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The UK National Minimum Wage's Impact on Productivity

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Low pay poses issues for managers internationally. We examine productivity in low-paying sectors in Britain, since the introduction of the National Minimum Wage (NMW). We use a multiple channel analytical strategy, emphasizing the wage incentives channel and linking it to a model of unobserved productivity. We estimate firm-specific productivity measures and aggregate them to the level of low-paying sectors. Difference-in-differences analysis illustrates that the NMW positively affected aggregate low-paying sector productivity. These findings highlight increased wage incentive effects with implications for management practice and public policy since 'living' wages may be productivity enhancing.

Introduction

We examine the impact of the National Minimum Wage (NMW) on productivity, building on the *British Journal of Management*'s first virtual edition: Employee responses to changing work practices (Frynas and Croucher, 2015). Managing wages at the bottom of the distribution and the relationship between efficiency and equity are increasing concerns for managers and governments internationally. Debates around the recent introduction of a national minimum wage in Germany, discussions of the level of state and federal minima in the USA, calls for a European minimum wage and low pay concerns in multinational corporation supply chains pose significant issues for managers. So, too, do British calls for organizations voluntarily to implement 'living wages' (Atkinson, 2015). Meanwhile, productivity concerns preoccupy British commentators (Atkinson, 2015). Yet evidence on the minimum wage–productivity link is scarce and inconclusive. Existing studies (e.g. Croucher and Rizov, 2012; Galindo-Rueda and Pereira, 2004; Riley and Rosazza-Bondibene, 2015) use labour productivity measures and industry level data (Forth and O'Mahony, 2003). The NMW's impact on total factor productivity has not previously been explicitly studied with micro data. However, some recent indirect evidence on wages, employment and profits in the UK (Bernini and Riley, 2016) and case studies in the USA (Hirsch, Kaufman and Zelenska, 2015) suggest that minimum wages may raise total factor productivity.

In the UK, the impact of minimum wages on firms has commonly been studied from neoclassical perspectives. Wage increases raise firms' marginal costs, inducing them to reduce mark-ups (e.g. Draca, Machin and Van Reenen, 2011; Galindo-Rueda and Pereira, 2004; Riley and Rosazza-Bondibene, 2015), making firms appear less productive. However, firms experiencing high factor costs may pass some on as higher output prices, fully compensating for mark-ups (Wadsworth, 2010). The extent of labour market competition also has important implications for input prices and productivity (Dickens, Machin and Manning, 1999; Machin and Manning, 1994). For large (monopsonistic) firms, minimum wages can reduce marginal costs, increasing demand for labour and in turn increasing output and, possibly, productivity. In competitive labour markets, minimum wages will bring higher costs; capital-for-labour substitution would be the prevailing adjustment mechanism, leading possibly to productivity improvements (Machin and Manning, 1994). Clearly, neo-classical models' predictions depend on assumptions influenced by market conditions.

We investigate the issues from an alternative, behavioural stance.[1] Several early theoretical studies on the implications of efficiency wages link wage increases and higher productivity (e.g. Lazear, 1981; Salop, 1979; Shapiro and Stiglitz, 1984). In related but more behaviourally focused frameworks, Akerlof (1982), Akerlof and Yellen (1990) and Levine (1991) argue that perceived reciprocity and fairness affect workers' productivity. Fair wage–effort theory (Akerlof and Yellen, 1990) suggests that when workers receive less than the wage they 'deserve', they reduce effort. In determining their 'fair wage', individuals compare themselves with others dependent on market conditions, resulting in relative reductions in wage differentials. Levine (1991) argues that reducing wage dispersion can increase work team cohesiveness, promoting productivity. We use these arguments in developing our analytical strategy.

The UK's introduction of the NMW constitutes a relevant natural experiment. We propose that introducing a minimum wage improved incentives and thus productivity either through efficiency wage mechanisms or by aligning real and fair wages. We model the link between total factor productivity (TFP) and the NMW in a novel way using a structural productivity estimation approach based on Olley and Pakes (1996). Previous studies relating productivity to the NMW employ a two-step analysis where in the first step productivity is estimated without controlling for the NMW's effects and then, in a second step, the NMW's association with the productivity measures is analysed. The productivity measures estimated in the first step are likely to suffer from omitted variable bias. Our approach explicitly models the unobserved productivity and directly incorporates the effects of the NMW into an integrated semiparametric estimation algorithm. Our analysis therefore generates robust empirical evidence on the relationship between the introduction of the NMW and improved productivity over time.

[1]Lester (1960) offered the first institutional-behavioural explanation of minimum wage effects on labour market outcomes. Kaufman (2010) and Hirsch, Kaufman and Zelenska (2015) extend Lester's ideas, proposing a multiple channels of adjustment approach.

Selective literature review

Numerous studies on minimum wage effects use neo-classical economics models. Effects on employment and wage distributions have been extensively studied in the USA (e.g. Card and Krueger, 1994, 1995; DiNardo, Fortin and Lemieux, 1996; Hirsch, Kaufman and Zelenska, 2015; Katz and Krueger, 1992; Lee, 1999; Slonimczyk and Skott, 2012) and in the UK (e.g. Dickens, Machin and Manning, 1999; Georgiadis, 2013; Machin and Manning, 1994, 2004; Machin, Manning and Rahman, 2003; Metcalf, 2002, 2008; Riley and Rosazza-Bondibene, 2015; Stewart, 2002, 2004). Consensus exists that the overall effect on employment is neutral and accompanies (modest) wage distribution compression. Recently, Bernini and Riley (2016) and Hirsch, Kaufman and Zelenska (2015) both concluded that minimum-wage-induced adjustments through channels identified by neo-classical models are relatively insignificant. They suggest that institutional-behavioural models could have more explanatory power.[2] Grimshaw (2013) advances similar views.

Therefore, our focus is on wage incentive effects, which have been central in identifying sources of increasing productivity at firm and wider economy level. Economists have developed efficiency wage (Shapiro and Stiglitz, 1984) and labour extraction function (Bowles, 1985) models, where wages and monitoring levels are traded off to elicit workers' effort.[3] Wages are set above the market clearing wage, creating incentives for increased worker effort due to the increased opportunity costs of finding another job.[4]

[2]Hirsch, Kaufman and Zelenska (2015) argue that all three main labour market models (competitive, monopsony and institutional-behavioural) capture important elements regarding adjustment effects, making comparison and empirical discrimination difficult.

[3]Georgiadis (2013) tests a shirking model within efficiency wage theory by studying the NMW's impact on the UK's care home industry. In his framework the NMW generates an increase in the average wage in an organization which results in reduced supervision costs, and by implication increased productivity.

[4]Unemployment has been seen as a crucial component of the efficiency wage incentive scheme to work. How-

Another related but theoretically distinct set of models posits that social norms and comparisons are important for workers. In Akerlof (1982), workers and employers create implicit gift exchange relationships, which are more valuable for incumbent workers and employers than external options, thus inducing higher effort and productivity. Akerlof and Yellen's (1990) model is particularly relevant for low paid contexts: through comparisons with a reference group, workers conceive of a fair wage, which if above the actual wage results in reduced effort and productivity; at wage levels above the fair wage no productivity effect arises. Their argument draws on observations of behaviour consistent with psychologists' equity theory (Adams, 1963) and sociologists' social exchange theory (Blau, 1964; Homans, 1961). In both theoretical constructs, equity notions are crucial and are generally strongly empirically supported. When workers perceive their wages as fair they are more proactive and willing to participate in company affairs (Levine, 1993). Perceived fairness in the presence of appropriate group norms promotes labour force cohesiveness and synergies (Beal *et al.*, 2003; Cartwright, 1968) potentially producing monitoring savings.

Selecting the most appropriate reference group in a perceived fairness/equity comparison remains a contested endeavour. Using equity theory (Adams, 1965) as the underlying framework requires individuals to decide if they are being rewarded equitably by comparing their inputs and outputs with those of others. Here, both rewards and productive contributions matter. Relative deprivation theory (Crosby, 1976; Davis, 1959) proposes a referential framework based only on rewards comparisons. The implications for suitable reference groups are quite different. Following equity theory, employees compare themselves with similarly skilled and productive individuals, whereas relative deprivation theory suggests that individuals are sensitive to pay differentials with dissimilar groups. Reconciling these theories in the context of a large set of occupations, Dornstein (1988, p. 233) stipulates that employee comparisons are made 'first and foremost with those in the same or in similar occupations outside the organization'. This finding reflects high sensitivity towards overall market trends in pay.[5] In the case of low paid workers in Britain, dual labour market theory also suggests that workers in the 'secondary' segment are strongly oriented towards external labour markets (Riley and Szivas, 2003). Empirical studies confirm the proposition (May *et al.*, 2010).

Another complexity arising from within-firm reference groups derives from information (signals) effects of wage comparisons, which may be stronger than comparison (status) effects. Simply put, in such a scenario we would expect that workers are happier the more others earn, i.e. the more wages are dispersed. Some studies have indeed uncovered a positive well-being effect from others' income (e.g. Clark, Kristensen and Westergard-Nielsen, 2009; Kingdon and Knight, 2007; Senik, 2004). Potentially counter-intuitive, this finding has been explained by reference to Hirschman's tunnel effect (Hirschman and Rothschild, 1973), which stipulates that others' good fortunes create expectations in observers. Clearly, such arguments apply to occupations with steep wage profiles and are less relevant to low pay sectors where career progression prospects are limited. Thus, fair wage considerations arguably rely more on status than on signal effects. The balance between status and signal is driven by the strength of the correlation between a reference group's income and a worker's future earnings. As Clark, Kristensen and Westergard-Nielsen (2009) suggest, at occupational peer group or geographical level, the correlation is expected to be small. A discernible status effect is thus arguably far greater when reference groups within the same firm are avoided.

Both efficiency and fair wage theories have important implications for market equilibrium. Efficiency wage theory implies higher wages paid by firms to targeted worker groups. If firms are heterogeneous there will be a distribution of wages where firms that find shirking particularly costly will offer higher wages to identical workers than other firms (Shapiro and Stiglitz, 1984).

ever, Brown, Falk and Fehr (2012) show that even without unemployment the incentive structure remains effective. Higher wages induced by competition for labour bring higher effort out of concerns for reciprocity – a channel suggested by Akerlof (1982) and Shapiro and Stiglitz (1984).

[5]Experimental literature often considers 'vertical' comparisons, between workers and employers (see Fehr, Goette and Zehnder, 2009); however, the importance of 'horizontal' comparisons is recognized (e.g. Bartling and von Siemens, 2011; Clark and Senik, 2010) as suggested by Akerlof and Yellen (1990).

Nevertheless, depending on labour market conditions (unemployment levels, monitoring costs, turnover) efficiency wage theory motivates rightward shifts in the firm wage distribution. Fair wage–effort theory in turn implies wage distribution compression (Akerlof and Yellen, 1990; Levine, 1991), which would usually also be associated with increases in the average wage. If firms must pay a high wage to some workers – perhaps those in short supply – pay equity demands will raise wages for other workers in the firm.[6]

Both theories suggest that some market interventions could be Pareto efficient. In the context of their efficiency wage model, Shapiro and Stiglitz (1984, p. 434) argue that 'in some circumstances wage subsidies are desirable', e.g. to curtail excessive labour turnover. To maintain egalitarianism and cohesiveness firms must also pay an efficiency wage to the lower end of their wage distribution to reduce the firm wage differential. Left to the market, these higher wages will be under-provided in equilibrium. Levine (1991) concludes that policies affecting either prices (e.g. minimum wage) or quantities (e.g. labour mobility restrictions) can increase efficiency in economies.

The NMW's bite

Our analytical strategy comprises two stages – estimation and validation. First, we estimate firm level (total factor) productivity based on the Olley and Pakes (1996) semiparametric algorithm, modified to directly account for the NMW incentive effects while controlling for technology, input decisions, selection and market conditions. Second, we apply commonly used difference-in-differences analysis to validate and illustrate NMW effects on productivity and, to facilitate interpretation, on wages and capital–labour ratios at the level of individual low-paying sectors.

Identification at the productivity estimation stage

We first identify the NMW's observable bite on wage distributions at firm and industry levels. Next, we directly account for the effects through a measure of the bite in the production function estimation algorithm, controlling for other technology and market factors. We thereby capture *ceteris paribus* the NMW's incentives driven effects on (total factor) productivity.

To identify the effects we use data for average wages at firm level.[7] The NMW's bite observed as an average wage increase may derive from three channels as discussed by Lee (1999) who formally models the relationship between the minimum wage's bite and observed wage distributions in the USA. First, there may be no spillovers and no disemployment, which represents the *censoring* case. The only NMW effect is to raise the wages of those initially earning less than the minimum, implying compression of the wage distribution. A second channel is characterized by *spillovers* but no disemployment, occurring when the NMW affects higher percentiles; at the (unlikely) extreme, there may be no wage distribution compression but a rightward shift of the whole distribution. A third channel represents *truncation*: no spillovers but full disemployment. Here, the NMW has no impact on workers with wages already above the minimum and causes job loss for those earning below it, implying wage distribution compression. Any of these channels or a combination would lead to an observed increase in the average firm wage. Clearly, the (net) incentives effect obtained would confine 'standard' efficiency wage and fair wage forces.[8]

The effect's magnitude depends on the initial firm wage distribution. For firms for which shirking is costly and which have unilaterally opted to pay higher wages, the NMW's impact on the average firm wage would be negligible. The NMW's impact on the average wage in firms where the share of low pay workers is minimal will also be negligible. These inferences have important implications for the industry wage distribution's behaviour. Clearly, at industry level, on NMW inception (or upgrading), there will be larger increases in low wage firms' average wages, on the distribution's left

[6]Falk, Fehr and Zehnder (2005) show that temporary introduction of a minimum wage brings rises in subjects' reservation wages, which persist after the minimum wage has been removed. Thus, economic policy may affect behaviours by shaping perceptions of fair transactions and creating entitlement effects.

[7]We use the large FAME data rather than more detailed private micro surveys. FAME is a large and highly representative dataset for firms in UK industries. A detailed description of FAME is provided in the section Data and estimation results.

[8]To separately identify efficiency wage and fair wage effects we need information on unavailable within-firm wage distributions.

side.[9] Compression of the industry wage distribution from below will result. We measure the extent of the compression, which represents the observed NMW's bite following Lee (1999), through the tenth–fiftieth percentile (log) wage differential.

There are two important advantages in considering the industry (average firm) wage distribution in deriving our measure of the NMW's bite. First, the compression of the industry wage distribution will capture both efficiency and fair wage effects within firms. Further, for low paid workers who have flat wage profiles and predominantly rely on horizontal comparisons, the appropriate reference group would be the industry median. Thus, the compression of the industry wage distribution would capture an important incentives effect at occupational level, as suggested by fair wage–effort theory. Second, by considering average wages relative to the industry median we can control for general, industry-wide wage shifts driven by non-NMW factors.[10]

We indeed observe sectoral wage compression from below in our data.[11] We calculate dispersion measures at homogeneous units formed at four-digit SIC industries and the Low Pay Commission's (LPC's) firm size groups.[12] Table 1 summarizes dispersion measures for the LPC sectors with high NMW incidence and two composite counterfactuals for manufacturing (M) and services (S), respectively. Since its 1999 introduction, the NMW has increased in real terms and we, like others, find this is associated with reduced wage dispersion throughout the period; the reduction is very significant over the first three years for several LPC industries. For the majority of LPC industries no evidence of such reduction in dispersion existed before 1999.

Identification at the verification stage

We verify and illustrate the NMW's impact on aggregate productivity by difference-in-differences analysis. We identify treatment and control groups of firms within the low pay sectors based on average wage information from FAME. Athey and Imbens (2006) show that when the distributions of treatment and control groups are the same a simple means difference-in-differences estimator is consistent. In selecting firms for our treatment and control groups we are guided by this condition, which implies that for the control group to constitute a valid counterfactual two equivalent conditions – common trends and a stable composition of the two groups – must be satisfied (Blundell *et al.*, 2004). Furthermore, we follow Draca, Machin and Van Reenen (2011) who used the same dataset and conducted extensive robustness analysis of the two conditions. We replicated Draca, Machin and Van Reenen (2011)'s tests with our data and confirmed the trends and counterfactuals; the test results are available from the authors.

The treatment group ($T = 1$) includes low wage firms with an average annual wage of less than £12,000 over the three years prior to the NMW's introduction in April 1999. The control group ($T = 0$) contains similar firms but with an average annual wage between £12,000 and £24,000, close to our samples' median firm wage.[13] Firms with higher average wages are quite different and

[9]Draca, Machin and Van Reenen (2011) identify stronger NMW effects in lower average-wage firms compared with higher average-wage firms. They verify that the threshold of £12,000 is appropriate for the UK (FAME) sample by extensively experimenting with the threshold cut-off and examining segregation and average wages in an alternative dataset – WERS. We also tested the relationship between average wage change and initial average wage in 1995–96 and 1998–99 and found, similar to Draca, Machin and Van Reenen (2011) and Machin, Manning and Rahman (2003), that in the earlier period the relationship was often insignificant while around the NMW implementation period it was negative and significant. Our results at low pay sector level are available on request.

[10]An important condition for the median wage change being a good control for non-NMW factors is that the NMW does not impact the median. It is reasonable to assume that the condition holds and studies for the USA (e.g. DiNardo, Fortin and Lemieux, 1996; Lee, 1999) and the UK (e.g. Draca, Machin and Van Reenen, 2011; Machin, Manning and Rahman, 2003) demonstrate that the spillovers from the NMW on the (occupational) wage distribution are limited to the area around the NMW level and do not exceed the median.

[11]We have checked the evolution of the fiftieth–ninetieth percentile of (log) wage differentials over time for all low pay sectors and found that these were stable suggesting that the NMW's impact did not spill over beyond the low pay segment. These results are available from the authors.

[12]To better control for factors such as market conditions, work group norms, labour management practices and compliance, we divide our sectoral samples by firm size into large, medium and small categories.

[13]Several studies on the NMW's impact on firms using FAME data, notably Draca, Machin and Van Reenen (2011) and Riley and Rosazza-Bondibene (2015), apply similar identification strategies and select the cut-off point

Table 1. NMW and tenth–fiftieth percentiles of log(wage) differentials by LPC sectors

Year	NMW, £	Tenth–fiftieth percentile log(wage) differentials											
		Social care	Retail	Hospitality	Cleaning	Security	Hairdressing	Textiles	Agriculture	Food process	Leisure	Counterfactual M	Counterfactual S
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1996	–	−0.76	−0.80	−0.82	−1.01	−0.86	−0.57	−0.80	−1.00	−0.75	−1.02	−0.38	−0.88
1997	–	−0.78	−0.78	−0.84	−1.02	−0.85	−0.66	−0.90	−1.02	−0.76	−1.00	−0.36	−0.92
1998	–	−0.76	−0.77	−0.82	−1.06	−0.84	−0.58	−0.82	−0.96	−0.75	−1.02	−0.42	−0.90
1999	3.90	−0.77	−0.75	−0.75	−1.02	−1.07	−0.59	−0.78	−0.90	−0.67	−0.96	−0.41	−0.94
2000	3.97	−0.75	−0.72	−0.71	−0.96	−0.95	−0.52	−0.70	−0.91	−0.58	−0.92	−0.43	−0.95
2001	4.35	−0.68	−0.64	−0.62	−0.84	−0.74	−0.56	−0.63	−0.90	−0.45	−0.92	−0.45	−0.96
2002	4.40	−0.68	−0.60	−0.57	−0.79	−0.59	−0.54	−0.59	−0.88	−0.38	−0.89	−0.42	−0.95
2003	4.65	−0.67	−0.60	−0.61	−0.77	−0.70	−0.44	−0.52	−0.87	−0.37	−0.88	−0.48	−0.94
2004	4.95	−0.60	−0.61	−0.58	−0.82	−0.70	−0.48	−0.50	−0.87	−0.36	−0.89	−0.46	−0.98
2005	5.05	−0.62	−0.62	−0.60	−0.87	−0.71	−0.54	−0.51	−0.92	−0.40	−0.93	−0.45	−0.97
2006	5.23	−0.64	−0.63	−0.58	−0.86	−0.80	−0.58	−0.51	−0.91	−0.44	−0.92	−0.42	−0.98
2007	5.27	−0.61	−0.65	−0.58	−0.85	−0.84	−0.57	−0.55	−0.85	−0.40	−0.92	−0.45	−1.00
2008	5.28	−0.53	−0.64	−0.61	−0.86	−0.74	−0.57	−0.60	−0.77	−0.37	−0.89	−0.45	−1.00

Note: Counterfactual M comprises the non-LPC manufacturing industries counterfactual and counterfactual S the non-LPC service industries counterfactual.

therefore subject to different unobserved trends compared to the treatment (and control) group firms. We expect that wages of firms below the cut-off point will experience a significant boost from the NMW introduction relative to higher wage firms. Furthermore, we evaluate effects before (NMW = 0) and after (NMW = 1) the NMW introduction, in an aggregate of all LPC sectors, separate aggregates of manufacturing and service sectors, and by individual LPC sectors; detailed results are available on request. Thus, the unconditional difference-in-differences (DiD) estimator of the impact of the NMW on aggregate productivity (TFP) is

$$\begin{aligned}\mathrm{DiD} = &\left(\mathrm{TFP}^{T=1}_{\mathrm{NMW}=1} - \mathrm{TFP}^{T=1}_{\mathrm{NMW}=0}\right)\\ &- \left(\mathrm{TFP}^{T=0}_{\mathrm{NMW}=1} - \mathrm{TFP}^{T=0}_{\mathrm{NMW}=0}\right) \qquad (1)\end{aligned}$$

To facilitate interpretation of results we also apply equation (1) to aggregate wages ($\ln(w)$) to verify the NMW's impact on the sectoral wage distribution and to aggregate capital–labour (K/L) ratios to examine possible technology adjustments as an alternative source of productivity change.

Furthermore, we also create alternative manufacturing (M) and services (S) sector composite counterfactuals outside the low pay sectors where firms are probably unaffected by the NMW's introduction. This additional analytical dimension supports our conclusions.

Model of productivity and estimation algorithm

Following the productivity literature summarized in Ackerberg *et al.* (2007) we first specify a Cobb–Douglas production function

$$Y_{jt} = \Omega_{jt}\left(L^{\beta_l}_{jt}, K^{\beta_k}_{jt}\right) \qquad (2)$$

where j and t indicate firm and time, respectively. Y represents output (often measured as value added); L and K represent the common inputs used in production, labour and physical capital respectively. The β values are the factor shares of the production inputs. The index Ω_{jt} is a measure of the TFP

of £12,000 after experimenting with different cut-offs. In this analysis, we also experimented with £10,000 and £14,000 cut-offs .The results were qualitatively similar albeit less pronounced.

of firm j at time t. Olley and Pakes (1996) formulate a model of the (unobserved) TFP as a function of the firm's state variables (capital K and age A) and a control variable (investment I), which is monotonically related to unobserved productivity. The model is derived by inverting the firm investment demand function, which is a solution to the firm profit maximization problem.

Following our identification strategy and modelling ideas developed in Ackerberg *et al.* (2007), we extend the Olley–Pakes TFP model with the wage dispersion measure NMW_{it} (i denotes industry-firm-size units) constructed as discussed in the section Identification at the productivity estimation stage, capturing the NMW's incentives impact on firm productivity. The wage dispersion here acts as a second control variable which, as discussed above, should be inversely (and monotonically) associated with unobserved productivity. Market environment characteristics that the firm faces are also controlled for by a vector $\vec{R}$, containing geographical, sector and time-specific effects. The TFP model becomes

$$\Omega_{jt} = f_j(K_{jt}, A_{jt}, I_{jt}, \mathrm{NMW}_{it}, \vec{R}) \qquad (3)$$

The original Olley–Pakes formulation allows market environment factors to change longitudinally, although they are assumed constant across firms in a given period. Here, we extend the model by using an explicit measure of the NMW's incentives impact on firms and a vector of other market environment controls. Thus, the information content of the state space would vary by narrowly defined location and firm size group within four-digit SIC industries and longitudinally. Since we deflate value added and capital with industry-wide deflators, introducing market environment controls in the TFP model helps control for the fact that output and factor prices might differ across firm types and/or evolve differently longitudinally.

The treatment of the TFP leads to an estimating equation of the production function resembling a multilevel modelling approach. Following Olley and Pakes (1996), we estimate a log-linear transformation of the Cobb–Douglas production function (equation (2)), incorporating the TFP model (equation (3)):

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_a a_{jt} + \beta_l l_{jt} + \omega_{jt} + \eta_{jt} \qquad (4)$$

Small letters represent the respective variables' natural logarithms; β coefficients represent the elasticity of output (value added) with respect to inputs; ω_{jt} is unobserved productivity and η is the (iid) error term. As in Olley and Pakes (1996), we include firm age in the specification, to control for managerial and technology differences, and cohort effects on firm productivity, which improves the coefficient estimates' precision.

Because productivity ω_{jt} (as defined in equation (3)) is not observed directly in the data, estimating equation (4) is affected by simultaneity and selection biases. Simultaneity means that if more productive firms tend to hire more workers because of higher current and anticipated future productivity, an ordinary least squares (OLS) estimator will provide upwardly biased estimates on the input coefficients. Selection occurs because exit depends on productivity as well as on state variables (capital and age). Thus, the coefficient on capital is likely to be underestimated by OLS as higher capital stocks allow firms to survive at lower productivity levels, implying a negative relationship between capital and ω_{jt} (Olley and Pakes, 1996).

To control for these biases, Olley and Pakes (1996) developed a two-stage semiparametric estimation algorithm using a non-parametric control function of productivity. Following Olley and Pakes, equation (4) can be re-written as

$$\begin{aligned} y_{jt} = {} & \beta_0 + \beta_k k_{jt} + \beta_a a_{jt} + \beta_l l_{jt} \\ & + h_t(i_{jt}, \mathrm{nmw}_{it}, \vec{r}, k_{jt}, a_{jt}) + \eta_{jt} \end{aligned} \qquad (5)$$

In equation (5) the productivity function $\omega_{jt} = h_t(.)$ is treated non-parametrically using a polynomial (we use a third-degree polynomial throughout). The non-parametric treatment, however, results in collinearity and requires the constant, k_{jt} and a_{jt} terms to be combined into a function $\varphi_t(i_{jt}, nmw_{it}, \vec{r}, k_{jt}, a_{jt})$ such that equation (5) becomes

$$y_{jt} = \beta_l l_{jt} + \phi_t(i_{jt}, \mathrm{nmw}_{it}, \vec{r}, k_{jt}, a_{jt}) + \eta_{jt} \qquad (6)$$

Equation (6) represents the first stage of the estimation algorithm and is estimated by OLS.

In the first stage, only the labour coefficient is identified while capital and age coefficients are identified in the algorithm's second stage. An estimate $\hat{\phi}_{jt}$ is also obtained for use in the second stage where ω_{jt} is expressed as

$$\hat{\omega}_{jt} = \hat{\phi}_{jt} - \beta_0 - \beta_k k_{jt} - \beta_a a_{jt} \quad (7)$$

The first stage is unaffected by endogenous selection because the function ϕ_t fully controls for the unobservable affecting firm's choices; by construction η_{jt} represents unobservable factors unknown by the firm when making investment and exit decisions. In contrast, the estimation algorithm's second stage is affected by endogenous selection because the exit decision in period t depends directly on ω_{jt}.

To clarify the timing of production decisions, ω_{jt} can be decomposed into its conditional expectation given the information about productivity known by the firm in the $t-1$ period and a residual: $\omega_{jt} = E[\omega_{jt}|\omega_{jt-1}] + \xi_{jt} = g(\omega_{jt-1}) + \xi_{jt}$. By construction, ξ_{jt} is uncorrelated with information in $t-1$ and thus with k_{jt} and a_{jt} which are determined prior to time t. The firm's exit decision in period t depends directly on ω_{jt} and thus the decision will be correlated with ξ_{jt}.[14] To account for endogenous selection on productivity the $g(.)$ function can be extended with survival information.

$$\omega_{jt} = g'(\omega_{jt-1}, \hat{P}_{jt}) + \xi_{jt} \quad (8)$$

where $\hat{P}_{jt}$ is the survival propensity score which controls for the impact of selection on the expectation of ω_{jt}, i.e. firms with lower survival propensity which survive to time t probably have higher ω_{jt}values than those with higher survival propensity. $\hat{P}_{jt}$ is estimated semiparametrically using a probit model with a polynomial approximation.

The capital and age coefficients are identified in the algorithm's second stage. Equations (8) and (7) are substituted into equation (5) leading to

$$y_{jt} - \underset{l}{\widehat{\beta}} l_{jt} = \beta_k k_{jt} + \beta_a a_{jt} + g'(\hat{\phi}_{jt-1} - \beta_k k_{jt-1} - \beta_a a_{jt-1}, \underset{jt}{\widehat{P}}) + \varepsilon_{jt} \quad (9)$$

where the two β_0 terms have been encompassed into the non-parametric function $g'(.)$ and ε_{jt} is a composite error term composed of η_{jt} and ξ_{jt}. The lagged $\hat{\phi}_{jt-1}$ variable is obtained from the first stage estimates at the $t-1$ period. Equation (9) is estimated by a non-linear least squares (NLLS) search routine approximating $g'(.)$ with a polynomial.

In sum, in the algorithm's first stage we estimate the labour coefficient $\hat{\beta}_l$ by OLS while the capital $\hat{\beta}_k$ coefficient (as well as the age coefficient) is estimated in the second stage by NLLS. We use the production function coefficients $\hat{\beta}_k$ and $\hat{\beta}_l$ consistently estimated to back out unbiased firm-specific TFP measures, calculated as

$$\begin{aligned} TFP_{jt} &= \omega_{jt} + \beta_a a_{jt} + \eta_{jt} \\ &= y_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_l l_{jt} \end{aligned} \quad (10)$$

Our TFP measure captures the NMW's effects on firm productivity while accounting for possible technology changes through capital for labour substitutions and selection due to firm exits.

Data and estimation results

Data

We estimate the production functions specified above using the FAME dataset, covering all firms filed at Companies House. Information on firm level financial statements, remuneration costs, ownership structure and location is used. The data contain annual records for over 360,000 firms, for the period 1995–2008. The data's coverage is highly representative compared to aggregate statistics for the industries analysed as reported by the UK Office for National Statistics (ONS); for employment, it is approximately 82%. The sectors analysed are identified following LPC groupings of low-paying industries at the four-digit SIC level. We also create counterfactuals from manufacturing and service non-LPC industries: composites of a set of four-digit industries identified in the Labour Force Survey and WERS as having high levels of pay, high employee skills, high unionization and hence minimal use of the NMW in-company, as evidenced in successive LPC reports.[15] All nominal monetary variables

[14]This correlation assumes that firms exit the market quickly, in the same period as the decision is made. If exit was decided in the period before actual exit then, although there is attrition *per se*, exit would be uncorrelated with ξ_{jt} and there will be no selection bias.

[15]The four-digit industries included in the counterfactuals came from the following two-digit SIC industries: 23, 27, 29, 33, 34, 35, 40 for the manufacturing counterfactual

are converted into real values by deflating with the appropriate four-digit SIC deflators taken from ONS. We use the Producer Price Index to deflate sales and materials costs and asset price deflators for capital and fixed investment variables.

We seek to estimate an unbiased and consistent TFP measure at firm level, capturing the NMW's incentive effects and to document the evolution of aggregate productivity. The strategy implies running regressions within all four-digit low-paying and counterfactual industries. After lags are applied and missing values deleted, over 160,000 observations remain. The estimated samples within individual LPC sectors account for between 52% and 70% of employment. The correlations between the ONS aggregate statistics series and the estimated sample series are sales –0.90 to 0.96, employment –0.90 to 0.97. Descriptive statistics calculated from the estimated FAME samples within LPC sectors and the counterfactuals are reported in Table 2.

Productivity estimation results

Table 3 summarizes the aggregated coefficients on labour and capital for LPC sectors and the non-LPC counterfactuals. The aggregated coefficients are weighted averages of the estimated industry coefficients using numbers of employees as weightings. Differences exist across LPC sectors with respect to capital and labour elasticities, especially between manufacturing and services. The coefficient on labour ranges between 0.50 and 0.94 and is highest in service industries. The capital coefficient ranges between 0.09 and 0.30 and is lowest in social care and leisure.

Table 3 also reports means of the aggregated productivity measure calculated from the Olley–Pakes (TFP) models and a labour productivity measure; the two appear broadly comparable. The sectors with highest aggregate productivity by the TFP measure are security and retail; social care shows the lowest productivity.

Our TFP estimates are designed to capture the NMW's productivity impact. A simple way to demonstrate this is to calculate elasticities of productivity with respect to the NMW longitudinally for the aggregate of LPC sectors, for separate aggregates of manufacturing and service sectors and by individual LPC sector. We find that the NMW had a positive impact on aggregate productivity in low-paying sectors. The elasticity of aggregate productivity with respect to the NMW is around 1; the productivity of service sectors is twice as sensitive as that of manufacturing to NMW increases; across individual LPC sectors substantial heterogeneity exists (see Table 3, bottom row). The high impact in services may derive from the greater productivity significance of labour rather than capital inputs in those industries.

Difference-in-differences analysis

Given our strategy to control for all relevant factors at the productivity estimation stage, we obtain firm-specific TFP measures that capture all relevant effects. Therefore, we follow an unconditional difference-in-differences approach (equation (1)) and the identification strategy described above, which is similar to several other NMW studies. The difference-in-differences results are reported in Tables 4–6. In each table's first three rows we verify for all samples (total sample aggregate A, manufacturing M and services S) that compared to $T = 0$ wages rise by more in $T = 1$, after 1999. Stronger wage effects exist for the treatment groups. In addition, we note our results on the changes over time in the magnitude of sectoral tenth–fiftieth percentile wage differentials reported in Table 1, showing a decline after 1999. The two results suggest that potential effects on productivity of the treatment group firms can be attributed to the NMW's bite, creating in-firm significant incentive effects. To check the robustness of our results we also use counterfactuals (A, M and S) containing firms from (non-LPC) industries where the NMW's bite is weak and where therefore effects on wages and productivity will also probably be weaker. The empirical findings confirm our expectations.

Results for the NMW's TFP effects are reported in the second three rows of Tables 4–6.[16] Our findings are consistent across individual LPC sectors, for which the results are available from the authors. Firms in the treatment groups experienced relative increases in productivity during the period 1999–2008. The effects are statistically significant

and 64, 65, 66, 67 for the services counterfactual. In selecting counterfactuals, we were guided by Labour Force Survey and LPC statistics in estimating NMW exposure.

[16]The results by Croucher and Rizov (2012) based on labour productivity measures are similar to those reported.

Table 2. Summary statistics by LPC sector, 1996–2008

Variables	Social care	Retail	Hospitality	Cleaning	Security	Hairdressing	Textiles	Agriculture	Food process	Leisure	Counterfactual M	Counterfactual S
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Means (SD)												
Value added, £000	1615	13045	4449	4971	16011	1255	6052	1097	18836	4583	52946	13256
	(7284)	(162869)	(24991)	(36823)	(191088)	(4833)	(30598)	(3957)	(121504)	(25568)	(491646)	(222233)
Fixed assets, £000	4698	17303	17114	11108	15711	719	4597	2547	26542	8398	140916	39147
	(39576)	(278458)	(158836)	(117243)	(172632)	(3253)	(31690)	(10899)	(222056)	(71295)	(1729177)	(1302974)
Investment, £000	1289	3279	2761	2734	3319	182	965	450	4947	2057	27284	9038
	(18887)	(56147)	(37952)	(33480)	(44148)	(1074)	(9980)	(2489)	(53139)	(24281)	(487335)	(173691)
Number of employees	174	470	336	1305	2872	80	328	55	557	121	659	156
	(728)	(5148)	(5030)	(6947)	(34567)	(360)	(2339)	(335)	(3057)	(694)	(3835)	(1483)
Age, years	17	24	19	22	11	11	31	30	26	24	27	14
	(17)	(20)	(19)	(21)	(8)	(10)	(26)	(19)	(23)	(24)	(24)	(13)
Shares												
Exits 1998	0.02	0.01	0.00	0.01	0.01	0.03	0.01	0.01	0.01	0.01	0.01	0.01
Exits 2002	0.01	0.01	0.01	0.01	0.02	0.02	0.00	0.01	0.01	0.00	0.01	0.02
Exits 2008	0.02	0.05	0.02	0.04	0.05	0.02	0.02	0.01	0.02	0.02	0.01	0.03
Urban	0.90	0.90	0.88	0.93	0.96	0.90	0.92	0.44	0.82	0.87	0.89	0.93
Rural less sparse	0.09	0.08	0.10	0.05	0.03	0.09	0.06	0.52	0.15	0.12	0.10	0.07
Rural sparse	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.04	0.03	0.01	0.01	0.00
Number of observations	5156	70668	22019	3491	935	1864	8232	13408	10169	24665	15325	30681

Note: Unweighted means and standard deviations (SD) are reported for the monetary variables, employment and age. Counterfactual M comprises the non-LPC manufacturing industries counterfactual and counterfactual S the non-LPC service industries counterfactual.

Table 3. Production function coefficients and TFP and labour productivity estimates by LPC sector, 1996–2008

Coefficients	Social care	Retail	Hospitality	Cleaning	Security	Hairdressing	Textiles	Agriculture	Food process	Leisure	Counterfactual M	Counterfactual S
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Labour	0.88	0.66	0.56	0.54	0.58	0.64	0.50	0.65	0.52	0.94	0.65	0.73
	(0.04)	(0.02)	(0.03)	(0.05)	(0.07)	(0.06)	(0.04)	(0.04)	(0.03)	(0.04)	(0.07)	(0.04)
Capital	0.09	0.10	0.14	0.20	0.14	0.22	0.30	0.17	0.30	0.09	0.23	0.23
	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)	(0.04)	(0.02)
Adj R^2	0.90	0.97	0.96	0.97	0.97	0.97	0.97	0.91	0.97	0.92	0.95	0.92
Aggregate TFP	1.96	4.08	2,83	2.01	3.60	2.20	3.17	2.42	2.78	2.12	3.33	3.14
	(0.29)	(1.32)	(1.42)	(0.67)	(0.41)	(0.50)	(0.40)	(0.34)	(0.27)	(0.33)	(0.52)	(0.47)
Aggregate LP	1.60	3.12	2.32	1.98	2.96	2.24	2.81	2.38	3.12	2.25	3.12	3.08
	(0.37)	(1.17)	(1.28)	(1.02)	(0.74)	(0.64)	(0.23)	(0.60)	(0.17)	(0.19)	(0.31)	(0.73)
Elasticity TFP/NMW	1.80	1.36	0.96	1.28	1.63	−1.66	0.52	1.37	0.75	0.08	0.22	0.78
	(5.59)	(5.34)	(2.47)	(5.24)	(3.11)	(7.06)	(2.17)	(7.73)	(2.41)	(0.43)	(1.73)	(1.55)

Note: The reported coefficients and aggregate productivity are weighted averages, using number of employees as weight, from four-digit industry regressions on firm level data. The R^2 reported are from the last stage of the estimation algorithm. Standard errors (standard deviations for productivity) are reported in parentheses. Counterfactual M comprises the non-LPC manufacturing industries counterfactual and counterfactual S the non-LPC service industries counterfactual.

in all sectors except hairdressing, leisure and agriculture. In these industries, compliance levels are comparatively low as they employ high proportions of women and (undocumented) migrant workers shown to be especially susceptible to under-payment and to worker–employer complicity in that regard (Bloch and McKay, 2015; Ipsos MORI, 2012; LeRoux, Lucchino and Wilkinson, 2013). Besides, the non-effect in agriculture is probably due to the Agricultural Wage Board's wage-fixing throughout the period of investigation. The largest relative increases in productivity are in large firms in the aggregated total and in the aggregated service sector samples. In manufacturing, relative productivity increases are also large for medium-size firms.

In Tables 4–6, third set of three rows, we report the capital–labour (*K*/*L*) ratio. Changes in the ratio may reflect technology adjustments, which can be seen as alternative and long-term NMW effects. In estimating our TFP measure we control for technology changes (and survival bias). In hospitality and social care, productivity improvements indeed appear to be affected by substitution of capital for labour to a higher degree compared with other LPC, mostly manufacturing, sectors. For the aggregate services sample, some evidence exists of substitution of capital for labour in low-paying sectors while in the non-LPC counterfactual sample such evidence is absent.[17]

An alternative explanation is firm exit. In Table 2, we reported exit rates by LPC sector for 1998, 2002 and 2008, i.e. just before, three and nine years after NMW implementation. Over the first three years, exit rates do not seem to change compared to 1998. By 2008, however, in sectors with relative productivity gains where capital for labour substitution is weaker, exit rates were somewhat higher, apparently supporting the argument that less productive firms exit in the long run. In estimating our TFP productivity measure we control for survival bias.

[17]In a short-run (robustness) analysis, covering 2000–2002, we found the capital for labour substitution effect was much weaker and statistically insignificant, while increases in wages and productivity in the treatment groups were significant albeit smaller in magnitude than in the long run. These findings are consistent with Falk, Fehr and Zehnder's (2005) experimental finding that introducing a minimum wage creates persistent impacts on reservation wages and employment.

Table 4. Difference-in-differences analysis of wages, TFP and K/L *for the aggregate LPC sectors and counterfactual A*

	Total sample			Small firms			Medium firms			Large firms		
Sectors and subsamples	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference
Aggregate LPC (T) ln(*w*)	1.970	2.106	+0.136	1.916	2.023	+0.107	2.089	2.267	+0.178	1.980	2.140	+0.161
	(0.008)	(0.009)	(0.010)	(0.011)	(0.012)	(0.008)	(0.014)	(0.013)	(0.014)	(0.025)	(0.024)	(0.012)
Aggregate LPC (C) ln(*w*)	2.802	2.857	+0.055	2.804	2.821	+0.017	2.804	2.882	+0.078	2.790	2.875	+0.085
	(0.002)	(0.004)	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)	(0.007)	(0.006)	(0.006)	(0.009)	(0.007)
			+0.081***			***+0.090******			***+0.100******			***+0.076******
			(*0.007*)			**(*0.009*)**			**(*0.013*)**			**(*0.013*)**
Aggregate LPC (T) TFP	2.834	2.866	+0.032	2.676	2.659	−0.017	2.936	2.968	+0.032	3.371	3.486	+0.116
	(0.015)	(0.016)	(0.008)	(0.018)	(0.019)	(0.009)	(0.030)	(0.031)	(0.015)	(0.043)	(0.042)	(0.020)
Aggregate LPC (C) TFP	3.168	3.136	−0.033	3.113	3.069	−0.044	3.158	3.133	−0.025	3.418	3.421	+0.003
	(0.012)	(0.012)	(0.006)	(0.015)	(0.016)	(0.008)	(0.021)	(0.021)	(0.009)	(0.042)	(0.042)	(0.019)
			+0.064***			***+0.027******			***+0.057******			***+0.113******
			(*0.010*)			**(*0.012*)**			**(*0.017*)**			**(*0.027*)**
Aggregate LPC (T) *K*/*L*	1.929	2.222	+0.293	1.998	2.246	+0.249	1.937	2.297	+0.360	1.533	1.804	+0.271
	(0.024)	(0.025)	(0.012)	(0.030)	(0.032)	(0.016)	(0.042)	(0.045)	(0.025)	(0.072)	(0.074)	(0.030)
Aggregate LPC (C) *K*/*L*	2.354	2.615	+0.261	2.240	2.483	+0.244	2.447	2.744	+0.297	2.570	2.800	+0.230
	(0.018)	(0.018)	(0.010)	(0.025)	(0.027)	(0.014)	(0.028)	(0.027)	(0.016)	(0.048)	(0.047)	(0.028)
			+0.032			*+0.005*			*+0.063*			*+0.041*
			(*0.026*)			(*0.021*)			(*0.039*)			(*0.042*)
Counterfactual A (T) ln(*w*)	2.336	2.290	−0.047	2.295	2.222	−0.073	2.637	2.624	−0.013	2.478	2.531	+0.053
	(0.083)	(0.069)	(0.038)	(0.094)	(0.080)	(0.033)	(0.210)	(0.161)	(0.106)	(0.229)	(0.128)	(0.150)
Counterfactual A (C) ln(*w*)	3.051	2.981	−0.070	3.102	3.015	−0.087	3.032	2.966	−0.066	2.932	2.902	−0.029
	(0.028)	(0.00)	(0.018)	(0.041)	(0.031)	(0.019)	(0.037)	(0.031)	(0.018)	(0.071)	(0.059)	(0.037)
			+0.023			*+0.014*			*+0.053*			*+0.082*
			(*0.046*)			(*0.040*)			(*0.083*)			(*0.150*)
Counterfactual A (T) TFP	2.543	2.551	+0.007	2.546	2.516	−0.029	2.654	2.769	+0.115	2.715	3.021	+0.306
	(0.074)	(0.076)	(0.062)	(0.072)	(0.075)	(0.062)	(0.299)	(0.266)	(0.177)	(0.924)	(0.375)	(0.661)
Counterfactual A (C) TFP	2.849	2.872	+0.023	2.798	2.805	+0.007	2.802	2.860	+0.058	3.139	3.093	−0.046
	(0.034)	(0.033)	(0.024)	(0.041)	(0.040)	(0.032)	(0.066)	(0.060)	(0.055)	(0.104)	(0.122)	(0.094)
			−0.016			*−0.036*			*+0.057*			*+0.352*
			(*0.058*)			(*0.065*)			(*0.202*)			(*0.414*)
Counterfactual A (T) *K*/*L*	1.430	1.842	+0.412	1.285	1.703	+0.418	2.546	2.724	+0.115	2.397	3.333	+0.936
	(0.111)	(0.119)	(0.057)	(0.114)	(0.125)	(0.059)	(0.495)	(0.473)	(0.177)	(0.369)	(0.442)	(0.225)
Counterfactual A (C) *K*/*L*	1.646	2.102	+0.456	1.176	1.651	+0.475	2.054	2.398	+0.343	2.599	2.972	+0.373
	(0.042)	(0.044)	(0.026)	(0.054)	(0.059)	(0.033)	(0.073)	(0.073)	(0.044)	(0.095)	(0.101)	(0.070)
			−0.044			*−0.057*			*−0.166*			***+0.563*****
			(*0.061*)			(*0.065*)			(*0.180*)			**(*0.291*)**

Note: Figures in italics indicate the difference-in-differences (DiD) and figures in bold indicate sectors and firm size groups with statistically significant (at 10% or better) difference-in-differences in wages, productivity (TFP) or *K*/*L* ratio after 1999. The levels of significance are denoted as follows: ***1%; **5%; *10%. (T) denotes the treatment group and (C) denotes the comparison group. Counterfactual A is an aggregate of manufacturing (M) and services (S) counterfactuals.

Table 5. Difference-in-differences analysis of wages, TFP and K/L *for the manufacturing LPC sectors and counterfactual M*

	Total sample			Small firms			Medium firms			Large firms		
Sectors and subsamples	Pre-1999	Post-999	Difference	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference
Manufacturing LPC (T) ln(*w*)	1.933	2.099	+0.166	1.848	1.928	+0.080	2.210	2.460	+0.250	2.052	2.270	+0.218
	(0.020)	(0.022)	(0.014)	(0.026)	(0.027)	(0.016)	(0.023)	(0.025)	(0.028)	(0.064)	(0.068)	(0.020)
Manufacturing LPC (C) ln(*w*)	2.786	2.894	+0.108	2.796	2.843	+0.046	2.783	2.901	+0.118	2.782	2.934	+0.152
	(0.005)	(0.008)	(0.007)	(0.008)	(0.014)	(0.012)	(0.008)	(0.011)	(0.009)	(0.010)	(0.015)	(0.010)
			+0.059***			***+0.034****			***+0.112******			***+0.066******
			(0.014)			***(0.020)***			***(0.022)***			***(0.021)***
Manufacturing LPC (T) TFP	2.264	2.306	+0.042	2.124	2.116	−0.008	2.530	2.586	+0.056	2.696	2.857	+0.161
	(0.032)	(0.034)	(0.019)	(0.044)	(0.046)	(0.026)	(0.046)	(0.052)	(0.033)	(0.069)	(0.077)	(0.039)
Manufacturing LPC (C) TFP	2.927	2.906	−0.021	2.790	2.742	−0.048	2.996	2.943	−0.053	3.115	3.165	+0.050
	(0.023)	(0.024)	(0.015)	(0.042)	(0.044)	(0.024)	(0.029)	(0.030)	(0.019)	(0.041)	(0.046)	(0.030)
			+0.063***			*+0.040*			***+0.109******			***+0.111*****
			(0.024)			*(0.035)*			***(0.037)***			***(0.053)***
Manufacturing LPC (T) *K*/*L*	2.454	2.653	+0.199	2.767	2.931	+0.164	1.849	2.117	+0.268	1.774	1.981	+0.207
	(0.048)	(0.053)	(0.026)	(0.064)	(0.071)	(0.031)	(0.065)	(0.078)	(0.049)	(0.077)	(0.085)	(0.054)
Manufacturing LPC (C) *K*/*L*	2.829	3.037	+0.208	3.102	3.260	+0.158	2.541	2.827	+0.286	2.805	2.959	+0.154
	(0.032)	(0.033)	(0.017)	(0.059)	(0.062)	(0.026)	(0.045)	(0.043)	(0.026)	(0.047)	(0.055)	(0.037)
			−0.009			*+0.006*			*−0.018*			*+0.053*
			(0.030)			*(0.041)*			*(0.052)*			*(0.066)*
Counterfactual M (T) ln(*w*)	2.269	2.266	−0.003	2.157	2.119	−0.037	2.478	2.515	+0.037	2.407	2.618	+0.211
	(0.171)	(0.156)	(0.080)	(0.248)	(0.234)	(0.076)	(0.137)	(0.134)	(0.051)	(0.422)	(0.066)	(0.371)
Counterfactual M (C) ln(*w*)	2.969	2.930	−0.039	3.070	2.997	−0.073	2.965	2.968	+0.003	2.861	2.897	+0.036
	(0.036)	(0.026)	(0.022)	(0.077)	(0.058)	(0.036)	(0.037)	(0.028)	(0.020)	(0.082)	(0.072)	(0.032)
			+0.036			*+0.035*			*+0.034*			*+0.175*
			(0.082)			*(0.088)*			*(0.102)*			*(0.186)*
Counterfactual M (T) TFP	2.695	2.667	−0.028	2.618	2.640	+0.022	2.952	2.843	−0.109	3.370	3.268	−0.102
	(0.124)	(0.139)	(0.072)	(0.129)	(0.139)	(0.084)	(0.461)	(0.585)	(0.183)	(0.518)	(0.443)	(0.249)
Counterfactual M (C) TFP	2.953	2.974	+0.021	2.857	2.881	+0.024	2.890	2.902	+0.012	3.218	3.199	−0.019
	(0.038)	(0.040)	(0.022)	(0.054)	(0.056)	(0.032)	(0.052)	(0.057)	(0.028)	(0.108)	(0.123)	(0.082)
			−0.049			*−0.002*			*−0.121*			*−0.083*
			(0.066)			*(0.075)*			*(0.137)*			*(0.474)*
Counterfactual M (T) *K*/*L*	1.962	2.198	+0.236	2.006	2.127	+0.122	1.435	2.048	+0.612	2.346	3.250	+0.904
	(0.179)	(0.178)	(0.094)	(0.204)	(0.207)	(0.096)	(0.457)	(0.314)	(0.293)	(0.132)	(0.323)	(0.385)
Counterfactual M (C) *K*/*L*	2.169	2.418	+0.249	1.837	2.043	+0.206	2.202	2.419	+0.218	2.791	3.057	+0.266
	(0.046)	(0.049)	(0.037)	(0.073)	(0.084)	(0.054)	(0.067)	(0.066)	(0.046)	(0.079)	(0.078)	(0.077)
			−0.013			*−0.084*			***+0.394*****			***+0.638****
			(0.107)			*(0.114)*			***(0.228)***			***(0.445)***

Note: Figures in italics indicate the difference-in-differences (DiD) and figures in bold indicate sectors and firm size groups with statistically significant (at 10% or better) difference-in-differences in wages, productivity (TFP) or *K*/*L* ratio after the implementation of the NMW in 1999. The levels of significance are denoted as follows: ***1%; **5%; *10%. (T) denotes the treatment group and (C) denotes the comparison group.

Table 6. Difference-in-differences analysis of wages, TFP and K/L *for the service LPC sectors and counterfactual S*

Sectors and subsamples	Total sample			Small firms			Medium firms			Large firms		
	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference	Pre-1999	Post-1999	Difference
Services LPC	1.972	2.116	+0.144	1.933	2.050	+0.117	2.055	2.220	+0.165	1.955	2.112	+0.157
(T) ln(*w*)	(0.009)	(0.09)	(0.008)	(0.013)	(0.012)	(0.010)	(0.017)	(0.015)	(0.016)	(0.027)	(0.025)	(0.014)
Services LPC	2.806	2.842	+0.036	2.806	2.814	+0.008	2.813	2.867	+0.054	2.792	2.843	+0.050
(C) ln(*w*)	(0.003)	(0.005)	(0.004)	(0.004)	(0.006)	(0.005)	(0.005)	(0.008)	(0.007)	(0.008)	(0.011)	(0.008)
			+0.108***			***+0.109******			***+0.110******			***+0.107******
			(***0.008***)			(***0.011***)			(***0.016***)			(***0.016***)
Services LPC	2.989	3.013	+0.025	2.803	2.797	−0.046	3.027	3.052	+0.025	3.486	3.611	+0.125
(T) TFP	(0.017)	(0.018)	(0.008)	(0.020)	(0.020)	(0.010)	(0.037)	(0.037)	(0.017)	(0.048)	(0.046)	(0.022)
Services LPC	3.239	3.200	−0.039	3.174	3.134	−0.040	3.216	3.198	−0.018	3.586	3.560	−0.026
(C) TFP	(0.013)	(0.014)	(0.007)	(0.016)	(0.017)	(0.009)	(0.028)	(0.027)	(0.012)	(0.059)	(0.059)	(0.023)
			+0.064***			*+0.034*			***+0.043*****			***+0.151******
			(***0.010***)			(*0.023*)			(***0.021***)			(***0.032***)
Services LPC	1.791	2.110	+0.319	1.790	2.063	+0.273	1.954	2.351	+0.397	1.486	1.771	+0.285
(T) *K/L*	(0.027)	(0.028)	(0.014)	(0.033)	(0.035)	(0.018)	(0.050)	(0.052)	(0.027)	(0.085)	(0.088)	(0.034)
Services LPC	2.207	2.481	+0.274	2.049	2.313	+0.264	2.407	2.714	+0.306	2.446	2.725	+0.279
(C) *K/L*	(0.020)	(0.022)	(0.012)	(0.027)	(0.029)	(0.016)	(0.035)	(0.034)	(0.021)	(0.067)	(0.064)	(0.038)
			+0.046			*+0.009*			***+0.091*****			*+0.006*
			(*0.029*)			(*0.024*)			(***0.044***)			(*0.051*)
Counterfactual	2.365	2.286	−0.079	2.326	2.252	−0.073	2.701	2.657	−0.044	2.444	2.369	−0.076
S (T) ln(*w*)	(0.094)	(0.077)	(0.043)	(0.102)	(0.086)	(0.036)	(0.369)	(0.279)	(0.186)	(0.328)	(0.289)	(0.157)
Counterfactual	3.150	2.993	−0.157	3.110	3.011	−0.099	3.150	2.998	−0.152	3.108	2.903	−0.205
S (C) ln(*w*)	(0.041)	(0.028)	(0.024)	(0.049)	(0.037)	(0.022)	(0.086)	(0.076)	(0.032)	(0.144)	(0.109)	(0.101)
			+0.078			*+0.026*			*+0.108*			*+0.129*
			(*0.054*)			(*0.046*)			(*0.123*)			(*0.291*)
Counterfactual	2.522	2.531	+0.009	2.525	2.478	−0.047	2.703	3.009	+0.306	2.142	2.098	−0.044
S (T) TFP	(0.092)	(0.090)	(0.079)	(0.086)	(0.088)	(0.078)	(0.428)	(0.308)	(0.233)	(0.602)	(0.574)	(0.080)
Counterfactual	2.743	2.773	+0.030	2.775	2.775	−0.000	2.681	2.786	+0.105	2.956	2.848	−0.108
S (C) TFP	(0.054)	(0.050)	(0.039)	(0.054)	(0.056)	(0.044)	(0.157)	(0.137)	(0.143)	(0.216)	(0.271)	(0.219)
			−0.021			*−0.047*			*+0.200*			*+0.064*
			(*0.082*)			(*0.086*)			(*0.384*)			(*0.630*)
Counterfactual	1.237	1.941	+0.703	1.075	1.592	+0.517	2.349	2.852	+0.503	2.395	3.240	+0.845
S (T) *K/L*	(0.134)	(0.149)	(0.072)	(0.132)	(0.150)	(0.071)	(0.727)	(0.722)	(0.450)	(0.562)	(0.686)	(0.349)
Counterfactual	1.178	1.812	+0.634	0.976	1.449	+0.472	1.737	2.247	+0.510	2.222	2.771	+0.549
S (C) *K/L*	(0.064)	(0.068)	(0.037)	(0.067)	(0.074)	(0.040)	(0.158)	(0.165)	(0.087)	(0.236)	(0.263)	(0.142)
			+0.069			*+0.045*			*−0.007*			*+0.296*
			(*0.076*)			(*0.078*)			(*0.284*)			(*0.425*)

Note: Figures in italics indicate the difference-in-differences (DiD) and figures in bold indicate sectors and firm size groups with statistically significant (at 10% or better) difference-in-differences in wages, productivity (TFP) or *K/L* ratio after the implementation of the NMW in 1999. The levels of significance are denoted as follows: ***1%; **5%; *10%. (T) denotes the treatment group and (C) denotes the comparison group.

Conclusion

We empirically evaluated the NMW impact on firm and sector productivity using a multiple channel of adjustment analytical framework, emphasizing the behavioural perspective. Our analytical strategy was to account for the NMW's impact on incentives and productivity, recognizing that multiple channels generate the net effect, controlling for factors identified by previous studies. Previous studies did not account for the NMW's impact in the productivity estimation algorithm. Our contribution is that while others have analysed profitability (Draca, Machin and Van Reenen, 2011) and wages, employment and labour productivity impacts (e.g. Riley and Rosazza-Bondibene (2015)) from neo-classical viewpoints, we show the value of a behavioural and broader social science theoretical perspective in addressing productivity effects. We thereby confirm and demonstrate the incentives created by the NMW suggested by Bernini and Riley (2016) and Hirsch, Kaufman and Zelenska (2015) to be an important channel of adjustment.

We show improvements in TFP in low-paying sectors after 1999. We also demonstrate substantial heterogeneity across and within sectors, and between firm size groups. Positive effects are strongest in larger firms. While compatible with possible pass-through and mark-up effects in firms with more monopoly power (Wadsworth, 2010), the result may be taken to reflect more sophisticated labour management practices and high levels of NMW compliance (LeRoux, Lucchino and Wilkinson, 2013) since 'micro' and small firms typically have fragmented and reactive management practices (Cagliano, Blackman and Voss, 2001). In theoretical terms, our results support Hirsch, Kaufman and Zelenska's (2015) framework envisaging multiple channels of adjustment to minimum wage impact; besides the main wage incentives effect, we find some evidence of technological change and attrition as potential sources of productivity improvements. We thus position our model not as a replacement for others, but as an alternative.

Our analysis has implications for managers who may not have grasped potential productivity benefits (Luce, 2004). Similarly, small firm strategies focused on staying 'below the radar' to avoid NMW compliance may not always be appropriate. We do not argue that employers should simply pay a 'living wage' to raise employee incentives. This would be simplistic since non-financial factors also count to low paid workers (Elfani, 2014). For national policy makers, we provide retrospective justification for the upward trend in minimum wages for the decade following inception.

Our results thus highlight a behavioural perspective's utility. Beyond implications for management practice, our findings also speak to contemporary wage policy discussions, not least since 'living wages' may also enhance productivity.

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