Do workers share in the returns to firm-level R&D activity?

Evidence from labour markdowns in UK Manufacturing

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Abstract

This study examines whether firms' research and development (R&D) investment shapes labour market power by affecting the wedge between workers' marginal revenue product and wages.

Motivated by existing theories emphasising the role of worker outside options and turnover costs, we test whether R&D increases firms' dependence on research-intensive workers whose skills are both transferable and embedded in firm-specific production processes. Using matched administrative data from the UK Annual Respondents Database X (ARDx) and the Business Expenditure on Research and Development (BERD) survey, and applying production-function-based markdown estimators, we find that higher R&D investment is associated with lower labour markdowns.

This relationship is driven by internally financed and in-house R&D, particularly experimental development, and is concentrated in firms that rely more heavily on high-skilled research personnel and in settings where labour is less substitutable. The effect also strengthens over time, consistent with the accumulation of firm-specific knowledge and rising turnover costs. Overall, the results indicate that R&D investment weakens employer wage-setting power by increasing firms' reliance on a small set of skilled workers whose knowledge is valuable and difficult
to replace.

1 Introduction

The extent to which firms' research and development (R&D) activity shapes market power has long been a central concern in industrial organisation and labour economics. A substantial body of research shows that innovation and technological advancement are frequently associated with higher product-market markups through productivity gains, product differentiation, and the creation of entry barriers (Bloom et al., 2013; De Loecker and Warzynski, 2012; Syverson, 2011). However, this literature has largely focused on realised innovation outcomes, such as patents and productivity growth, and their implications for price-setting power in output markets, overlooking the dynamic process through which market power is formed. Because these outcomes are themselves the result of prior R&D investment, an exclusive focus on realised innovation obscures the role of ongoing knowledge accumulation in shaping market structure (De Ridder, 2024). In particular, R&D may influence firms' bargaining position and the distribution of rents well before innovation outcomes fully materialise. This perspective has become increasingly relevant in light of rising market concentration alongside declining labour shares in many advanced economies (Autor et al., 2020), pointing to the need to better understand how firm-level knowledge investment shapes not only prices and profits but also the allocation of rents between capital and labour.

One key mechanism through which these distributional effects may arise is labour market power. When firms possess wage-setting power, they can pay wages below workers' marginal revenue products, generating a wedge that reflects their ability to capture rents from labour (Berger et al., 2022). A substantial empirical literature documents that such wedges are pervasive across industries and countries (Sokolova and Sorensen, 2021) and that their magnitude varies systematically with both institutional settings and firms' production environments. In particular, weaker collective bargaining structures, such as declining union coverage, can increase the scope for firm-level wage-setting,[1] while technological and organisational changes associated with knowledge investment can reshape skill demand, workforce composition, and the substitutability of labour (Autor et al., 2003; Bresnahan et al., 2002; Vivarelli, 2014). Building on these insights, R&D investment may influence labour market power by altering firms' production technologies and workers' outside options, thereby affecting the extent to which firms can extract rents from labour. However, much of the existing evidence on R&D and labour outcomes focuses on wages, employment, or skill composition (Machin and Van Reenen, 1998), rather than on the firm-level wedge between marginal revenue product and wages, leaving limited direct evidence on how R&D investment relates to buyer-side labour market power.

This paper addresses this gap by linking firm-level R&D investment directly to firm-level labour markdown measures. Following Brooks et al. (2021b) and Yeh et al. (2022),

[1] For instance, in the United Kingdom, trade-union membership among employees declined to 22.0 percent by 2024, the lowest level since the mid-1990s (Department for Business and Trade, 2025). This decline has been accompanied by a widening gap between productivity growth and wage growth over the same period, suggesting a reduced role of collective bargaining in rent distribution, although the relationship is not necessarily causal and may reflect broader structural and technological changes in the labour market.

we use the term labour markdown to refer to the ratio of workers' marginal revenue product to observed wages. A higher markdown indicates greater employer wage-setting power, while a lower markdown implies a smaller wedge between the value of labour and wages. Using administrative microdata on UK manufacturing firms from the Annual Respondents Database X (ARDx), we construct firm-level markdown measures following production-function-based approaches (Brooks et al., 2021b; Yeh et al., 2022) and link them to R&D information from the Business Expenditure on Research and Development (BERD) survey over the period 1997–2019. We find that higher R&D intensity is associated with significantly lower labour markdowns, with effects strengthening over time. This relationship is driven by internally financed and internally executed R&D and operates through changes in workforce composition, particularly increased reliance on research-intensive workers.

These findings are consistent with a mechanism in which R&D investment simultaneously increases workers' outside options and the cost of their replacement. On the one hand, participation in R&D activities equips workers with transferable, frontier-relevant skills that raise their value in the external labour market (Abis and Veldkamp, 2023; Flinn et al., 2017). On the other hand, R&D work is embedded in firm-specific projects, teams, and organisational routines, making worker turnover costly and disruptive (Kline et al., 2019). This combination weakens firms' incentives to suppress wages, as the gains from wage suppression are increasingly offset by the risks associated with worker exit. As a result, labour markdowns decline as firms become more dependent on a relatively small group of research workers whose knowledge is both externally valuable and internally difficult to replace. In contrast, R&D that is purchased or weakly integrated into the firm's production process does not generate the same combination of mobility and embeddedness, and therefore does not impose comparable constraints on wage-setting.

This study makes two main contributions to the literature. First, it contributes to the literature on innovation, market structure, and rent distribution by bringing labour-market power into a research agenda that has been dominated by product-market outcomes. A large literature studies how innovation and competition interact through patents, productivity, markups, and market concentration, emphasising that innovation can either intensify rivalry or reinforce market power depending on industry structure and the appropriability of knowledge (Aghion et al., 2005; Autor et al., 2020; Sutton, 1991). More recent work links markups directly to the private and external value of patented innovation, showing that innovative activity and product-market power are closely intertwined (Martin et al., 2025). Yet most of this literature evaluates innovation through its effects on prices, profits, concentration, or patent value, and says much less about how innovation shapes the distribution of rents inside the firm through wage-setting. By linking firm-level R&D investment to labour markdowns, this paper extends the innovation–market-power nexus from the output market to the labour market, and from realised innovation outcomes to the underlying knowledge investments through which market power and rent allocation are formed.

Second, the paper contributes to the literature on human capital, organisational economics, and labour-market frictions by providing firm-level evidence for a mechanism that is often discussed theoretically but rarely examined directly in the context of innovation. Becker's distinction between general and firm-specific human capital, Acemoglu and Pischke's emphasis on imperfect labour markets and compressed wages, and Lazear's skill-weights approach all imply that workers' bargaining positions depend not only on the transferability of skills, but also on how those skills are combined and embedded within particular firms and production processes (Acemoglu and Pischke, 1999; Becker, 1962; Lazear, 2009). This insight is especially relevant in innovative activity. Research on inventor and scientist mobility shows that knowledge travels with workers across firms, improving outside options and diffusing frontier capabilities (Almeida and Kogut, 1999; Kim and Marschke, 2005). At the same time, work on organisational change and task content shows that new technology raises demand for non-routine, problem-solving labour that is complementary to firm-specific organisational structures (Autor et al., 2003; Bresnahan et al., 2002). Our paper speaks directly to this literature by showing that the relevant margin is not innovation per se, but organisationally embedded innovation: labour-market power is weakest precisely where knowledge investment is internal to the firm and where production depends more heavily on research workers whose skills are both externally valuable and internally difficult to replace.

The remainder of the paper proceeds as follows. Section 2 introduces the theoretical framework. Section 3 describes the data and stylised facts. Section 4 presents the empirical results, and Section 5 concludes.

2 Theoretical framework

Firms invest in research and development (R&D) to enhance productivity, sustain innovation, and maintain competitiveness in product markets (Bloom et al., 2020, 2013). In technologically dynamic environments, continuous R&D engagement is often necessary for survival, as firms compete to develop new products, processes, and technological capabilities. This competitive pressure implies that firms cannot readily reduce R&D investment without jeopardising their long-run market position.

Although the role of R&D in shaping product-market outcomes is well established, its implications for labor-market dynamics, particularly wage-setting, are less clearly understood. To examine this link, it is useful to consider firms' wage-setting behaviour in imperfect labour markets. Within a monopsony framework, firms possess wage-setting power when labour supply to the individual firm is imperfectly elastic, allowing wages to fall below workers' marginal revenue product (Bhaskar et al., 2002). This power is strengthened by search frictions, mobility costs, and the gradual adjustment of job matches (Azar et al., 2022), and is particularly pronounced when workers are easily replaceable and labour turnover imposes limited disruption to production (Kline et al., 2019). Conversely, when the opportunity cost of worker exit rises, firms face reduced incentives to suppress wages (Campbell, 1993). Accordingly, monopsony power depends critically on workers' outside options and the costs associated with labour turnover.

Human capital theory provides a useful lens for understanding these dynamics. The distinction between general and firm-specific human capital implies that when skills are closely tied to the current employer, their value depends on continued employment within the firm (Becker, 1962; Lazear, 2009). In the presence of labour market frictions, such dependence limits workers' outside options and strengthens firms' wage-setting power (Acemoglu and Pischke, 1999). Accordingly, organisational investments that deepen firm-specific knowledge can enhance firms' ability to extract monopsonistic rents.

R&D activities differ from other organisational investments in the type of human capital they generate. Unlike routine, firm-embedded tasks, R&D involves experimentation, problem solving, and engagement with evolving technological opportunities, often requiring workers to operate at or near the technological frontier (West and Iansiti, 2003). Through participation in these activities, workers develop not only firm-specific experience but also transferable, innovation-oriented capabilities, including problem-solving skills and exposure to emerging technologies (Bartel et al., 2007; Hatch and Dyer, 2004). Moreover, knowledge generated through R&D is partly embodied in workers and may move across firms, including to potential competitors (Kim and Marschke, 2005). Hence, R&D shifts the composition of human capital toward more portable and externally valuable skills, rendering workers more footloose in the labour market and strengthening their outside options. In contrast to routine-based skill accumulation that binds workers more closely to the firm, this increased mobility limits firms' ability to suppress wages and thereby weakens monopsonistic rent extraction.

At the same time, R&D work is deeply embedded within firm-specific projects, teams, and organisational routines. Innovation relies on cumulative and often tacit knowledge, as well as the coordination of specialised tasks across workers (Jaravel et al., 2018; Jones, 2009). Therefore, employees engaged in R&D become integral to ongoing projects, and their departure can disrupt innovation processes and delay knowledge transmission (Grinza and Quatraro, 2019). Importantly, these costs are not eliminated by hiring similarly skilled workers. Even when replacement employees possess comparable frontier knowledge, they require time to adapt to firm-specific technologies, internal systems, and team structures (Blatter et al., 2012). Consequently, labour adjustment in R&D settings involves not only hiring costs but also the costly reconstruction of project-specific knowledge and coordination capacity. This combination of high external mobility and strong internal embeddedness raises the cost of worker turnover, strengthening firms' incentives to retain R&D-relevant employees.

These changes in workers' outside options and turnover costs have direct implications for wage-setting. On the one hand, R&D increases workers' mobility and attractiveness to competing firms by equipping them with transferable, frontier-relevant knowledge. On the other hand, it raises the cost of losing such workers due to their embeddedness in ongoing innovation processes. As both the likelihood and the cost of worker exit increase, the gains from wage suppression are increasingly outweighed by the risks associated with turnover. Firms therefore face stronger incentives to retain R&D-relevant employees, which may lead to higher wages and reduced labour markdowns.

Taken together, the preceding arguments highlight a tension between firms' innovation activities and their labour-market power. While firms invest in R&D to enhance productivity and sustain competitiveness, such investments do not necessarily guarantee successful innovation outcomes. At the same time, by increasing the transferability of workers' skills and the cost of replacing them, R&D may weaken firms' monopsony power by strengthening workers' bargaining position. This effect is likely to be particularly pronounced in activities such as experimental development, where workers are directly engaged in novel technological domains and accumulate highly valuable, externally relevant knowledge. Overall, these arguments suggest that R&D investment reshapes the composition of human capital and alters the balance of power between firms and workers, reducing firms' incentives to set wages below marginal revenue product.

3 Data and Stylised Facts

3.1 Data and Summary Statistics

This study combines two administrative datasets provided by the UK Office for National Statistics: the Annual Respondents Database X (ARDx) and the Business Expenditure on Research and Development (BERD) survey. ARDx contains firm-level information on output, employment, material inputs, capital stock, and labour costs (Office for National Statistics, 2024), while BERD provides detailed information on firms' in-house R&D expenditure and related characteristics (Office for National Statistics, 2025). The analysis focuses on the period 1997-2019, as the 2020 BERD wave is preliminary and lacks sufficient breakdown detail.

The sample is restricted to manufacturing firms defined using two-digit Standard Industrial Classification codes 10–33, where production inputs and outputs are consistently recorded and production-function-based measures of labour-market power can be plausibly estimated. Firm-level markdowns are first estimated using the full ARDx manufacturing panel and subsequently merged with BERD to analyse the relationship between R&D investment and labour-market power. The final matched panel contains approximately 48,224 firm-year observations. Detailed data construction and cleaning procedures are reported in the Appendix A.

The dependent variable is labour markdown. In the empirical analysis, both markdown and R&D investment are expressed in natural logarithms, so the estimated coefficients can be interpreted approximately as elasticities. Following Brooks et al. (2021b), we construct three alternative markdown measures based on the De Loecker and Warzynski (2012) (DLW), Cobb-Douglas (CD), and constant returns to scale (CRS) approaches, which differ in their production-function assumptions and estimation strategies. We use the DLW estimator in the main analysis because it is widely used in the literature (Xie et al., 2024). R&D investment is measured as the natural logarithm of total in-house capital and non-capital expenditure on R&D. Control variables include firm output, subsidies, software investment, foreign ownership, and multi-plant status. Detailed construction of the markdown measures is provided in Appendix B, while the definitions of the other variables are reported in Appendix C. Table A9 summarises the definitions and data sources of all variables.

Table 1 presents summary statistics of the main variables used in the empirical analysis. The average markdown exceeds unity across alternative estimators, indicating the presence of employer wage-setting power on average. Table A5 reports the distribution of average markups (product market power) and markdowns across industries. Under perfect competition in the labour market, the markdown equals one, meaning that wages are equal to the marginal revenue product of labour. By contrast, our estimates show markdowns consistently above one, suggesting the presence of labour market power. Substantial cross-industry heterogeneity is observed: for example, Industry 19 (manufacturing of coke and refined petroleum products) exhibits the highest average markdown, while Industry 22 (manufacturing of basic pharmaceutical products and pharmaceutical preparations) shows the highest average markup.

R&D activity is also widespread but highly heterogeneous across firms. The average level of log R&D investment is 10.17, with a standard deviation of 1.73, indicating substantial dispersion in innovation intensity. Disaggregated R&D expenditure reveals that firms rely on both internally financed and externally sourced R&D, with own-funded R&D exceeding purchased R&D on average. Moreover, firms engage in a range of innovation activities, including basic research, applied research, and experimental development, suggesting that R&D investment is multifaceted and varies in its degree of proximity to production.

These patterns highlight that R&D is not only unevenly distributed across firms but also differs in its composition, raising the possibility that its relationship with labour market outcomes may vary systematically across firms and activities. We therefore turn next to descriptive evidence on the evolution of R&D investment and labour markdowns, as well as their raw relationship in the data.

3.2 R&D, Markdown, and Firm Characteristics

We begin by examining the evolution of R&D investment and labour markdowns over time. Figure 1 plots the average level of log R&D investment between 1997 and 2019. R&D intensity declines during the early 2000s, followed by a recovery in the late 2000s and early 2010s, reflecting cyclical variation alongside longer-term changes in knowledge investment.

Figure 2 presents the corresponding evolution of log labour markdowns. Markdown measures exhibit a broadly U-shaped pattern, declining in the early 2000s before rising sharply in the late 2000s and early 2010s. These aggregate patterns suggest substantial time variation in both R&D activity and labour market power, but do not by themselves reveal the relationship between the two.

A key feature of the data is the strong role of firm size. Figure 3 shows that both R&D intensity and labour markdowns increase monotonically with firm size. Larger firms invest substantially more in R&D and simultaneously exhibit higher markdowns, suggesting that firm size is a central source of variation in both variables.

Consistent with this interpretation, Figure 4 examines the relationship at the sector level and finds little systematic correlation between average R&D intensity and markdowns across industries. This indicates that the relationship between R&D and labour market power is not driven by differences across sectors, but instead reflects within-industry heterogeneity.

To examine the firm-level relationship more directly, Figure 5 plots the binned relationship between residualised log R&D investment and residualised log markdown. Panel A controls for year and industry fixed effects and shows a positive relationship, with firms that invest more in R&D also exhibiting higher markdowns. However, once firm size is accounted for in Panel B, by additionally residualising with respect to employment, the relationship becomes substantially weaker and even turns slightly negative.

This contrast highlights the central role of firm size in shaping the raw correlation between R&D and labour markdowns. The positive association observed in the data is largely driven by larger firms simultaneously exhibiting higher R&D intensity and greater wage-setting power, rather than reflecting a structural relationship between R&D and labour market power.

Taken together, these descriptive patterns highlight a central empirical challenge. The positive association between R&D investment and labour markdowns in the raw data appears to be driven primarily by firm size and other firm-level differences within industries, rather than by a systematic relationship across sectors. Larger firms both invest more in R&D and exhibit higher markdowns, generating a positive cross-sectional correlation that is likely confounded. Identifying the effect of R&D therefore requires controlling for firm characteristics and unobserved heterogeneity, and exploiting within-firm variation over time. The next section develops an empirical framework that enables a more credible identification of this relationship.

4 Empirical strategy & Findings

4.1 Model specification

To examine the effect of R&D investment on labour market power, we estimate a reduced-form specification that relates firm-level markdowns to R&D investment while controlling for observable characteristics and high-dimensional fixed effects. Following Brooks et al. (2021a) and Xie et al. (2024), our baseline regression is given by:

$$ln(markdown_{it}) = \beta_1 ln(RD_{it}) + \beta_2 X_{it} + \alpha_i + \tau_t + \delta_s + \theta_r + \epsilon_{it} \quad (1)$$

where markdown$_{it}$ denotes firm i's markdown in year t; RD_{it} is R&D investment for firm i in year t. Both variables are expressed in natural logarithms. The coefficient β_1 captures the effect of R&D investment on markdown and represents the key parameter of interest in this study, capturing the effect of R&D investment on labour market power. X_{it} is a vector of firm-level control variables, with corresponding coefficients β_2. α_i, τ_t, δ_s, θ_r represent firm, year, industry, and regional fixed effects, respectively. ϵ_{it} is an error term.

Controlled fixed effects cover 9,305 firms over 23 years (from 1997 to 2019), 22 two-digit SIC industries, [2] and 14 government regional codes corresponding to first-level International Territorial Level (ITL1) regions or nations across Great Britain (excluding Northern Ireland as ARDx surveying does not cover it). We further include industry-by-year, region-by-year, and industry-by-region fixed effects. This rich fixed-effects structure absorbs time-varying industry and regional heterogeneity, as well as persistent industry–region differences. The specification (1) is estimated using Ordinary Least Squares (OLS), with robust standard errors clustered at the firm level.

4.2 Basic results

Table 2 presents the estimates of specification (1). Across all three markdown estimators, DLW, CD, and CRS, the coefficient on R&D investment is negative and highly significant at the 1% level, ranging from -0.015 to -0.025. The DLW estimate in column (1) suggests that a 10% increase in R&D investment is associated with a 0.15% decline in markdown with controlling firm characteristics and a full set of fixed effects. In standard-deviation terms, a one-standard-deviation increase in R&D investment is associated with roughly a 2.6 percent (0.015 × 1.732) decline in markdown, highlighting the economic relevance of large-scale R&D investment. Columns (2) and (3) provide robustness checks using alternative estimators: the CD estimator and the CRS estimator, respectively. The results indicate that, across all markdown estimators, the estimated effect of R&D investment remains consistently negative and statistically significant.

We also conduct robustness checks to rule out alternative explanations. First, to account for the outlier industry SIC 19 (coke and refined petroleum products), where markdown levels are unusually high, we re-estimate the models excluding this industry. As shown in Table B1 of the appendix, the coefficients remain unchanged at -0.015, -0.025, and -0.018, respectively. Second, as an alternative specification, we replace continuous R&D investment with a binary indicator for R&D engagement. The results in Table B2 show that R&D-active firms exhibit markdowns around 1.7% lower than those of non-R&D firms, with the effect robust across estimators and when excluding SIC 19. Taken together, these checks indicate that the relationship between R&D investment and labour markdowns is not driven by industry composition or by the specific measurement of R&D activity.

To further address concerns about potential endogeneity of R&D investment, we implement an instrumental-variable (IV) strategy estimated by two-stage least squares (2SLS). We exploit exogenous variation in firms' exposure to aggregate R&D shocks using a shift–share design that interacts predetermined firm-level exposure shares with external R&D "shifters." Specifically, we construct two instruments. The first interacts contemporaneous U.S. industry-level R&D expenditure with the firm's lagged R&D share within its UK industry. [3] The second uses an analogous interaction based on UK

[2]Although the SIC classification includes 23 manufacturing industries (10 to 33), Tobacco (SIC 12) is excluded from the sample due to having fewer than 100 observations in the ARDx panel, which limits reliable estimation.

[3]US industry-level R&D expenditure data are obtained from the OECD Analytical Business Enter-

regional public R&D spending, interacting contemporaneous region-level public R&D expenditure with the firm's lagged exposure share to its region. [4] The data are available for 2001–2019; values for 1997–2000 are imputed using linear extrapolation by region. In both cases, identification comes from variation in aggregate R&D investment that is plausibly exogenous to firm-specific wage-setting and markdown dynamics, combined with predetermined differences in firms' exposure intensity.

Our specification absorbs a rich set of fixed effects: firm, year, industry, and region fixed effects, as well as all two-way interactions (year×industry, year×region, and industry×region). These controls account for time-invariant firm heterogeneity, aggregate macroeconomic shocks, industry-specific time shocks, region-specific time shocks, and persistent industry–region differences. As a result, identification is driven by differential exposure of firms, based on predetermined shares, to aggregate R&D shocks, conditional on these high-dimensional controls.

Under this structure, the exclusion restriction requires that the interaction terms affect UK firm markdowns only through their impact on contemporaneous firm R&D, rather than through direct channels correlated with local labour market conditions or industry-wide UK shocks—factors that are absorbed by the included fixed effects. The IV estimates therefore isolate a component of firm R&D that is driven by external R&D shocks and is orthogonal to a wide range of confounding influences.

Table 3 reports the IV results using both one-year and two-year lagged exposure shares. Panel A presents estimates based on one-year lagged exposure, while Panel B uses two-year lags. In each panel, columns (1) and (2) report 2SLS estimates using the U.S. industry-based instrument and the UK regional instrument, respectively, and column (3) reports the corresponding OLS estimate using the same estimation sample for comparability.

Across both panels, the IV estimates are negative and statistically significant. In Panel A, the estimated coefficients are -0.104 and -0.098, while in Panel B they are larger in magnitude, at -0.190 and -0.182. The corresponding OLS estimates remain negative and relatively small in magnitude. The first-stage statistics indicate that the instruments are relevant: the Kleibergen–Paap LM test rejects under-identification, and the Wald F statistics are well above conventional thresholds, suggesting that weak instrument concerns are unlikely to drive the results.

Overall, the consistency of the results across alternative instruments and lag structures provides strong evidence that higher R&D investment reduces labour markdowns, alleviating concerns about endogeneity.

4.3 Evidence on the theoretical mechanism

The baseline results establish that higher R&D investment is associated with lower labour markdowns. We now examine the mechanism underlying this relationship.

prise Research and Development (ANBERD) database; see the OECD ANBERD database.

[4]UKRegional public R&D expenditure data are obtained from the Office for National Statistics; see the ONS regional GERD. The data are available for 2001–2019; values for 1997–2000 are imputed using linear extrapolation by region.

The theoretical framework suggests that this effect does not arise from R&D investment per se, but from its impact on the composition of human capital—specifically, the development of research-intensive workers whose skills are both more transferable and more costly to replace. If this mechanism is correct, the markdown-reducing effect of R&D should be concentrated in activities that are organisationally embedded and among workers directly involved in knowledge creation.

We begin by distinguishing between alternative forms of R&D investment. Table 4 shows that purchased R&D work, defined as R&D activities performed outside the firm, is associated with a small but positive effect on markdown, suggesting that outsourcing R&D does not alleviate firms' labour market power. In contrast, own-funded in-house R&D is significantly associated with a reduction in markdown, while externally funded in-house R&D exhibits no statistically significant effect. This contrast indicates that only R&D activities that are both executed and financed internally—hence organisationally embedded—are effective in weakening firms' labour market power.

We further decompose in-house R&D by research content. While neither basic nor applied research exhibits a statistically significant effect on markdown, experimental development is associated with a sizeable and statistically significant reduction in markdown. Because experimental development directly transforms existing knowledge into production processes, it increases firms' reliance on workers engaged in implementation and problem-solving at the technological frontier. This finding is consistent with the theoretical prediction that R&D weakens monopsony power when it increases dependence on less substitutable, skill-intensive labour.

We next examine whether this effect is indeed driven by research workers. Table 5 provides direct evidence that the markdown-reducing effect of R&D is concentrated among research employees. The interaction between R&D investment and researcher FTE is negative and statistically significant, whereas the corresponding interactions with technicians and support staff are statistically insignificant. This indicates that the effect of R&D on labour market power does not arise from a general expansion of R&D-related employment but is instead driven by workers directly engaged in knowledge creation.

This pattern aligns closely with the occupational definitions used in the data. Researcher FTE refers to full-time equivalent researchers engaged in R&D activities, including PhD students, graduates, and scientists. These workers are directly involved in knowledge creation and the development of firm-specific technologies and are therefore more likely to possess transferable, frontier-relevant skills. In contrast, technicians perform technical or scientific support tasks, while support staff include skilled and unskilled crafts, clerical, and administrative workers participating in R&D projects. The absence of a significant interaction effect for these latter groups suggests that R&D reduces labour markdowns primarily through workers whose skills are both more valuable externally and less easily replaced internally.

Finally, Table 6 examines how R&D reshapes firms' wage and employment structure in ways that are consistent with this interpretation. Higher R&D investment is associated with a significant increase in the share of R&D-related labour costs in total labour costs, as well as a higher share of researchers and technicians within R&D employment. At the same time, R&D investment is positively related to both the overall labour share and the R&D labour share relative to output. These patterns indicate that R&D leads firms to reallocate their wage bills and factor payments toward R&D-related and skill-intensive labour, rather than merely expanding employment or output.

Taken together, these findings reveal a coherent mechanism. R&D investment shifts the composition of human capital toward research-intensive workers whose skills are both externally valuable and internally embedded within firm-specific processes. This combination increases both the likelihood and the cost of worker exit, thereby strengthening workers' bargaining position and reducing firms' ability to set wages below marginal revenue product.

4.4 Dynamic effects of R&D investment

The evidence in the previous subsection shows that the markdown-reducing effect of R&D operates through research-intensive workers whose skills are both more transferable and more costly to replace. A key implication of this mechanism is that its effects should unfold gradually over time. In particular, the strengthening of workers' outside options and their embeddedness in firm-specific production processes are not instantaneous, but depend on the accumulation of knowledge and experience within the firm.

As workers participate in R&D activities over time, they acquire firm-relevant knowledge, adapt to organisational routines, and become integrated into project-specific teams. At the same time, their exposure to frontier technologies enhances the external value of their skills, improving their outside options. Consequently, workers who have been engaged in R&D for longer periods are both more valuable to the firm and more costly to replace. Hiring new workers with similar observable qualifications does not fully offset this loss, as replacement workers require time to adjust to firm-specific technologies, internal systems, and team structures. This implies that the markdown-reducing effect of R&D should strengthen over time.

To examine the timing of this effect, we re-estimate the baseline specification using contemporaneous and lagged measures of R&D investment. To ensure comparability across specifications, the estimation sample is restricted to firms that are observed with non-missing R&D investment in the contemporaneous period and all three lagged periods ($t, t-1, t-2$, and $t-3$).

Consistent with this interpretation, Table 7 shows that the effect of R&D investment on labour markdown is not purely contemporaneous. While contemporaneous R&D input is associated with a modest reduction in markdown, the effect becomes stronger when lagged R&D measures are considered. In particular, the coefficient on two-period lagged R&D investment is larger in magnitude and highly statistically significant, indicating that the markdown-reducing effect of R&D materialises with a delay. The effect remains negative and statistically significant even at longer lags, though with a smaller magnitude.

These results reinforce the mechanism identified above. Rather than affecting wage-setting immediately, R&D gradually reshapes the composition of human capital and increases firms' dependence on workers whose knowledge is both valuable and difficult to replace. As a result, the cost of worker turnover rises over time, strengthening workers' bargaining position and reducing firms' ability to suppress wages.

4.5 Heterogeneity analysis

The preceding results establish that R&D reduces labour markdowns by increasing firms' reliance on research-intensive workers and that this effect strengthens over time as these workers accumulate firm-specific knowledge and become more embedded in production processes. A further implication of this mechanism is that the strength of the effect should vary systematically across firms and environments depending on the extent to which R&D activities are complementary to skill-intensive labour and the degree of labour substitutability.

To examine this implication, we first exploit heterogeneity in firms' technological orientation and wage structure. Table 8 shows that the markdown-reducing effect of R&D is significantly stronger among high-tech firms[5] than among firms in other industries, with the difference statistically significant. This pattern is consistent with the mechanism outlined above: in technologically advanced sectors, R&D is more tightly integrated into production processes and more complementary to high-skilled labour, which increases the importance of key research personnel and weakens firms' ability to exercise wage-setting power.

When firms are grouped by wage premium[6], R&D reduces markdown in both high- and low-wage-premium firms, with a somewhat larger effect among high-wage-premium firms, although the difference across groups is not statistically significant. This suggests that while pre-existing wage structures may shape the level of markdowns, the markdown-reducing effect of R&D does not depend primarily on firms' initial wage-setting position, but instead reflects changes in the composition and role of labour within the firm.

Table 9 provides complementary evidence along dimensions related to labour substitutability and outside options. The effect of R&D on markdown is insignificant in labour-intensive industries[7], but remains negative and highly significant in other

[5]With reference to definitions used by Office for National Statistics (2021) and Eurostat (2025), we define high-tech industries as those engaged in the manufacture of basic pharmaceutical products and pharmaceutical preparations (SIC 21), computer, electronic and optical products (SIC 26), and other transport equipment (SIC 30), such as aircraft, ships, and railway vehicles.

[6]We construct a firm-level wage premium as the log difference between a firm's average wage and the average wage in its local labour market, defined at the SIC 3-digit industry × region × year level. This measure captures the extent to which a firm pays wages above or below workers' outside options. Firms are further classified into high- and low-wage-premium groups based on the annual median of this distribution.

[7]Labour-intensive industries refer to low-technology sectors where production processes predominantly rely on manual labour: manufacture of textiles (SIC 13), wearing apparel (SIC 14), leather and related products (SIC 15), wood and wood products excluding furniture (SIC 16), printing and repro-

industries, and the difference between the two groups is statistically significant. In labour-intensive sectors, workers are more easily replaceable, limiting the extent to which R&D-induced organisational capital can translate into improved worker bargaining power. By contrast, in settings where production relies less on easily substitable labour, R&D increases firms' dependence on skill-intensive workers and more effectively constrains wage-setting power.

Finally, we examine heterogeneity across local labour market conditions. The markdown-reducing effect of R&D is present in both local labour markets with higher and lower labour demand[8], and the difference across these markets is small and statistically insignificant. This indicates that the effect of R&D is not primarily driven by external labour market tightness or firms' outside hiring opportunities, but rather by internal organisational changes induced by R&D investment.

Taken together, these results further reinforce the proposed mechanism. The markdown-reducing effect of R&D is strongest precisely in settings where workers are less substitutable and R&D activities are more tightly embedded in production, and it is weakest where labour can be easily replaced. This pattern is consistent with the view that R&D reduces labour market power by increasing both the value and the indispensability of key workers within the firm.

5 Conclusion

This paper studies how firms' R&D investment affects labour market power, measured through labour markdowns, using matched firm-level data from the UK ARDx and BERD surveys. Across a wide range of specifications and identification strategies, we document a robust and economically meaningful result: higher R&D investment is associated with lower labour markdowns.

Our baseline estimates show that a 10% increase in R&D investment reduces markdown by approximately 0.15%, indicating that R&D weakens firms' ability to set wages below workers' marginal revenue product. This relationship is stable across alternative markdown estimators, survives extensive robustness checks, and is supported by instrumental-variable estimates exploiting exogenous variation in firms' exposure to aggregate R&D shocks. Taken together, these findings provide strong evidence that R&D investment reduces firms' monopsony power.

The central contribution of the paper is to show that this relationship is not ad hoc, but arises from a clear and consistent economic mechanism. R&D investment reshapes

duction of recorded media (SIC 18), furniture (SIC 31), and other manufacturing (SIC 32), such as toys, jewellery, and stationery. Although industries like food, beverages, and tobacco are classified as low-technology, we exclude them from labour-intensive categories due to their higher capital intensity and automation.

[8] A local labour market is classified as having higher labour demand if the number of firms in a given year–region–3-digit industry cell is below the median across all such cells in that year, based on the full ARDx data.

the composition of human capital within the firm by increasing reliance on research-intensive workers whose skills are both transferable and deeply embedded in firm-specific production processes. As these workers accumulate experience, they become simultaneously more valuable externally and more costly to replace internally. This combination strengthens their outside options and raises the cost of labour turnover, thereby limiting firms' incentives and ability to suppress wages.

All additional evidence supports this mechanism. The markdown-reducing effect of R&D strengthens over time, consistent with the gradual accumulation of firm-specific knowledge and worker embeddedness. It is driven by in-house and internally financed R&D, rather than outsourced activities, highlighting the importance of organisational integration. It is concentrated in experimental development, where knowledge is directly embedded in production, and among research employees, rather than technicians or support staff. Finally, the effect is strongest in settings where labour is less substitutable and R&D is more complementary to skilled workers, and weaker where workers can be easily replaced.

Taken together, these findings point to a unified conclusion: R&D investment reduces labour market power by increasing firms' dependence on a small set of skilled, research-oriented workers whose knowledge is both valuable and difficult to replace. In doing so, R&D not only enhances productivity and innovation, but also shifts the balance of bargaining power in favour of workers.

These results have important policy implications. Policies that promote sustained, in-house R&D investment may generate not only technological and productivity gains but also distributional benefits by reducing wage suppression. By contrast, policies that primarily support outsourced or externally funded R&D are less likely to affect labour market outcomes, as they do not alter firms' internal dependence on skilled labour. More broadly, the effectiveness of R&D policy is likely to be enhanced when combined with investments in skills and workforce development that reinforce the role of knowledge-intensive labour.

Several limitations remain in this paper. First, we focus on R&D investment rather than realised innovation outcomes. Since not all R&D investment leads to successful innovation, the estimates should be interpreted as capturing the relationship between knowledge investment and labour markdowns, rather than the distributional effects of realised innovation rents. Future research linking R&D expenditure to innovation outputs, product-market rents, and worker-level earnings would be better placed to examine how innovation rents are shared within firms (Kline et al., 2019; Van Reenen, 1996). Second, the analysis is restricted to manufacturing firms, where markdown estimation is most credible, and extending this framework to service sectors remains an important avenue for future research.

Despite these limitations, the evidence presented in this paper highlights a fundamental insight: innovation and labour market power are closely intertwined. By altering the nature of work and the value of workers within the firm, R&D investment can reshape not only how firms compete in product markets, but also how they interact with their workforce.

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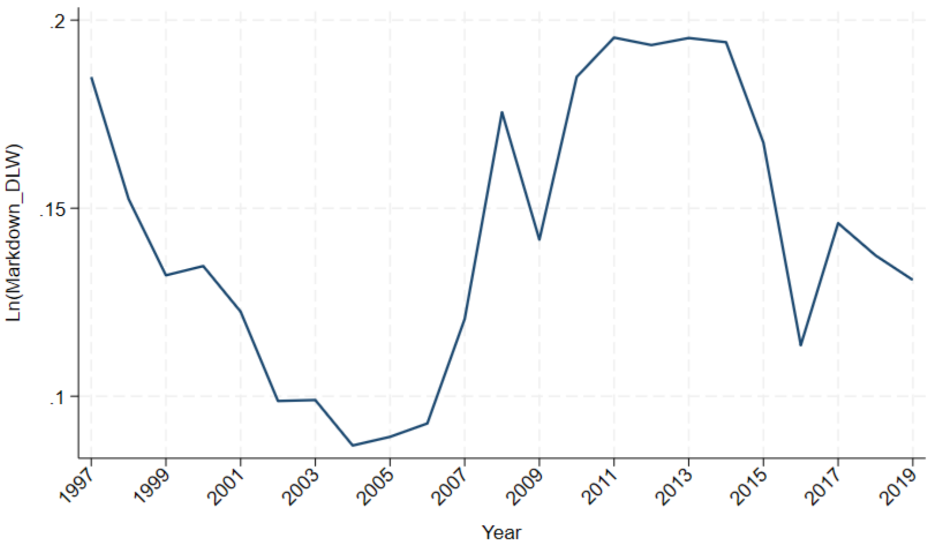
Figures and Tables

Figures

Figure 1: Average R&D Investment over Time (1997–2019)

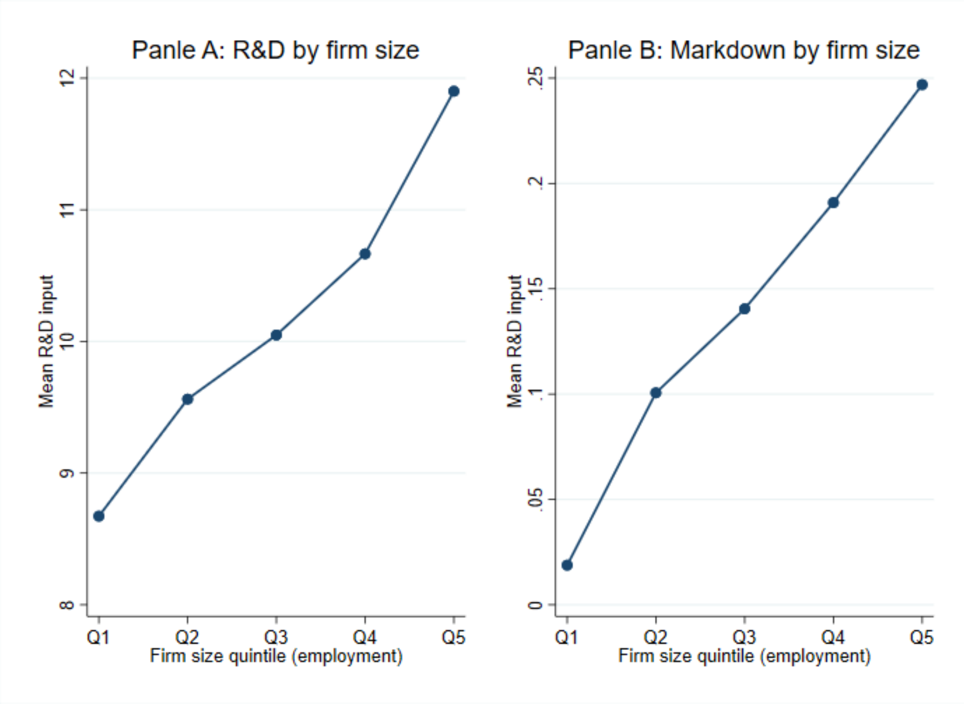
Notes: This figure plots the yearly mean of firm-level R&D input over the period 1997–2019 based on the merged ARDx-BERD data. R&D input is measured in logarithms. All variables are winsorised at the 1% level within each year and 2-digit SIC industry to mitigate the influence of outliers.
Source: Authors' own calculations from ONS ARDx and BERD data.

Figure 2: Average labour markdown over time (1997–2019)



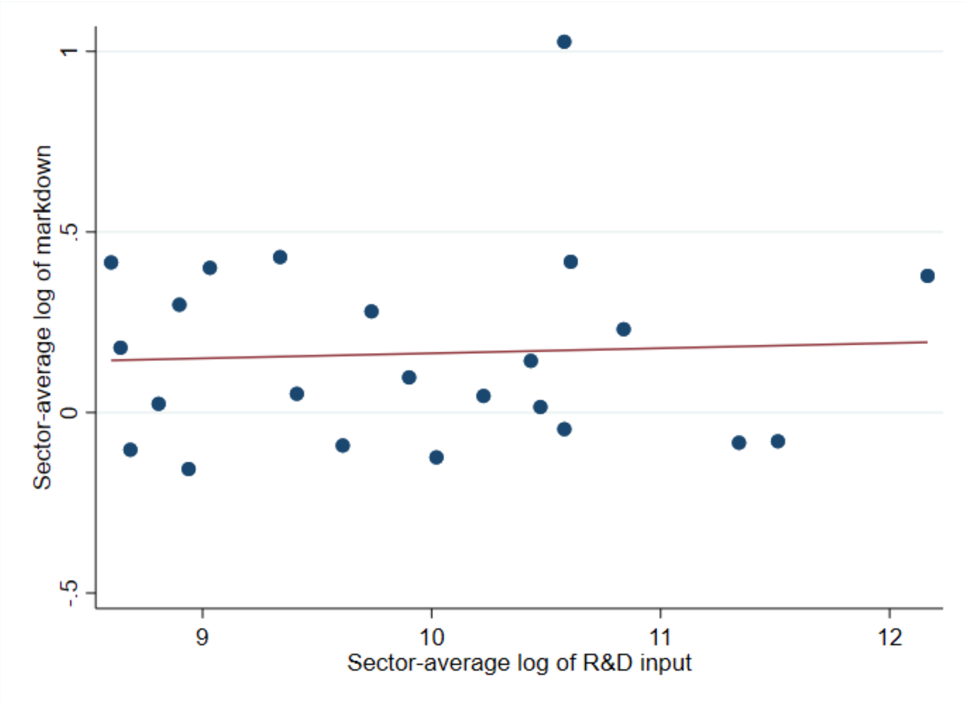
Notes: This figure shows the annual mean of firm-level labour markdown, measured as ln(markdown (DLW)), over the period 1997–2019. The figure is based on the merged ARDx-BERD sample, while the markdown measure is constructed from ARDx data following the DLW approach. The markdown variable is winsorised at the 3% level within each year and 2-digit SIC industry.
Source: Authors' own calculations from ONS ARDx and BERD data.

Figure 3: Firm-size heterogeneity in R&D input and markdown



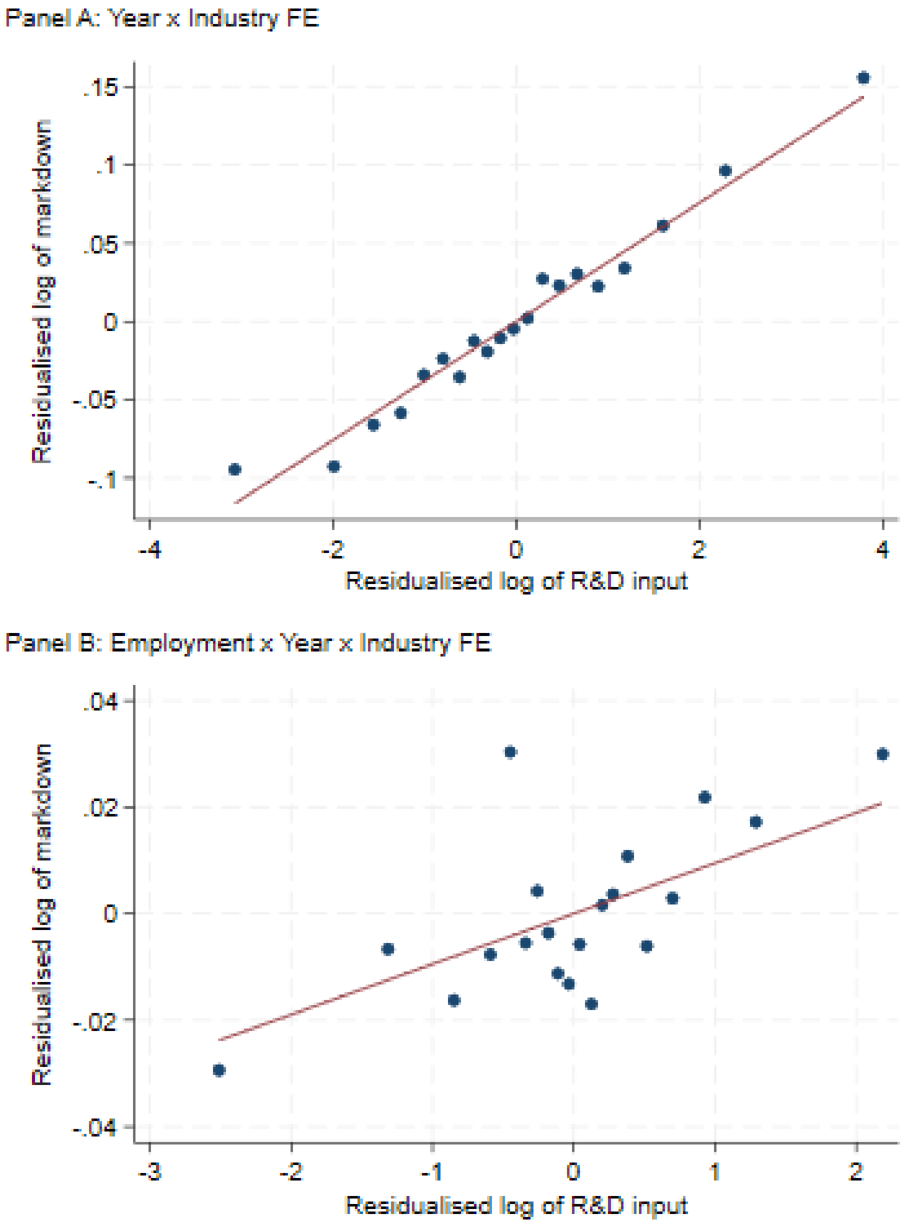
Notes: This figure is based on the merged ARDx- BERD data. Firms are divided into five groups based on employment quintiles. For each quintile, the figure reports the mean log R&D input (Panel A) and the mean ln(markdown (DLW)) (Panel B). Panel A plots firm size quintiles against average R&D input, while Panel B plots firm size quintiles against average labour markdown.
Source: Authors' own calculations from ONS ARDx and BERD data.

Figure 4: Sector-level relationship between R&D input and markdown



Notes: This figure presents a sector-level scatter plot based on the merged ARDx-BERD data. The data are collapsed to the 2-digit SIC sector level, yielding 22 sector-level observations. For each sector, the figure reports the mean log R&D input on the x-axis and the mean ln(markdown (DLW)) on the y-axis. Each point represents one 2-digit SIC sector. The solid line shows the fitted linear relationship.
Source: Authors' own calculations from ONS ARDx and BERD data.

Figure 5: R&D and markdown (residualised relationships)



Notes: This figure presents binscatter plots of the relationship between firm-level R&D input and labour markdown based on the merged ARDx-BERD data. In both panels, the x-axis shows residualised log R&D input and the y-axis shows residualised ln(markdown (DLW)). In Panel A, both variables are residualised with respect to year and 2-digit industry fixed effects. In Panel B, both variables are residualised with respect to year fixed effects, 2-digit industry fixed effects, and log employment. Each panel shows 20 bins, and the solid line represents the fitted linear relationship.
Source: Authors' own calculations from ONS ARDx and BERD data.

Tables

Table 1: Summary statistics of main variables

Variables	N	Mean	Std. Dev.
Markdown estimators			
ln (markdown (CD))	48,244	0.334	0.173
ln (markdown (CRS))	48,244	0.139	0.561
ln (markdown (DLW))	48,244	0.085	0.497
R&D variables			
R&D investment	48,244	10.167	1.732
Purchased R&D work	48,244	5.027	3.670
R&D own funding	48,244	9.755	1.915
R&D external funding	48,244	7.630	2.612
Basic research	48,244	8.971	2.289
Applied research	48,244	8.878	2.162
Experiment development	48,244	6.051	2.656
Mechanism variables			
Researcher FTE	48,244	1.405	1.094
Technician FTE	48,244	0.942	0.861
Supporter FTE	48,244	0.732	0.760
R&D salary share	48,244	0.056	0.524
R&D FTE share	48,244	0.806	0.151
Labour share	48,244	0.303	0.931
R&D labour share	48,244	0.016	0.115
Control Variables			
Output	48,244	14.504	1.491
Subsidies	48,244	0.220	1.333
Software investment	48,244	4.074	3.955
Foreign ownership	48,244	0.394	0.489
Multi plants	48,244	0.067	0.249

Notes: All markdown estimators are winsorised at the 3rd and 97th percentiles. All other continuous variables are winsorised at the 1st and 99th percentiles. All monetary variables are deflated using the GDP deflator provided by ARDx, with 2019 as the base year.
Source: Authors' own calculations from ONS ARDx and BERD data.

Table 2: Baseline results

Dependent variable:	ln(markdown (DLW))	ln(markdown (CD))	ln(markdown (CRS))
	(1)	(2)	(3)
R&D investment	-0.015***	-0.025***	-0.018***
	(0.002)	(0.003)	(0.002)
Output	0.136***	0.219***	0.154***
	(0.009)	(0.011)	(0.008)
Subsides	-0.003**	-0.002	-0.002
	(0.001)	(0.002)	(0.001)
Software investment	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)
Foreign ownership	-0.002	0.001	-0.003
	(0.006)	(0.008)	(0.005)
Multi plants	-0.012	-0.008	-0.011
	(0.022)	(0.026)	(0.019)
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year× region	Yes	Yes	Yes
Year× industry	Yes	Yes	Yes
Industry×region	Yes	Yes	Yes
N	48244	48244	48244
Adj. R-sq	0.774	0.780	0.807

Notes: Dependent variable in three columns are natural logarithm of markdown estimators using DLW, CD and CRS approach, respectively. All columns are estimated using OLS. Cluster robust standard errors at the firm level are reported in parentheses. Significance levels: *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Table 3: Instrumental-variable estimates of the effect of R&D investment on labour markdown

Dependent variable:	ln(markdown (DLW))		
	(1) US IV	(2) UK IV	(3) OLS
One-year lagged exposure			
R&D investment	-0.104***	-0.098***	-0.017***
	(0.021)	(0.019)	(0.003)
N	26,895	26,895	26,895
Adj. R-sq			0.816
KP LM stat	98.873	108.368	
p-value	0.000	0.000	
KP Wald F	122.542	138.736	
Two-year lagged exposure			
R&D investment	-0.190***	-0.182***	-0.018***
	(0.045)	(0.044)	(0.003)
N	19,382	19,382	19,382
Adj. R-sq			0.820
KP LM stat	41.445	45.125	
p-value	0.000	0.000	
KP Wald F	44.385	49.483	
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Year × region	Yes	Yes	Yes
Year × industry	Yes	Yes	Yes
Industry × region	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Columns (1) and (2) report 2SLS estimates using alternative instruments, while column (3) reports OLS estimates on the corresponding estimation sample. In the first panel, firm exposure shares are lagged by one year; in the second panel, they are lagged by two years. The US instrument is constructed as the interaction between U.S. industry-level R&D expenditure and the firm's lagged industry R&D share. The UK instrument is constructed as the interaction between UK regional public R&D expenditure and the firm's lagged regional R&D share. All specifications include controls for output, subsidies, software investment, foreign ownership, and a multi-plant indicator, as well as firm, year, industry, region, year×region, year×industry, and industry×region fixed effects. Standard errors are clustered at the firm level and reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Table 4: The effects of alternative R&D investment

Dependent variable:	ln(markdown (DLW))					
	(1)	(2)	(3)	(4)	(5)	(6)
Purchased R&D work	0.001*					
	(0.001)					
R&D own funding		-0.007***				
		(0.002)				
R&D external funding			-0.001			
			(0.001)			
Basic research				0.001		
				(0.001)		
Applied research					-0.002	
					(0.001)	
Experiment development						-0.005***
						(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Year× region	Yes	Yes	Yes	Yes	Yes	Yes
Year× industry	Yes	Yes	Yes	Yes	Yes	Yes
Industry× region	Yes	Yes	Yes	Yes	Yes	Yes
N	48244	48244	48244	48244	48244	48244
adj. R-sq	0.774	0.774	0.774	0.774	0.774	0.774

Notes: All columns are estimated using OLS. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. Cluster robust standard errors are reported at the firm level in parentheses. Significance levels: *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Table 5: The interaction effect of R&D employees

Dependent variable:	ln(markdown (DLW))		
	(1)	(2)	(3)
R&D investment	-0.003	-0.009***	-0.014***
	(0.003)	(0.003)	(0.003)
R&D investment × Researcher FTE	-0.004**		
	(0.002)		
R&D investment × Technicians FTE		-0.002	
		(0.002)	
R&D investment × Supporter FTE			-0.003
			(0.002)
Researcher FTE	0.024		
	(0.021)		
Technicians FTE		0.015	
		(0.026)	
Supporter FTE			0.028
			(0.029)
Controls	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year× region	Yes	Yes	Yes
Year× industry	Yes	Yes	Yes
Industry× region	Yes	Yes	Yes
N	48244	48244	48244
Adj. R^2	0.775	0.775	0.774

Notes: Researcher FTE, Technicians FTE, and Supporter FTE denote full-time equivalent employment in different R&D-related occupational categories. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. Cluster robust standard errors are reported at the firm level in parentheses. Significance levels: *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.
Source: Authors' own calculations from ONS ARDx and BERD data.

Table 6: Mechanism analysis

Dependent variable:	R&D-related outcomes			
	R&D salary share	R&D FTE share	Labour share	R&D labour share
	(1)	(2)	(3)	(4)
R&D investment	0.045***	0.013***	0.028***	0.015***
	(0.011)	(0.001)	(0.006)	(0.002)
Controls	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Year×region	Yes	Yes	Yes	Yes
Year×industry	Yes	Yes	Yes	Yes
Industry×region	Yes	Yes	Yes	Yes
N	48244	48244	48244	48244
Adj. R^2	0.535	0.659	0.831	0.575

Notes: R&D salary share is defined as R&D-related labour costs divided by total labour costs. R&D FTE share measures the share of researchers and technicians in total R&D employment (FTE). Labour share is defined as total labour costs divided by output. R&D labour share is defined as R&D-related labour costs divided by output. R&D investment is measured as real in-house R&D expenditure. All columns are estimated using OLS. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. Cluster-robust standard errors are reported at the firm level in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Table 7: The dynamic effect of R&D investment on markdown

Dependent variable:	ln(markdown (DLW))			
	(1)	(2)	(3)	(4)
R&D investment	-0.010**			
	(0.004)			
One-lagged R&D investment		-0.007*		
		(0.004)		
Two-period lagged R&D investment			-0.017***	
			(0.004)	
Three-period lagged R&D investment				-0.009**
				(0.004)
Controls	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Year $\times$ region	Yes	Yes	Yes	Yes
Year $\times$ industry	Yes	Yes	Yes	Yes
Industry $\times$ region	Yes	Yes	Yes	Yes
N	11454	11454	11454	11454
Adj. R^2	0.845	0.845	0.845	0.845

Notes: This table reports OLS estimates of the effect of R&D input on markdown, where contemporaneous and lagged values of R&D input are included separately across specifications. Column (1) includes contemporaneous R&D input. Columns (2)-(4) replace contemporaneous R&D input with one-period, two-period, and three-period lagged R&D input, respectively. The estimation sample is restricted to firms that are observed with non-missing R&D input for the contemporaneous period and all three lagged periods, ensuring a common sample across specifications. All columns are estimated using OLS. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. Cluster-robust standard errors are reported at the firm level in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Author's own calculations from ONS ARDx and BERD data.

Table 8: Heterogeneity analysis I

Dependent variable:	ln(markdown (DLW))			
	(1) High tech	(2) Other	(3) High premium	(4) Low premium
R&D input	-0.025***	-0.012***	-0.017***	-0.011***
	(0.006)	(0.002)	(0.003)	(0.004)
Controls	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Year× region	Yes	Yes	Yes	Yes
Year× industry	Yes	Yes	Yes	Yes
Industry× region	Yes	Yes	Yes	Yes
Difference	0.013***		0.007	
N	7038	40924	28283	16660
Adj. R^2	0.743	0.781	0.814	0.756

Notes: High-tech industries are defined as 2-digit SIC codes 21, 26, and 30. All columns are estimated using OLS. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. The firm-level wage premium is the log difference between a firm's average wage and the average wage in its local labour market, defined at the SIC 3-digit industry × region × year level. Firms are further classified into high- and low-wage-premium groups based on the annual median of this distribution. The sum of observations across subsamples does not equal the full sample size because some observations are dropped due to the inclusion of high-dimensional fixed effects in the subsample regressions. Difference reports the cross-group difference in the estimated coefficients on R&D input for columns (1) versus (2), and columns (3) versus (4), respectively. All columns are estimated using OLS. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. Cluster-robust standard errors are reported at the firm level in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Table 9: Heterogeneity analysis II

Dependent variable:	ln(markdown (DLW))			
	(1) Labour intensive	(2) Other	(3) More local demand	(4) Low local demand
R&D investment	-0.004	-0.016***	-0.010***	-0.014***
	(0.005)	(0.003)	(0.004)	(0.003)
Controls	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Year × region	Yes	Yes	Yes	Yes
Year × industry	Yes	Yes	Yes	Yes
Industry × region	Yes	Yes	Yes	Yes
Difference	-0.013*		0.005	
N	6184	41875	21648	24798
Adj. R^2	0.763	0.777	0.769	0.792

Notes: Labour-intensive industries are defined as 2-digit SIC codes 13, 14, 15, 16, 18, 31, and 32. Low local labour demand are defined as 3-digit industry–region–year cells with a firm count below the annual median, while high local labour demand are those above the median. The sum of observations across subsamples does not equal the full sample size because some observations are dropped due to the inclusion of high-dimensional fixed effects in the subsample regressions. Difference reports the cross-group difference in the estimated coefficients on R&D input for columns (1) versus (2), and columns (3) versus (4), respectively. All columns are estimated using OLS. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. Cluster-robust standard errors are reported at the firm level in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Table A1: Data cleaning procedure

Data cleaning procedure	N
Initial ARDx sample (1997–2019)	1,128,859
Exclude observations with no response	1,076,362
Retain manufacturing sector (SIC 10–33)	200,163
Exclude outliers and missing values in key variables	185,546
Exclude industries with fewer than 100 observations	185,447
Exclude outliers and missing values in markup estimation	183,961
Merge with BERD data (1997–2019)	52,886
Final sample used in regression	48,224

Notes: Source: Authors' own calculations from ONS ARDx and BERD data.

Table A2: Sample coverage

Variable	ARDx (%)	ARDx-BERD (%)
SMEs	81.08	65.92
Foreign ownership	37.07	39.44
Multi plants	5.69	6.66
High-tech	9.29	14.89
Work intensive	22.27	13.05
Low-wage-premium	50.00	38.34

Notes: SMEs are firms with fewer than 250 employees. High-tech industries are SIC 21, 26, 30. Labour-intensive industries are SIC 13, 14, 15, 16, 18, 31, 32. The wage premium is defined as the difference between a firm's average wage and the average wage at the 3-digit industry-region-year level. Low-wage-premium firms are those whose wage premium falls below the annual average wage premium. The reported percentages represent the share of firm-year observations in each subgroup relative to the total sample in the corresponding column.
Source: Authors' calculations based on ONS ARDx and BERD data.

Table A3: Summary statistics of the ARDx panel

Variable	N	Mean	Std. dev.
ln (output)	183,961	13.350	1.906
ln (number of employees)	183,961	4.097	1.521
ln (material)	183,961	12.797	2.115
ln (capital stock)	183,961	7.702	1.880
α^M	183,961	0.696	4.143
α^L	183,961	0.325	1.301

Notes: All monetary variables are deflated to 2019 prices. Variables are winsorised at the 1% tails.
Source: Authors' own calculations from ONS ARDx data.

Table A4: Summary statistics of markup and markdown measures

	ARDx		ARDx-BERD	
Variable	Mean	Std. dev.	Mean	Std. dev.
Markup (CD)	1.039	0.736	0.935	0.602
Markup (CRS)	1.150	0.355	1.117	0.316
Markup (DLW)	1.096	0.454	1.085	0.420
Markdown (CD)	1.730	1.905	1.818	1.787
Markdown (CRS)	1.211	1.003	1.257	0.940
Markdown (DLW)	1.361	1.134	1.366	1.039

Notes: Measures are winsorised at the 3% tails.
Source: Authors' own calculations from ONS ARDx and BERD data.

Table A5: Markup and markdown distribution by industries

	ARDx			ARDx-BERD		
2-digit SIC industry	N	Markup	Markdown	N	Markup	Markdown
Food products (10)	18,704	1.056	2.080	5,247	1.099	1.925
Beverages (11)	2,608	1.186	1.676	628	1.213	1.745
Textiles (13)	7,239	1.097	1.202	1,684	1.139	1.155
Wearing apparel (14)	4,265	1.088	1.330	257	1.080	1.064
Leather and related products (15)	1,063	1.199	1.393	230	1.095	1.535
Wood and of products of wood (16)	5,378	1.076	1.379	501	0.909	1.594
Paper and paper products (17)	6,213	0.982	1.512	1,098	1.038	1.488
Printing and reproduction of recorded media (18)	9,552	1.208	0.958	665	1.201	0.980
Coke and refined petroleum products (19)	809	1.143	5.061	239	1.018	4.627
Chemicals and chemical products (20)	10,448	0.992	1.856	4,734	1.005	1.787
Basic pharmaceutical products (21)	1,614	0.966	1.717	784	0.937	1.666
Rubber and plastic products (22)	11,776	1.037	1.283	2,921	1.101	1.192
Other non-metallic mineral products (23)	8,431	1.119	1.221	2,008	1.035	1.177
Basic metals (24)	7,094	1.077	1.718	1,294	1.078	1.763
Fabricated metal products (25)	22,240	1.202	0.962	3,914	1.176	1.021
Computer; electronic and optical products (26)	11,373	1.127	1.194	5,002	1.157	1.091
Electrical equipment (27)	7,017	1.051	1.196	2,817	1.097	1.129
Machinery and equipment (28)	17,785	1.037	1.199	6,126	0.971	1.277
Motor vehicles; trailers and semi-trailers (29)	7,082	1.067	1.424	2,374	1.099	1.413
Other transport equipment (30)	4,096	1.276	1.022	1,396	1.301	1.029
Furniture (31)	6,164	1.081	1.171	1,163	1.205	0.946
Other manufacturing (32)	7,304	1.089	1.225	1,795	0.997	1.213
Repair and installation (33)	5,706	1.155	1.117	1,367	1.120	1.107
Total	183,961	1.096	1.361	48,244	1.085	1.366

Notes: Markup and markdown estimates are measured by DLW and are winsorised at the 3 percent tails within each year and 2-digit SIC industry. Mean values are reported. Tobacco (12) is not included in our sample because it has fewer than 100 observations in the ARDx panel and is therefore dropped.
Source: Authors' own calculations from ONS ARDx and BERD data.

Table A6: Correlation matrix for markup estimators

	Markup (CD)	Markup (CRS)	Markup (DLW)
Panel A: ARDx data (N: 183,961)			
Markup (CD)	1.000		
Markup (CRS)	0.769	1.000	
Markup (DLW)	0.728	0.749	1.000
Panel B: ARDx-BERD data (N: 48,244)			
Markup (CD)	1.000		
Markup (CRS)	0.816	1.000	
Markup (DLW)	0.794	0.791	1.000

Notes: Correlation matrix across three markup estimators are reported.
Source: Authors' own calculations from ONS ARDx and BERD data.

Table A7: Correlation matrix for markdown estimators

	Markdown (CD)	Markdown (CRS)	Markdown (DLW)
Panel A: ARDx data (N: 183,961)			
Markdown (CD)	1.000		
Markdown (CRS)	1.000	1.000	
Markdown (DLW)	0.941	0.941	1.000
Panel B: ARDx-BERD data (N: 48,244)			
Markdown (CD)	1.000		
Markdown (CRS)	1.000	1.000	
Markdown (DLW)	0.955	0.955	1.000

Notes: Correlation matrix across three markdown estimators are reported.
Source: Authors' own calculations from ONS ARDx and BERD data.

Table A8: R&D distribution by industries

2-digit SIC industry	BERD N	BERD R&D	ARDx-BERD N	ARDx-BERD R&D
Food products (10)	5,633	9.245	5,247	9.339
Beverages (11)	677	8.922	628	9.032
Textiles (13)	1,801	8.780	1,684	8.808
Wearing apparel (14)	322	8.502	257	8.685
Leather and related products (15)	253	8.587	230	8.642
Wood and of products of wood (16)	578	8.531	501	8.601
Paper and paper products (17)	1,210	8.839	1,098	8.899
Printing and reproduction of recorded media (18)	874	8.749	665	8.939
Coke and refined petroleum products (19)	251	10.521	239	10.579
Chemicals and chemical products (20)	5,030	10.548	4,734	10.608
Basic pharmaceutical products (21)	839	12.083	784	12.166
Rubber and plastic products (22)	3,273	9.792	2,921	9.902
Other non-metallic mineral products (23)	2,177	9.350	2,008	9.412
Basic metals (24)	1,418	9.692	1,294	9.738
Fabricated metal products (25)	4,550	9.468	3,914	9.612
Computer; electronic and optical products (26)	5,486	11.221	5,002	11.342
Electrical equipment (27)	3,077	10.388	2,817	10.475
Machinery and equipment (28)	6,654	10.329	6,126	10.433
Motor vehicles; trailers and semi-trailers (29)	2,581	10.728	2,374	10.839
Other transport equipment (30)	1,492	11.402	1,396	11.512
Furniture (31)	1,319	9.893	1,163	10.021
Other manufacturing (32)	1,998	10.105	1,795	10.227
Repair and installation (33)	1,506	10.495	1,367	10.580
Total	52,999	10.060	48,244	10.167

Notes: This table reports means of log of R&D which are winsorised at the 1 percent tails within each year and 2-digit SIC industry. Mean values are reported. Tobacco (12) is not included in our sample as it has fewer than 100 observations in the ARDx panel and is therefore dropped.
Source: Authors' own calculations from ONS ARDx and BERD data.

Table A9: Definitions of variables

Variable	Definition	Source
Markdown estimators		
ln(markdown (CD))	Natural logarithm of markdown, estimated using Cobb–Douglas (CD) method	ARDx
ln(markdown (CRS))	Natural logarithm of markdown, estimated using constant returns to scale (CRS) method	ARDx
ln(markdown (DLW))	Natural logarithm of markdown, estimated using De Loecker and Warzynski (DLW) method	ARDx
R&D variables		
R&D investment	Natural logarithm of total in-house capital and non-capital expenditure for performing R&D	BERD
Purchased R&D work	Natural logarithm of expenditure on externally purchased R&D services	BERD
R&D own funding	Natural logarithm of R&D expenditure financed by the firm's own funds	BERD
R&D external funding	Natural logarithm of R&D expenditure funded by domestic and overseas organisations	BERD
Basic research	Natural logarithm of total expenditure on basic research	BERD
Applied research	Natural logarithm of total expenditure on applied research	BERD
Experimental development	Natural logarithm of total expenditure on experimental development	BERD
Mechanism variables		
Researcher FTE	Natural logarithm of the number of full-time equivalent (FTE) researchers	BERD
Technician FTE	Natural logarithm of the number of full-time equivalent (FTE) technicians	BERD
Supporter FTE	Natural logarithm of the number of full-time equivalent (FTE) support staff	BERD
R&D salary share	R&D-related labour cost divided by total labour cost	BERD
R&D FTE share	Share of researchers and technicians in total R&D employment (FTE)	BERD
Labour share	Total labour cost divided by output	ARDx
R&D labour share	R&D-related labour cost divided by output	BERD
Control variables		
Output	Natural logarithm of firm output	ARDx
Subsidies	Natural logarithm of total subsidies received	ARDx
Software investment	Natural logarithm of investment in purchased computer software	ARDx
Foreign ownership	Indicator equal to 1 if the firm is foreign-owned based on ultimate ownership, and 0 otherwise	ARDx
Multi plants	Indicator equal to 1 if the firm operates multiple plants, and 0 otherwise	ARDx

Table B1: The effect of R&D investment on markdown (Excluding SIC 19)

	(1)	(2)	(3)
R&D investment	-0.015***	-0.025***	-0.018***
	(0.002)	(0.003)	(0.002)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
N	48004	48004	48004
Adj. R^2	0.770	0.777	0.802

Notes: This table presents the baseline regression results excluding SIC industry 19, which shows outliers in markdown measures. The dependent variable in all three columns is the natural logarithm of markdown, estimated using DLW, CD, and CRS approaches, respectively. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. All columns are estimated using OLS. Cluster robust standard errors at the firm level are reported in parentheses. Significance levels: *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Table B2: The effect of R&D engagement on markdown

Dependent variable:	ln(markdown)		
	(1) DLW	(2) CD	(3) CRS
R&D dummy	-0.017***	-0.021***	-0.017***
	(-0.004)	(-0.004)	(0.003)
Controls	Yes	Yes	Yes
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Region	Yes	Yes	Yes
Year × region	Yes	Yes	Yes
Year × industry	Yes	Yes	Yes
Industry × region	Yes	Yes	Yes
N	155418	155418	155418
Adj. R^2	0.763	0.781	0.803

Notes: R&D dummy equals one if the firm is successfully merged with BERD, indicating active R&D engagement. The dependent variable in all three columns is the natural logarithm of markdown, estimated using DLW, CD, and CRS approaches, respectively. Column (4) re-estimates the DLW specification using a sample that excludes SIC 19, where extreme markdown outliers are observed. Control variables include output, subsidies, software investment, foreign ownership, and a multi-plant indicator. All columns are estimated using OLS. Cluster robust standard errors at the firm level are reported in parentheses. Significance levels: *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.
Source: Author's own calculations from ONS ARDx and BERD data.

Appendix

Appendix A. Data and Variable Construction

This study combines two firm-level administrative datasets provided by the UK Office for National Statistics (ONS): the Annual Respondents Database X (ARDx) and the Business Expenditure on Research and Development (BERD) survey.

ARDx is compiled from the Annual Business Inquiry (ABI, 1998–2008) and the Annual Business Survey (ABS, 2009 onward), which together represent the largest business administrative surveys in the United Kingdom and cover approximately two-thirds of registered businesses. ARDx provides annual firm-level information on output, material purchases, labour costs, employment, and capital investment. Employment figures after 2009 are supplemented using the Business Register and Employment Survey (BRES).

BERD is an annual survey focusing on firms engaged in research and development activities and reports detailed information on in-house R&D expenditure, R&D employment, and funding sources. The BERD sampling frame is compiled from ABS, the UK Innovation Survey, and other administrative sources. Although both ARDx and BERD extend to 2020, the 2020 BERD wave is preliminary and lacks sufficient detail; therefore, the analysis period is restricted to 1997–2019.

We implement a two-stage empirical design. In the first stage, firm-level markdowns are estimated using the full ARDx panel, which provides comprehensive production and labour cost information across a broad population of firms and therefore yields stable and precise estimates. In the second stage, the estimated markdown measures are merged with the BERD dataset to examine how R&D investment relate to labour market power. Because markdowns are estimated without using R&D variables, the two-stage structure avoids mechanical correlation between the dependent variable and R&D investment and separates the construction of labour-market power measures from innovation variables. This design improves conceptual clarity and reduces concerns that the estimated relationship is driven by shared inputs in the estimation procedure.

The initial ARDx panel contains 1.13 million firm-year observations. We apply a series of standard cleaning and sample-selection procedures to construct the estimation sample. Observations with extreme or implausibly small values (e.g. output, inputs, or materials below £1,000) and firms reporting only one employee are excluded. In addition, SIC industries with fewer than 100 firm-year observations are dropped to ensure sufficient within-industry variation. Restricting attention to manufacturing sectors (SIC 10–33) yields a cleaned ARDx manufacturing subsample of 183,961 firm-year observations. Merging this subsample with the BERD survey produces 48,224 valid matched firm-year observations used in the R&D analysis. The detailed data-cleaning and filtering procedures are documented in Table A1 of the Appendix.

Table A2 reports sample coverage for both the full ARDx dataset and the matched ARDx–BERD panel. Relative to the full ARDx sample, the matched panel exhibits a higher share of high-tech firms (14.9% versus 9.3%) and a lower share of small and medium-sized enterprises (SMEs) (65.9% versus 81.1%). Firms with low wage premia are also less prevalent in the matched sample (38.3% versus 50%). In addition, the proportion of labour-intensive industries is smaller (13.1% versus 22.3%), while multi-plant and foreign-owned firms are slightly more common. These patterns indicate that R&D activity is more frequently observed among technologically oriented and larger firms.

Appendix B. Construction of Markup and Markdown Indices

B1. Markup Definition

A markup is defined as the ratio of a firm's price to its marginal cost, representing the extent to which a firm charges above the cost of producing an additional unit of output. Higher markups suggest that firms can set prices above competitive levels, often due to market power, such as product differentiation, market concentration, or other barriers to competition. However, observing marginal costs directly can be difficult, as they are rarely recorded in firm-level datasets. To address this, many datasets provide revenue instead of price data, requiring careful separation of price effects from quantity effects.

In this context, the De Loecker and Warzynski (2012) methodology (referred to as DLW) offers a widely used practical approach to estimating markups. It leverages firms' cost-minimization behavior and links the marginal revenue product of an input to its marginal cost. By observing a firm's expenditure on a price-taking input and estimating the input's output elasticity from a production function, DLW allows markups to be inferred, even when marginal cost and price are unobserved. The DLW framework is applicable to datasets where only revenue is reported, as it uses input expenditure shares and estimated production elasticities, rather than requiring direct price data.

Using the DLW approach, firm-specific markups μ_{it}^{M} are expressed as:

$$\mu_{it}^{M} = \frac{\theta_{it}^{M}}{\alpha_{it}^{M}}$$

where θ_{it}^{M}[9] is the output elasticity with respect to a price-taking input M, and α_{it}^{M} is the input's cost share in total revenue. This method assumes input M is purchased in a perfectly competitive market, meaning firms choose input levels such that the marginal revenue product equals the input's marginal cost. If the input market is imperfectly competitive, this assumption breaks down, making it difficult to isolate product market power.

Output elasticities θ_{it}^{M} are obtained by estimating a Cobb–Douglas production function at the 2-digit SIC industry level using the Ackerberg–Caves–Frazer (ACF) procedure.

[9] A common approach in empirical firm-level production-function estimation is to recover output elasticities from a Cobb–Douglas specification at the 2-digit SIC industry level using the Ackerberg–Caves–Frazer (ACF) procedure; we follow this convention here.

B.2 Conceptual Link Between Markup and Markdown

The markdown index is designed to isolate labour-market distortions from product-market pricing power by comparing labour- and materials-based pricing wedges at the firm level. A firm's markup captures product-market power, while labour-market power reflects the firm's ability to pay wages below the marginal revenue product of labour. In this framework, materials inputs are used as the benchmark input under the assumption that they are purchased in perfectly competitive markets, so that the materials-based markup primarily reflects output-market pricing power rather than input-market distortions.

The identification intuition follows directly from this distinction: product-market power affects markup measures constructed from all inputs proportionally, whereas labour-market power affects only the labour-based measure. Comparing labour- and materials-based markups therefore allows labour-market distortions to be isolated from the common product-market component.

Formally, let μ_{it}^{L} denote the markup inferred from labour input and μ_{it}^{M} the markup inferred from materials. The markdown index is defined as

$$Markdown_{it} = \frac{\mu_{it}^{L}}{\mu_{it}^{M}}$$

When a firm possesses only output-market power but pays competitive wages, both markups rise together and the ratio remains close to one. If wages are suppressed relative to marginal productivity, the labour-based markup increases while the materials-based markup remains anchored to product-market conditions, causing the ratio to exceed one. The markdown therefore serves as a proxy for monopsony power in the labour market.

B.3 Markup and Markdown Estimators

Following Brooks et al. (2021b), we compute three alternative markup estimators, each implying a corresponding markdown measure. Using multiple estimators allows robustness checks across identifying assumptions and production-function specifications. The approaches differ mainly in how output elasticities are obtained and in the degree of functional-form restriction imposed.

DLW Estimator: The De Loecker and Warzynski (2012) approach recovers markups from firms' cost-minimisation conditions by linking the marginal revenue product of a flexible input to its expenditure share. Output elasticities are estimated from firm-level production functions (ACF), allowing heterogeneity across firms and time. The method does not require direct price data and is widely used in the IO literature, but it relies on correct production-function identification and can be sensitive to elasticity estimation, particularly for materials.

Constant Returns to Scale (CRS) Estimator: The CRS estimator defines markup as the ratio of total sales to total variable costs. It is simple to implement and avoids explicit production-function estimation, serving primarily as a robustness benchmark. However, it assumes perfectly competitive input markets, an assumption that may conflict with the presence of labour-market power and therefore tends to attenuate measured markdowns.

Cobb–Douglas (CD) Estimator: The CD estimator applies the same elasticity-share formula as DLW but fixes output elasticities at the industry level rather than estimating them at the firm level. This simplifies implementation and reduces identification concerns, though at the cost of limited firm-level flexibility and potential masking of within-industry heterogeneity.

These three approaches yield corresponding markdown indices, defined as the ratio of labour- to materials-based markups. Consistency across estimators indicates that measured labour-market distortions are not driven by a particular functional-form or identification choice.

B.4 Normalisation and Labour-Market Segmentation

To enhance interpretability, markdown indices are normalised to one for firms with negligible labour-market share, reflecting the assumption of no monopsony power at infinitesimal scale. Following Brooks et al. (2021b), the comovement between markdowns and labour-market share is estimated through

$$\frac{\mu_{it}^{L}}{\mu_{it}^{M}} = \Gamma_t + \delta_n + \beta s_{it}^{L} + \epsilon_{it}$$

where s_{it}^{L} denotes firm-level labour-market share. All markdown measures are winsorised at the 3-percent tails within year and industry. Labour markets are defined as segmented both geographically and occupationally, using provinces and 4-digit industries respectively, thereby allowing limited worker mobility across these dimensions.

B.5 Production Variables Used in Markdown Estimation (ARDx)

All variables are drawn exclusively from the Annual Respondents Database X (ARDx):

- Output: Approximate output adjusted for inventories, taxes, and resale items.
- Materials: Total purchases of energy, goods, materials, and services.
- Employment: Number of employees from the IDBR register.
- Labour Cost: Total employment costs including wages and employer contributions.
- Average Wage: Log labour cost per employee.
- Capital Stock: Constructed using the perpetual inventory method

All monetary variables are deflated to constant 2019 prices using ARDx deflators. Continuous production variables entering estimation are winsorised at the 3-percent tails within year and 2-digit SIC industries to reduce the influence of outliers. Table A3 reports summary statistics for the variables used in the construction of the markdown indices.

B.6 Distributional Properties and Robustness of Markup and Markdown Measures

Table A4 presents summary statistics of the estimated markup and markdown measures using the full ARDx sample. Mean markdown values exceed one across all estimators, indicating the presence of monopsony power on average, as firms pay wages below the marginal revenue product of labour. In contrast, mean markups are only modestly above unity, suggesting limited product-market power in the typical firm. Table A5 reports the distribution of average markups and markdowns across industries. Substantial cross-industry heterogeneity is observed: for example, Industry 19 (manufacture of coke and refined petroleum products) exhibits the highest average markdown, while Industry 22 (manufacture of basic pharmaceutical products and pharmaceutical preparations) shows the highest average markup.

Tables A6 and A7 present correlation matrices for the three alternative estimators of markup and markdown. The high degree of correlation across estimators indicates strong consistency and suggests that the constructed indices are not driven by a particular identifying assumption or functional-form choice.

For completeness, Table 1 in the main text reports corresponding summary statistics for the merged ARDx–BERD panel used in the empirical analysis. After merging with BERD, mean markups are slightly lower, while markdown means remain broadly comparable, reflecting the characteristics of R&D-active firms rather than structural changes in measurement.

Appendix C. Variable Definitions and Construction

Precise variable definitions, measurement units, and data sources are reported in Table A9, while summary statistics for the merged ARDx–BERD panel are presented in Table 1 of the main text.Table A8 reports the distribution of average R&D investment across industries.

All monetary variables are expressed in thousands of pounds sterling and deflated to constant 2019 prices using ARDx-provided deflators. To mitigate the influence of outliers, continuous production variables entering markup and markdown estimation are winsorised at the 1st and 99th percentiles within each year and two-digit SIC industry cells, while the markdown estimators themselves are winsorised at the 3rd and 97th percentiles to reduce the influence of measurement error. The empirical analysis is conducted on the matched ARDx–BERD firm-year panel, with supplementary robustness exercises performed on the full ARDx sample.