Do Low-Wage Workers Benefit from Productivity Growth Recovery?*

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Abstract

This work examines empirically whether productivity gains (losses) are shared with wages, and the sources of heterogeneity that characterise this link. We use matched employer-employee data from the UK Annual Survey of Household Earning and the Annual Business Survey for 2011 to 2015. We instrument Labour Productivity (LP) with real Total Factor Productivity (TFP), and use matched worker-firm fixed effects to identify the causal effect of productivity changes on wages. We consider LP growth at the level of the firm, industry and city as affecting wages of continuing employees. We look at the effects on wages across different age cohorts (16-24, 25-34, 35-65), wage quintiles, and unionised workers. We carry out the analysis on the whole UK economy and on the manufacturing sector, and several services (construction, trade, transport, financial, business services and creative industries) separately. We find that, overall, only (nominal) wage elasticity to industry-level productivity is statistically significant, very small and negative: -0.03. Elasticity is nil for manufacturing, and negative, albeit very small, for business services. We find the overall negative wage elasticity to industry productivity is concentrated in the 35-65 age cohort, and that unionisation at the industry level reduces rent sharing elasticity in the UK. These findings highlight a number of relevant policy issues that would add to the debate in the UK, for instance, on the Industrial Strategy, and on the identification of policy tools that would simultaneously improve productivity and wages.

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1 Introduction

Growth of output/hour/worker has slowed in the UK over the past two decades, with Labour Productivity (LP) falling sharply after the 2008 financial crisis and then recovering at an unprecedentedly slow pace (Blundell et al., 2014; Pessoa and Van Reenen, 2014a). Recovery to the pre-crisis period remains slow, to the extent that the average LP trend across market sectors is almost flat (Figure 1).

Productivity performance two years on from the financial crisis has been quite different across economic sectors (Figure 2) (Haldane, 2017b), with some experiencing nearly zero LP growth (Figure 3) over the whole period (e.g., manufacturing), some moving from negative to positive growth rates (e.g., wholesale & retail trade), and others experiencing mainly positive growth rates (e.g., business services and transport).[1]

Unlike earlier crises and other OECD economies, employment in the UK fell comparatively less during the 2008 crisis (Crawford et al., 2013; Pessoa and Van Reenen, 2014a), has recovered more rapidly and is at its highest rate for decades (Haldane, 2017b). It has been suggested that firms' have responded to the crisis by 'hoarding labour', in some cases reducing the hours of incumbent workers rather than making them redundant (Crawford et al., 2013). This would be consistent with evidence that, since the crisis, average real wages have fallen (Blundell et al., 2014; Gregg et al., 2014; Pessoa and Van Reenen, 2014a; Blanchflower et al., 2017) across *all* sectors, including those experiencing productivity growth, such as business services (figure 4),although this fall has been contained (0.6% according to Crawford et al. (2013)) and, generally, limited to the first three years after the crisis (2011).

Aggregate real wages have been more responsive to productivity changes during the years after the start of the crisis, than ever observed in the past (Gregg et al., 2014). At the same time, up to the outbreak of the crisis, the UK, in line with several other countries, was experiencing growing inequality, due partly to the increasing divide between low, median and top compensations (e.g. Gregg et al., 2014).

Resolving the UK's productivity slowdown has received substantial policy attention and interventions, especially in the form of austerity policies. Assuming that a full recovery will occur at some stage, a key question is **whether and to what extent nominal wages – most especially of bottom end earners – will benefit from the productivity increases that drive it**. The assumption underlying standard theories is that in a competitive market, increased productivity does not affect nominal wages. Empirical evidence shows that labour markets are not perfectly competitive, firms attempt to attract the best talents and workers are attracted by companies that pay higher wages, and it is common to observe a "rent sharing" elasticity larger than zero (Manning, 2011).[2] Empirical evidence shows also that labour shares have declined over the last three decades (Karabarbounis and Neiman, 2013), contradicting one of the most stable of Kaldor's stylised facts and creating an unprecedented wedge between productivity growth and (median) real wage growth. However, studies conducted on the UK and the US, suggest that either there is no decoupling between productivity and (average) real wages (Pessoa and Reenen, 2013) or, if there is, it is not due to the link between productivity and real (median) wages (Stansbury and Summers, 2017) being severed. Thus, another key question is **whether changes in the transmission mechanisms between productivity and nominal wages may explain the decoupling, if it exists, and/or the increased wage inequality**.

This paper addresses these two questions. Using employer-employee data **we study whether the (slow) productivity recovery that has followed the crisis slump has had any effect on nominal wages**. To ascertain whether there is a positive effect we go beyond the usual firm-level rent sharing and investigate also the effect of changes to productivity at the industry and local labour market levels. We then **estimate, for different groups of workers, the main sources of hetero-**

[1]It is well-known that the UK economy is comparatively and increasingly services-intensive. This raises questions about the mis-measurement of productivity performance, especially in terms of Total Factor Productivity (TFP). We do not enter the debate on the appropriateness of productivity indicators in services; we merely flag this issue, which we also discuss below. See (Grassano and Savona, 2014) for a review of the literature, and Financial Times for a recent view of this issue.

[2]Several papers study the relation between productivity (or other firm level performance measure) shocks and wages within and between firms, referred to as rent-sharing elasticity (how much of the rents created in the labour market, due to several frictions, are accrued by workers (Blanchflower et al., 1996; Manning, 2011)) – see Card et al. (2018) for an excellent review of papers investigating rent-sharing in association with firm profitability and productivity. Despite substantial differences in methods, country coverage and identification strategies, typically, a 10% increase in value added per worker, increases wages by between 0.5% and 1.5% (Card et al., 2018).

geneity that characterise this effect based on wage quintiles, age and level of unionisation.

We study the whole post crisis period (2009-15), to exploit negative and positive fluctuations in productivity, although focusing mainly on the recovery period, that is, the years **2011-2015**.

We consider **three levels** at which rent sharing may be different from zero: firm, industry and local labour market.[3]

At the firm level, several factors may induce firms to share part of the productivity gains with workers. Firms might pay wage premia or bonuses linked to performance (Lazear, 2000, 1986). Workers may have some degree of bargaining power, related to unionisation, especially in large firms where bargaining is conducted at the firm level (e.g. Abowd and Lemieux, 1993; Van Reenen, 1996), and might manage to appropriate some of the firm's surplus.[4] In the presence of an increase in demand and a positively sloped labour supply curve, or, alternatively, in times of high uncertainty, firms might be led to share the risks of losses and gains, with workers. In our context, we can probably rule out the role of unionisation, due to the low level of representation remaining in the UK; similarly, we can rule out the possibility of a demand shock, given the sluggish recovery and low demand in the UK and worldwide. This leaves efficiency wages and risk sharing as potential explanations for rent sharing at firm level.

At the industry level, a number of studies conduct preliminary investigations of rent-sharing elasticity using industry data and find positive elasticities (e.g. Blanchflower et al., 1996) that are larger than those found at the firm level. Wages might follow industry level productivity changes if workers gain from changing companies (e.g. Abowd et al., 1999), if bargaining is at the industry level or because of spillovers, forms of collusion or firm's strategic imitation (Manning, 2011). Another possibility is competition, which reduces the firm's options when setting wages (Juhn et al., 2018):for instance, if the industry experiences an average increase in productivity, which is shared among several firms, most firms will need to adjust their wages upwards to avoid losing the best employees to competitors. (Carlsson et al., 2016) find a rent sharing elasticity that is three-times higher in the case of industry productivity compared to firm productivity.

At the **local labour market** level, wages may be tied to urban premia (D'Costa and Overman, 2014) and geographical agglomeration of activities (Powell et al., 2002; Echeverri-Carroll and Ayala, 2009; Meliciani and Savona, 2014), which might affect labour market dynamics (Korpi, 2007; Matano and Naticchioni, 2011; Berger and Frey, 2016), jobs (Moretti, 2010), wages (Hornbeck and Moretti, 2015) and the wage distribution (Lee, 2011; Lee and Rodriguez-Pose, 2012).

In the light of growing wage inequality, we study the **distributive outcomes of the rent sharing elasticity**, that is, whether it differs along the age and wage distribution. We split the sample into different age cohorts and occupation quintiles (ranked by wages). To our knowledge, only three earlier studies have looked at the distributional aspects of rent-sharing elasticities: (Card et al., 2016), distinguishing by gender,[5] and Juhn et al. (2018) and Matano and Naticchioni (2017) by wage.[6]

Following earlier studies[7] we also **study the role of unions in rent-sharing elasticity.** Evidence suggests that real wages have been more responsive to negative changes in productivity in the year after the crisis than previous to it. This is most likely due to weakened unions and social welfare (Gregg et al., 2014), which might have forced workers to remain in work even with lower wages and working hours (Blundell et al., 2014), that is, an infinite elasticity of the labour supply curve.

Finally, we **extend our analysis to non-manufacturing sectors.** To our knowledge, only two studies compare the response of wages to productivity across sectors beyond manufacturing and find significant differences. Bagger et al. (2014) find that elasticity is highest in wholesale and retail trade firms, followed by manufacturing, real estate and business services, and transport and communication. Juhn et al. (2018) document quite small elasticities, ranging from 0.02 in

[3]Identifying the main underlying causes related to which level – firm, industry or city – prevailed in determining the productivity-wage link in the UK after the crisis is beyond the scope of this paper and is left for future research. Here, we attempt to disentangle the effects of firm, industry and city level productivity on wages and, based on comparison, identify which dominates.

[4]Due to the low levels of unionisation in the market sector, most union bargaining in the UK is at the company level, with some exceptions in the manufacturing industries – we drop public sectors from the analysis in this paper.

[5]Card et al. (2016) study pay premia across workers of different genders, for a sample of Portuguese firms. They study both the intensive and extensive margins and find that women are less likely to work in companies that pay higher wages, but also receive only 90% of the pay premium that benefits male workers.

[6]Discussed below.

[7]E.g. Blanchflower et al. (1996), Hildreth and Oswald (1997), Bronars and Famulari (2001), Estevao and Tevlin (2003), Matano and Naticchioni (2017).

manufacturing to 0.05 in professional services and no significant effect in finance.

We focus on incumbent employees; we study changes in nominal wages to avoid the confounding effects due to changes in prices (e.g. Blanchflower et al., 2017), and consider hourly wages to avoid the confounding effects due to changes in the number of hours worked (Crawford et al., 2013; Blundell et al., 2014). We use employer-employee data and a specification that controls for unobserved worker and firm characteristics, and the match between the two (Card et al., 2013; Carlsson et al., 2016). To avoid biases in the estimations due to reverse causality or unobserved heterogeneity,[8] we instrument labour productivity with an estimation of physical TFP (as in Carlsson et al., 2016). Physical TFP is obtained by estimating the residual using quantities of factors and output, washing away prices. To complement and verify the robustness of the results, we use a trade induced instrument Bloom et al. (following 2016), limited to the manufacturing sectors (because trade shocks are related mainly to this sector).

We **find** that, overall, during the UK's recovery from the crisis, the elasticity of wages to productivity growth at all levels (firm, industry and local labour market) is either quite small or negative. This is in line with evidence that real wages generally have been falling since the crisis, except for non-tradable services such as wholesale & retail trade, food & accommodation, and transport, where they have experienced some signs of recovery (figure 4). We observe that part of this fall is due to nominal wages and is linked to productivity growth in some of the sectors, especially business services.

In the **manufacturing** sector, where measures of productivity and the identification strategy are the most reliable, we find no evidence of rent sharing. If nominal wages increased in this sector during the recovery, this is not due to greater productivity. To our knowledge, the smallest rent sharing elasticity found in empirical papers using employer-employee data is that documented by Juhn et al. (2018) for the US (1998-11), which is only 2%, but still positive and significant. Based on their result, we can conclude that the UK labour market has been perfectly competitive during the recovery from the crisis; or that this result is due to slow productivity growth in the UK since the recovery (2011); or that it is due to a particular bargaining process, which led to an agreement to keep wages low until productivity growth recovers to pre-crisis rates.

Averaging across sectors, at the **firm level**, elasticity is as small as 0.5% and is found mainly in the wholesale & retail trade sectors. At the **industry level**, an increase in productivity is found to have a small negative impact on nominal wages in the UK: the positive rent sharing found in construction (+17%) affects too small a share of workers to contrast the fall in wages driven by business services (about -20%).

Across **wage quintiles and age cohorts**, firm level productivity benefits mainly low wage occupations and young workers (especially in food & accommodation services). At the industry level, productivity growth may lead to *increased wage inequality*, as a result of the negative impact across all quintiles in business services combined with the positive impact only on top quintiles in construction and transport.[9]. In both cases, those mostly affected (by both gains and losses) are the older cohorts (35-65).

At the local labour market level, we also find an unequal distribution of productivity gains, benefiting the top quintile (but not the oldest cohort) in business services, and penalising the bottom quintile in transport.

Unionisation is often found to reduce rent sharing elasticity. We find similar results at the firm and city levels (and the industry level for construction), but these seem to be related more to the heterogeneity of unionisation levels: the gains observed at these levels are concentrated in young and low paid workers, which are the least unionised, in food & accommodation, and wholesale & retail trade services, which are also among the least unionised sectors. However, unionisation seems to explain part of the negative elasticity of nominal wages with respect to productivity, especially in business services, but seems also to drive up nominal wages in the transport sector. Overall, the effect of unions on rent sharing varies substantially by sector [10].

Our findings differ substantially from earlier studies and there are some nuances that are worth discussing in more depth. For example, our analysis is focused on a specific period (2011-

[8]For instance, value added per worker may increase due to inflation, which may also affect nominal wages. Or, following an increase in (minimum) wages, firms may increase their prices (assuming some market power), resulting in a positive association.

[9]See also wage growth trends depicted in Figure 4

[10]This requires further investigation into the composition of workers and the different bargaining regimes (Rusinek and Rycx, 2013)

15), which is substantially different from earlier studies using employer-employee data,[11]. This makes it less a country comparison and more a first test of the impact of (productivity) recovery on different types of workers. Also, as already mentioned, our results of a zero-sharing elasticity in manufacturing and a small negative effect of productivity on nominal wages at the industry level, are unprecedented in the literature. Juhn et al. (2018) and Graetz and Michaels (2015) find low, but still positive elasticities. Earlier studies focusing on innovation rather than productivity in the UK, find large elasticities Van Reenen (1996).

We find only a limited (and not always significant) effect of productivity on wage inequality. Earlier studies on the UK (Bell and Van Reenen, 2012, 2014) found that productivity gains accrue mainly to the top 1%, particularly in the form of bonuses.[12] This work is focused mainly on the financial sector and CEOs. Our results also suggest important differences across sectors. Juhn et al. (2018) confirm higher rent sharing in the top 5% in manufacturing and professional services in the US, and higher rent sharing in the bottom quintile in the wholesale & retail sector. Across sectors, Matano and Naticchioni (2017) also find higher rent sharing among Italian workers in the bottom quintiles, especially blue collars.

We find a controversial role of unions, raising rent shares in only one sector, and for the top quintile. It should be stressed that the finding that unions reduce wage flexibility, in both good and bad times, is not new (Rusinek and Rycx, 2013). Matano and Naticchioni (2017) is an exception; they find a relevant role of unions in the bottom quintile rent sharing. This can be explained by country specificity: historically, unions play a stronger role in Italy than in the UK.

Our results are in line with recent debate on the decoupling between productivity and median wage growth (Machin, 2016; Schwellnus et al., 2017). However, results for the UK (Pessoa and Reenen, 2013) and the US (Stansbury and Summers, 2017) seem to suggest that average (rather than median) real wages tend to follow productivity growth. Our estimation strategy, which relies on matched employer-employee data, indicates that for employees who continue to be employed in the manufacturing sector, the effect of productivity growth on wages is missing (when not negative). However, this macro evidence and our micro evidence are difficult to reconcile since they are based on different measures of productivity and wages, and we refer to hourly, nominal wages only of continuing employees.

Overall, our results identify a worrying trend: since the recovery, very few categories of workers have benefited from productivity gains. Also, there is little evidence that, with the exception of few sectors, real wages have been increasing (figure 4). Some have seen nominal wages falling as a result of productivity increases. Jointly, these effects tend to increase wage inequality. Possible reasons for this trend might be a high labour supply, unresponsive to wages, unionised workers' loss of already negligible bargaining power, and vulnerability of workers that suffer income slumps caused by both the recession and the welfare cuts that occurred before and after the crisis Van Reenen (2004); Blundell et al. (2004); Pessoa and Van Reenen (2014b). These findings highlight a number of important policy issues that add to debate in the UK, for instance, on industry strategy, which is discussed briefly in the final section of the paper.

To summarise, our work adds to the literature in three ways.

First, to our knowledge, this is the first paper that systematically investigates the extent to which UK wages in the market sector (manufacturing and services) react to firm productivity, controlling for worker fixed effects, using a sample of employer-employee data.[13] This is particularly relevant because most of the extant work (Card et al. (2018)) with the exception of Juhn et al. (2018), focuses on countries where unions play a substantially stronger role than in the UK (Freeman, 2007).

Second, similar to what Juhn et al. (2018) do for the US, we investigate **a large number of heterogeneous effects** that affect the productivity-pay link. We compare the effects of productivity at the firm, industry and spatial (local labour market) levels; we compare differences between workers with respect to age cohorts and wage quintiles; we distinguish between relatively homogeneous sectors; we include the effect of unionisation on the productivity-wage link.

Third, we provide a first consideration of what happens to nominal wages in a period of increasing wage inequality and following the austerity policies enacted in a bid to recover from

[11] E.g. Card et al. (2014), Carlsson et al. (2016), Card et al. (2016), Bagger et al. (2014).

[12] Unfortunately, we do not have information on full compensations, and the Annual Survey of Hours and Earnings (ASHE) is not very representative of top incomes. In this paper, we are more interested in the bottom percentiles: in future work it would be useful to unpack the top percentiles at a finer level than in this paper.

[13] Following Carlsson et al. (2016), we are more restrictive and control for the match between employer and employee fixed effects.

the financial crisis.

The remainder of the paper is structured as follows. Section 2 reviews a selection of the literature relevant to this work; Section 3 describes the data sources and empirical strategy in detail; Section 4 discusses our findings and Section 5 concludes.

2 Related Literature

There is an extensive literature investigating the wage elasticity to changes in firms' productivity performance, measured in different ways (rent sharing elasticity). Card et al. (2018) provide an excellent and comprehensive review of methods, applications and results.[14] The review distinguishes usefully between studies that explore the wage benefits for the workers within firms (the incumbents) and those that also considers workers moving between firms.

Our work builds mainly on two recent studies.

Carlsson et al. (2016) make two contributions to the literature. First, they investigate, within the same framework, whether changes in wages are influenced by productivity growth (measured as sales per worker) originating mainly at the firm, or mainly at the industry level, that is, productivity shocks that are common to firms belonging to the same sector. Their study uses detailed employer-employee data from Sweden for the period 1990 to 1996. Second, they use employer-employee fixed effects, which allows them to control for unobservable characteristics in the matching between employers and employees. They find that the *industry level effect* is three times larger than the idiosyncratic firm effect: workers in Sweden over the period considered gained more from competitors' increased productivity than from increased productivity in the company employing them.

Juhn et al. (2018) focus on incumbent workers in the US and investigate whether shocks to firm performance are transmitted to workers who remain employed by the same firm. They look at the impact of revenue shocks on wage volatility, by estimating the effect of a change in the firm's total revenue on a change in the wages of its employees. By examining different time periods and instrumenting firm performance, they correct for measurement errors and endogeneity and account for the fact that changes in firm performance may take time to transfer to wages. Interestingly, they find a significant positive "rent sharing", but with very small coefficients. The largest elasticities are found for retail and professional services – but no more than 7% and 5% respectively, followed by manufacturing – only 2%. For finance, where the strongest relation between performance and pay might be expected, they do not find a significant result. Juhn et al. (2018) explain these low elasticities mainly by unionisation.[15] The authors compare Ordinary Least Square (OLS) elasticities to both negative and positive shocks (booms and busts) and find that coefficients are higher for negative shocks (wage cuts following a reduction in firm performance, are more common than wage increases following an increase in firm performance). They consider also whether elasticity changes for workers in different percentiles of the wage distribution and find that the highest elasticities are for the third quintile in manufacturing and professional services and, especially, the top 5% of the wage distribution. Workers in the bottom quintile seem not to benefit (or suffer) from any change in wages following a change in firm performance. However, for the retail sector, the opposite is true and the bottom quintile seems to gain the most. The results do not seem to be driven by job tenure.

A relevant and related set of contributions studies the relation between the financial crisis, the "productivity puzzle" and wages (Haldane, 2017a,b). Blundell et al. (2014) investigate the productivity puzzle in the UK, which they find is explained by sticky wages following the recession and the productivity slump. They conclude that, in contrast to previous recessions, real wages did fall, and did not recover, and that continuing employees are responsible for most of this fall. It is suggested that the fall may be due to a high supply of labour due to reduced household income. Also, labour dynamics differ significantly across age cohorts and wage percentiles: the wages in the top percentiles fell the most, whereas the bottom percentile seems to have been protected, thanks, most likely, to the minimum wage regulations introduced before the crisis. Blanchflower

[14] The review is part of a special issue, which includes other relevant contributions in this area, including (Lazear and Shaw, 2018). For instance, Juhn et al. (2018) summarises the literature that looks at the relation between firm productivity and wages as an insurance mechanism that protects workers from firm shocks.

[15] It is worth noting that all other studies of rent sharing using employer-employee data focus on continental Europe, which has higher levels of unionisation than the US (or, indeed, the UK). This is an aspect that we return to when discussing the results.

et al. (2017) find very similar results with respect to age cohorts and wage deciles. Interestingly, Crawford et al. (2013) report that UK firms hoarded labour immediately after the outbreak of the recession, by increasing the number of part-time workers and reducing incumbent workers' hours rather than making them redundant, which is consistent with the fall in weekly wages. Gregg et al. (2014) suggest that real wages have been more responsive to negative changes in productivity in the year after the crisis than before it, due largely to weakened unions (see also figure 6) and social welfare.

We extend the exercise in (Carlsson et al., 2016) and (Juhn et al., 2018) in a number of ways, which are crucial for shedding light on the productivity-pay link in the UK, specifically for the bottom earners after the crisis, adding to the debate on the relation between productivity and wages in the UK.

First, the UK is an important extension to the Swedish case analysed in (Card et al., 2018), since, in the UK, levels of social welfare and unionisation of private sector workers are lower than in Sweden. Relatedly, we chose to focus on incumbent workers. Second, we look at the pre- and post-crisis period to study whether the slow productivity recovery has benefited nominal wages to some extent, and whether and how wages have been protected during the crisis. Third, we focus on incumbent workers and nominal wages since real wages are likely to be affected indirectly by productivity via prices. If nominal wages respond to productivity recovery, but real wages continue to fall, we need to rely on macro-level explanations related to structural changes in the supply of labour, as in (Blundell et al., 2014), since general trends related to decoupling of the productivity-pay link seem not to apply to the UK (Pessoa and Van Reenen, 2014a). Fourth, we extend (Card et al., 2018) by exploring not only productivity changes at the firm and industry levels, but also at the city level, building on (Moretti, 2010) and (Hornbeck and Moretti, 2015). The UK has a peculiar spatial distribution of economic activities that might entail a city wage premium and contribute to spatial wage inequality. Fifth, we explore a large set of sources of heterogeneity that might affect the relationship between productivity and wages. Bearing in mind the specific economic structure, we extend the analysis to all market non-manufacturing sectors that include traditional non-tradable services (construction, transport, trade and hotels), and knowledge intensive (mainly tradable) services such as financial and business services. We also include some of the creative industries. We use the median wage within occupations to define wage quintiles and check heterogeneous effects by age, and include also the effect of unions.

3 Data and Methodology

3.1 Data

This section describes the data sources, sampling, merging procedures and characteristics for the sample of workers and firms that we analyse.

The unit of observation is the employed individual in the UK. We combine individual data from ASHE and firm data from the Annual Business Survey (ABS).

From ASHE, we use information on individuals' wages and other characteristics. ASHE is one of the largest surveys of individual earnings in the UK. It collects data on wages, paid hours of work and basic work characteristics for almost one per cent of the working population.[16] The ASHE sample is drawn from National Insurance (NI) records of working individuals, and the survey forms are sent to the relevant employers to complete.

While limited in terms of personal characteristics compared to surveys such as the Labour Force Survey (LFS), we use ASHE because of its larger sample size, the less subjective responses regarding wages and hours because they are provided by employers and, most importantly, because ASHE links the individual to the employing firm, making this the only accessible dataset in the UK, so far, that can be used to match employers and employees. Another advantage of ASHE is that data for some individuals that do not exit the labour market are collected each year. Therefore, it is possible to construct a panel dataset of responses for each individual and to track how occupations, earnings and working hours change for individuals over time.

As we discuss below, in our analysis, we exploit the panel dimension of ASHE to control for individuals' unobservable characteristics which might affect estimation of the effect of labour

[16] The universe of ASHE is all working individuals aged 16 years and older, residing and working in the UK in 1997-2016. Every year ONS collects information on around 140,000 individuals. More details on ASHE sampling methods can be found in https://discover.ukdataservice.ac.uk/catalogue/?sn=6689.

productivity on wages. However, ASHE is not designed as a longitudinal dataset, so the panel dimension is available when individuals are randomly sampled for more than one period.

We use the ABS to estimate labour and TFP for firms, industries, and Travel To Work Areas (TTWA).[17] The ABS covers annually around 48,000 businesses in Great Britain registered for VAT and/or PAYE between 2008-2015.[18] It is an "annual survey of businesses covering the production, construction, distribution and service industries, which represents about two-thirds of the UK economy in terms of Gross Value Added (GVA)".[19] It is a one-stage, stratified random sample, covering the census of all large businesses (400 employees or more), and samples of medium and small businesses. The survey population is stratified by industry (SIC 2007) and country.

We match individuals' information to firms using the Inter-Departmental Business Register (IDBR) reference numbers (*entref* in the dataset). Note that we are matching two different datasets, each with a different sample design: the IDBR number allows us to link some of the workers sampled by ASHE with some of the firms sampled by ABS. That is, not all workers surveyed in ASHE, work in firms surveyed in ABS; and not all firms surveyed in ABS, employ workers that are surveyed in ASHE.

We follow a cleaning procedure which includes dropping inconsistent observations due to the fact that NI numbers that become free by individuals leaving the NI scheme, are re-assigned to newly registered individuals. Since ASHE's sampling is based on NI numbers, for the same NI number we include only individuals with the same gender through time and a consistent aging pattern. We drop firms that switch industries across periods.[20]

As a result of these cleaning and matching procedures, we are left with employer-employee matched data for approximately 44,000 individuals and 7,000 firms over 7 years which yields around 312,000 observations for the period 2009-2015. Initially, we use the 2009-2015 period to estimate our baseline results and then split the sample into a crisis period (2009-2010), and a post-crisis period (2011-2015). The bulk of our results focus on the later period, because our main relation of interest is tested when productivity growth is positive.

To capture the distributional effects of productivity on wages, we segment the sample according to the individual's age and wage quintile. As is standard in the literature, wage quintiles are defined using individuals' occupations. We use hourly wage data from ASHE and split the sample into five occupation quintiles ordered by wage. To build the quintiles, we rank occupations (approximately 342) by the median hourly wage in 2002. We then collapse the 342 occupations into 5 categories from lowest to highest. We control for type of appointment (part-time or full-time), tenure (number of years in post) and age. We distinguish our estimations by degree of unionisation in the 2-digit industry.[21]

Table 1 provides a snapshot of the characteristics of our sample by wage quintile. It reports average values across all individuals pertaining to each wage quintile with respect to their age, gender, full-time status, tenure and probability of unionisation (estimated based on the individual's employing industry). It shows that the first quintile differs significantly from the other four.[22] With respect to the rest of the population, workers in the bottom 20% of the wage quintile are significantly younger, mainly female, more likely to be part-time, have worked in the same organisation for a shorter time (lower tenure), and are less likely to belong to a union. This group of workers represents the relative majority of workers, nearly 40% of the sample.

Interestingly, when we look at the profile of the remaining 60%, although their wages differ significantly, we find no remarkable differences in average age, or likelihood of being employed part-time or being a union member. Only the third quintile shows some relevant differences for gender (mainly men) and tenure (the longest, 10 years on average).

One possible source of rent-sharing at the industry level (the impact of an increase in industry productivity on the wages of workers in the same industry) and at the TTWA level (the impact of an increase in the productivity of all companies in a TTWA on the wages of workers in the same TTWA) is moving to a company that is more productive and pays higher wages, or to a TTWA

[17] TTWA are defined by the UK Office for National Statistics (ONS) using census data for commuting between wards, in particular, information on different individual home and work address locations. They represent local areas where more than 70% of individuals both work and live.

[18] ABS replaced the Annual Respondent Database which was the source of firm data from 1973-2009. ARD progressively included more industries up to the full set of industries covered in ABS.

[19] https://discover.ukdataservice.ac.uk/catalogue/?sn=7451

[20] All these changes account for less than 1% of the original sample.

[21] Estimated from the Quarterly LFS (QLFS).

[22] The p-value of the T-Test associated to the difference across categories is smaller than 0.05.

Table 1: Average Characteristics by Wage Quintile

Q	Age	Male	FT	Tenure	Union	N	%
1	36.42	0.46	0.53	5.55	0.19	143,191	39.61
2	40.19	0.61	0.84	8.48	0.23	70,851	19.60
3	41.19	0.73	0.91	10.00	0.24	45,781	12.66
4	40.88	0.59	0.90	8.91	0.23	39,666	10.97
5	41.38	0.66	0.93	9.62	0.21	62,043	17.16

The table reports means across individuals. *Q* is the wage quintile, constructed using the median wage per occupation in 2002; *Age* represent the average age of all workers in the quintile; *Male* is the share male workers; *FT* is the share of workers in full time employment; *Tenure* is the number of years a worker is employed by the same company; *Union* is the degree of unionisation in the 2-digits industry in which the worker is employed; *N* is the sample size; and % is the share of workers in a given quintile. All the information in ASHE is provided by the company that employed the worker, rather than self-reported.
Source: Own elaboration based on ASHE

which, on average, is more productive and pays higher wages. Tables 2 and 3 report the share of workers in our sample that, in the period 2009-2015, changed firms or TTWA. In both cases, around one third of workers remained employed, but in a different firm/TTWA.

Table 2: Frequency and percentage of workers that changed firm between 2009-2015

Status	Frequency	Percentage
Changed firm	118,740	31.49
Did not change firm	258,315	68.51

Switch is defined as a worker present in our data base who appears in different firms between 2009 and 2015
Source: own elaboration based on ASHE.

Table 3: Frequency and percentage of workers that changed city between 2009-2015

Status	Frequency	Percentage
Changed city	123,937	32.87
Did not change city	253,118	67.13

Switch is defined as a worker present in our data base who appears in different TTWA between 2009 and 2015
Source: own elaboration based on ASHE.

We expect, also, that the effect of labour productivity on wages varies across sectors. We limit our analysis to eight sectors. The choice of the sectors is quite standard in the literature on this topic. We exclude agriculture (section A); mining (section B); energy, gas, steam and air conditioning supply, water supply, sewage, waste management and remediation activities (sections D and E); public administration and defence, compulsory social security (section O); education (section P); human health and social work activities (section Q); activities of households as employers; undifferentiated goods-and service-producing activities of households for own use (section T); and activities of extraterritorial organizations and bodies (section U).

Our choice of industries seeks to diminish measurement error in the estimation of production functions within these industries. For instance, in the agriculture industry, a large share of employment is temporary and with a substantial seasonal component. Mining and energy are industries with little employment absorption. Labour productivity in public or quasi-public sectors might be subject to mis-measurement or may not be fully comparable to market sectors. Therefore, we focus on industries that are relatively homogeneous. Table 4 lists the sectors included and the description based on the 2007 SIC classification: manufacturing, construction, wholesale & retail, food & accommodation, transport, financial services, business services, and other service activities (including arts and creative services). Unlike most of the standard literature, we focus also on non-manufacturing sectors to address aspects of rent-sharing heterogeneity that usually are overlooked.[23]

Table 4: Sectors

Sector	2007 SIC Section and Description	Sample Share (%)
Manufacturing	C: Manufacture	15.6
Construction	F: Construction	3.0
Wholesales & retail	G: Wholesales and retail trade; Repair of motor vehicles and motor cycles	36.7
Food & accommodation	I: Accommodation and food service activities	7.2
Transport	H, J: (exc. division 64): Transport and storage	7.9
Finance	K: Financial and insurance activities	3.6
Business Services	L, M, N (inc. division 64): Real state activities. Processional, scientific and technical activities. Administrative and support activities. Information and communication	20.4
Other	R, S: Arts, entertainment and recreation. Other service activities	4.5

3.2 Empirical Strategy

3.2.1 Main Relation

We estimate the effect of labour productivity changes on hourly wages ($wage$) – the rent-sharing – over the period 2009-2015. Combining the empirical strategy proposed in Carlsson et al. (2016) and Hornbeck and Moretti (2015), we decompose the effect into three components: firm idiosyncratic productivity (LP_{ft}); sector wide productivity (across the UK); (LP_{jt}); and productivity in the local labour market (LP_{ct}) – or city: the TTWA (across sectors). We test the following (reduced form) equation:

$$\ln wage_{itfjc} = \alpha + \beta_f LP_{ft} + \beta_j LP_{jt} + \beta_c LP_{ct} + \chi X_{it} + \mu_i \times \mu_f + \tau_t + \gamma_a + \varepsilon_{itfjc} \quad (1)$$

where $\ln wage_{itfjc}$ is the hourly wage (in logs) for worker i in year t working for firm f in industry j located in city (TTWA) c; α, β_f, β_j, and β_c are the estimated coefficients; χ is a vector of the coefficients; μ_i and μ_f are individual and firm fixed effects; τ_t are year dummies; γ_a are age dummies; X_{it} is a vector of individual characteristics such as tenure in current job and full-time employment;[24] and ε_{ifjct} are robust individual/firm/city specific standard errors.

Wages are measured as ***hourly*** nominal values to capture the extent to which changes in productivity are shared with workers, irrespective of changes in prices.[25] The inclusion of year dummies accounts for changes in prices over the period. The hourly wage allows us to exclude changes due to reductions in the hours worked.[26]

Labour productivity (LP) at all levels – firm (f), industry (j) and TTWA (c) – is matched to the individual information. Because labour costs are available only at the business level, we estimate labour productivity at the firm level LP_f as the firm's value added over the number of employees, and average it weighting by the local unit employment, at the industry and TTWA levels, to obtain LP_j and LP_c.

[23]However, , as we explain in the next section, the choice to enlarge our sectoral coverage might represent a trade-off with respect to our choice of specification and instrumentation strategy.

[24]To account for evidence that career discontinuities and shorter working hours per week may have a negative effect on wages (e.g. Bertrand et al., 2010).

[25]The recent reduction in real wages is due in part to changes in prices (Blanchflower et al., 2017).

[26]There is evidence that, after the financial crisis, UK firms hoarded labour and reduced the number of working hours (more workers going part-time) (Blanchflower et al., 2017), possibly due to the drop in income (Crawford et al., 2013). Such changes would bias our estimates of the transmission of productivity growth on wage growth.

Our measure of LP uses use value added rather than output to account for varying cost structures of materials across firms and industries, which may differ due to vertical integration, and to avoid measurement errors due to stocking of materials (Hsieh and Klenow, 2014).

The use of matched worker-firm fixed effects ($\mu_i \times \mu_f$) allows us to control for non-observable characteristics that are fixed at the individual, firm and individual-firm levels, including sorting employer-employee and endogenous quality of the match (Carlsson et al., 2016).[27] After including worker and firm fixed effects and their match, we want to identify the effect of LP, stemming from productivity changes within the firm, industry and city, over time.

Even after including employer-employee match fixed effects, estimates of equation 1 using OLS could be biased due to unobserved heterogeneity affecting both wages and LP. For instance, higher inflation could give rise to higher value added per person because prices increase and wages could increase simultaneously if they are adjusted annually for inflation. In this case, a positive association between value added per worker and wages would be spurious. Reverse causality is another problem: following an increase in wages, firms are obliged to increase their prices (assuming some market power) to cope with increased costs, resulting in a positive association.

To cope with unobserved heterogeneity and reverse causality, we implement an Instrumental Variables (IV) approach, which isolates changes in LP derived from physical changes in TFP (physical quantities cleaned of prices).

The identification strategy requires a measure of physical TFP growth to be associated to exogenous shifts in the firm's production function (i.e., the introduction of a new technology), which increases LP, and is not related to factor prices.[28] We assume that this increase in labour productivity is not a consequence of unobserved heterogeneity in prices or a response to variations in wages, but is the result of something inherently new in the way the firm (or the industry, or the city) operates. This assumption is supported by evidence that capital investment is lumpy. In sum, we rely on industry price deflators to construct our measure of quantity (physical) TFP. Appendix B details the construction of the IV.

It should be noted that our results are estimates of **the intensive margin**, that is, the wages of those already in the labour market. Our data contain only employed workers and, in the case of panel observations, workers in the same firm. Considering that (i) we account also for the matched employer-employee fixed effects, (ii) following the financial crisis firms hoarded labour by reducing their hours (Crawford et al., 2013), and (iii) real wages stagnated due mainly to those workers remaining in the labour market rather than to changes in labour market composition (Blundell et al., 2014), our results should be net of the effect that changes in productivity may have on wages through changes in labour composition (e.g., firms firing the least productive workers).

The limitation of this strategy is that we remain agnostic about **the extensive margin**: we cannot say anything about the creation of new employment and its wage dynamics or the effect of productivity on income, considering, for example, poor matches between employer and employee, low skilled workers, self-employed or workers that enter and exit the labour market.[29]

3.2.2 Heterogeneity: Age, Occupation, Unionisation and the Crisis

We expect equation 1 to vary across different population groups and economic sectors. In our analysis we try to combine how these different population groups (by age and occupational categories) are affected by labour productivity growth across sectors.

In order to assess how the estimated effect in equation 1 changes across different groups, we estimate equation 2:

$$\ln wage_{itfjc} = \alpha + \theta_k \times [LP_{ft} + LP_{jt} + LP_{ct}] + \theta_k + X_{it} + \mu_i * \mu_f + \tau_t + \gamma_a + \varepsilon_{itfjc} \tag{2}$$

where θ_k refers to the group to which the individual belongs. In particular, we explore two different groupings: by age, and by type of occupation. In the first case, we see only whether

[27] For instance, this might be the result of productive worker hoarding by productive firms, sectors and cities.

[28] Assuming a Cobb-Douglas function $Y = P(AK^{\alpha}L^{1-\alpha})$, where Y is production, P prices, A technological innovation, K the use of capital and L the use of labour, if we measure all variables in nominal values, we may confound a shift in productivity ΔA with a change due to prices, ΔPA. The use of deflators to estimate a physical TFP in practices means scaling our production measure by prices and, therefore, avoiding them acting as a confounder.

[29] These effects of productivity on the distribution of income through the labour market are left for future research.

the effect of productivity growth varies across three age groups: 16-24, 25-34, and 35-65. In the second case, we build five occupation quintiles, which denote a range between highly paid and poorly paid occupations. To build the quintiles, we rank occupations (approximately 342) by their median hourly wage in 2002. We then collapse the 342 occupations into 5 categories from lowest to highest. We control for type of appointment (part-time or full-time), tenure (number of years in post) and age.

We further investigate whether the effect varies by the degree of unionisation in the industry (2-digit SIC code). Equation 3 interacts the three measures of labour productivity with our measure of unionisation. Figure 6 in Appendix D plots the proportion of unionised employees from 1996 to 2015 for the whole UK economy. Overall, unionisation decreased from 32.4% of employees in 1996, to 23.5% in 2016. During our period of analysis, this indicator fell by 2.7 percentage points. This decline was more pronounced in the public sector, where the rate of unionisation fell by 1.2 percentage points between 2009 and 2015, while in the market sector this decline was less acute and the proportion of unionised employees fell by 1.8 percentage points. Figure 7 in Appendix D plots changes in the share of unionised workers by industry using QLFS data: unionisation is significantly different across sectors and, with the exception of construction and wholesale & retail , all sectors experienced a decline in unionisation between 2008-2015. When interpreting the results we evaluate our effects using the median share of unionisation across industries, which is 0.2.

$$\ln wage_{itfjc} = \alpha + Union_{tj} \times [LP_{ft} + LP_{jt} + LP_{ct}] + Union_{tj} + X_{it} + \mu_i * \mu_f + \tau_t + \gamma_a + \varepsilon_{itfjc} \quad (3)$$

4 Results

4.1 Baseline

We start by presenting results for the whole sample. Table 5 reports six different estimations of equation 1. The first column reports the OLS estimation for the whole period 2009-2015. The elasticities for the within-firm and city labour productivity measures (LP_f and LP_c) are positive and statistically significant, but small, respectively 0.5% and 1.9% . Columns 2 and 3 split the sample into two periods. Column 2 reports the OLS estimates for 2009-2010 (immediately after the crisis, during the productivity slump) and column 3 reports the coefficients for the 2011-2015 period (during the sluggish recovery). The purpose of this distinction is to determine whether the relation we find is stable during negative and positive phases of the recession. We find that the positive association between firm LP and wages is observed only during 2011-15, whereas the positive association between city LP and wages is observed only for 2009-10. This suggests that nominal wages within the firm move with LP only during the sluggish recovery (i.e., they increase), and nominal wages in a labour market (TTWA) seem to follow the local market productivity slump during the recession. The small and negative coefficient of the industry's LP (0.8% elasticity) is statistically significant only during 2011-15, suggesting that, on average, nominal wages do not follow the sluggish productivity recovery and continue to fall. For the reasons discussed above, OLS results are likely to be biased and provide little indication of the effect of a change in productivity on nominal wages.

Table 5: Baseline results for all industries together

	OLS			IV		
	Whole	2009-10	2011-15	Whole	2009-10	2011-15
	(1)	(2)	(3)	(4)	(5)	(6)
LP_f	0.005***	-0.000	0.003***	0.002	0.002	0.005***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)
LP_j	-0.001	0.006	-0.008**	-0.044***	-0.066***	-0.038***
	(0.002)	(0.004)	(0.003)	(0.009)	(0.015)	(0.009)
LP_c	0.019***	0.020**	0.010	0.017	0.011	0.019
	(0.005)	(0.010)	(0.006)	(0.015)	(0.050)	(0.015)
Obs.	458837	160985	297852	323479	65942	257537

Notes: [1] All regressions include year dummies and individual controls: age dummies, tenure in current job, a dummy to identify switch to full time job. [2] We use robust standard errors and statistical significance follows the system: ***1%, **5% and *10%.

Columns 4, 5 and 6 provide the same estimates, but using two stage least squares with the instrument described above and in Appendix B, physical TFP. The results in column 4 indicate that, when instrumenting LFP with physical TFP and averaging across industries and periods, the (negative) elasticity of wages to industry LP holds. The coefficient is small: a 10% increase in industry LP results in 0.4% decrease in wages. Columns 5 and 6 indicate that this coefficient remains significant in both sub-periods, but is larger during the downturn (2009-10). This suggests that industries that experienced the strongest fall in LP during 2009-10, experienced a small increase in wages. These same industries, during the recovery (positive LP growth), experienced a small reduction in wages (as in the OLS results). Although firm and TTWA productivity and nominal wages may co-move, this is not due to a change in LP. Firm LP confirms the OLS results for the 2011-15 period, suggesting evidence of a small rent-sharing during the sluggish recovery: a 10% increase in firm LP induces an increase in nominal wages of 0.05%, on average, across all market sectors. Compared to the evidence for other countries also using employer employee data, our results indicate an extremely small elasticity overall (Card et al., 2018). This may be due to a combination of factors: most studies estimate the rent share in countries that are more unionised than the UK (Freeman, 2007). For instance, for the US, Juhn et al. (2018) also finds a low impact of changes in firm revenues on wages. Also, with the exception of Juhn et al. (2018) which include two years of the recession, the previous studies focus on periods that precede the financial crisis.[30] This is a period of quite slow productivity growth, which may leave no trace on wages.[31] It should also be considered that an average effect may hide difference across sectors that experienced different LP, wages and unionisation dynamics.

In what follows, we focus on the 2011-15 sample (column 6): we are interested in how wages respond to LP growth during the recovery, as this could provide further indications as to how the benefits of a proper recovery are shared, and whether and how they differ across sectors.

4.1.1 Sectoral Differences

Table 6 reports the estimates in Table 5 column 6, on the 8 sectors outlined above. These are, manufacturing (15.6% of the sample), construction, (3%), wholesale & retail trade (36.7%), hotels & restaurants (7.2%), transport (7.9%), financial services (3.6%), business services (20.4%) and other (4.5%).

The negative coefficient estimated for industry LP on wages is driven by *business services* (column 7), and only partially compensated for by the (small, positive) elasticity in the *construction* sector (column 2), where a 10% increase in LP increases wages by 1.7%. The coefficient estimated in column 7 indicates that in business services, for a 10% increase in LP, wages decrease by 2%.[32] Besides representing over 20% of our sample, business services comprises the *knowledge intensive business services* and those services linked to Information and Communication Technologies (ICTs), which are likely to face continuous demand for new managerial strategies, or other factors intrinsic to the firm but which are continuously changing. Business services also includes low tech services such as administrative support, cleaning services and real estate. Overall, amongst the sectors covered here, business services has experienced one of the most dramatic drops in wages, which would corroborate a negative elasticity of wages to industry LP changes.[33].

The positive coefficient estimated for firm LP on wages seems, instead, to be driven by *wholesale and retail trade* (column 3), which represents 37% of the economy. In fact, this is one of the few sectors where real wages seem to grow after the recession.[34] Wholesale & retail trade also suggest a small positive elasticity at the industry level, which, however, is only significant at 10%.

Despite *Manufacturing* being the sector where estimation of physical TFP and the identification strategy are most reliable, it is also the sector where we find no (econometric and economic) significant elasticity of wages to industry LP over the recovery period, at any standard statistical

[30]Juhn et al. (2018): 1998-11 for manufacturing, 2002-11 for finance, and 1992-11 for professional services; Matano and Naticchioni (2017): 1996-2003; Card et al. (2014): 1995-01; Carlsson et al. (2016): 1990-6; Card et al. (2016): 2002-9; Bagger et al. (2014): 1995-97.

[31]See Figure 3 in Appendix D.

[32]Bear in mind, that some caution is needed in relation to these interpretations, since the TFP measure estimated for (business) services may be subject to measurement error and a variety of unobservable characteristics that vary across time within the same firm and which our estimator is not able to control for.

[33]Figure 4 in Appendix D.

[34]Figure 4 in Appendix D.

Table 6: IV 2011-15, by sectors

	Manufacture (1)	Construction (2)	Wholesales (3)	Hotels (4)	Transport (5)	Financial (6)	Bus, Serv. (7)	Other (8)
LP_f	-0.002	0.002	0.007***	0.008	-0.000	0.011	0.005	-0.000
	(0.004)	(0.008)	(0.002)	(0.007)	(0.004)	(0.012)	(0.007)	(0.008)
LP_j	0.004	0.173***	0.037*	0.056	0.037	-0.075	-0.204***	-0.032
	(0.010)	(0.054)	(0.022)	(0.053)	(0.031)	(0.067)	(0.034)	(0.029)
LP_c	0.009	-0.017	-0.001	-0.003	-0.004	-0.004	-0.012	0.155**
	(0.014)	(0.018)	(0.024)	(0.047)	(0.021)	(0.016)	(0.013)	(0.067)
Obs.	40220	7838	94427	18485	20450	9265	52694	11698

Notes: [1] All regressions include year dummies and individual controls: age dummies, tenure in current job, a dummy to identify switch to full time job. [2] We use robust standard errors and statistical significance follows the system: ***1%, **5% and *10%.

threshold[35] (Column 1 in table 6). That is, the manufacturing sectors experience no rent sharing within the firm, nor do they benefit from spillovers from the industry or the local labour market (TTWA). This result may be indicative of a perfectly competitive labour market in the UK for manufacturing, in which all firms are wage takers and labour supply is infinitely elastic. While we cannot exclude this hypothesis, to our knowledge, this would be the first case identified using employer-employee data to estimate rent sharing, to reveal no room for sharing part of the increase in firm performance with workers. This becomes even more surprising when we extend our estimation framework to the overall industry (for which elasticity tends to be higher (Carlsson et al., 2016)) and the whole labour market (for which there is substantial evidence on labour and wage multipliers).

Instead, there are two other more likely explanations for these results. First, the lack of productivity growth in manufacturing, on average, between 2011 and 2015.[36] Second, the lag related to firms' and workers' willingness to postpone sharing any productivity gain with nominal wages, to exploit a competitive advantage, and to recover from the losses experienced from hoarding labour during the recession years.[37] Both hypotheses need further investigation, for instance, by extending the data to compare the rent sharing before and after the recession and by exploiting lags, and by focusing on different subsamples of firms. We hope to pursue both directions in future research.

City productivity change generally has no detectable effect on wages with the exception of the *creative industries* (included in other sectors, Column 8), which, interestingly, experience a city-level wage premium of productivity growth with an elasticity of 15.5%. Workers in the arts, entertainment and recreation sectors seem to gain by working in or moving to local labour markets that experience productivity growth.

4.2 Heterogeneity Results: Wage Quintiles, Age, and Unionisation

How are the small, but negative effects of productivity growth on wages in business services spread across different types of workers? How is the small but positive firm level elasticity in wholesale & retail spread across workers? Is the lack of any rent sharing in manufacturing an effect of aggregation across different types of workers? Does union membership influence this relation?

We now turn to the results of the estimation of equation 2 for all sectors during the recovery period (2011-15) across different groups of workers.

4.2.1 Labour Productivity and Wages Across Wage Quintiles

We begin by interacting the measures of LP with wage quintiles, that is, distinguishing workers by occupations that earn different wages. Table 7 reports the results for the heterogeneous effect across wage quintiles. The table includes three panels, each referring to the interaction of the quintile dummy and the labour productivity measure. Panel (a) shows the results for firm LP_f,

[35] Appendix C discusses an alternative estimation for wage elasticity to firm productivity for the manufacturing sector which confirms this result.

[36] Figure 3 in Appendix D.

[37] This might be compatible with an explanation of rent sharing based on labour contract models where both workers and firms are risk averse and share gains and losses.

panel (b) for industry LP_j, and panel c for city LP_c. Column 1 reports the results for the sample of employees in the manufacturing sector; Columns 2-8 refer to the different service sectors, and Column 9 refers to the whole sample.

Table 7: IV 2011-15, By wage quintile

	Manufacture (1)	Construction (2)	Wholesales (3)	Hotels (4)	Transport (5)	Financial (6)	Bus, Serv. (7)	Other (8)	All (9)
Panel a. Firm									
1	0.013	0.045	-0.037	0.016*	0.017	0.111	0.009	0.028	0.010***
	(0.010)	(0.048)	(1.161)	(0.008)	(0.027)	(0.121)	(0.028)	(0.022)	(0.003)
2	-0.001	0.035	-0.660	-0.004	-0.001	-0.040*	-0.003	-0.001	0.003
	(0.008)	(0.029)	(15.504)	(0.054)	(0.008)	(0.023)	(0.022)	(0.035)	(0.006)
3	-0.002	-0.053**	0.042	-0.033	0.008	0.024	-0.001	0.038	0.001
	(0.007)	(0.023)	(0.769)	(0.055)	(0.008)	(0.091)	(0.015)	(0.139)	(0.004)
4	-0.035**	-0.011	0.460	-0.021	-0.011	-0.008	-0.010	0.011	-0.001
	(0.016)	(0.030)	(10.861)	(0.107)	(0.013)	(0.029)	(0.017)	(0.027)	(0.007)
5	0.005	0.007	-0.337	0.117	-0.001	0.042	0.011	-0.022	-0.007
	(0.009)	(0.010)	(7.186)	(0.510)	(0.010)	(0.048)	(0.008)	(0.053)	(0.006)
Panel b. Industry									
1	-0.037	0.000	7.141	0.068	-0.137*	-0.387	-0.164***	-0.062	-0.042**
	(0.031)	(0.147)	(163.973)	(0.068)	(0.083)	(0.539)	(0.044)	(0.131)	(0.017)
2	0.006	0.160**	16.766	0.032	0.021	-0.033	-0.161***	0.127	-0.174***
	(0.021)	(0.065)	(382.698)	(0.200)	(0.041)	(0.242)	(0.051)	(0.451)	(0.034)
3	-0.003	0.043	0.367	0.118	0.004	-0.056	-0.415***	-0.362	-0.040**
	(0.014)	(0.064)	(5.780)	(0.126)	(0.033)	(0.250)	(0.058)	(0.643)	(0.018)
4	0.006	0.179**	-37.468	0.250	0.134	0.086	-0.198***	0.288	-0.040
	(0.018)	(0.075)	(870.074)	(0.812)	(0.096)	(0.153)	(0.043)	(0.607)	(0.034)
5	0.028	0.234***	-11.644	0.152	0.131**	-0.078	-0.161***	0.059	0.151***
	(0.017)	(0.059)	(257.020)	(0.527)	(0.054)	(0.213)	(0.037)	(0.511)	(0.045)
Panel c. City									
1	-0.012	-0.202	-9.559	0.044	-0.222**	-0.269	0.003	0.059	-0.022
	(0.033)	(0.190)	(221.119)	(0.086)	(0.092)	(0.351)	(0.028)	(0.169)	(0.018)
2	0.009	0.006	-20.749	-0.013	0.018	0.032	0.026	0.153	-0.037
	(0.031)	(0.031)	(469.282)	(0.317)	(0.028)	(0.157)	(0.047)	(0.183)	(0.026)
3	0.015	-0.107**	5.278	0.184	-0.089**	-0.014	-0.113***	0.196	0.033
	(0.025)	(0.043)	(121.160)	(0.213)	(0.043)	(0.136)	(0.029)	(0.326)	(0.022)
4	0.006	-0.001	66.682	0.666	0.073*	0.169*	0.047	0.302	0.038
	(0.034)	(0.063)	(1547.298)	(3.024)	(0.044)	(0.101)	(0.034)	(0.349)	(0.029)
5	0.014	-0.006	14.137	-4.491	-0.040	0.014	0.066**	0.163	0.225***
	(0.025)	(0.020)	(286.070)	(14.143)	(0.053)	(0.186)	(0.028)	(0.301)	(0.037)
Obs.	40211	7837	94422	18470	20439	9250	52693	11691	257537

Notes: [1] All regressions include year dummies and individual controls: age dummies, tenure in current job, a dummy to identify switch to full time job. [2] Within each panel we evaluate the coefficient for each occupation quintile, ranked by median 2002 wage. 1 represents the bottom quintile while 5 is the top quintile. [3] We use robust standard errors and statistical significance follows the system: ***1%, **5% and *10%.

We start with the aggregate (Column 9). The results suggest that productivity growth at firm level, averaged across sectors, has a positive significant (albeit, again small) effect on the bottom quintile (panel (a)). A 10% increase in the firm's LP leads to a 0.1% increase in the wages of the lowest quintile. Across sectors, only *accommodation & food services* seem to contribute to this increase. Wholesale & retail trade, which enjoy an idiosyncratic positive rent share (firm level), do not show any significant difference across quintiles.

Unlike the firm level result, the effect of productivity growth at the industry level may increase wage inequality (panel b). The elasticities estimated for the lower quintiles are negative and, while the coefficient for the 4th quantile is not statistically significant, wages in the top quintile grow with industry LP growth. The coefficients of the three bottom quintiles, however, do not differ at any statistical threshold, although they are statistically significantly different from the top quintile. They range from 4% to 17%. The elasticity for the top quintile is 15%. Thus, while a 10% increase in labour productivity in this combination of sectors leads to a decrease in wages for the bottom three quintiles, which range between 0.4% and 1.7%, the top quintile experiences wage growth of 1.5%.

When looking at the different sectors, the results suggest that the potential increase in inequality might result from what occurs in *business services*, *construction* and *transport*. As observed earlier, industry LP growth has a negative impact on wages in business services (column 7): although the effect is particularly strong for occupations in the third wage quintile, all quintiles are affected negatively. The magnitude of this effect ranges between 16.1% and 41.5% (only the coefficient of the third quintile is significantly different from the other four, which show no statistically significant difference). That is, for a 10% increase in industry labour productivity in this sector, wages respond with a decrease of between 1.6% and 4.1%. However, the magnitude of the standard errors does not allow us to state a clear difference of effects across quintiles. Instead, in both *construction* and *transport*, a 10% growth in industry LP increases respective wages in the top quintile by 2.3% and 1.3%. Also, in construction, the fourth and second quintile are positive and significant, but this does not compensate for the negative effect of business services in the aggregate. (Although the point estimates for each quantile in the construction sector are different, statistically they are the same.) In sum, the previously observed negative impact of industry level LP on wages is relatively equally distributed across workers in business services (the coefficient of the middle quintile is larger, but no statistically significant difference was detected) and construction also might contribute to the inequality (but no statistically significant differences emerge).

The average effect (across sectors) of productivity growth in the local labour market (TTWA) also increases inequality: only the top quintile has a positive and statistically significant elasticity (22%). This is driven mainly by business services (column 8) where employees in the top quintile do experience an increase in wages (6.6%) as local productivity increases (or they move to more productive cities). Transport may also induce an increase in inequality, given the negative impact of TTWA LP growth on wages in the first and third quintiles (column 5).

Focusing on the manufacturing sectors (column 1), the interaction of the labour productivity measure (at firm, industry and TTWA levels) with the quintile category, yields no statistically significant result except for the 4th quintile interacted with the firm labour productivity. If anything, employees in this quintile see their wages negatively associated to firm productivity growth. However, as in the general case, the elasticity is very small at 3.5%.

In column 3, all the coefficients have very large standard errors, hence, none is statistically significant. Columns 4, 6 and 8 which present the results for the remaining sectors, show no statistically significant results.

Taking all these results together, we observe that the small link between LP and wages across sectors remains when we evaluate this link across different wage quintiles, especially at the industry level. This might be increasing inequality at the industry level, but we found no strong statistically significance evidence of that.

4.2.2 Labour Productivity and Wages Across Age Groups

As observed earlier, workers in the bottom quintile tend to be younger: is there any evidence of inequality across cohorts? Table 8 reports the results of the estimates of equation 2, considering different age groups: 16-24, 25-34 and 36-65, each interacted with the productivity measures.

Table 8: IV 2011-15, By Age

	Manufacture (1)	Construction (2)	Wholesales (3)	Hotels (4)	Transport (5)	Financial (6)	Bus, Serv. (7)	Other (8)	All (9)
Panel a. Firm									
16-24	-0.034	-0.031	0.013	0.024**	-0.005	0.393	-0.010	0.005	0.017**
	(0.026)	(0.063)	(0.009)	(0.012)	(0.042)	(4.635)	(0.027)	(0.021)	(0.007)
25-34	-0.006	0.009	0.016*	0.013	-0.005	1.246	-0.012	0.030*	0.006
	(0.011)	(0.021)	(0.009)	(0.013)	(0.009)	(20.775)	(0.014)	(0.017)	(0.004)
35-65	0.000	0.001	0.004	-0.012	0.001	-0.470	0.015*	-0.015	0.001
	(0.004)	(0.009)	(0.003)	(0.013)	(0.005)	(7.988)	(0.009)	(0.011)	(0.002)
Panel b. Industry									
16-24	-0.088**	0.174	-0.498*	0.169**	0.035	-3.437	-0.185***	-0.090	0.007
	(0.041)	(0.143)	(0.302)	(0.082)	(0.113)	(55.754)	(0.059)	(0.154)	(0.059)
25-34	0.011	0.226***	0.397	0.018	0.011	0.792	-0.132***	-0.034	-0.087*
	(0.022)	(0.067)	(0.412)	(0.084)	(0.055)	(14.293)	(0.046)	(0.116)	(0.048)
35-65	0.006	0.160***	0.042	-0.002	0.046	14.669	-0.236***	-0.015	-0.030***
	(0.010)	(0.056)	(0.200)	(0.083)	(0.033)	(250.712)	(0.036)	(0.067)	(0.011)
Panel c. City									
16-24	0.057	-0.057	0.509***	-0.158	0.069	-10.945	-0.012	0.049	0.038
	(0.067)	(0.107)	(0.191)	(0.097)	(0.122)	(185.963)	(0.049)	(0.135)	(0.043)
25-34	-0.009	-0.025	-0.343	0.084	0.031	-6.306	0.060	0.155*	-0.013
	(0.030)	(0.037)	(0.254)	(0.116)	(0.057)	(107.340)	(0.037)	(0.087)	(0.037)
35-65	0.011	-0.010	-0.016	0.046	-0.014	2.426	-0.034**	0.177**	0.027*
	(0.016)	(0.019)	(0.109)	(0.067)	(0.022)	(41.389)	(0.015)	(0.086)	(0.016)
Obs.	40220	7838	94427	18485	20450	9265	52694	11698	257537

Notes: [1] All regressions include year dummies and individual controls: age dummies, tenure in current job, a dummy to identify switch to full time job. [2] Within each panel we evaluate the coefficient by age group: 16-24, 25-34 and 35-65. [3] We use robust standard errors and statistical significance follows the system: ***1%, **5% and *10%.

Column 9 reports the results for the full sample. The results in panel (a) indicate that only the youngest cohort gains from LP growth in the firm: a 10% growth in firm LP leads to a 0.17% increase in wages. Confirming the results for the wage quintiles, *accommodation & food services* seems to be the only sector that contributes to wage increases for the youngest and lowest paid workers. Wholesale & retail trade, which enjoy an idiosyncratic positive rent share (firm level), does not show any significant differences across age groups.

At the industry level (panel b) the small negative effect of LP on wages is borne by the oldest cohort. A 10% increase in industry productivity (averaged across sector) leads to a reduction of 0.3% in wages for individuals aged between 35-65. The negative effect on the oldest cohort is driven mainly by business services (a 10% increase in industry LP leads to a reduction in wages of 2.36%) which is not compensated for by the positive effect of the much smaller construction sector (1.6% increase in wages for a 10% productivity growth).

Although the youngest cohorts do not seem, on average, to be affected by industry LP growth, the effect is negative in some sectors. In business services (column 7) there is no statistically significant difference between the effects on the oldest and the other cohorts. A 10% increase in industry LP in the business services sector leads to a reduction in wages of 1.3% and 1.9% for the 25-34 and the 16-24 groups, respectively. In the manufacturing sector, the youngest cohort experiences a reduction in wages (column 1, 0.8%), but in the case of trade sectors (column 3) this reduction is barely significant. The only sector where the youngest cohort gains from an increase in industry LP is accommodation & food services (column 4, 16.9%), which is in line with the results at firm level (column 4) and the findings across wage quintiles.

The average effect (across sectors) of productivity growth in the local labour market (TTWA) (panel c) is not statistically significant. However, in wholesale & retail trade (column 3), the youngest cohort gains substantially from an increase in the TTWA LP: 50.9%. This is the highest elasticity estimated so far. With respect to business services (column 7), the results in panel (c) indicate, also, that TTWA LP growth leads to a reduction in the wages of the oldest cohort. The magnitude of this effect is very small (0.034), that is, a 10% increase in business services productivity in the local labour market leads to a reduction of 0.34% in the wages of the oldest cohort. Taken together with the results for the wage quintiles, at the TTWA level workers in the best paid occupations gain from an increase in TTWA productivity, but these are not among the older cohorts (which are less likely to move to more productive cities). The results show also that the increase in wages in the creative industries (column 8) discussed above, is concentrated on the oldest cohort, though barely significant.

Focusing on manufacturing (column 1), we find that decomposing by age does not improve the results: there is no evidence of rent sharing across age cohorts. As just discussed above, the only significant coefficient is for the interaction between industry labour productivity and the youngest cohort.

In sum, older cohorts in business services lose out (although the same cohorts in construction gain) from industry increases; the youngest cohorts see their nominal wages increasing in food & accommodation services (from LP growth in both firm and industry) and wholesale & retail trade (from LP growth in the TTWA), but otherwise are negatively affected by industry level productivity growth. Overall, there are few differences across age groups in the transmission of labour productivity on wages.

4.2.3 The Role of Unions

Do unions matter for increasing the bargaining power of workers and accruing some of the productivity gains (Matano and Naticchioni, 2017), or do they curb rent sharing by fixing wages, and making the firm labour supply curve more wage elastic (Manning, 2011; Blanchflower et al., 1996)?

Table 9 reports the results from estimating equation 3 for all sectors. We measure unionisation (*union*) as the industry share of unionised employment. For this particular case, we calculate share of unionisation at the 2-digit industry level. The median share of unionisation across 2-digit industries is 0.2, hence, we use this as the reference when interpreting the results.

At the firm level, averaging across sectors (column 9), unionisation seems not to play a significant role in the small rent share accruing from firm level LP. In wholesale & retail (column 3), which was shown to be responsible for this rent share (Table 6), unionisation is not significant. However, in the case of food & accommodation services (column 4), where the lowest quintile

Table 9: Union interaction

	Manufacture (1)	Construction (2)	Wholesales (3)	Hotels (4)	Transport (5)	Financial (6)	Bus, Serv. (7)	Other (8)	All (9)
LP_f	0.005	0.004	0.004	0.029***	0.002	0.063*	0.018*	0.037*	0.003
	(0.007)	(0.043)	(0.005)	(0.011)	(0.005)	(0.036)	(0.010)	(0.020)	(0.003)
$LP_f \times union$	-0.037	-0.041	0.018	-0.584**	-0.016	-0.421**	-0.059	-0.285**	0.012
	(0.026)	(0.257)	(0.024)	(0.258)	(0.014)	(0.211)	(0.053)	(0.132)	(0.011)
LP_j	0.028	0.997**	0.076***	0.056	0.052*	-0.191*	-0.136***	-0.033	-0.015
	(0.018)	(0.451)	(0.024)	(0.042)	(0.027)	(0.101)	(0.033)	(0.030)	(0.016)
$LP_j \times union$	-0.070	-5.346*	-0.142	0.770	0.293**	1.884**	-0.607***	-0.137	-0.143***
	(0.046)	(2.898)	(0.096)	(0.563)	(0.119)	(0.839)	(0.092)	(0.121)	(0.044)
LP_c	0.003	0.343	0.144**	-0.035	-0.019	-0.133**	0.073***	0.234***	0.022
	(0.024)	(0.213)	(0.068)	(0.091)	(0.034)	(0.057)	(0.024)	(0.078)	(0.018)
$LP_c \times union$	0.024	-2.250*	-0.833**	0.572	0.021	1.037**	-0.263***	-0.344***	0.007
	(0.065)	(1.340)	(0.339)	(1.855)	(0.082)	(0.479)	(0.065)	(0.127)	(0.040)
Obs.	39900	7838	94427	18485	20450	9265	52684	11698	257206

Notes: [1] All regressions include year dummies and individual controls: age dummies, tenure in current job, a dummy to identify switch to full time job. [2] We use robust standard errors and statistical significance follows the system: ***1%, **5% and *10%.

and the youngest employees seem to gain from firm LP growth (although significance levels are not the highest – Tables 7 and 8), the interaction between unionisation and firm LP is negative: a 10% increase in firm LP leads to a general increase in wages of 0.3%, however, for every additional percentage point of unionisation, this effect declines by 0.1% [10% × 0.02 × -0.584]. This is probably related to the fact that the youngest cohorts and the lowest quintile occupations are also the least unionised in the sample, with food & accommodation services not even 5% unionisation.[38]

At the industry level, the results for the estimation on the overall sample (column 9) indicate that the negative association between industry LP and wages is statistically significant when interacted with the union variable. We evaluate these results at the median of share of unionisation (0.2): a 10% increase in industry LP leads to a reduction of 0.28% [10% × 0.143 × 0.2] in the wages of workers in industries unionised at the median.

This result seems to be influenced by the business services sector: a 10% increase in LP reduces business services wages by 1.4%, and every extra percentage point for share of unionisation increases the absolute magnitude of this effect by 0.0012 [10% × 0.02 × -0.607] (in line with the results in Table 5). On the other hand, the positive effects of TTWA LP growth on wages in construction (column 2) and wholesale & retail trade (column 3) seem not to be related to unionisation. Moreover, unionisation may be related to the potential effect on inequality of LP growth in transport (column 5, see Table 7). For every percentage point increase in the share of unionisation, a 10% increase in industry productivity leads to 0.06% [10% × 0.02 × 0.293] increase in wages.

At city level, averaging across sectors (column 9), unionisation still shows no effect of LP on wages. Results for the wholesale & retail trade (column 3) suggest that unionisation has a negative effect when interacted with TTWA LP: a 10% increase in local labour market LP is generally associated with a 1.4% increase in wages, but for every additional percentage point of unionisation within the industry, this effect declines by 0.16% [10% × 0.02 × -0.833]. As discussed in the case of food & accommodation, this is probably an artefact of the 16-24 cohort (also the least unionised) experiencing the highest gains (Table 8). In the case of business services (column 7), the results tell a similar story. A 10% increase in TTWA LP leads to 0.7% increase in wages, but for every percentage point of unionisation in the industry, the effect is reduced by 0.05% [10% × 0.02 × -0.263]. We know also that TTWA LP growth has a negative effect on the oldest cohort, which is likely to be the most unionised. In sum, in both cases, the TTWA effect may be due to both age or unionisation (or a combination of the two).

In the case of the creative industries, the union interaction is statistically significant for city productivity, reducing its normally positive effect on wages, by 0.07%.

When we evaluate the manufacturing sector (column 1) we find that interacting our three measures of LP with the share of unionisation in the 2-digit industry serves to confirm only lack of any rent sharing. None of the three interactions result in statistically significant coefficients. Since, in line with earlier studies,[39] we do not find that unionisation reduces rent sharing, the absence of a link between productivity and wages in manufacturing can be ascribed to lack of any

[38] Figure 7 in Appendix D.

[39] E.g. Blanchflower et al. (1996), Hildreth and Oswald (1997), Bronars and Famulari (2001), Estevao and Tevlin (2003).

significant recovery in productivity after the recession and an implicit agreement that, following initial labour hoarding and relatively high employment rates, initial productivity gains will not be shared (or at least not immediately).

In sum, in countries, such as the UK, where unions have comparatively little bargaining power, the main effect of unionisation seems to be to make labour supply more elastic (Manning, 2011; Blanchflower et al., 1996), reduce rent sharing and, in some cases, increase wage inequality (transport). The remaining effects seem to be confounded by the composition of the unionised population, which is neither the youngest not the lowest paid.

5 Summary and Discussion

This work examined the extent to which productivity growth in the UK, following the financial crisis, has been shared with workers in the form of wage increases, and the potential heterogeneity of this relationship. We proposed an articulated empirical analysis of a baseline rent sharing estimation, and of several sources of heterogeneity: by sectors, age cohorts, occupational categories grouped in wage quintiles, and degree of unionisation at the industry level. Most of the analysis focused on the 2011-2015 period of slow recovery following the 2009 crisis. Most importantly, and unlike most of the extant literature, we are able to attribute wage elasticities to firm, sectoral and city level productivity changes. The overarching question we address is whether productivity trends in the UK are leading to increasing wage inequality by benefiting mostly top versus low end earners. In this respect, we add to the few, very recent studies reviewed in (Card et al., 2018), and extend them in a number of ways, as discussed in Section 2.

Before summarising our findings, it is relevant to discuss some of our methodological choices. First, our study focuses on "continuing employees" (which includes employees who change firms and/or local labour markets).[40] Second, we do not consider the effects on non-wage types of compensations, such as pensions, bonuses and performance premia. These would likely downward bias our results for the top earners (Pessoa and Reenen, 2013; Bell and Van Reenen, 2012). Third, we do not consider changes to the number of hours worked (although we control for part time workers), since we chose to use hourly nominal wages.[41] Fourth, all micro-econometric studies, as suggested by Card et al. (2018), depend on the type of instrumentation strategy adopted. The choice to use physical TFP to instrument LP might affect the estimations on services and other intangible sectors where the quantification of firm output and productivity are less established than in manufacturing. Any interpretation of the results should take account of all problems related to mis-measuring productivity in services.[42]

Overall, we find that productivity growth, following the recession, has led to a reduction in nominal wages in the case of growth at the industry level. When distinguishing *across sectors and levels of productivity growth*, we find that in most cases **there is little association between any measure of labour productivity and wages**. Elasticity is nil (not significantly different from zero) for manufacturing and negative for *business services*, at the industry level.[43] When it occurs, most of the effect is at the industry level: very little is transmitted through idiosyncratic increases in productivity (apart from wholesale & retail trade and food & accommodation in the lowest quintiles).

Across wage quintiles, the results for the whole sample suggest that productivity growth at

[40] We chose not to consider the extensive margin (entry and exit from the labour market) or the self-employed. This latter category shows an interesting dynamic (see (Ciarli et al., 2018)): workers who become unemployed and/or self-employed, particularly as a result of increases in R&D investments (and, therefore, most productivity) (Ciarli et al., 2018), might represent a substantial share of low income workers. This could bias upwards our results for the effects of productivity growth on low-end earners. Nevertheless, we are able here to provide evidence on the direct, heterogeneous effects of firm, industry and city level productivity shocks on wages.

[41] As discussed in Section 1, based on Crawford et al. (2013); Blundell et al. (2014), the financial crisis and the slow recovery over the very recent years have led to a very peculiar trend in the UK productivity. On the one hand, firms have preferred to 'hoard labour', i.e., to avoid making workers redundant and have coped with the crisis by reducing the hours of incumbent workers. If, on the one hand, this has protected the incumbents in the labour market, it might also be responsible for the substantial fall in hourly wages. On the other hand, as suggested by Pessoa and Van Reenen (2014a), part of the productivity fall in the UK might be due to the very sluggish wage dynamics because firms found it more convenient, *cæteris paribus*, to invest less in capital and hire more workers at a comparatively lower cost.

[42] Section 3.2 and Appendix B detail our empirical strategy.

[43] As already mentioned, caution is advised in the interpretation of this result since output and value added in this sector are likely to be subject to measurement error, and the changing importance of un-observed heterogeneity over time (which we cannot control for) is high.

industry level may increase inequality (although differences across quintiles are not statistically significant): the negative association between industry labour productivity and wages is significant and varies across quintiles, with a **negative elasticity for the lowest three quintiles and a positive elasticity for the top quintile**. The negative elasticity seems to be driven by business services, and possibly is compensated partially by the (positive) elasticity in the construction and transport sectors.

Across age groups, the **overall negative wage elasticity to industry productivity is focused on the 35-65 cohort**, while at the firm level the youngest employed in food & accommodation seem to gain more.

At the *city* level, there is little statistical association between wages and productivity with the notable exception of the 16-24 cohort in the wholesale& retail trade sector.

The *creative sector* shows a peculiar pattern, with wage increases occurring only for productivity growth at city level and for the top quintile and the older cohort (although less for the older cohorts).[44]

It is well known that *unionisation* reduces rent sharing elasticity and, in the case of business services, it increases the negative impact of productivity growth on wages.

These findings suggest a number of relevant questions and policy issues related to the UK's Industrial Strategy. The main issue is to reconcile these findings with the identification of policy recipes to improve productivity on the one hand, and lift wages, especially the lowest, on the other. We outline some recommendations below.

It is worth noting that, in relation to the *time-frame of our analysis*, our findings are not directly comparable to extant studies based on matched employer/employee data. To our knowledge, the present work is the first to test the productivity-pay link after the crisis, so our results are possibly (and partially) comparable only to Juhn et al. (2018), whose analysis, however, is limited to manufacturing (1998-11), finance (2002-11) and professional services (1992-11). Similar studies focus on earlier time-spans and, thus, are not necessarily long-term (e.g. Carlsson et al. (2016): 1990-6; Card et al. (2016): 2002-9; Bagger et al. (2014): 1995-97). Therefore, concluding that in rent-share elasticity in the UK is lowest would not be appropriate.

In relation to the role of *institutions and bargaining power*, our findings are in line with what might be expected in relation to a perfectly competitive market, that is, the bulk of the transmission of productivity gains to wages, affects *real* rather than *nominal* wages. Therefore, this is a first potential explanation of our findings: compared to other institutional contexts, the UK labour market is more flexible and more frictionless than others. However plausible, this interpretation does not explain the negative elasticity in some sectors, or the differences across groups of workers.

A second potential explanation is the sheer low pace of the recovery, on average, which does not lead to any detectable changes in productivity, especially in manufacturing where productivity growth is close to nil. The problem with this explanation is that, the flat average growth rate hides significant heterogeneity across firms Haldane (2017a).

A third potential explanation is related to the risk averse labour contract interpretation in Blanchflower et al. (1996): labour hoarding, limited impact of the financial crisis on employment and high employment rates in the UK, and the contemporaneous reduction in real wages and income, which maintain a high effective labour supply. Workers are willing to work, even for lower pay, and firms, which feel they have borne their share of risk by hoarding labour, are not willing to share the small increases in productivity gained following the recovery.

Our findings suggest, also, that inequality across wage quintiles may increase, as a result of industry level productivity growth. The negative effects on the three lowest quintiles seem to be driven by the results for business services (which include a set of heterogeneous activities ranging from real estate services to knowledge intensive business services). The positive results at the top are driven by construction and transport. Overall, these results are of interest for industrial policy, although, as suggested in several places, the appropriateness of traditional productivity measures (for instance, TFP) for service sectors is not established, and the assessment of productivity gains in services may be subject to errors and biases.

The crucial questions, as policies are aimed at increasing productivity across the board, are whether bargaining between workers and firms will change and whether productivity growth will be shared partly with nominal wages, and how these will be shared across groups of workers.

[44] Again, these results need to be considered with caution for measurement reasons and because of the relatively low number of observations.

Based on the above considerations, it is difficult to offer unequivocal lessons in terms of policies to reconcile productivity growth with low wage gains. It is likely that targeting specific sectors might turn out to be less important in a context where the productivity-pay link is less clear-cut. The few uncontroversial lessons about what might be the most effective policy to lift the wages of low paid workers are mostly at the firm level, where the transmission was found to be (weakly) positive. On-the-job training, ICT adoption and adaptation in organisations could contribute to the diffusion of productivity to the 'long tail', which includes largest and possibly most diffused gains.

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A Construction of Labour Productivity

We construct measures of labour productivity (LP) at the firm, industry and city level. Data from ABS are available at many different levels that require a degree of harmonization in order to produce the relevant LP measure. This section details the procedure we use for this.

The most detailed set of information contained in ABS is available at the firm level (*entref*), which is the registered firm. In order to calculate our measure of labour productivity in the city we require information on the local activities of the firm. In the case of a single-plant firm this is not a problem, however, in some cases a firm could have many local branches. ABS records the postcode of each local unit belonging to the firm, and this is the level of geographical detail we employ.

We match each postcode to the TTWA it belongs into. We use the 2011 TTWA boundaries published by ONS that correspond to the 2011 census.

The first step consists on calculating the measure of labour productivity at the firm level. In some cases firms operate in more than one industry, and ABS firm data set reports information at the firm-industry code level. This is not trivial in our case since we estimate the elasticity of labour productivity on wages by sectors.

We collapse the information on gross value added (GVA), number of employees and turnover at the firm-industry code match. For the industry code we use the 2003 SIC code at 3-digits level.

In the second step we collapse the data roster at the firm level for the relevant sector. For instance, when we focus on manufacture we keep only firms with manufacturing activity and aggregate the variables GVA, number of employees and turnover at the firm (*entref*) level. We then the calculate labour productivity as the ratio between GVA and number of employees. Thus, the information we have in this case is the aggregate manufacturing activity at the firm level.

In the third step we match the firm labour productivity to all its local units that belong to the same sector. With the information on the number of employees in each local unit we distribute the firm's labour productivity to all the local units based on their labour share. The result of this is a data set at the local unit level that we can use to estimate our three measures of LP.

Finally, we estimate a turnover weighted regression of the local unit labour productivity on a set of dummies for the 3-digit industries and a set of dummies for TTWAs, each interacted with time. Therefore, the projection on the industry dummies is our measure of industry LP, while the projection on the TTWA dummies is our measure of city LP. The residuals are our measure of local unit LP that we further re-aggregate to the firm level using the employment shares.

B Instrumentation strategy: TFP Estimation

In the IV estimation we instrument each LP measure with its corresponding TFP measure, which we calculate as follows.

The basic idea behind the identification strategy is that we use a measure of physical (or quantity) productivity which allows us to isolate variation in labour productivity that is independent from price changes, or reverse causality from wages to labour productivity. This strategy relies on estimating a quantity measure of TFP. We convey this by using industry price deflators in the construction of our TFP measure.

We estimate TFP as the residual from the log form of a standard production function in three steps. First, we estimate the residual of the production function using panel firm level data:

$$\Delta(\ln VA_{ft}) = \alpha + \beta_1 \Delta(\ln n_{ft}) + \beta_2 \Delta(\ln k_{ft}) + \tau + \eta_d \tau + \Delta\epsilon_{ft} \tag{4}$$

where the firm's output (VA_{ft}) is measured as gross value added at factor prices – to simplify from the measurement of material inputs, which may differ across firms due to vertical integration, and to avoid measurement errors due to stocking; n_{ft} is the labour input, measured as the firm wage bill;[45] k_{ft} is the capital input, measured as the value of capital assets at the end of the period; τ is a year dummy that controls for macro productivity trends, while ϵ_{ft} is our measure of

[45] As in Hsieh and Klenow (2009), we measure labour input as the wage bill to take into account variations in the number of hours worked, and the skill composition of the labour input within the firm

TFP.[46] We estimate TFP using first-differences to get rid of fixed non-observable variation at the firm level that may bias the estimation of the returns to labour and capital. We deflate all variables using the industry deflators provided by ONS (Ayoubkhani, 2014). The data do not allow us to construct firm-specific price deflators as in Carlsson et al. (2016) because we cannot observe what products the firm produces. In the second step we integrate into a log level technology series using the following recursion $tfp_{ft} = tfp_{f0} + \sum_{r=1}^{r=t} \Delta\epsilon_{fr}$. The initial level of technology tfp_{f0} is a firm-specific constant unobserved for the econometrician but will be absorbed in the firm-fixed effect we use in the main specification.

In the final step we estimate the projection of this firm-level technological level on industry and TTWA dummies that also vary with time. As with the estimation of labour productivity we rely on local unit employment shares to estimate TTWA TFP. The projection on the (three-digits) industry dummies is our measure of industry TFP; the projection on the TTWA dummies is our measure of the city TFP; the residual is our measure of final firm TFP measure purged from TTWA and industry effects.

C Trade Induced Productivity Instrument

As an alternative to our measure of quantity TFP we implemented an instrumentation strategy that exploited the industry trade exposition to China imports as an exogenous source of variation for labour productivity. This strategy follows Bloom et al. (2016) and we define a measure of industry exposition to imports from China which we interact with the growth of China imports for the U.S.

We can only implement this strategy for the manufacturing sector since this strategy relies on the exposition of goods that can be traded internationally and are also affected by the production of China (mainly textiles).

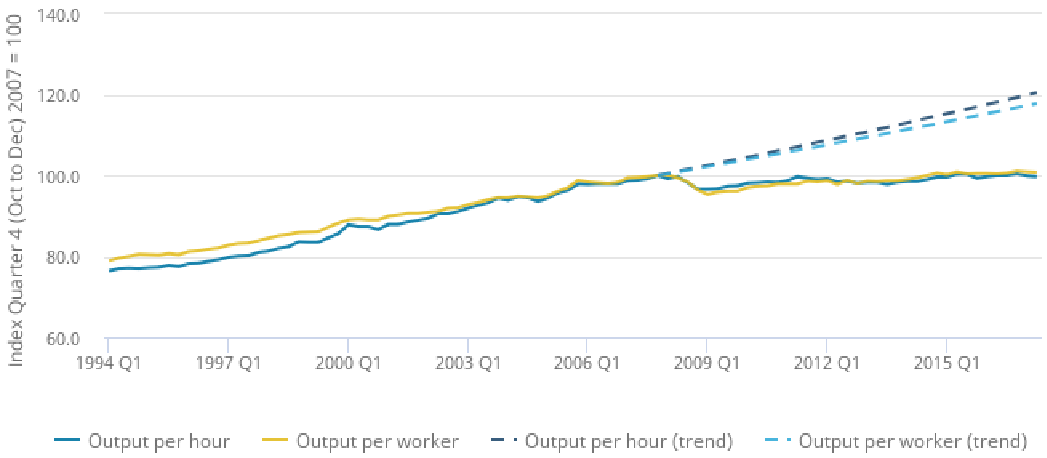
We expect that China's accession to the World Trade Organization in 2001 triggered competition in some manufacturing industries. We use the change of U.S. imports from China across 3-digits industries for the period 2004-2001 and weight these changes by the 1999 labour share across the same industries in the UK. UK industries that were more **exposed** to China's competition would have to be more competitive to cope with the next context. We expect that as a consequence UK firms in the exposed industries increase their labour productivity, and this improvement should be independent from prices, which is the source of variation w utilize in the identification strategy.

We apply this strategy only for the firm productivity and results do not change: firm labour productivity in the manufacturing sector is unrelated to wages.

[46]Because capital and wages bill information is available only at the business level, we first estimate firms' TFP and then spread this value across all local units of the business using the employment shares of each local unit. This allows us to estimate TFP at the city level.

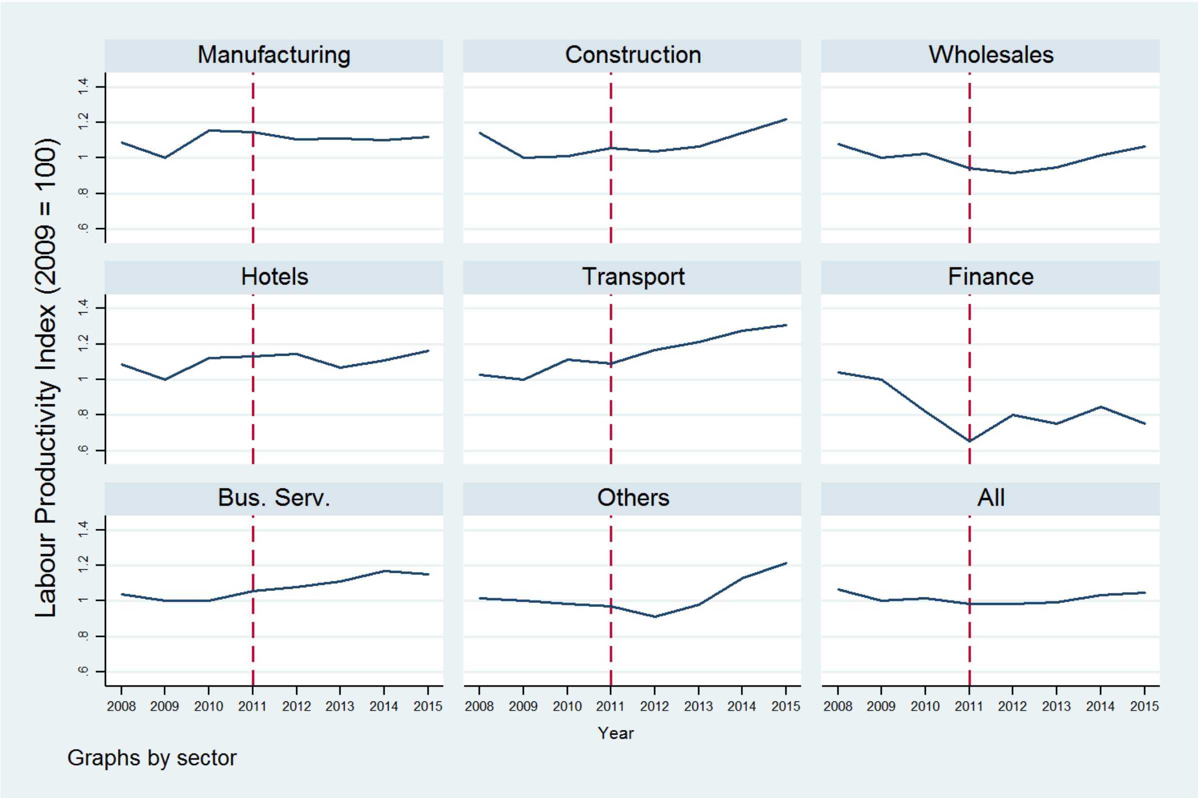
D Figures

Figure 1: Productivity: Output per hour and output per worker



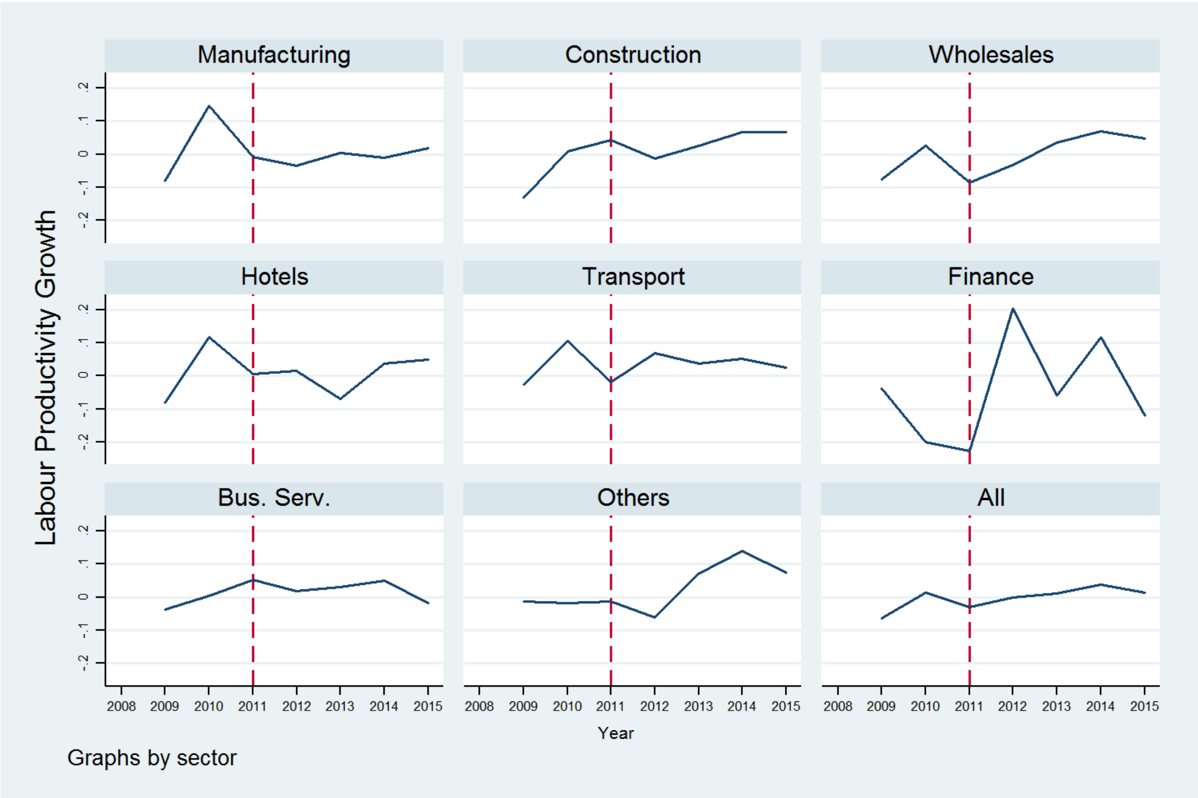
Source: Office for National Statistics

Figure 2: Labour Productivity Index (base=2009)



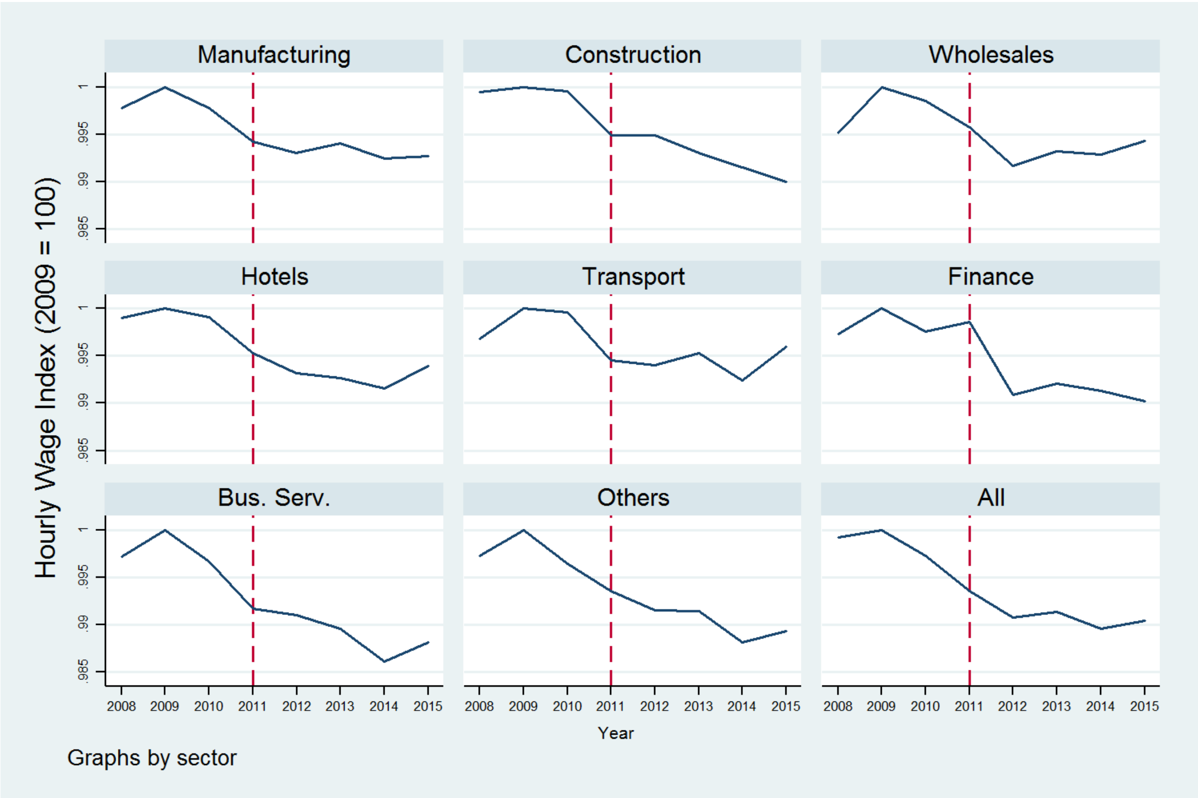
Notes: Calculated with data from ABS. Vertical red dashed line marks 2011. Values deflated with annual CPI.

Figure 3: Labour Productivity Annual (log) Growth



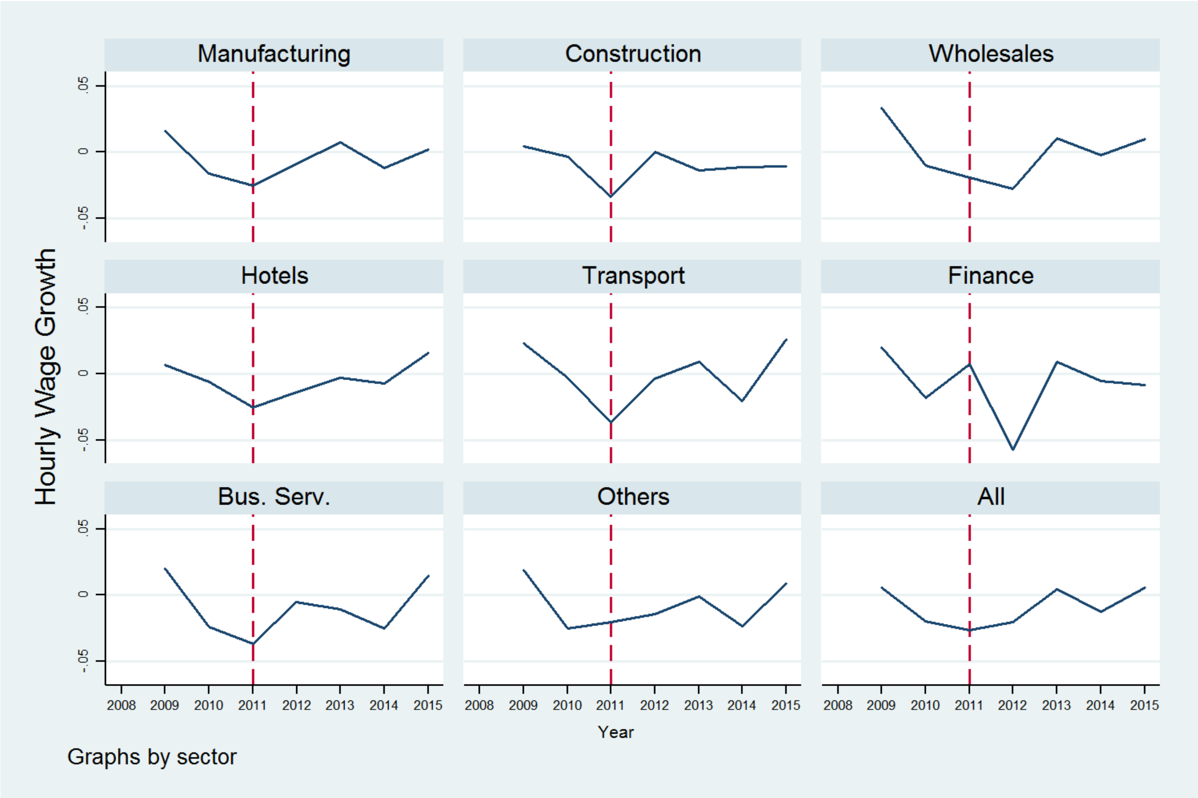
Notes: Calculated with data from ABS. Vertical red dashed line marks 2011. Values deflated with annual CPI.

Figure 4: Hourly Wage Index



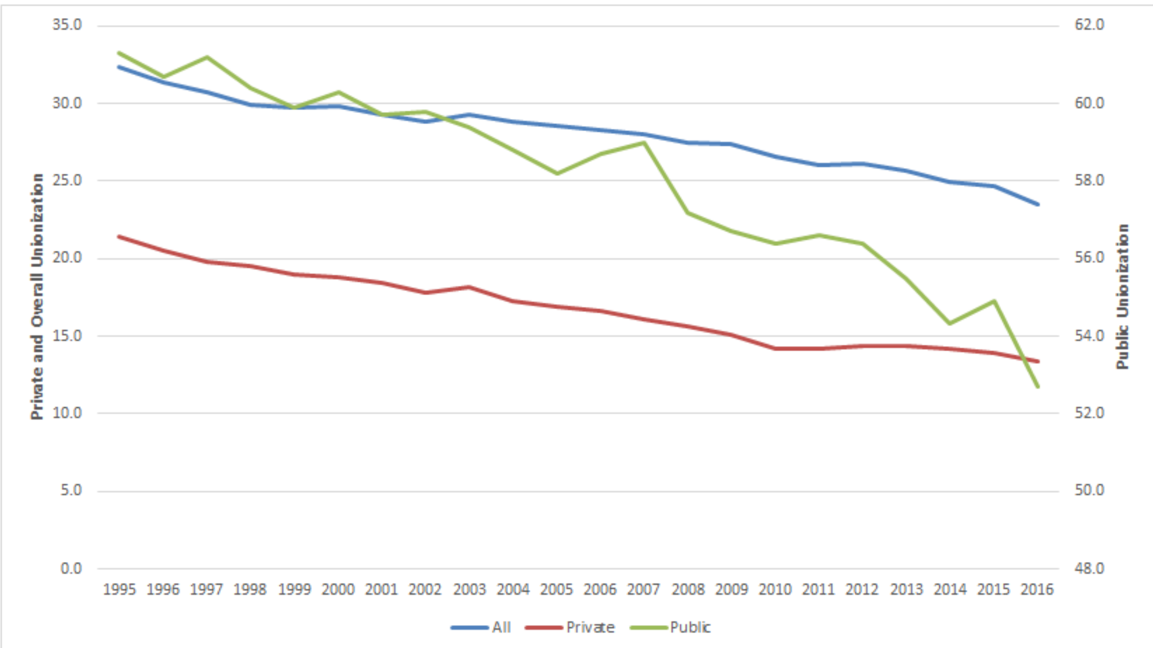
Notes: Calculated with data from ASHE. Vertical red dashed line marks 2011. Values deflated with annual CPI.

Figure 5: Hourly Wage Annual (log) Growth



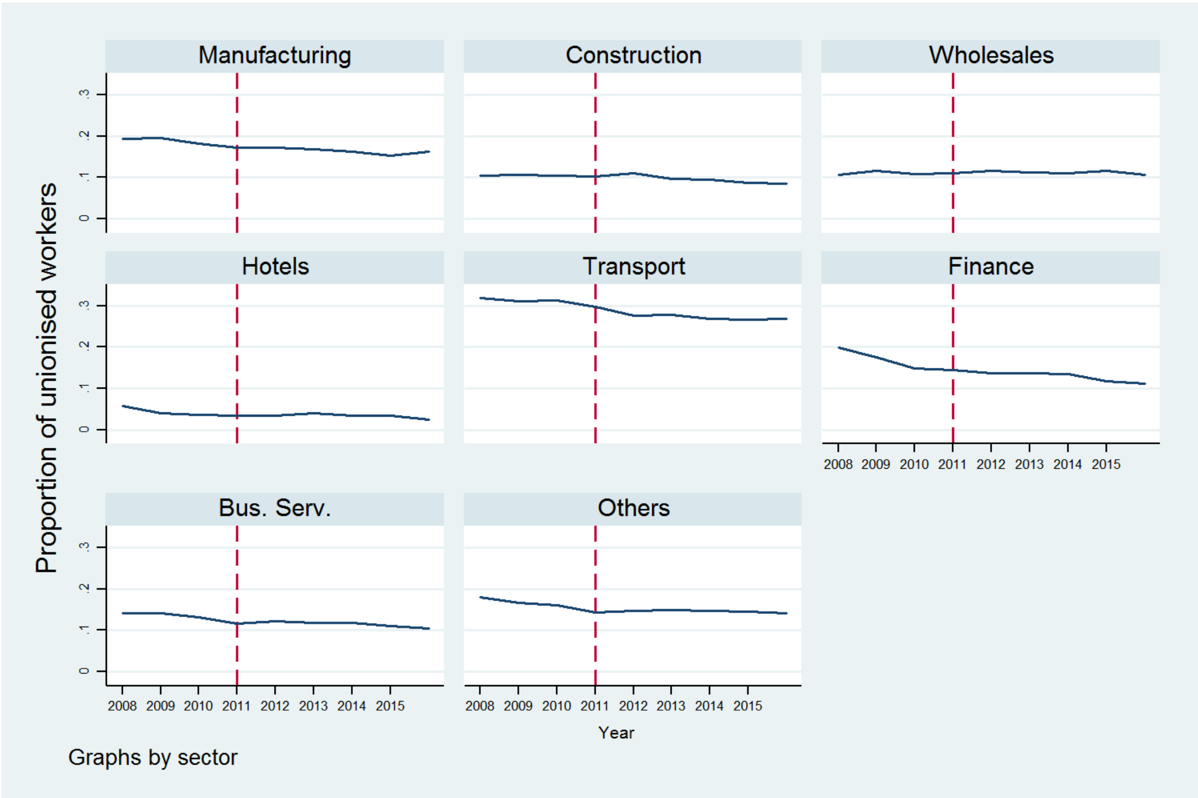
Notes: Calculated with data from ASHE. Vertical red dashed line marks 2011. Values deflated with annual CPI.

Figure 6: Ratio of Unionized Employees



Source: Labour Force Survey, Office for National Statistics

Figure 7: Unionisation Rate by Economic Sector



Notes: Computed using the October-December quarter of QLFS. The red line is 2011