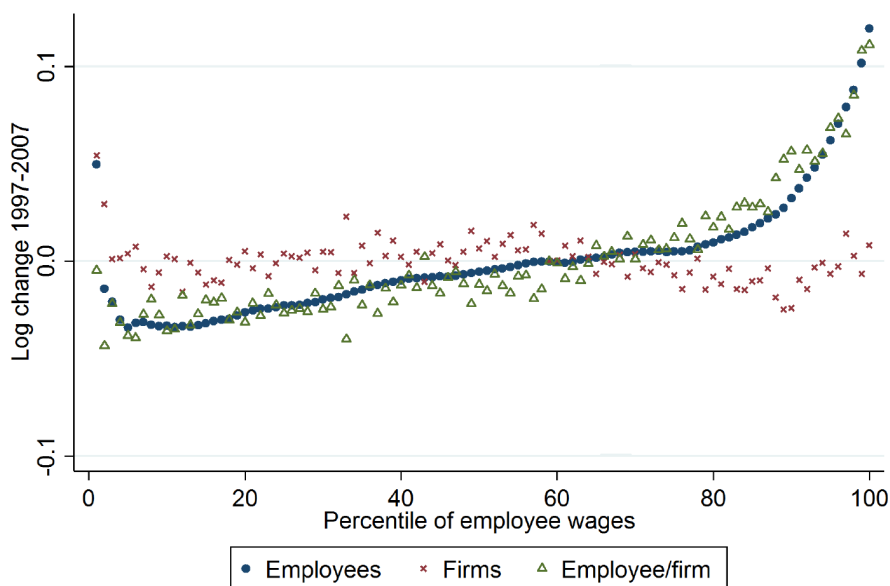
4.2 Unobservable wage heterogeneity

Figure 9 shows an equivalent decomposition for 1997-2007 as Figure 7, but only for the estimated unobservable part of wages $\hat{\psi}_{ij}$, including firm-specific effects, and controlling for occupation groups:

$$\underbrace{\hat{\psi}_{ij}}_{\text{Employees}} = \underbrace{\bar{\hat{\psi}}_j}_{\text{Firms}} + \underbrace{\left[\hat{\psi}_{ij} - \bar{\hat{\psi}}_j\right]}_{\text{Employee/firm}}, \quad (7)$$

where $\bar{\hat{\psi}}_j = \hat{\alpha}_j$ and $\left[\hat{\psi}_{ij} - \bar{\hat{\psi}}_j\right] = \hat{\varepsilon}_{ij}$.

FIGURE 9: Change 1997-2007 in the average real unobservable log weekly wage by percentile of employees, and the contribution from firms



Note.- author calculations using NESPD, age 16-64, full-time employees only. Weekly exclude overtime. The data is for all firms in the NESPD who have at least ten full-time employee observations. Unobservable log wages are estimated using a regression with controls for sex, age, age squared, major regions, ISCO 3-digit groups and firm-specific effects. $\gamma = 1.00$. See notes for Figure 7 or the text for a description of how series are calculated and interpretation.

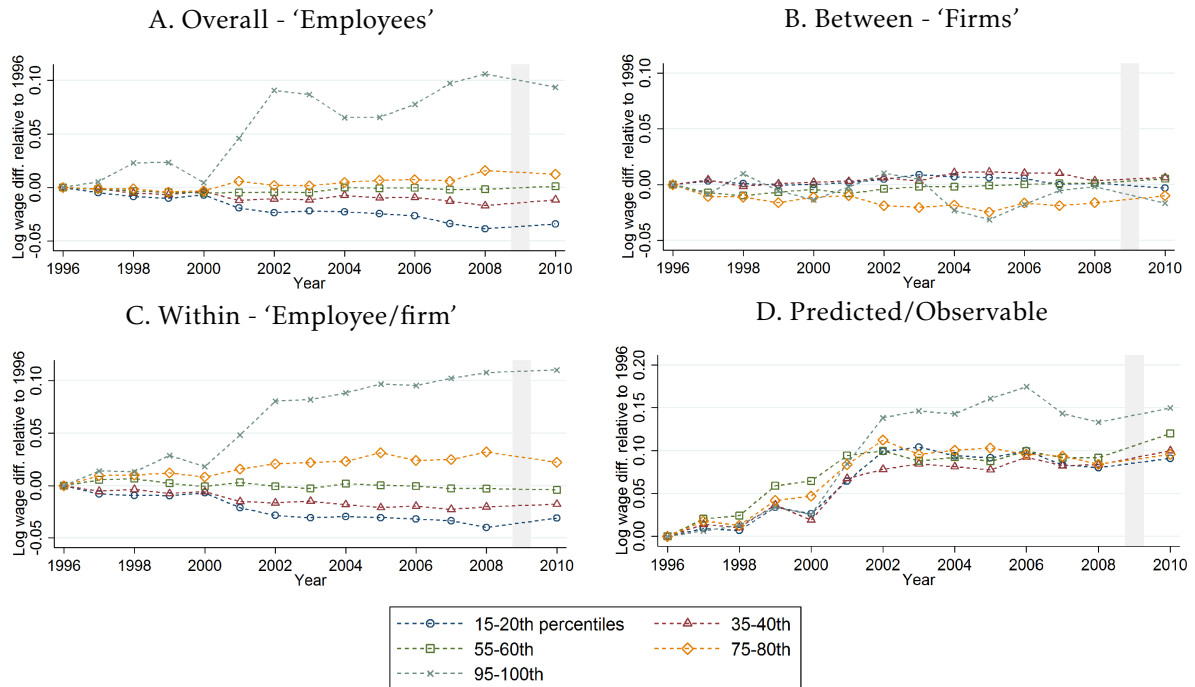
The pattern of unobservable employee wage changes across percentiles noticeably differs. There is rising inequality across the distribution, with the slope becoming steeper from the eightieth percentile upwards. Firm average unobservable wages did not account for these dynamics: neither for rises below the eightieth percentile, nor the greater increase in the highest wages, $\gamma = 1.00$.¹⁴ In Figure C12 we consider alternative estimates of unobservable wages. In panel A, we can see that other controls, including the firm-specific effects, are not driving this result. In panel B, controlling for less detailed occupation groups still relatively reduces the estimated role for firm-level differences. In panels C and D we show that not including firm-specific effects would lead us to overestimate the role of occupational inequality. This leads us to conclude that any change in the differences in average wages between large firms is mostly due to some combination of between-occupation inequality and the concentration of high- or low-wage occupations within firms. Further, given that the main

¹⁴Where γ , with the inclusion of firm-specific effects, is measured by $cov(\Delta\bar{\varepsilon}_p, \Delta\bar{\psi}_p)/var(\Delta\bar{\psi}_p)$.

result here does not qualitatively depend on firm-specific controls, it is possible that results in other studies, which assign some of the importance of changes in the between-firm component to industrial change, are to an extent misrepresenting a more significant role of occupations.

Figure 10 replicates Figure 8 but instead for unobservable wages. There is no substantial contribution from between-firm inequality to the dynamics of the unobservable part of the wage distribution since 1996. Panel D also includes the contribution from the observable or predicted part of the real wage distribution, $\Delta\{\hat{\mu} + \hat{\beta}'\mathbf{x}_{ij}\}_p$. Here we can see explicitly how wage premiums and the prevalence of high paying occupations in our sample particularly account for the rise in inequality at the top of the employee wage distribution. Figure C13 further demonstrates the robustness of this result across all percentiles, considering changes over other ten-year periods, each beginning in a year between 1996-2000.

FIGURE 10: Average real (un)observable log weekly wage of employees in selected ventiles, relative to 1996, and contributions from firms



Note.- see Figure 9.

4.3 Additional results and robustness checks

So far in this section we have only discussed the dynamics of weekly wages for full-time employees working for firms with at least ten job observations in the NESPD in any given year. We can also check whether results change for the period 1997-2007 when we alter these aspects of the sample. Figures C14-C16 decompose the log change in the weekly wages of full-time employees who are employed by large enterprises with at least one, five or twenty employee job observations. For actual wages, as we increase the sample size and include some smaller firms, it becomes clearer graphically that the firms component cannot explain inequality dynamics. Considering the unobservable part of wages, with controls for occupations, the results are also qualitatively unchanged as we vary the average firm size in our sample.

In Figure C17 we return to our baseline sample, but now study only private sector employees. Again the results are unaffected. Further, Figure C18 shows that there is no qualitative difference in results if we decompose hourly wage dynamics as opposed to weekly. For annual wages, Figure C19 demonstrates that for actual wage inequality the majority of the dynamics across percentiles are explained by the changing picture within firms. This is also the case when we turn to the inequality in unobservable annual wages. Finally, we also consider the picture for weekly wages including part-time employees, and after conditioning on employee characteristics, there is no suggestion in Figure C20 that firm average wages have driven inequality dynamics in this case also.

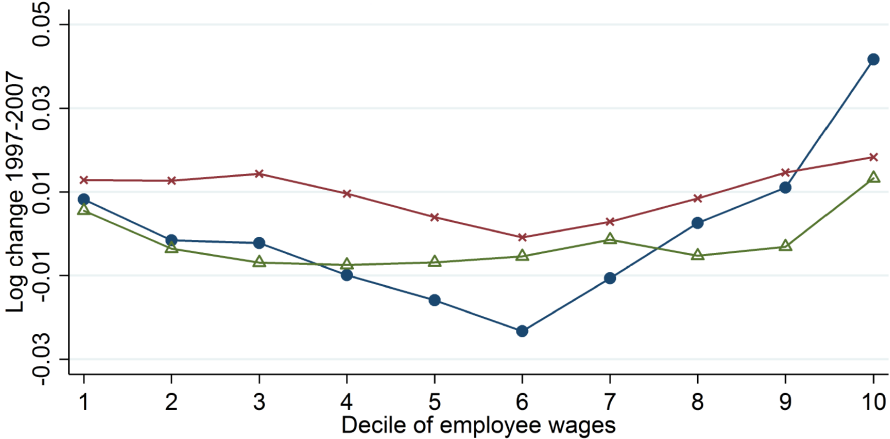
Returning to weekly wages and our baseline sample, Figure C21 looks at changes across all percentiles for five-year sub-periods. Notably for robustness, these are periods where the classification of occupations used in the NESPD is constant, and thus cross-walking was not necessary. As also seen above, the majority of recent increases in employee wage inequality occurred in the five years to 2001. There is no contribution to this from the firms component for unobservable log wages. This is also the case for actual wage inequality, apart from some contribution to greater changes above the ninety-fifth percentile. For 2002-07 and 2005-10, the rise in wage inequality is small, and is driven by greater wage changes for only the highest earners. But in both later sub-periods, once we account for the observable content of wages, the role of firm average wage differences is reduced.

To expand on these findings further, we focus on the ‘Firms’ component of the change between 1997 and 2007 in weekly wage residuals for full-time employees, represented by Figure C12A: i.e. the estimated firm-specific effects, with controls for some employee observables but not occupations in the log wage regression. Averaging these across employee wage percentiles, we carry out a shift-share decomposition. This accounts for the role of the changing occupational structure of the firms represented in each decile (see Online Appendix B.2 for details). Figure 11 shows the results of this decomposition. The ‘Wages’ component, which is computed by holding the occupational structure of firms representing the employees in each decile constant, and allowing only wages to change, does correlate across percentiles with the overall ‘Firms’ component. However, the between-firm inequality increase through the top deciles is mostly accounted for by the changing occupational structure of the firms who pay the highest wages, holding occupation wages constant.

5 Summary and further discussion

We have used well-known methods to answer whether recent trends in British wage inequality, viewed through a sample of employees at mostly very large firms, can be accounted for by between-firm inequality. We have found substantial evidence that in the last two decades this has not been the case. This is also clear when we consider estimates of unobservable wage heterogeneity, controlling for changes to occupational premiums and firm-specific effects. At first look, this would appear to contradict what is becoming a stylised fact, across several countries, that between-firm wage inequality is the most important driver of overall trends. But this is not the first paper to suggest that some part could be accounted for by the changing

FIGURE 11: Decomposing the firm component of employee real wage inequality patterns, 1997-2007: the role of changing firm occupation shares vs wages



Note.- this figure takes the average over deciles of the firm component of wage changes in Figure C12A (circle markers), and carries out a shift-share decomposition. The two components thereof reported here are as follows: first holding the average across employees of firm occupation shares constant, and considering only average occupational wage changes (cross markers), and second holding the average across employees of firm average occupational wages, in a decile, constant, but varying only firm occupation shares (diamond markers).

supply and demand of occupations across firms and labour markets (see Card et al., 2013; Song et al., 2016). We further believe our results can be reconciled with some of these previous studies. The analysis here is dominated by the very largest firms in Britain. Already Song et al. (2016) have shown that in the US firm size matters. Larger firms come from the starting point of having more diverse workforces and complex pay structures, and so there is far more scope for changes over time in the dispersion of wages within as they evolve. Second, we believe our results chime with another hypothesis from Song et al. (2016): the reason why within-firm inequality cannot account for overall dynamics, in most studies, could be due to the increasing occupational concentration, or specialisation, of firms, coinciding with falling costs of outsourcing work tasks, and their greater tendency to focus on so-called ‘core-competencies.’ The very large and long-lived firms, which dominate our sample, are where we might expect such changes in specialisation to mostly occur. Adding to this the continued trend of increasingly polarised demand for occupations in the British labour market (Goos & Manning, 2007; Williams, 2013), it is then not surprising that once we focus on the inequality dynamics of the estimated unobservable part of wages, with controls for changing occupational premiums and the composition of the workforce, the role of firm-specific differences becomes markedly weaker, or even non-existent.

The results here suggest that future analyses of this kind should attempt to seek out data which can address the possible role of the changing occupational structure of firms. Otherwise it could be challenging to identify whether inequality changes are accounted for by some greater segregation of workers across firms, or whether this to some extent reflects only the combined effects of changes to the occupational polarisation of employment and firm-level specialisation. In other words, the estimated role of assortative matching over innate firm and worker productivities could be overstated, if firms simultaneously alter their demand for occupations and skills.

A limitation of the analysis here is that we are restricted to studying repeated cross-sectional data of jobs and wages, since employers cannot be identified reliably across time for an extended period in the NESPD. Furthermore, the results only reflect what has happened for wages in mostly very large firms. We believe this is the limit of what can be achieved using current available British data sources, without small sample biases totally confounding any analysis. In a very recent paper, [Lee \(2016\)](#) attempts to overcome this and analyses the joint role of worker and firm heterogeneity in the level of UK wage inequality for 2002-2014, using the ASHE and estimating the [Abowd et al. \(1999\)](#) wage model. Although comparisons are somewhat suspect to the data, she nonetheless finds a smaller role for firm-level pay premiums than in other European countries. There is also some evidence in this analysis to suggest that firm pay levels are type-specific, with type referring to occupation or skill levels. To go further than this paper and our own results, we hope that existing UK administrative earnings data, for all employees and their employers, will be made available for research in the near future. Only then can the continuing large evidence gap regarding the determinants of British wage inequality be more completely addressed, with the NESPD's more detailed records of job characteristics, such as hours and occupations, serving as a useful supplementary data source.

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Recent changes in British wage inequality: Evidence from firms and occupations

Online Appendix

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Appendix A. Further description of the data and sample construction

In what follows we give some additional details regarding the datasets used, and how we have constructed the sub-samples thereof. All the relevant documentation and variable descriptions attached to these datasets are publicly available from the UK Data Service. The ONS has also published various documents concerning the data quality and consistency of the NESPD and ASHE. We will publish our replication files for the analysis and sample construction.

We focus on methodological details through the period 1996-2015. From 1975 to 2003, under its guise as the NESPD, very little changed in the methodology and construction of the longitudinal panel dataset. Throughout this period, it should be a true random sample of all employees in employment, irrespective of employment type, occupation, size of employer etc. Given the legal obligation of employers to respond, and their use of payrolls, it has a very high response rate and is believed to be accurate. There is also no cumulative attrition from the panel, as any individual not included in the NESPD in any year, for whatever reason, remains in the sampling frame the following year. Conditional on a hundred percent response, the NESPD would be a true one percent random sample of employees. However there are two major sources of undersampling, both occurring if individuals do not have a current tax record. This could occur for some individuals who have recently moved job, or for those who earn very little (mostly part-time), and so do not have to pay tax or National Insurance. From 2004 the ASHE replaced the NESPD. This aimed to sample some of those employees under-represented in the NESPD. It added supplementary responses for those without a PAYE reference, and also attempted to represent employees whose jobs changed between the determination of the sampling frame in January and the reference period in April. Since the ONS states that the bias these amendments were introduced to address were actually small, we do not believe they could affect our results substantially. The ASHE also introduced some imputations, using similar matched ‘donor’ observations where responses were, for example, missing an entry of basic hours but had recorded pay. These imputations were added for weighting purposes. We ignore these weights throughout our analysis because they are based only on employee data (age, sex, occupation and region of work place) to match population estimates obtained from the Labour Force Survey. Therefore using them would no longer allow us to claim that the ASHE and our results are based on random samples of employees within firms. From 2005, a new questionnaire was also created which was intended to reduce the latitude for respondents’ own interpretations of what was being asked of them. From 2007 there were further notable changes. Beforehand, occupations were classified as follows: either, if the respondent stated an employee’s job had not changed in the past year, the previous year’s occupational classification was applied. Otherwise, it was manually coded. Afterwards an automatic coding, text recognition, tool was used. “The effect of using ACTR was to code more

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jobs into higher paying occupations. The jobs that tended to be recoded into these higher paying occupations generally had lower levels of pay than the jobs already coded to those occupations. Conversely, they tended to have higher levels of pay than the other jobs in the occupations that they were recoded out of. The impact of this was to lower the average pay of both the occupation group that they had moved from and that they had moved to.” As such, this would certainly increase within occupation wage inequality for the highest earners, and reduce it for the lowest earners. Nonetheless, we do not believe this is significant in affecting our results. In the main text, we focus the graphical analysis on changes across the period 1997-2007, but also find our results are unchanged for the periods 1996-2006 and 1996-2001. From 2007, the sample size of the ASHE was reduced by twenty percent, with reductions targeted on those industries that exhibit the least variation in their earnings patterns. However, we do not believe this could have affected our results substantially.

To construct the sub-samples from the panel dataset for 1975-2015, for the analysis of hourly or weekly pay, we first drop a few cases of duplicates over all variables. Then, using the panel identifier, year, the information from the IDBR concerning enterprise status and number of employees, industry classification and gross weekly pay including overtime, we also drop some cases which are then determined to be the same job. We do not drop observations where an individual has multiple jobs. We keep only observations for individuals aged 16-64, and which have not been marked as having a loss of pay in the reference period through absence, employment starting in the period, or short-time working, and which are marked as being on an adult rate of pay (i.e. dropping trainees and apprenticeships). This is practically the same filter applied for ONS published results using the NESPD or ASHE. We also drop all observations with zero or missing values for basic hours, and hourly or weekly pay excluding overtime. Basic hours are intended to be a record for the employee in a normal week, excluding overtime and meal breaks. Gross weekly pay is the main recorded value in the survey, and from this overtime records are then simply subtracted. Hourly rates are then derived from dividing by basic hours worked. We drop observations with over a hundred basic hours worked, as these could reflect measurement error and inclusion of overtime. Full-time is defined as working over thirty basic hours in a week. But there are a tiny number of discrepancies in some years, we believe relating to teaching contracts, where the definition applied by the ONS differs. We however recode these such that for all observations the thirty hours threshold applies. To further address some potential for measurement error, especially in the recorded basic hours, we drop observations whose hourly rate of pay excluding overtime is less than eighty percent of the National Minimum Wage (NMW) which applies each April, with allowance for the different age-dependent rates of the NMW over time. We set the threshold lower to avoid dropping observations where employers have rounded figures about the NMW, where the degree of rounding could vary with the actual value of the NMW, a behaviour which has been hypothesised by the ONS. To then construct the large firms sample, we drop all employers whose exact enterprise reference number of employees from the IDBR, which is only available from 1996 onwards, is less than 250. We also drop observations where the IDBR status, number of employees or industry classification is missing. We then identify each employer in the dataset using the combination of their 5-digit industry code, IDBR status and exact number of IDBR enterprise employees, within each year. For large firms we are confident this can uniquely identify the reporting organisation of the NESPD. The large firms samples we subsequently analyse then condition on there being a minimum number of remaining job observations per firm in a year. For annual pay, we construct the large firms samples in the same way, except we additionally filter out observations where the employee is reported to not have been in the same job for twelve months, and drop observations with zero or missing values of annual gross pay in place of hours or weekly pay. When handling the ASHE annual cross-section datasets we use the exact same approach, except here there is a unique enterprise level identifier which we can use to identify the firms within each year.

For 1996-2001 occupations are classified using the 3-digit ONS 1990 Standard Occupational Classification (SOC). For 2002-2010, this is replaced with the 4-digit SOC 2000, and for 2011-2015, with the SOC 2010. We experimented using the ONS' publicly available cross-walk from 2010 and 2000 to 1990 classification, but discovered that this causes a large structural break in the distribution of occupations. In particular, it causes a substantial additional degree of polarisation of work from 2002 onwards, which would potentially generate erroneous and large increases in within occupation inequality around this date. To address this we rely on a conversion of SOC 1990 and 2000 to the 1988 International Standard Classification of Occupations (ISCO). We obtain these conversions from the Cambridge Social Interaction and Stratification Scale (CAMSIS) project. For the industry classification, we convert ONS Standard Industrial Classification (SIC) 2007 to 2003, using files made available by the UK Data Service. This conversion uses the 2008 Annual Respondents Dataset where both classifications were applied, and where any 2007 code mapping to multiple 2003 codes is decided using whichever of the two bore a greater share of economic output. For 1996-2002, the work region of the employee is missing, and so we derive this ourselves consistent with the ONS geo-maps, using the more detailed work area variable.

TABLE A1: Comparison of the baseline sample's firm size distribution, and represented employees, with the UK population of enterprises, 2013

| Enterprise size [†] | Number of obs. | | Total employees in enterprises (000s) [†] | |
|------------------------------|---------------------------|----------------|--|----------------|
| | Sample firms [‡] | UK enterprises | Sample firms | UK enterprises |
| 250 - 999 | 92 | 6,400 | 69 | 2,927 |
| 1,000 - 1,999 | 308 | 1,050 | 469 | 1,455 |
| 2,000 - 4,999 | 644 | 830 | 2,098 | 2,612 |
| 5,000+ | 596 | 635 | 8,204 | 8,805 |
| Total | 1,640 | 8,915 | 10,804 | 15,799 |

[†] Values for sample firms use the IDBR record of the number of employees in the enterprise, which includes the firm. This is not the number of observations of employee jobs in the sample.

[‡] All firms in the baseline sample with a minimum of ten full-time employee observations in the NESPD in 2013, and subject to the other sampling criteria described in the text.

Note.- author calculations using the NESPD. UK enterprises population figures from UK Business: Activity, Size and Location (IDBR, March 2015).

TABLE A2: Baseline sample's number of firm and employee observations by employer size, 1997 & 2007

| Enterprise size [†] | Firms | | | Employees | | | IDBR ent. employees (000s) [†] | | |
|------------------------------|-------|-------|-----------------|-----------|--------|-----------------|---|--------|-----------------|
| | 1997 | 2007 | Change in share | 1997 | 2007 | Change in share | 1997 | 2007 | Change in share |
| 250 - 999 | 125 | 43 | -0.05 | 1,729 | 497 | -0.03 | 89 | 32 | 0.00 |
| 1,000 - 1,999 | 352 | 214 | -0.08 | 5,322 | 2,814 | -0.06 | 539 | 328 | -0.02 |
| 2,000 - 4,999 | 512 | 548 | 0.05 | 10,068 | 9,789 | -0.03 | 1,612 | 1,817 | 0.03 |
| 5,000+ | 485 | 569 | 0.09 | 26,915 | 36,242 | 0.12 | 9,431 | 8,350 | -0.01 |
| Total | 1,474 | 1,374 | | 44,034 | 49,342 | | 11,671 | 10,525 | |

[†] Values use the IDBR record of the number of employees in the enterprise, which includes the firm.

Note.- author calculations using the NESPD.

TABLE A3: Baseline sample's incidence of ISCO88 major occupation groups

| Major group [†] | 1997 | 2007 | Change |
|--------------------------|------|------|--------|
| 1 | 0.12 | 0.15 | -0.02 |
| 2 | 0.22 | 0.16 | 0.06 |
| 3 | 0.09 | 0.14 | -0.05 |
| 4 | 0.24 | 0.20 | 0.03 |
| 5 | 0.11 | 0.14 | -0.03 |
| 6 & 7 | 0.08 | 0.04 | 0.04 |
| 8 | 0.08 | 0.05 | 0.03 |
| 9 | 0.05 | 0.11 | -0.06 |

[†] Key: 1. Legislators, senior officials and managers, 2. Professionals, 3. Technicians and associate professionals, 4. Clerks, 5. Service workers and shop and market sales workers, 6. Skilled agricultural and fishery workers, 7. Craft and related trades workers, 8. Plant and machine operators and assemblers, 9. Elementary occupations.
Note.- author calculations using the NESPD.

Appendix B. Mathematical details

B.1 Variance decomposition - hours and wages

From the main text, we can re-write (1), the total variance of log weekly wages as follows, where ω and η denote the hourly non-log wage rate and hours worked respectively, θ denotes the log hourly wage rate, and h denotes log hours. Recalling from the main text that i denotes a worker and j a firm, terms with a bar above refer to average values within the given subscript. For example, \bar{h}_j refers to the sample mean of log weekly hours worked for the employees within firm j . Terms without a subscript but a bar above refer to averages in the whole sample, across all employees and firms.

$$\underbrace{\frac{1}{N} \sum_j \sum_i^{N_j} [\ln(\omega_{ij}\eta_{ij}) - \overline{\ln(\omega_{ij}\eta_{ij})}]^2}_{\text{Overall - } V_e} = \underbrace{\frac{1}{N} \sum_j \sum_i^{N_j} [\ln(\omega_{ij}\eta_{ij}) - \overline{\ln(\omega_j\eta_j)}]^2}_{\text{Within-firm - } V_{wf}} + \underbrace{\sum_j \frac{N_j}{N} [\overline{\ln(\omega_j\eta_j)} - \overline{\ln(\omega\eta)}]^2}_{\text{Between-firm - } V_{bf}}, \quad (8)$$

with

$$V_{wf} = \underbrace{\frac{1}{N} \sum_j \sum_i^{N_j} [\theta_{ij} - \bar{\theta}_j]^2}_{V_{wf}^\theta} + \underbrace{\frac{1}{N} \sum_j \sum_i^{N_j} [h_{ij} - \bar{h}_j]^2}_{V_{wf}^h} + \underbrace{\frac{2}{N^2} \sum_j \sum_i^{N_j} [(\theta_{ij} - \bar{\theta}_j)(h_{ij} - \bar{h}_j)]}_{2cov_{wf}(\theta, h)} \quad (9)$$

and

$$V_{bf} = \underbrace{\sum_j \frac{N_j}{N} [\bar{\theta}_j - \bar{\theta}]^2}_{V_{bf}^\theta} + \underbrace{\sum_j \frac{N_j}{N} [\bar{h}_j - \bar{h}]^2}_{V_{bf}^h} + \underbrace{2 \sum_j \frac{N_j}{N^2} [(\bar{\theta}_j - \bar{\theta})(\bar{h}_j - \bar{h})]}_{2cov_{bf}(\theta, h)}. \quad (10)$$

B.2 Shift-share analysis of the change in the firm component of employee wages

Let each decile be denoted by d , where N^d is all employees observed in a period in that decile of the unobservable wage distribution. Let k denote an employment type, with K types in total. The share of all employees, irrespective of decile, in type k in the firm of an employee i is given by λ_{ki} , where the dependence of k on i is implicit. The mean log weekly wage of type k in the firm of employee i is given by $\hat{\psi}_{ki}$. We let this value be zero where a firm does not employ anybody of type k . Taking the estimated firm-specific component of the log wage $\hat{\alpha}_j$, we can write the mean of these values for employees within a decile of the distribution of estimated unobservable wages $\hat{\psi}_{ij}$ as

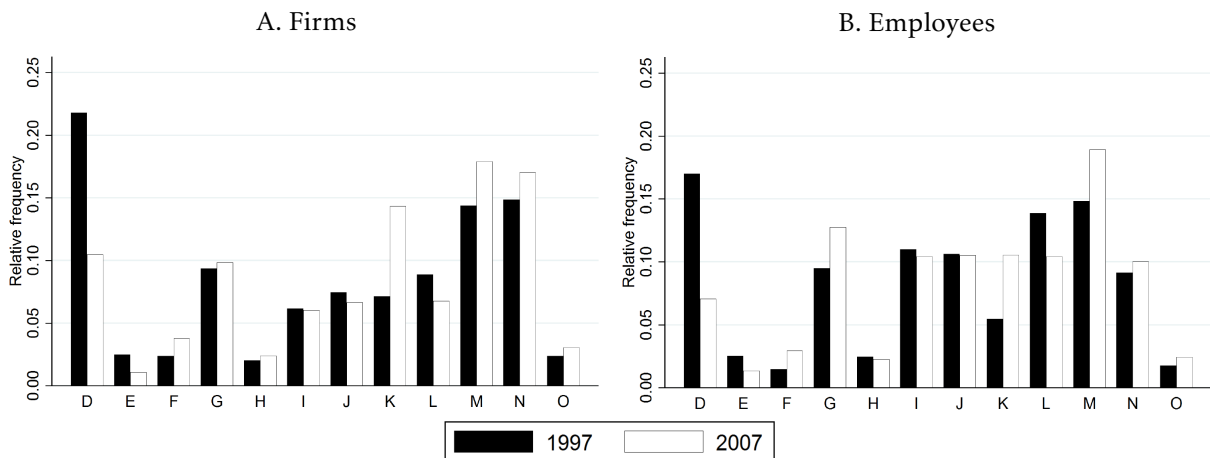
$$\begin{aligned} \frac{1}{N^d} \sum_{i \in d} \{\hat{\alpha}_j\}_i &= \frac{1}{N^d} \sum_k \sum_{i \in d} \lambda_{ki} \hat{\psi}_{ki} \\ &= \sum_k \left[\underbrace{\left(\frac{1}{N^d} \sum_{i \in d} \lambda_{ki} \right)}_{\bar{\lambda}_k} \underbrace{\left(\frac{1}{N^d} \sum_{i \in d} \hat{\psi}_{ki} \right)}_{\bar{\psi}_k} + \underbrace{\frac{1}{N^d} \sum_{i \in d} (\lambda_{ki} - \bar{\lambda}_k) (\hat{\psi}_{ki} - \bar{\psi}_k)}_{cov(\lambda_k, \hat{\psi}_k)} \right]. \end{aligned} \quad (11)$$

Using (11), denoting historical values by $'$, and representing the difference operator by Δ , we can write the change over time (between two years) in the mean of firm-specific log wages for employees in some decile as

$$\sum_k \left[\underbrace{\bar{\lambda}'_k \Delta \bar{\psi}_k}_{\text{Wages effect}} + \underbrace{\bar{\psi}'_k \Delta \bar{\lambda}_k}_{\text{Shares effect}} + \underbrace{\Delta \bar{\lambda}_k \Delta \bar{\psi}_k}_{\text{Interaction effect}} + \underbrace{\Delta cov(\lambda_k, \hat{\psi}_k)}_{\text{Covar. effect}} \right]. \quad (12)$$

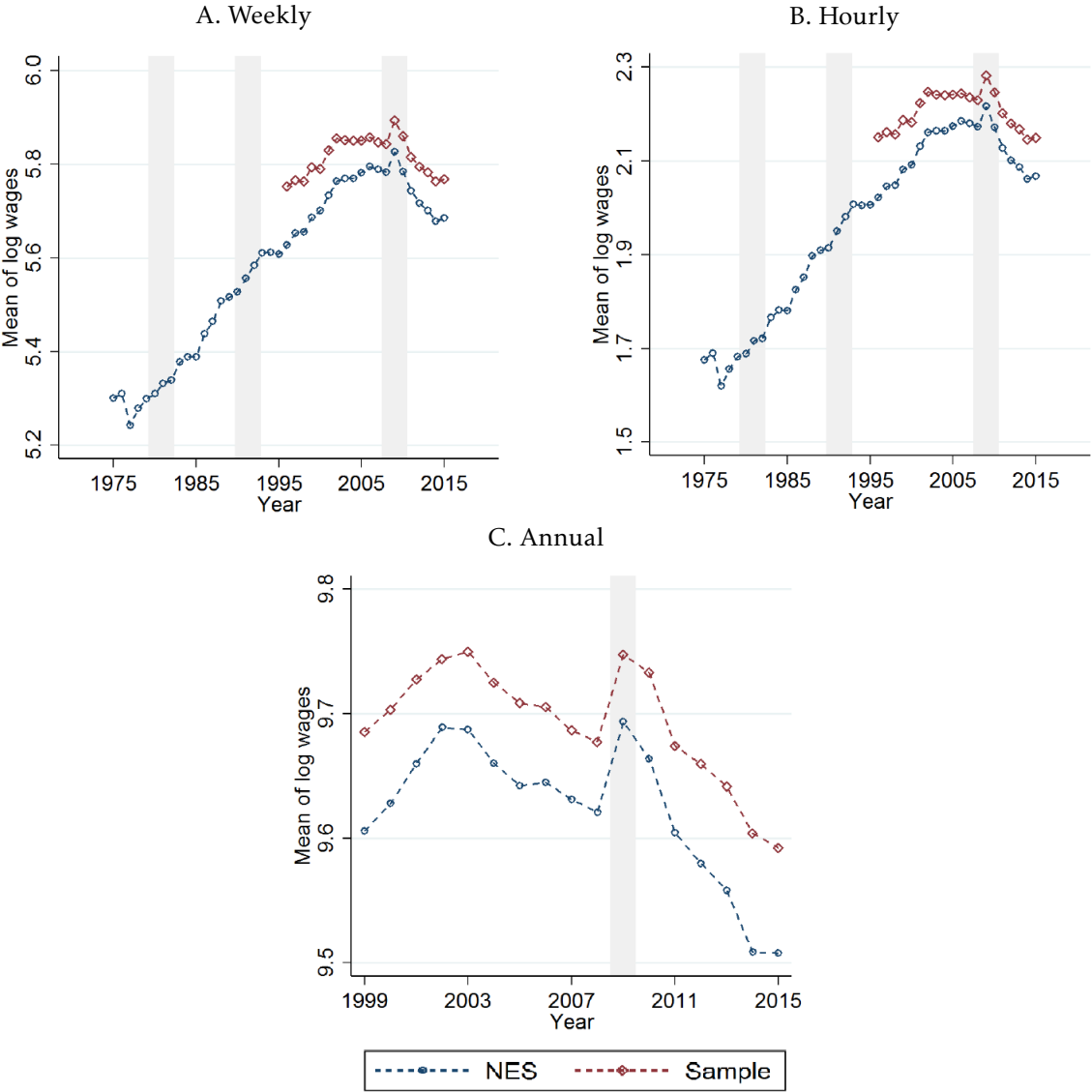
Appendix C. Additional figures

FIGURE C1: Shares of firms and employees in the baseline sample in SIC 2003 sectors, 1997 & 2007



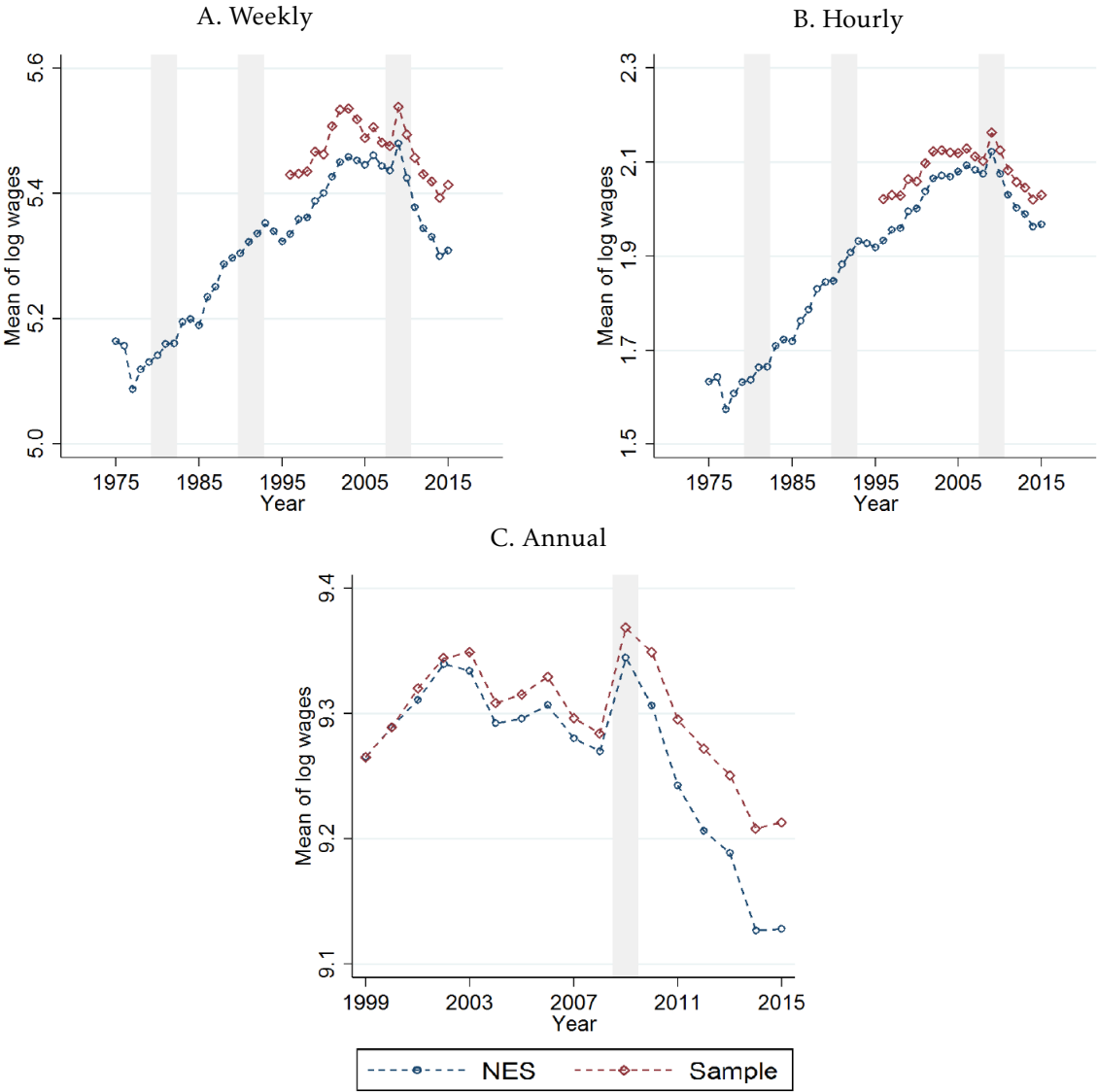
Note.- author calculations using the NESPD. See the text for description of the sample. SIC2003 codes: D. Manufacturing, E. Utilities, F. Construction, G. Wholesale and retail, H. Hotels and restaurant, I. Transport and telecommunication, J. Financial intermediation, K. Real estate, business services, L. Public admin and defence, social security, M. Education, N. Health and social work, O. Other community and social services. SIC2003 categories A-C are omitted due to too small cell sizes.

FIGURE C2: Mean of real log wages in large firms, full-time employees only, and comparison the with the whole NESPD sample, 1975-2015



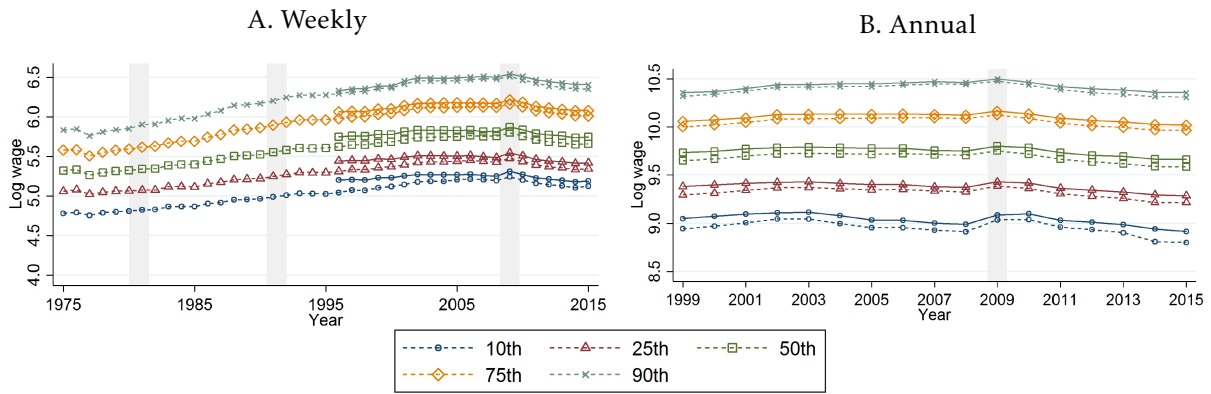
Note.- see Figure 1. The top one percent of wage observations in any year are excluded from all calculations here.

FIGURE C3: Mean of real log wages in large firms, all employees, and comparison with the whole NESPD sample, 1975-2015



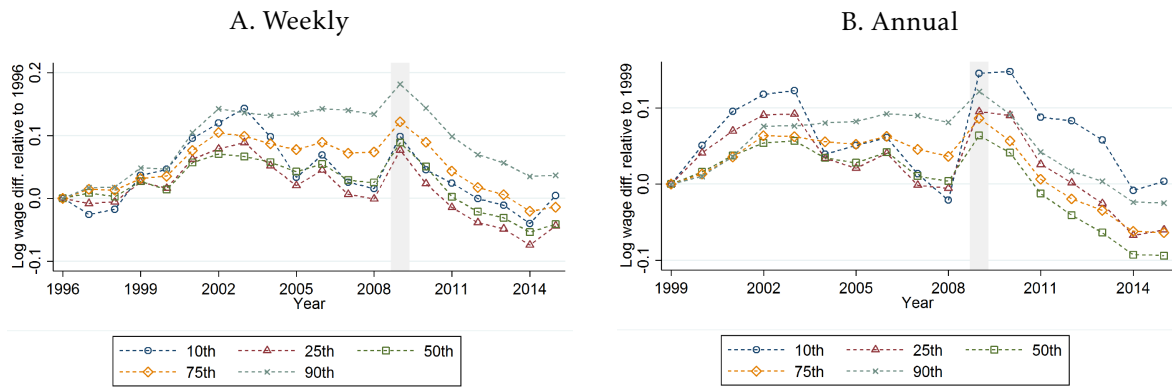
Note.- see Figure 1, except here is with all employees. The top one percent of wage observations in any year are excluded from all calculations here.

FIGURE C4: Percentiles of real log wages in large firms, all employees, and comparison with the whole NESPD sample, 1975-2015



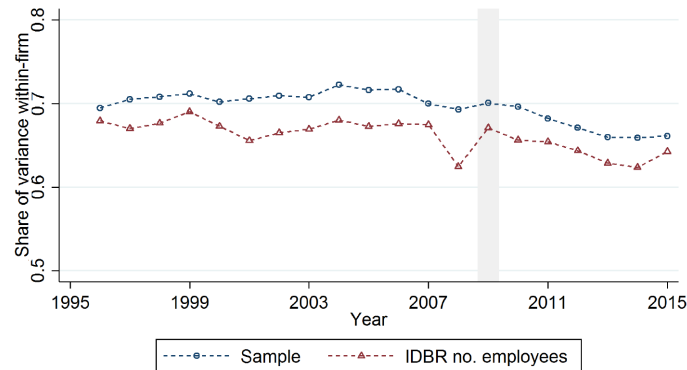
Note.- see Figure 1, except here is with all employees. Solid lines are the series for the large firms sample of the NESPD.

FIGURE C5: Percentiles of real log wages in large firms, all employees: differences relative to 1996/9



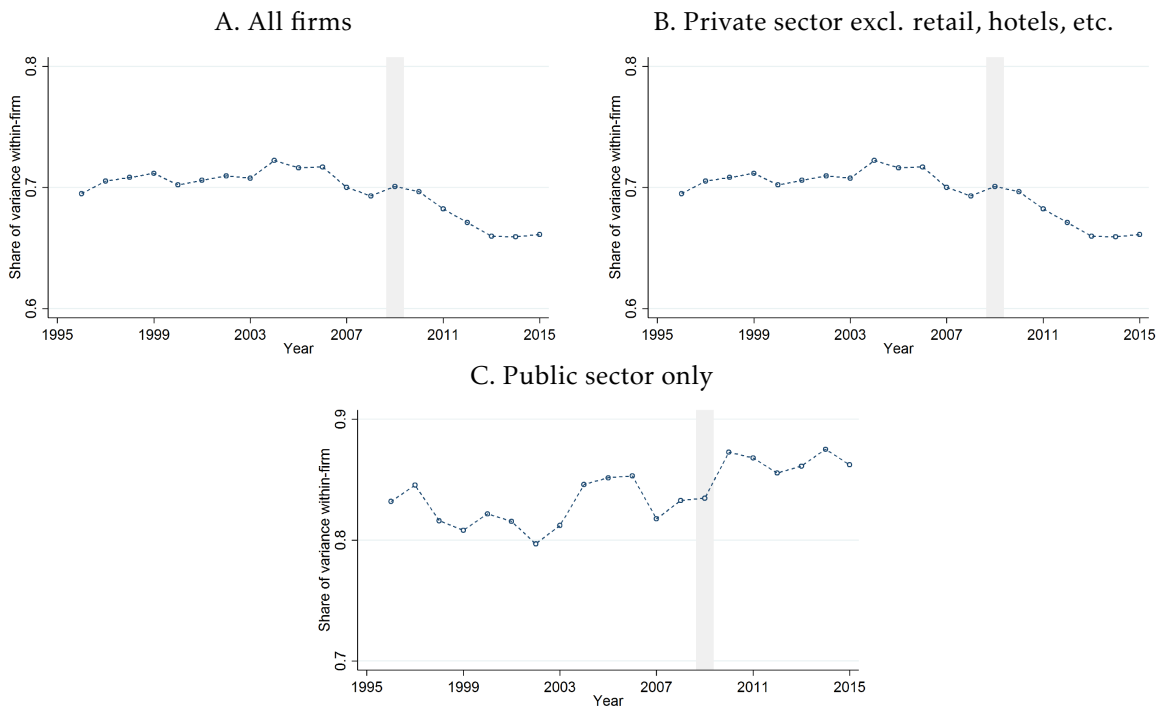
Note.- see Figure 2, except here is with all employees.

FIGURE C6: Share of variance in log weekly employee wages from within-firm component, 1996-2015: comparison of firm weights



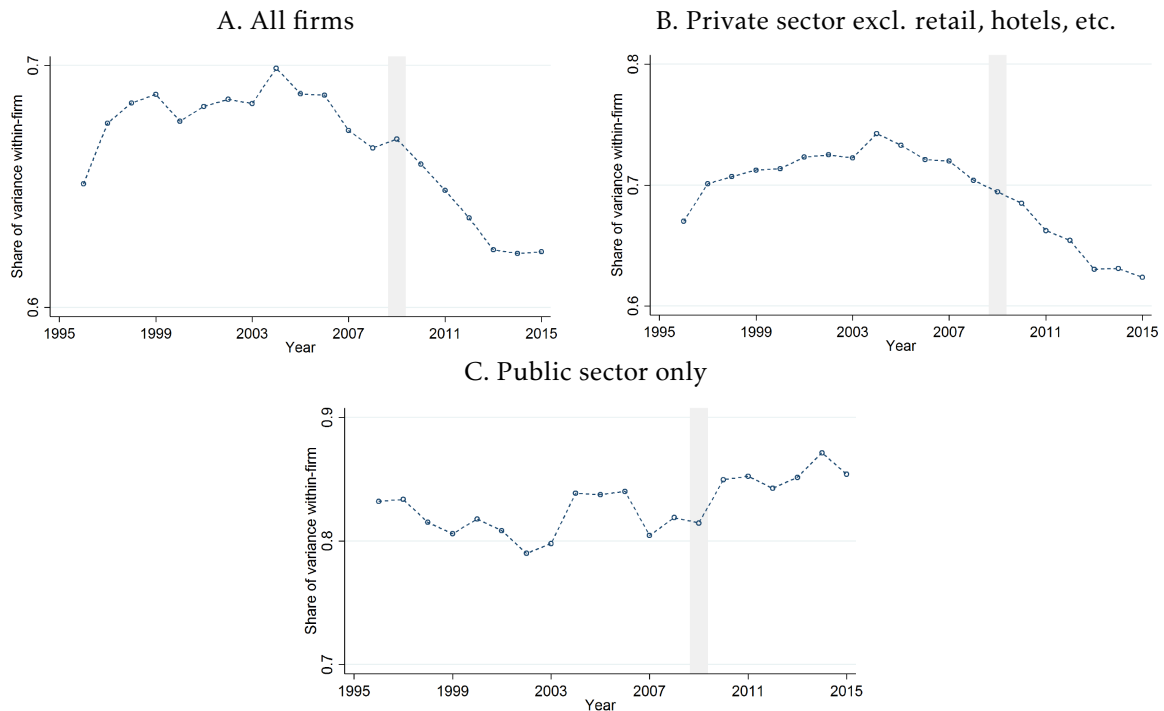
Note.- see Figure 3. 'Sample' gives results where firms are weighted using their share of sample observations in that year. 'IDBR...' gives results where firms are weighted using their administrative record of enterprise size from the IDBR.

FIGURE C7: Share of variance in log weekly employee wages from within-firm component



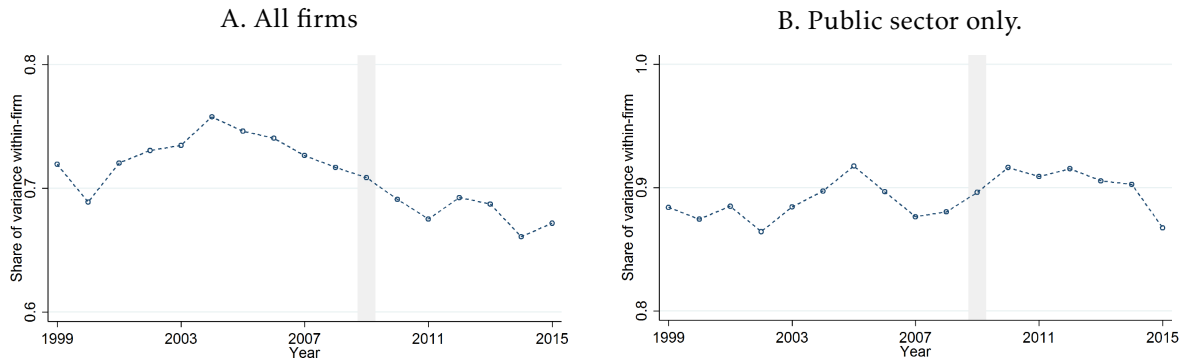
Note.- see Figure 3. Panel B excludes major SIC 2003 sectors G & H. Public sector is represented by public corporation or nationalised industry, central government and local authority employers.

FIGURE C8: Share of variance in log hourly employee wages from within-firm component



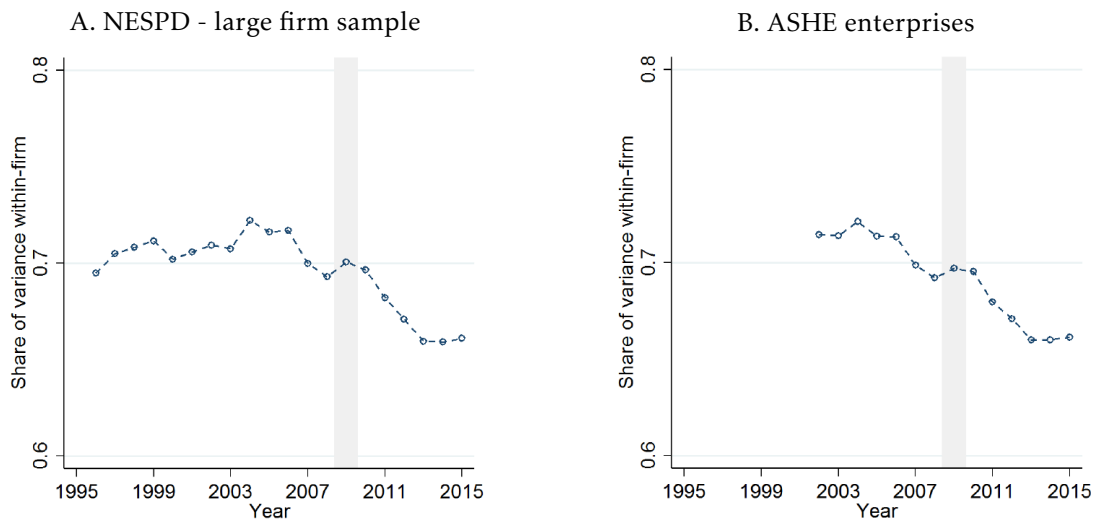
Note.- see Figure C7

FIGURE C9: Share of variance in log annual employee wages from within-firm component



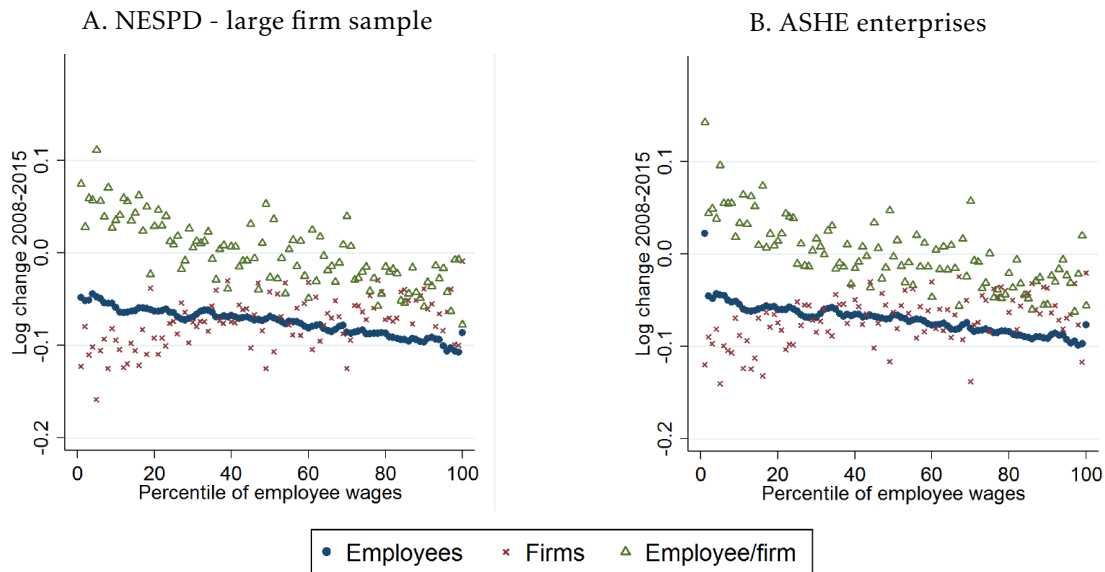
Note.- see Figure 3 and see Figure C7.

FIGURE C10: Share of variance in log weekly employee wages from within-firm component: NESPD large firms sample vs ASHE enterprises



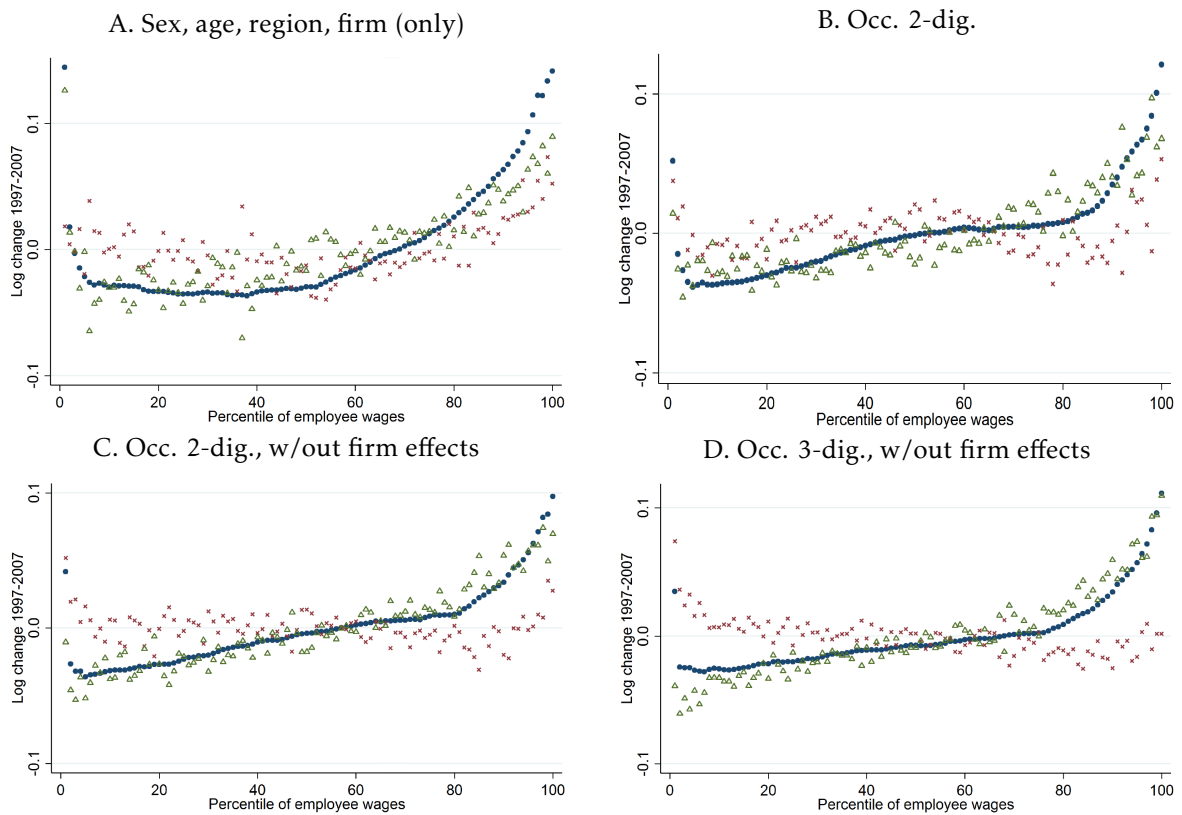
Note.- author calculations using the NESPD and Annual Survey of Hours and Earnings, age 16-64 only, all employees. Weekly wages exclude overtime. In the left panel the data is for all large firms in the NESPD who have at least ten employee observations in a year. The right panel is the equivalent but using IDBR enterprise identifiers in the ASHE, instead of a looser definition of a 'firm'. Shaded areas represent official UK recessions.

FIGURE C11: Change 2008-2015 in the average real log weekly wage by percentile of employees and the contribution from firms: NESPD large firms sample vs ASHE large enterprises



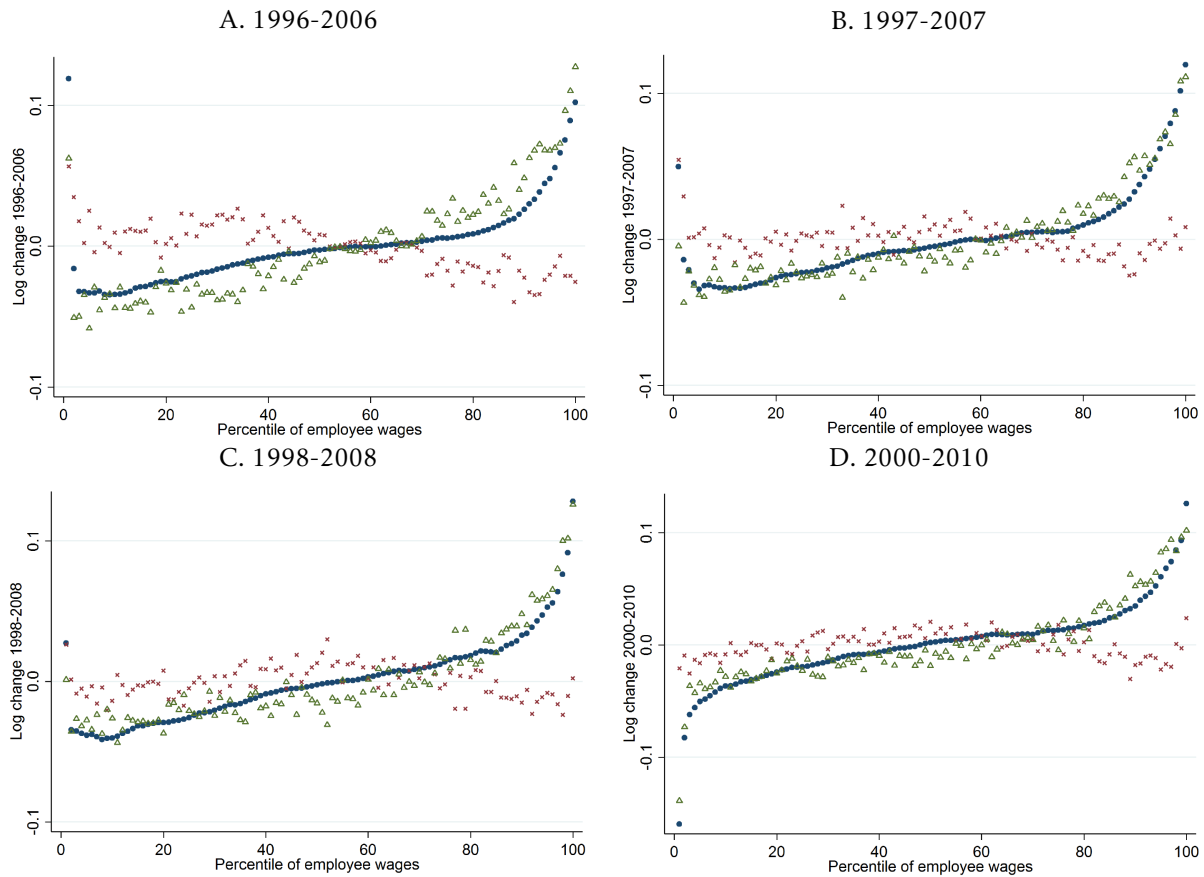
Note.- see Figure 7 and Figure C10: for NESPD $\gamma = 1.87$, for ASHE $\gamma = 1.72$.

FIGURE C12: Change 1997-2007 in the average real unobservable log weekly wage by percentile of employees and the contribution from firms



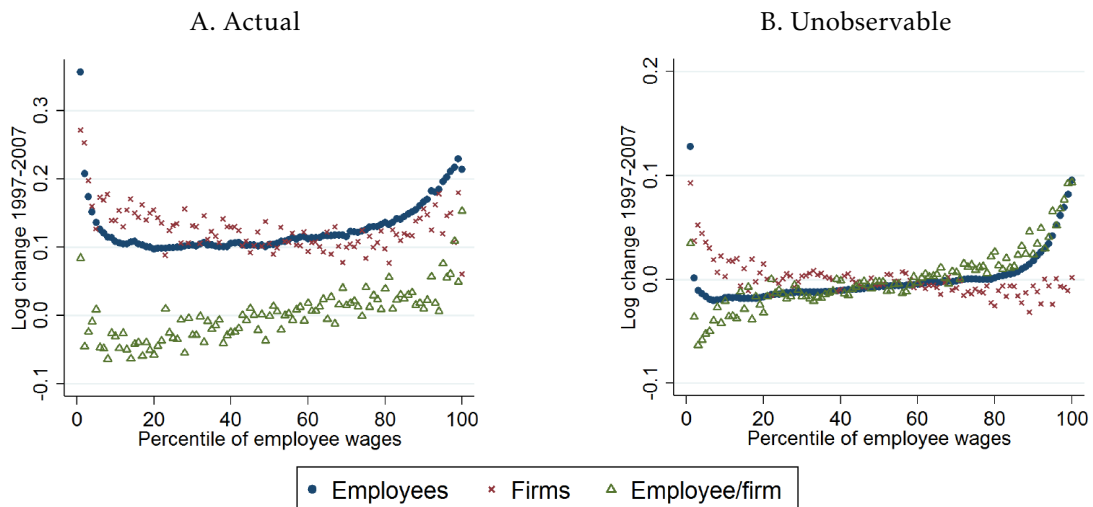
Note.- see Figure 7. Unobservable log wages are estimated using a regression with controls for sex, age, age squared, major regions and firm-specific effects, in addition to those labelled above each panel. A: $\gamma = 0.67$. B: $\gamma = 0.81$. C: $\gamma = 0.96$. D: $\gamma = 1.14$.

FIGURE C13: Change in the average real unobservable log weekly wage by percentile of employees and the contribution from firms: other ten-year time periods



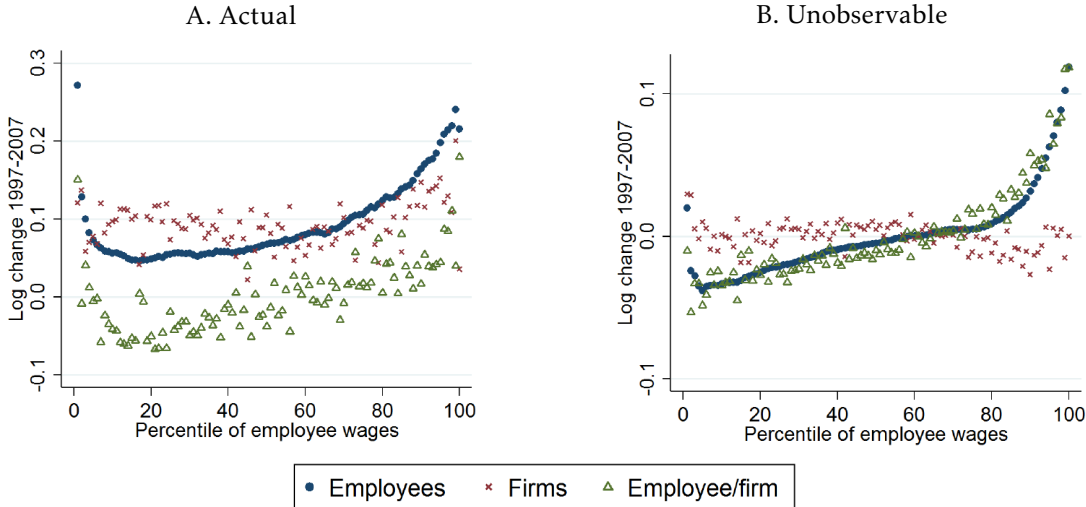
Note.- see Figure 7 and Figure 9. A: $\gamma = 1.30$. B: $\gamma = 1.00$. C: $\gamma = 1.03$. D: $\gamma = 0.96$.

FIGURE C14: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms: all large firms in the NESPD with 1+ employee observations



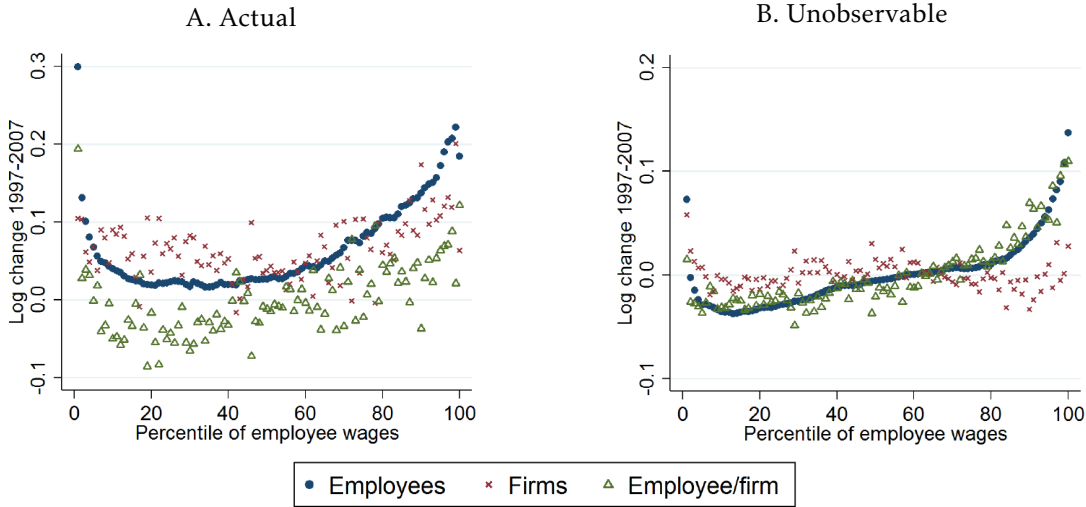
Note.- see Figure 7 and Figure 9. The data used here is for all large firms who have at least one employee observation in the NESPD in a year. A: $\gamma = 0.61$. B: $\gamma = 0.98$.

FIGURE C15: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms: all large firms in the NESPD with 5+ employee observations



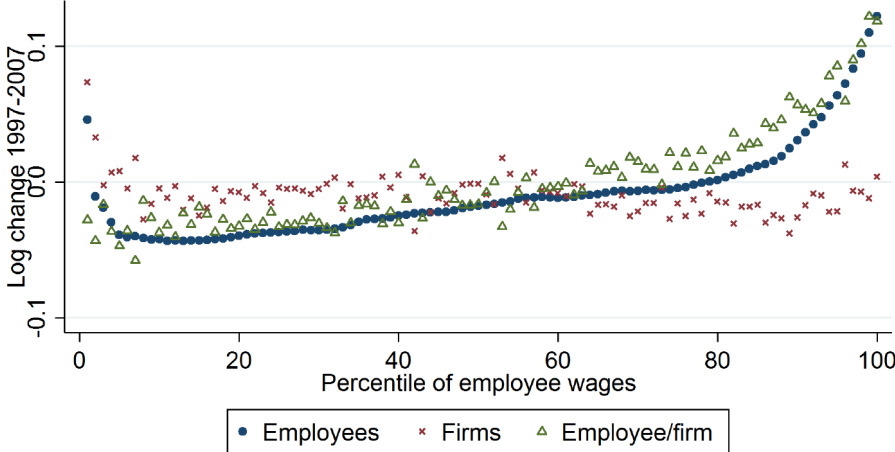
Note.- see Figure C14, except the data used here are for all large firms who have at least five employee observations in the NESPD in a year. A: $\gamma = 0.75$. B: $\gamma = 1.08$.

FIGURE C16: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms: all large firms in the NESPD with 20+ employee observations



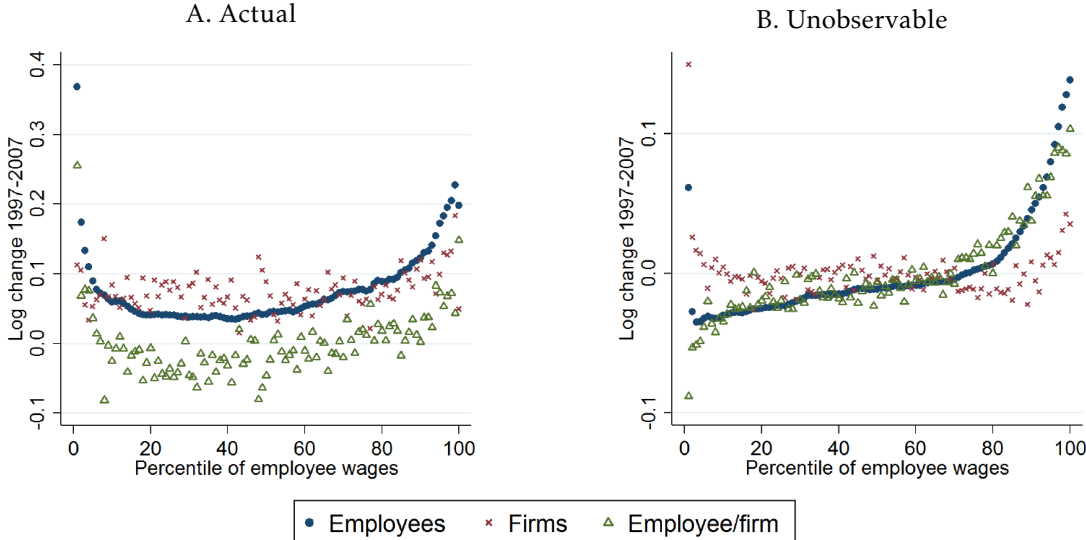
Note.- see Figure C14, except the data used here are for all large firms who have at least twenty employee observations in the NESPD in a year. A: $\gamma = 0.61$. B: $\gamma = 0.93$.

FIGURE C17: Change 1997-2007 in the average real unobservable log weekly wage by percentile of employees and the contribution from firms: private sector only



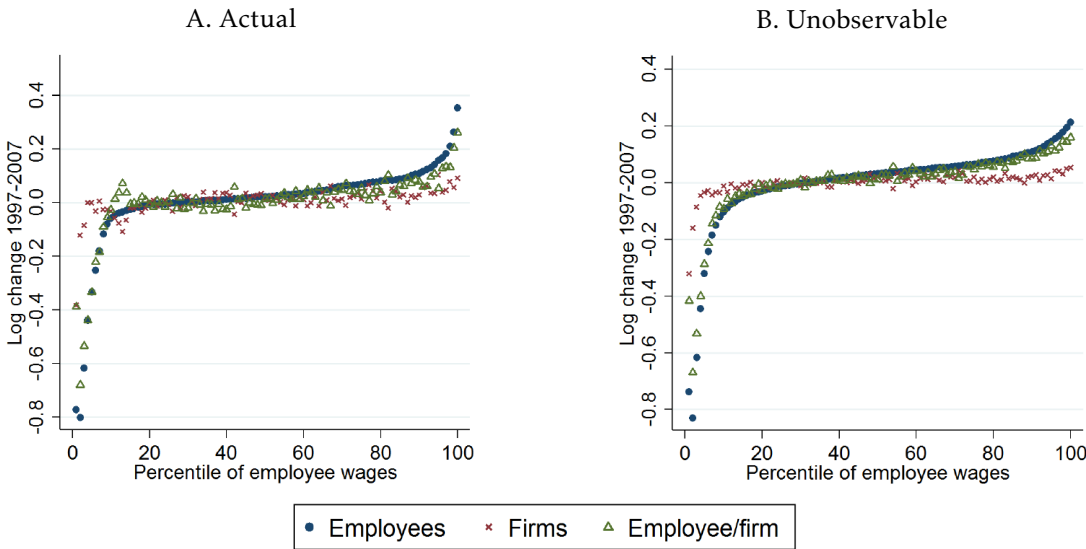
Note.- see Figure 7 and Figure 9, except the data used here is for all large private sector firms in the NESPD who have at least ten full-time employee observations in a year. $\gamma = 1.00$.

FIGURE C18: Change 1997-2007 in the average real log hourly wage by percentile of employees and the contribution from firms: comparison with unobservable wages



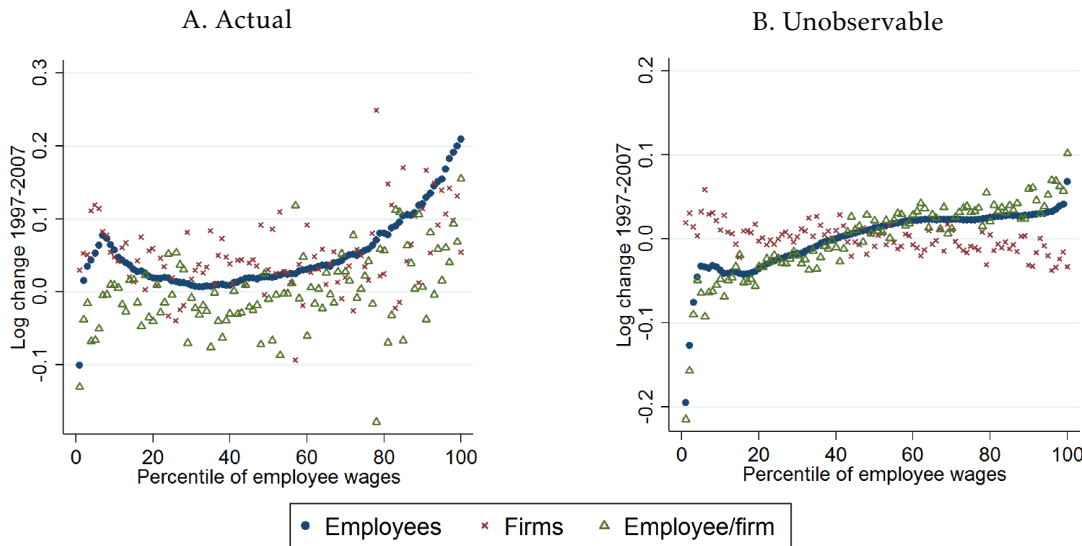
Note.- see Figure 7 and Figure 9. A: $\gamma = 0.75$. B: $\gamma = 0.80$.

FIGURE C19: Change 1997-2007 in the average real log annual wage by percentile of employees and the contribution from firms: comparison with unobservable wages



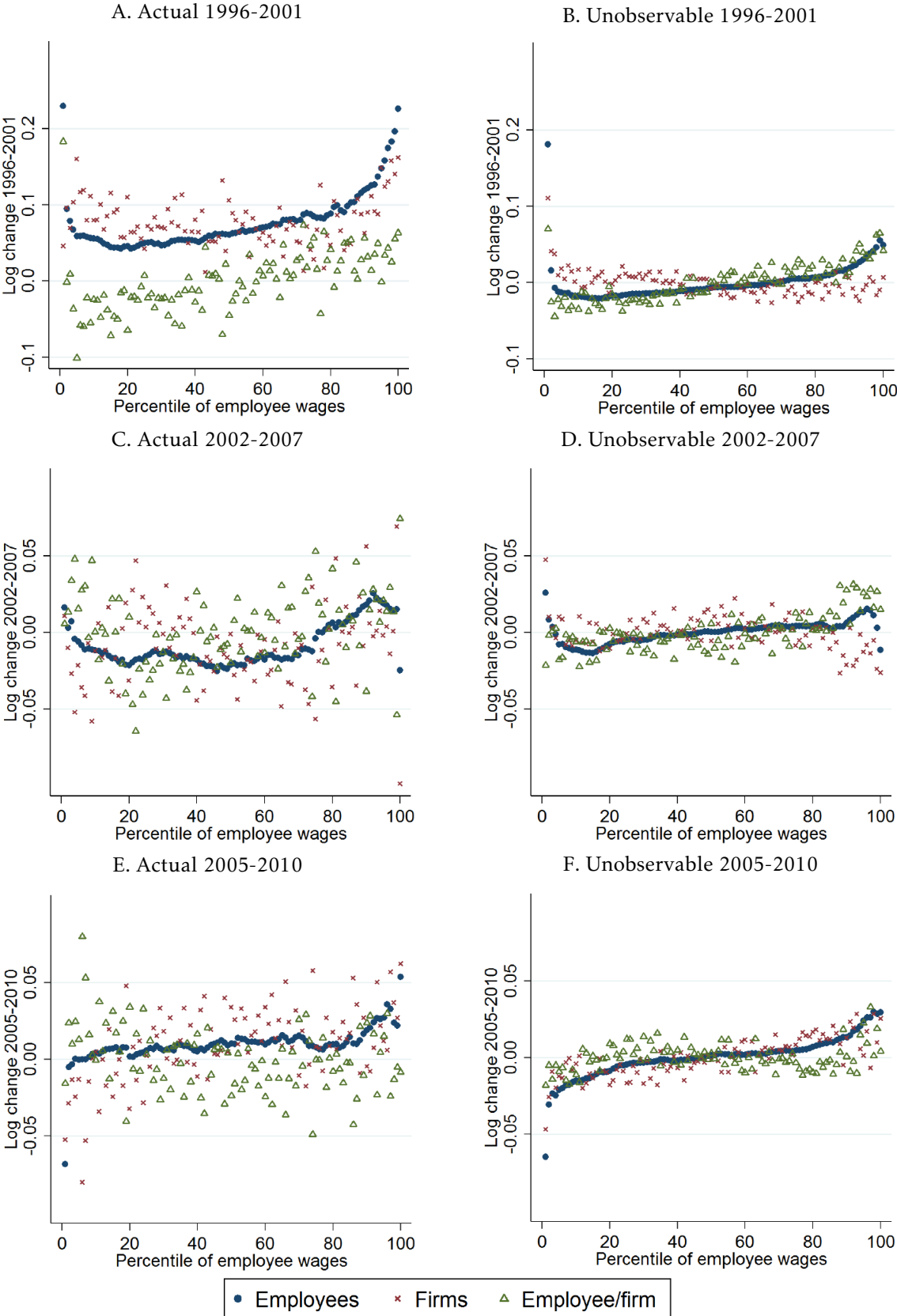
Note.- see Figure 7 and Figure 9, except the data used here is for all large firms who have at least ten employee observations in the NESPD in a year, who have been with the firm at least a year. A: $\gamma = 0.75$. B: $\gamma = 0.77$.

FIGURE C20: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms, full & part-time workers: comparison with unobservable wages



Note.- see Figure 7 and Figure 9, except here the data is for all employees, not full-time only. A: $\gamma = 0.52$. B: $\gamma = 1.25$.

FIGURE C21: Change in the average real unobservable log weekly wage by percentile of employees and the contribution from firms: other five-year time periods



Note.- see Figure 7 and Figure 9. A: $\gamma = 0.73$. B: $\gamma = 0.77$. C: $\gamma = 0.45$. D: $\gamma = 0.82$. E: $\gamma = -0.14$. F: $\gamma = 0.27$.