

Navigating the Trade-Offs: Temporary Agency Workers, Wage Suppression, and Firm Productivity in the UK

Abstract

Informed by Radical Political Economics perspective, this paper investigates the impact of temporary agency workers (TAWs) on firm-level outcomes in the United Kingdom. Drawing on a comprehensive dataset from the Office for National Statistics' Annual Business Survey—comprising firm-level observations of more than 44 thousand firms between 2011 and 2018—we employ fixed-effects regression models and Coarsened Exact Matching techniques to isolate the causal effects of TAW usage on key growth metrics. Our analysis reveals that an increased reliance on TAWs is significantly associated with a decline in the wage growth of permanent employees and a reduction in total factor productivity. Moreover, we document evidence of a non-linear relationship, whereby the flexibility benefits of TAWs at low levels are outweighed by adverse substitution effects at higher levels. These findings contribute to the existing literature by corroborating earlier studies and by providing robust evidence that the cost savings from employing TAWs are not fully reinvested in productivity-enhancing activities. The results have important implications for policymakers and business leaders, highlighting the need for balanced labour market reforms that support both short-term flexibility and long-term investments in human capital.

Keywords: Temporary Agency Workers; Employment; Wages; Productivity; Total Factor Productivity; Radical Political Economic Theory

Introduction

Temporary agency workers (TAWs) have become an increasingly common feature of the modern labour market in advanced economies, reshaping the way businesses manage their workforce (Forde and Slater, 2016). As firms grapple with the challenge of reducing costs while maintaining flexibility, traditional employment structures are being re-examined. Studies—for example, Fisher and Connelly (2016) and Ordine, Rose, and Vella (2017)—have provided valuable insights into the dual nature of TAW usage. On one hand, TAWs can offer much-needed flexibility and help firms respond rapidly to market fluctuations; on the other hand, their use may come with adverse spillover effects, including wage suppression for permanent staff and a reduction in firm-specific human capital.

Building on these prior findings, our study seeks to contribute to this ongoing debate by rigorously examining the impact of TAWs on firm-level outcomes in the United Kingdom. In doing so, we not only extend the existing literature but also refine the empirical approach to better isolate the causal effects of TAW usage. Our investigation utilises a large and comprehensive dataset collected annually between 2011 and 2018 by the Office for National Statistics (ONS), encompassing approximately 44,000 to 49,000 businesses. This rich dataset allows us to observe changes in employment practices over time and offers a level of statistical power that helps overcome limitations found in earlier studies.

To ensure the robustness of our findings, we employ advanced econometric techniques—specifically, fixed-effects regression models in tandem with Coarsened Exact Matching (CEM). This combination of methods not only helps control for unobserved heterogeneity and potential endogeneity but also provides a more nuanced understanding of how TAW usage influences key performance indicators such as permanent wage growth, overall employment expansion, and total factor productivity (TFP).

Our theoretical framework is anchored in the Radical Political Economics (RPE), which posits that employers strategically differentiate between forms of employment to weaken collective worker bargaining and preserve cost advantages. The cost savings achieved through the use of Temporary Agency Workers (TAWs) are often redirected towards capital accumulation rather than being reinvested in measures that enhance long-term productivity. This dynamic is particularly pertinent in the post-2008 economic landscape of the United Kingdom, where, despite record-high levels of employment, labour productivity has remained largely stagnant. For instance, HM Treasury (2020) reported that labour productivity grew by only 0.5% in 2018, while OECD data indicate that the UK's GDP per hour worked lags behind that of other advanced economies.

Against this backdrop, our paper positions itself as an effort to clarify the complex trade-offs inherent in modern employment practices. By integrating our robust empirical findings with well-established theoretical insights, we aim to offer guidance for both academic debate and policy formulation. In essence, our study deepens our understanding of the immediate benefits and hidden costs of TAW usage, while also illuminating the broader implications for sustainable growth and productivity.

The paper is structured as follows. First, we present the development of our hypotheses, drawing on established theoretical insights and previous empirical findings. Next, we describe the dataset and the empirical methods employed, including our use of fixed-effects regression models and Coarsened Exact Matching to robustly isolate the effects of TAW usage. We then present our results and discuss their implications for firm performance and economic productivity. Finally, we consider the broader policy implications of our findings and suggest avenues for future research. Through this careful and comprehensive approach,

our study contributes valuable insights into modern labour market dynamics while gently advancing the discussion on the trade-offs associated with temporary agency work.

Hypotheses Development

Our study builds the Radical Organisational Transformation (ROT) framework by synthesising established insights from Radical Political Economics (RPE) with contemporary empirical evidence on temporary agency work. RPE, as demonstrated by scholars such as Kim (2018) and Worland (1972), argues that economic institutions and labour market practices are not neutral but are deliberately structured to consolidate power and promote capital accumulation. We extend this logic to the organisational level, proposing that firms strategically use temporary employment arrangements—specifically, Temporary Agency Workers (TAWs)—as deliberate manoeuvres to fragment the workforce and weaken collective bargaining power.

In the United Kingdom, TAWs (commonly known as temps) are hired by staffing agencies and deployed to client firms on a short-term or flexible basis. Forde and Slater (2016) document how the scale and complexity of temporary agency work have increased markedly over the past 30 years, evolving from models that merely provided numerical flexibility into core components of many firms' employment strategies. This evolution reflects a shift in contractual arrangements and regulatory frameworks that enable firms to secure cost savings while minimising long-term investments in human capital.

RPE encourages us to view these arrangements not merely as responses to market fluctuations but as calculated manoeuvres. The substitution of permanent staff with TAWs is a deliberate strategy for reducing direct wage costs and curbing wage growth. By undermining the stability and solidarity of the permanent workforce, firms maintain lower wage structures and reallocate savings toward capital investments. Forde and Slater (2016) illustrate that such strategic reorganisation is further reinforced by complex contractual arrangements and evolving regulatory frameworks, which together enable firms to secure numerical flexibility while minimising their long-term investment in human capital. This perspective has profound implications for both firm performance and overall labour market dynamics.

The empirical literature on temporary agency workers, however, offers a complex and sometimes contradictory picture. Bryson (2013) found that while TAW usage was weakly associated with improved financial performance (e.g., higher sales per employee), there was no significant effect on gross value added per employee. Moreover, studies that report a positive association between TAW presence and higher wages in certain roles do not find this relationship consistent across different occupational categories. Böheim and Zweimüller (2012) further note that the presence of trade unions does not significantly affect the hiring of TAWs, suggesting that union activity may have little influence on firms' reliance on temporary labour.

Proponents argue that TAWs provide the necessary flexibility for firms to respond swiftly to market fluctuations and reduce direct wage costs. Yet, research by Fisher and Connelly (2016) cautions that immediate cost reductions may be offset by adverse outcomes such as diminished employee morale and productivity losses. In practice, agency staff often lack the detailed firm-specific knowledge required for optimal performance, necessitating additional training and time to integrate into established workflows. High turnover—common in agency placements—further disrupts continuity and wastes valuable resources. In sectors such as home care and pharmacy services, firms frequently depend on agency staff out of necessity, even though these workers are often more expensive and less productive than permanent employees. Ordine, Rose and Vella (2017) provide evidence that temporary agency arrangements can even suppress the

wages of permanent staff, reinforcing the view that the hidden costs of using TAWs may outweigh their benefits.

Forde and Slater (2016) enhance this argument by documenting how the rapid evolution and increased complexity of temporary agency work in the UK have led to contractual arrangements that amplify these cost-saving strategies. Their research shows that as agencies and client firms negotiate more complex relationships—often involving preferred supplier arrangements and derogation contracts—the cost savings from using TAWs are increasingly channelled into capital accumulation rather than reinvested in long-term workforce development. Such contractual and regulatory dynamics, which serve to maintain a fragmented and flexible labour force, are consistent with the RPE perspective that temporary agency work is a deliberate organisational strategy.

Drawing on these insights, the ROT framework makes it evident that firms strategically differentiate between employment types to achieve cost savings and consolidate power. Economic institutions, as demonstrated by Kim (2018) and Worland (1972), are purposefully structured to fragment the workforce and weaken collective bargaining. In this context, the use of TAWs is not a passive market response but a calculated manoeuvre to suppress wage growth by substituting permanent employees with a more flexible, less costly labour force. By deploying TAWs, firms reduce direct wage costs and channel the resultant savings towards capital accumulation rather than long-term investments in workforce development. This reorganisation of employment practices, as posited by RPE, ultimately undermines wage stability and diminishes collective bargaining power. In line with this reasoning, we propose:

H1: An increase in the share of TAWs is associated with a decline in the growth rate of permanent wages.

Beyond wage dynamics, the RPE perspective also illuminates how an overreliance on temporary work can reshape overall employment structures. Evidence from Eldor and Cappelli (2021) suggests that heavy dependence on temporary labour may slow overall employment growth, as firms opt for short-term staffing solutions over permanent hires. Moreover, Mueller (2012) and Nielen and Schiersch (2014) highlight a substitution effect: while moderate TAW usage can provide necessary operational flexibility, excessive reliance on temporary workers replaces permanent positions and constrains sustainable workforce expansion. This strategic shift reflects deliberate decisions that prioritise immediate cost advantages over long-term employment stability. Consequently, we further hypothesise:

H2: An increased reliance on TAWs is associated with slower overall employment growth.

When considering productivity, several factors suggest that TAW usage may have detrimental long-term effects. Although Damiani et al. (2016) report positive impacts on total factor productivity in some European contexts, the United Kingdom's persistent productivity stagnation (HM Treasury, 2020) tells a different story. Agency staff, lacking firm-specific knowledge and requiring ongoing training, contribute less effectively to productivity. The cost savings from employing TAWs are typically redirected towards capital accumulation, leaving little room for investments in enhancing long-term productivity. Supporting this view, Wiengarten et al. (2021) find that such practices undermine the cumulative growth of TFP. Therefore, we propose:

H3: A higher share of TAWs is negatively related to TFP growth.

Finally, several studies suggest that the relationship between TAW usage and firm performance may not be strictly linear. Research by Mueller (2012) and Nielen and Schiersch (2014) indicates a U-shaped relationship: low levels of TAW usage might provide beneficial flexibility, but beyond a critical threshold, the negative substitution effects—exacerbated by the productivity costs of continually training and integrating new agency staff—become dominant. Supporting this perspective, Jahn and Pozzoli (2013) observed that although an initial wage gap exists between agency and permanent workers, this gap narrows over time, hinting at a non-linear adjustment process. In line with these findings and the non-linear dynamics reported by Wiengarten et al. (2021), we conclude with the following hypothesis:

H4: The relationship between the share of TAWs and growth outcomes (permanent wage growth, overall employment growth, and TFP growth) is non-linear, with benefits at low levels of TAW usage and adverse effects beyond a critical threshold.

By building the ROT framework based on RPE, our analysis provides a theoretical foundation for these hypotheses. The combined evidence underscores how strategic employment practices—characterised by the deliberate use of TAWs to fragment workforce cohesion and redirect cost savings—play a critical role in shaping wage dynamics, employment growth, and productivity outcomes in the UK. This integrated perspective reframes temporary agency work as a organisational strategy, highlighting the profound implications of ROT on contemporary labour market practices.

Research Design

Data

To test our hypotheses, we rely on an empirical strategy that leverages one of the largest business surveys in the United Kingdom. Our analysis uses data from the Office for National Statistics' Annual Business Survey (ABS), which is the largest business survey in terms of both respondents and variables. Organisations are legally required to complete the ABS, ensuring high response rates and resulting in annual observations from approximately 44,000 to 49,000 businesses. The sample framework is constructed using administrative data on employment and turnover from PAYE and VAT-registered firms. For firms with 250 or more employees, this survey essentially provides a census, while a complex stratified sample is used for smaller firms. Our analysis is conducted at the reporting unit (RU) level, and the survey covers around 600 questions.

Table 1 provides an overview of the key variables used in our study. These include measures such as TAW costs (expressed as a percentage share of total employment costs), employment (L), revenue or turnover (T), labour productivity (lp), total factor productivity (ω), and gross wages and salaries (v). In addition, we control for other factors like tax, foreign ownership, region, and sector. Although our dataset is highly expansive, we acknowledge that it is limited by the available variables; for example, we cannot control for gender, other types of contracts, or trade union influences.

Table 1 Names, Notations and Descriptions of Variables

<i>Variable (Notation)</i>	<i>Description</i>
<i>TAW costs relate to all employment costs (a)</i>	Percentage share of TAW costs in relation to total employment costs that include gross wages and salaries, redundancy and severance payments to employees, employers' national insurance contributions and contributions to pension funds and payments to TAWs
<i>Employment (L)</i>	Number of employees
<i>Revenue or Turnover (T)</i>	Income that a firm generates through trading its goods and services in thousand £
<i>Labour productivity (lp)*</i>	Gross value added (γ) per employment(L)
<i>Total factor productivity (ω)*</i>	See equation (6)
<i>Gross wages and salaries (v)</i>	Gross wages and salaries, excluding redundancy and severance payments to employees, employers' national insurance contributions and contributions to pension funds
<i>Tax</i>	Total rates, duties, levies and taxes
<i>Foreign ownership*</i>	A dummy taking the value of 1 when ownership is outside of UK.
<i>Region (r)</i>	Wales, Scotland, North East, North West, Yorkshire and Humberside, East of England, East Midlands, West Midlands, London, South East and South West
<i>Sector (s)</i>	Wholesale, catering, construction, production, property, motor trade, retail and other services

* *derived variables.*

To test our hypotheses, we estimate four separate regression equations using fixed-effects models.¹ These models are designed to capture the dynamic relationships between TAW usage and changes in key outcome variables. Our key independent variable, a_{it} , is defined as the percentage share of TAW costs in relation to total employment costs for each firm i in period t . Additionally, we calculate the relative change in TAW share from one period to the next, denoted by Δa_{it} , in line with other variables that were previously defined in Table 1, where:

$$\Delta a_{it} = \left(\frac{a_{it}}{a_{i(t-1)}} \right) - 1 \quad (1)$$

a_{it} is the independent variable of interest. It is a percentage share of TAW costs in relation to total employment costs for each firm i in period t . Δa_{it} is a relative difference between the previous and current share of TAW costs in relation to total employment costs, . X_{it} contains other control variables, namely region, sector, foreign ownership, tax, employment, turnover, gross wages, total factor productivity, labour productivity, but excludes the dependent variable for that equation. The dependent variables capture changes in labour productivity (Δlp), total factor productivity ($\Delta \omega$), gross wages (Δv) and employment (ΔL).

X_{it} consists of all other control variables. We control for the key number of characteristics that are likely to influence the performance of firms. Firstly, we include the broad sectors (s) of wholesale, catering, construction, production, property, retail and other services, as these were

¹ Hausman test informed the decision to use the within transformation for the analysis. As there is variation over time, the dummy variables are also included.

often associated with differences in productivity (Oulton, 1998; Harris and Moffat, 2017). We incorporate regions and nations (r) of Wales, Scotland, North East, North West, Yorkshire and Humberside, East of England, East Midlands, West Midlands, London, South East and South West to account for discrepancies in regional differences. We also control for foreign ownership with the dummy variable that takes 1 for firms with a foreign majority owner and exporting taking 1 for those exporting abroad.

The four regression equations estimated are as follows:

$$\Delta p_{it} = \beta_a a_{it} + \beta_{a^2} (a_{it})^2 + \beta_{\Delta a} \Delta a_{it} + \beta_v \Delta v_{it} + \beta_\omega \Delta \omega_{it} + \beta_L \Delta L_{it} + \beta_x X_{it} \quad (2)$$

$$\Delta \omega_{it} = \beta_a a_{it} + \beta_{a^2} (a_{it})^2 + \beta_{\Delta a} \Delta a_{it} + \beta_v \Delta v_{it} + \beta_{lp} \Delta p_{it} + \beta_L \Delta L_{it} + \beta_x X_{it} \quad (3)$$

$$\Delta v_{it} = \beta_a a_{it} + \beta_{a^2} (a_{it})^2 + \beta_{\Delta a} \Delta a_{it} + \beta_\omega \Delta \omega_{it} + \beta_{lp} \Delta p_{it} + \beta_L \Delta L_{it} + \beta_x X_{it} \quad (4)$$

$$\Delta L_{it} = \beta_a a_{it} + \beta_{a^2} (a_{it})^2 + \beta_{\Delta a} \Delta a_{it} + \beta_\omega \Delta \omega_{it} + \beta_{lp} \Delta p_{it} + \beta_v \Delta v_{it} + \beta_x X_{it} \quad (5)$$

Total Factor Productivity Decomposition

Total Factor Productivity (TFP), denoted as ω , is not directly observable from production functions. Instead, it must be derived by estimating the weighted sum of a firm's inputs while controlling for simultaneity and selection biases. In our study, we employ control function approaches, a common method in production function estimation used to correct for transmission bias (Griliches and Mairesse, 1995). Transmission bias arises when factor input choices are correlated with unobserved productivity; for instance, firms with higher productivity may invest more, and past productivity levels can influence current input decisions.

Olley and Pakes (1996) first formalised a two-step procedure that uses firm investment as a proxy for unobserved productivity. However, due to the prevalence of zero investment observations in many firms, Levinsohn and Petrin (2003) later proposed using intermediate inputs as a proxy, which has become a widely accepted solution.

Our preferred approach is Wooldridge's (2009) one-step Generalised Method of Moments (GMM) estimator, which integrates these ideas into a single estimation step. This method addresses previous criticisms (e.g. Akerberg et al., 2015) regarding inconsistent estimates of the labour coefficient in two-step procedures. We assume a Cobb–Douglas production function of the form:

$$\omega_{it} = \ln \gamma_{it} - \beta_{krs} \ln K_{it} - \beta_{lrs} \ln L_{it}, \quad (6)$$

where ω_{it} is total factor productivity of the it th firm in period t , $\ln \gamma_{it}$ is the firm's logarithmic gross value added in order to simplify the model and eliminate intermediate inputs, K is capital and L is labour. In line with the existing literature, separate coefficients were estimated for each region, r , and sector, s . As reported in Table 3, $\Delta \omega$ and Δp had a high correlation coefficient of 0.788, indicating a successful estimation.

Coarsened Exact Matching

To address potential endogeneity bias and ensure that our comparisons are made between similar firms, we apply Coarsened Exact Matching (CEM).² This quasi-natural experiment

² CEM does not use the random pruning applied in Propensity Score Matching, which is shown to increase the level of imbalance (King and Nielsen, 2019).

design³ reduces sample heterogeneity by restricting the analysis to firms with comparable characteristics. In our application, we divide the population into two groups based on their expected TAW usage: one group consists of firms that will spend at least 10% of their employment costs on TAWs in the future, while the other group comprises firms where TAW spending does not exceed 1% between 2011 and 2018. Firms with TAW costs below 1% are assumed to use agency staff primarily for ancillary functions (e.g. recruitment) rather than as a core substitute for permanent labour.

CEM works by recoding each variable into meaningful groups, so that similar values are assigned the same category. CEM is employed on a number of key characteristics presented in Table 1. For the matching process, we ensure that in the year of matching, both groups of firms have less than 1% of their employment costs allocated to TAWs; the matching years are then excluded from further analysis. This procedure yields a final dataset of 2,048 observations from 768 reporting units, with 384 reporting units having a TAW share of at least 10% and 384 with a TAW share below 1%. This matching process strengthens the validity of our estimates by ensuring that our comparisons are made between firms that are similar on key characteristics.

Data Validation and Robustness Checks

To ensure robustness and validity, extensive data validation and manual checks were undertaken, as illustrated in Appendix A. After merging annual observations, the dataset consisted of 517,965 observations from 335,201 reporting units. Some variables consisted of missing values and thus the estimation of TFP reduced the sample to 343,806 RUs and 513,951. Then further validation of the data took place. Finally, the sample size was further reduced to 39,675 RUs and 95,771 observations because after further inspection, numerous missing values, unreasonable high values and 0s as well as those RUs with only one observation because growth variables could not be estimated otherwise.

Before proceeding with the analysis, the collinearity checks were also conducted as reported in Table 3 as well as standard statistical tests like R^2 and F-statistics reported with results in Table 3. The highly significant F-statistics in all regressions allowed us to comfortably reject the null hypothesis that all of the regression coefficients are equal to zero, whilst the R^2 varied from 0.33 to 0.79, indicating that a relatively large proportion of variation of dependent variables was explained by the independent variables in all models.

Results and Discussion

Descriptive Statistics

Our descriptive analysis reveals that the majority of UK firms did not heavily employ temporary agency workers (TAWs). In fact, 72% of unique reporting units (RUs) reported that their maximum TAW expenditure between 2008 and 2018 was less than 1% of their total employment costs. In contrast, 23% of RUs reported TAW spending between 1% and 10%, while 5% of RUs exceeded 10% and less than 1% exceeded 30%.

³ Another alternative is instrumental variable, but they require strong instruments influencing some variables but not others.

Table 2 Descriptive statistics of firms with varying % of TAWs.

	$a < 1\%$		$1\% \leq a < 10\%$		$a \geq 10\%$	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
T	83,125.09	664,372.4	167,839.0	1,071,522.0	252,730.8	1,502,902.0
L	517.44	2,077.95	928.19	6,069.64	869.61	2,096.92
ω	1,033.05	10,724.22	1,874.52	24,338.07	2,374.58	20,282.28
lp	846.46	17,119.69	1,150.55	17,990.54	953.78	12,720.83
$R\&D$	0.41	0.49	0.42	0.49	0.43	0.49
$Exporter$	0.14	0.35	0.23	0.42	0.25	0.43
Tax	2,505.77	85,014.17	5,563.78	92,278.33	5,682.91	119,147.10
v	81.68	1,195.58	140.24	2,401.16	53.39	412.95

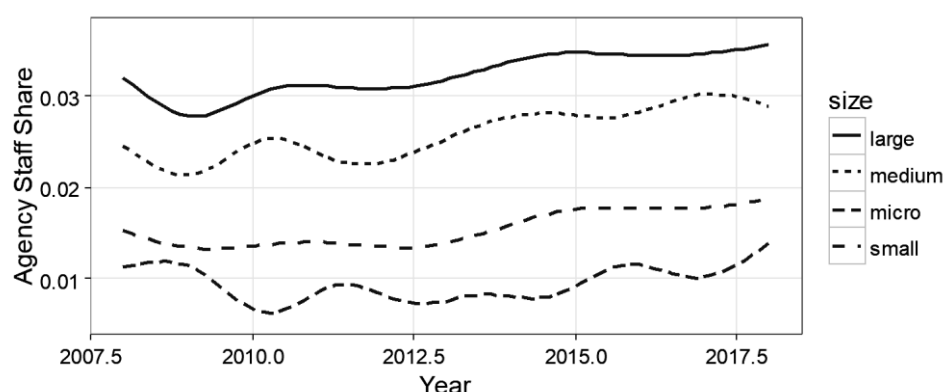
See To test our hypotheses, we rely on an empirical strategy that leverages one of the largest business surveys in the United Kingdom. Our analysis uses data from the Office for National Statistics' Annual Business Survey (ABS), which is the largest business survey in terms of both respondents and variables. Organisations are legally required to complete the ABS, ensuring high response rates and resulting in annual observations from approximately 44,000 to 49,000 businesses. The sample framework is constructed using administrative data on employment and turnover from PAYE and VAT-registered firms. For firms with 250 or more employees, this survey essentially provides a census, while a complex stratified sample is used for smaller firms. Our analysis is conducted at the reporting unit (RU) level, and the survey covers around 600 questions.

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Table 1 (p. 5) for variable descriptions and Appendix B for sector and region statistics.

Table 2 shows that firms with a higher share of TAWs tend to have higher turnover, total factor productivity, tax liabilities, and a greater likelihood of exporting, as well as higher investment in R&D. However, this trend does not extend to employment, labour productivity, and salaries per employee, where firms with a TAW share between 1% and 10% tend to report higher values. Figure 1 further illustrates the upward trend in TAW share over time across different firm size thresholds. Notably, larger firms generally employ a higher absolute number of TAWs, yet micro firms tend to have a higher TAW share relative to their size. These patterns underscore the importance of focusing on growth metrics rather than absolute values in our subsequent analyses.

Figure 1 TAW Share across firm size and year.



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Similarly, initial correlation analysis (detailed in Table 3) confirms that larger companies with higher turnover and employment levels tend to utilise a greater proportion of agency staff. Moreover, this analysis uncovers weak but negative relationships between the growth in agency staff share and other key variables, further justifying our focus on the dynamic effects of TAW usage.

Table 3 Correlation Matrix

	<i>a</i>	Δa	$\Delta \omega$	ΔL	Δlp	Δv	<i>t</i>
<i>a</i>	1						
Δa	0.169	1					
$\Delta \omega$	-0.011	-0.047	1				
ΔL	0.001	-0.004	-0.04	1			
Δlp	-0.004	-0.04	0.788	-0.228	1		
Δv	0.003	-0.027	0.187	-0.391	0.303	1	
<i>t</i>	0.017	0.024	0.025	0.05	0.011	0.031	1

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Hypotheses Testing

Table 4 presents the main relationships from the regression outputs for each dependent variable (changes in TFP, labour productivity, gross wages, and employment), for both the full and matched samples. In our analysis, we formally test a series of hypotheses regarding the impacts of TAWs on permanent wage growth, overall employment growth, and total factor productivity growth using both the full dataset and a matched sample of UK firms.

Our first hypothesis posits that an increase in the share of TAWs is associated with a decline in the growth rate of permanent wages. In the full sample regression, the coefficient for TAW share on wage growth is -0.012 ($p < 0.001$), indicating that each one-percentage point increase in TAW share is linked to a 1.2% decline in wage growth for permanent employees. This result is consistent with findings from Ordine, Rose, and Vella (2017) and is corroborated by our matched sample analysis, which yields a similar coefficient of -0.009 ($p < 0.001$). These results

enable us to reject the null hypothesis of no effect and confirm H1, demonstrating that firms with higher TAW shares experience significantly lower permanent wage growth.

The second hypothesis (H2) predicted that increased reliance on TAWs would slow overall employment growth. The full sample results indeed show a statistically significant negative coefficient for employment growth, suggesting that firms with higher TAW shares experience lower total employment increases. However, once we control for confounding factors using CEM, the effect on employment growth becomes statistically insignificant. This indicates that while there is evidence of a substitution effect in the broader sample, the impact on employment growth is more nuanced and depends on firm-specific characteristics. Thus, H2 is only partially supported by our tests.

Our third hypothesis contends that a higher share of TAWs is negatively related to TFP growth. The regression results strongly support this: in the full sample, the coefficient for TAW share on TFP growth is -0.014 ($p < 0.001$), and in the matched sample, the negative effect is even more pronounced at -0.050 ($p < 0.05$). This result aligns with RPET, which argues that the savings from employing TAWs are mainly channelled towards capital accumulation rather than productivity-enhancing investments. Thus, we reject the null hypothesis of no effect on TFP growth, confirming H3.

Our final hypothesis posits that the relationship between TAW usage and growth outcomes is non-linear. Specifically, low levels of TAW usage might offer some operational flexibility benefits, while excessive reliance leads to negative substitution effects that adversely impact permanent wage growth, overall employment growth, and TFP. In the full sample, the squared term for TAW share is statistically significant, suggesting a U-shaped relationship consistent with the findings of Hirsch and Mueller (2012) and non-linear dynamics noted by Wiengarten et al. (2021). However, after imposing further endogeneity controls through CEM, the significance of the squared term diminishes. This attenuation suggests that the non-linear relationship may depend on underlying firm heterogeneity, and that once matched, the evidence for a robust U-shaped effect weakens.

Additional analysis on labour productivity reveals a nuanced picture. Prior to matching, we observe a significantly positive relationship between TAW growth and labour productivity, which partially aligns with the findings of Giuliano et al. (2017). Yet, after matching, overall labour productivity exhibits significantly negative coefficients—consistent with Wang and Heyes (2020) on the impact of fixed-term employment.

Table 4 Main relationships from the regression outputs.

Data	Dependent variable	IV - Δa	IV - a	IV - Δa^2	R^2	F Statistic
All Data	$\Delta\omega$	-0.014*** (0.003)	0.049 (0.056)	-0.180* (0.109)	0.701	1715*** (df = 49; 35718)
	Δlp	0.011*** (0.002)	-0.025 (0.049)	0.189** (0.094)	0.729	1922*** (df=50; 35717)
	Δv	-0.012*** (0.002)	0.304*** (0.039)	-0.759 (0.075)	0.310	320*** (df=50; 35717)
	ΔL	-0.009*** (0.001)	0.148*** (0.027)	-0.244 (0.052)	0.330	351*** (df=50; 35717)
Matched Sample	$\Delta\omega$	-0.050** (0.020)	0.388 (0.339)	-0.763 (0.617)	0.771	61*** (df = 30; 541)
	Δlp	0.024 (0.019)	-0.526* (0.312)	0.189 (0.569)	0.787	67*** (df=30; 541)
	Δv	-0.045*** (0.015)	0.557** (0.253)	-0.999** (0.461)	0.355	10*** (df=30; 541)
	ΔL	-0.018 (0.011)	0.365* (0.187)	-0.488 (0.341)	0.372	11*** (df=30; 541)

Signif. Codes: <0.001 '***' 0.001 '**' 0.01 '*'; See Table 1 (p. 2) for variable descriptions.

More detailed regression outputs are available in Appendix C.

We report more detailed regression outputs in Appendix C. Other than the main findings, we uncovered a tight positive relationship between TFP and growth in both employment and labour productivity with both full and matched data. On the other hand, labour productivity is negatively impacted by the increase in employment, but this is because of how labour productivity is estimated where output is divided by the total employment. Having said that, we also observe that the increase in gross wages result in higher labour productivity in both matched and unmatched samples, unlike TFP where this was not sustained after matching. Once we investigate the change in gross wages as a dependent variable, we also see that increase in employment, not just agency staff share, tend to reduce the gross wages. We also find that the exporting firms positively impact gross wages and employment growth, but this is not sustained after matching, indicating more nuanced relationships. We also found no significant relationships between the wish to invest in R&D and the outcomes of the firm.

In summary, our hypothesis testing reveals that increased TAW reliance has clear negative effects on permanent wage growth (H1) and TFP growth (H3). The evidence for overall employment growth (H2) is mixed and sensitive to model specifications, while the non-linear effects (H4) are evident in the full sample but become less robust after controlling for firm-specific heterogeneity via CEM. These results highlight that while TAWs may offer short-term cost savings and flexibility, these benefits are largely offset by adverse long-term impacts—a finding that supports the insights of Fisher & Connelly (2016) and Eldor & Cappelli (2021) and underscores the need for balanced labour market reforms.

Conclusions

Our analysis demonstrates that an increasing share of TAWs has a clear detrimental effect on both permanent employees' compensation and TFP. In both the full dataset and the matched sample, higher TAW usage is robustly associated with lower wage growth for permanent

staff and a decline in TFP, even after accounting for firm-specific heterogeneity. These findings reinforce the core predictions of RPE and align with previous research suggesting that TAWs tend to receive lower compensation (Drenik et al., 2021) and may induce firms to cut wages for other employees in an effort to reduce overall costs.

The evidence concerning TFP is particularly striking. Consistent with earlier studies on various forms of temporary contracts (Damiani and Pompei, 2010; Cappellari et al., 2012; Addessi, 2014; Castellani et al., 2020), our results indicate that a growing share of TAWs is associated with lower TFP growth. This negative effect persists even in the presence of additional employment protections in the UK—where temporary workers enjoy nearly the same rights as permanent employees after 12 weeks—suggesting that the cost savings achieved through TAW usage are largely diverted away from investments that enhance productivity.

It would be overly simplistic, however, to attribute the decline in TFP solely to reduced reinvestment in productivity-enhancing activities. Other factors may contribute as well. For instance, TAWs often possess lower firm-specific knowledge, requiring additional training and ‘hand-holding’ that can reduce overall efficiency. Furthermore, lower firm-specific human capital (Hirsch and Mueller, 2012), tighter employment regulations (Green, 2008), dysfunctional internal relationships (Moser and Galais, 2009), and diminished worker satisfaction (Aletraris, 2010) may also limit a firm's ability to convert cost savings into meaningful productivity gains.

Our study makes a contribution to the existing literature by providing robust empirical evidence that challenges the notion of TAWs as a cost-effective solution for modern firms. By showing that the short-term flexibility and cost savings achieved through TAWs are coupled by negative impacts on wage growth and productivity, our findings underscore the need for a more balanced approach to labour market reform. For managers, while TAWs can provide valuable short-term flexibility and cost savings, an overreliance on temporary contracts may undermine long-term investments in stable, high-quality employment. As a result, business strategies should aim to strike a careful balance between achieving labour market flexibility and fostering sustainable human capital development. For policymakers, our findings suggest that reforms should not disproportionately promote temporary employment at the expense of permanent contracts. Instead, policy initiatives should focus on enhancing wage growth and productivity by encouraging investments in employee skills and firm-specific knowledge, while ensuring that temporary employment remains a supplement rather than a substitute for secure, long-term work.

Despite the robustness of our results, several limitations must be acknowledged. First, our analysis is based on firm-level data, which may mask important within-firm variations, such as differences related to gender, contract types, or the influence of trade unions. Second, while we have used fixed-effects models and CEM to address endogeneity concerns, unobserved factors may still influence the observed relationships. Finally, the extent to which our findings can be generalised to other contexts or economies remains an open question. Future research should explore these issues through cross-country comparisons and by incorporating more granular measures of labour market institutions.

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Appendices

Appendix A: Data Cleaning

Steps in Data Analysis	Unique Reporting Units	Observations
Full Data	335,201	517,965
After TFP Estimation	334,806	513,951
After further validation (removing missing values, or 0s or unlikely high values) and estimating growth variables	39,675	95,771
After matching	384x2	3,730

Appendix B: Average of a and Δa across sectors and regions

Region	Average of a	Average of Δa
North East	0.026	0.032
North West	0.022	0.035
Yorkshire & Humberside	0.028	0.035
East Midlands	0.034	0.040
West Midlands	0.032	0.050
East of England	0.028	0.042
London	0.023	0.030
South East	0.026	0.041
South West	0.023	0.045
Wales	0.027	0.041
Scotland	0.019	0.034
Not available	0.018	0.049

Sector	Average of a	Average of Δa
Advertising	0.015	0.013
Commission Industry	0.012	0.008
Construction	0.028	0.038
Catering	0.013	0.015
Gas and Electricity	0.035	0.025
Fishing	0.027	0.000
Forestry	0.002	-0.011
Non Marketing Organisations	0.021	0.044
Animal Husbandry and Hunting	0.045	-0.045
Insurance Organisations	0.027	0.040
Computer Industry	0.006	0.036
Employment Agencies	0.011	0.008
Motor Trades	0.009	0.028
Duty	0.049	0.045
Mineral Oil	0.018	-0.011
Postal Activities	0.029	-0.028
Property	0.028	0.052
Standard Production	0.037	0.052
Retail	0.014	0.041
Shipbuilding	0.049	0.011
Computer Services	0.026	0.015
Betting and Gaming	0.005	0.027
Standard Services	0.017	0.036
Transport	0.045	0.028
Water	0.032	-0.016
Wholesale	0.021	0.043

Appendix C

Table 4.1 Full data. Dependent variable – change in TFP ($\Delta\omega$).

	Estimate	Std. Error	t-value	Pr(> t)	
Δa	-0.01479	0.002798	-5.2873	1.25E-07	***
a	0.048681	0.056307	0.8646	0.38729	
a^2	-0.18012	0.108697	-1.6571	0.09751	.
Δv	-0.04445	0.007681	-5.7873	7.21E-09	***
Δlp	0.96192	0.003424	280.9446	< 0.01	***
ΔL	0.489988	0.010845	45.1817	< 0.01	***
L	2.44E-06	1.77E-06	1.3764	0.168705	
T	1.9E-09	3.21E-09	0.5923	0.553658	
ω	1.91E-07	1E-07	1.897	0.057834	.
lp	1.17E-08	1.53E-07	0.0766	0.938982	
v	4.78E-07	1.81E-06	0.2634	0.792206	
<i>R&D Dummy</i>	-0.00278	0.002255	-1.235	0.216852	
<i>Exporter Dummy</i>	-0.00135	0.003241	-0.4173	0.676437	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.

Table 4.2 Full data. Dependent variable – change in LP.

	Estimate	Std. Error	t-value	Pr(> t)	
Δa	0.010988	0.002413	4.553	5.31E-06	***
a	-0.02465	0.04857	-0.5075	0.611775	
a^2	0.188959	0.093759	2.0154	0.043873	*
Δv	0.187536	0.006554	28.616	< 0.01	***
ΔL	-0.48764	0.009266	-52.6285	< 0.01	***
$\Delta\omega$	0.715715	0.002548	280.9446	< 0.01	***
L	-2.3E-06	1.53E-06	-1.5113	0.13073	
T	-6.9E-09	2.77E-09	-2.5036	0.012297	*
ω	2.23E-07	8.67E-08	2.576	0.009998	**
lp	-6.9E-08	1.32E-07	-0.5232	0.600847	
v	-1.1E-07	1.56E-06	-0.0693	0.94474	
<i>R&D Dummy</i>	0.003061	0.001945	1.5739	0.115526	
<i>Exporter Dummy</i>	-0.00541	0.002796	-1.9345	0.05306	.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.

Table 4.3 Full data. Dependent variable – change in gross wages.

	Estimate	Std. Error	t-value	Pr(> t)	
Δa	-0.01303	0.001926	-6.7648	1.36E-11	***
a	0.303857	0.03874	7.8434	4.51E-15	***
a^2	-0.75853	0.074744	-10.1483	< 0.01	***
Δlp	0.119513	0.004176	28.616	< 0.01	***
ΔL	-0.64876	0.006868	-94.4609	< 0.01	***
$\Delta \omega$	-0.02108	0.003642	-5.7873	7.21E-09	***
L	-3.1E-06	1.22E-06	-2.5722	0.010108	*
T	-4.9E-09	2.21E-09	-2.1951	0.028162	*
ω	6.13E-08	6.92E-08	0.8866	0.375313	
lp	-1.8E-07	1.05E-07	-1.7544	0.079366	.
v	4.4E-06	1.25E-06	3.5226	0.000428	***
<i>R&D Dummy</i>	-0.00032	0.001553	-0.2084	0.83494	
<i>Exporter Dummy</i>	0.014285	0.002231	6.4036	1.54E-10	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.

Table 4.4 Full data. Dependent variable – change in employment growth.

	Estimate	Std. Error	t-value	Pr(> t)	
Δa	-0.00854	0.001327	-6.4312	1.28E-10	***
a	0.148281	0.026709	5.5518	2.85E-08	***
a^2	-0.24378	0.051567	-4.7274	2.28E-06	***
Δv	-0.3081	0.003262	-94.4609	2.2E-16	***
Δlp	-0.14758	0.002804	-52.6285	2.2E-16	***
$\Delta \omega$	0.110338	0.002442	45.1817	2.2E-16	***
L	1.24E-05	8.38E-07	14.8601	2.2E-16	***
T	-9.2E-09	1.52E-09	-6.0663	1.32E-09	***
ω	6.45E-08	4.77E-08	1.3533	0.175954	
lp	-5.5E-08	7.26E-08	-0.7554	0.450001	
v	1.03E-06	8.6E-07	1.1923	0.233141	
<i>R&D Dummy</i>	0.001579	0.00107	1.4752	0.140178	
<i>Exporter Dummy</i>	0.012366	0.001537	8.0467	8.77E-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.

Table 4.5 Matched data. Dependent variable – change in TFP.

	Estimate	Error	t-value	Pr(> t)	
Δa	-0.04994	0.020002	-2.4967	0.012831	*
a	0.387695	0.338748	1.1445	0.252924	
a^2	-0.76295	0.616904	-1.2367	0.216721	
Δv	-0.09118	0.057195	-1.5942	0.11148	
Δlp	0.930023	0.023889	38.9316	< 0.01	***
ΔL	0.401044	0.075921	5.2824	1.85E-07	***
L	1.15E-05	1.45E-05	0.7904	0.429622	
T	-3E-08	4.92E-08	-0.6108	0.541622	
ω	1.41E-05	4.46E-06	3.1602	0.001665	**
lp	-5.8E-06	5.66E-05	-0.1022	0.918605	
v	-0.00081	0.000713	-1.1427	0.253688	
<i>R&D Dummy</i>	-0.0076	0.017134	-0.4437	0.657454	
<i>Exporter Dummy</i>	-0.0058	0.025788	-0.2248	0.822234	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.

Table 4.6 Matched data. Dependent variable – change in LP.

	Estimate	Std. Error	t-value	Pr(> t)	
Δa	0.024066	0.01854	1.2981	0.194816	
a	-0.52561	0.312244	-1.6833	0.092889	.
a^2	0.894499	0.568941	1.5722	0.116485	
Δv	0.182823	0.052331	3.4936	0.000516	***
ΔL	-0.45801	0.069113	-6.6271	8.29E-11	***
$\Delta \omega$	0.792404	0.020354	38.9316	< 0.01	***
L	-1.5E-05	1.34E-05	-1.1095	0.267697	
T	2.66E-08	4.54E-08	0.5851	0.558748	
ω	-3.5E-06	4.15E-06	-0.8359	0.403597	
lp	-1.1E-05	5.22E-05	-0.2157	0.829341	
v	0.001011	0.000657	1.5381	0.124609	
<i>R&D Dummy</i>	0.006605	0.015816	0.4176	0.676401	
<i>Exporter Dummy</i>	-0.01504	0.023796	-0.6322	0.527526	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.

Table 4.6 Matched data. Dependent variable – change in gross wages.

	Estimate	Std. Error	t-value	Pr(> t)	
Δa	-0.04506	0.014962	-3.0117	0.002719	**
a	0.557452	0.253216	2.2015	0.028123	*
a^2	-0.99941	0.461297	-2.1665	0.030707	*
Δlp	0.120679	0.034543	3.4936	0.000516	***
ΔL	-0.58901	0.052608	-11.1963	< 0.01	***
$\Delta \omega$	-0.05128	0.032167	-1.5942	0.11148	
L	1.44E-05	1.09E-05	1.3218	0.186787	
T	-1.2E-08	3.69E-08	-0.3317	0.740274	
ω	-2.1E-06	3.37E-06	-0.6263	0.531413	
lp	-1.1E-05	4.24E-05	-0.2506	0.802189	
v	0.00235	0.000526	4.4703	9.52E-06	***
<i>R&D Dummy</i>	0.00035	0.012852	0.0273	0.978254	
<i>Exporter Dummy</i>	-0.01638	0.019328	-0.8476	0.397035	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.

Table 4.6 Matched data. Dependent variable – change in employment.

	Estimate	Std. Error	t-value	Pr(> t)	
Δa	-0.0179	0.011083	-1.6148	0.106946	
a	0.364676	0.186636	1.9539	0.051223	.
a^2	-0.48775	0.34051	-1.4324	0.152603	
Δv	-0.31939	0.028526	-11.1963	< 0.01	***
Δlp	-0.16393	0.024737	-6.6271	8.29E-11	***
$\Delta \omega$	0.122302	0.023153	5.2824	1.85E-07	***
L	2.57E-05	7.94E-06	3.2424	0.001258	**
T	-1.9E-08	2.72E-08	-0.7078	0.479401	
ω	4.89E-07	2.48E-06	0.1969	0.843948	
lp	-5.1E-05	3.12E-05	-1.6259	0.104543	
v	0.000466	0.000394	1.1843	0.236801	
<i>R&D Dummy</i>	0.004015	0.009462	0.4243	0.671482	
<i>Exporter Dummy</i>	-0.00964	0.014236	-0.6773	0.498482	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Sector, year and region dummies were included but not reported. See Table 1 (p. 2) for variable descriptions.