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Effects of innovation and markups on employment and labour share in OECD industries

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ABSTRACT

This paper takes issue with what I describe as a single focus on either innovation or market power as potential determinants of employment or labour share. Drawing on a constant elasticity of substitution (CES) production function and EU- KLEMS data on OECD industries, I demonstrate that the unifocal approach is not justified theoretically or empirically. I report that: (i) employment and labour share depends on both innovation and market power; (ii) market power's direct effects on both outcomes are always negative and large; (iii) innovation's direct effects are small and depend on the elasticity of substitution between capital and labour; and (iv) innovation and market power have substitute interactive effects that exacerbate the fall in employment or labour share. I conclude that the main driver of the decline in labour share and/or employment is not technological innovation as such but the level of rents that innovating firms are able to extract.

1. Introduction

The debate on employment effects of technological innovation is varied and has a long history. As Vivarelli (2014) has observed, workers and their unions have emphasized the risks of technological unemployment whereas policy makers and business representatives have tended to consider technological change as essential for growth and job creation. In between, economists have emphasized the need to consider the factors that affect the balance between job-creating and job-destroying effects of technological innovation. Currently, the attention is focussed on how automation, robot adoption and artificial intelligence (AI) affect the level of employment, the quality of jobs, and the wage structure (see, for example, Montobbio et al., 2023).

In one strand of research, the focus in on *compensation mechanisms* that mitigate or offset the job-destroying effects of innovation through job creation driven by lower prices and/or higher output and investment. Evidence from this line of research (recently reviewed by Calvino and Virgillitto, 2018; Hötte et al., 2022; Mondolo, 2022) indicates that the net effect depends on innovation types (e.g., product vs. process; embodied vs. disembodied innovation); the level of aggregation (e.g., firm vs. industry level); price and income effects; macroeconomic conditions; and labour market institutions.

In another strand, the focus is on skill-biased technological change (SBTC). Here, employment falls in technological change if the latter complements skills and the elasticity of substitution is greater than one (Katz and Murphy, 1992; Acemoglu, 1998, 1999, 2002, 2003). In the more recent work that focuses on *routine-biased* technological change (RBTC), the net employment effect depends on the balance between the rate of task creation and that of job destruction caused by automation (Acemoglu and Autor, 2011; Goos, 2018; Acemoglu and Restrepo, 2018; 2019; D. 2020).

A common thread in the empirical literature in both strands has been the lack of attention to market power as an additional determinant that may affect employment directly or indirectly. This has remained the case even though innovation and market power are correlated; and market power can reduce the demand for labour either because of higher prices or lower output that stifles the compensation mechanisms (Bogliacino and Vivarelli, 2012). The single focus has also persisted even though firms in the SBTC/RBTC model innovate to exploit excess profit opportunities (see, for example, Acemoglu, 1998, 2003; for a critique, see Bogliacino 2014).

The empirical work on labour share reflects a similarly one-sided focus too. Here, labour share falls in market power because markups enable firms to maximise profits before the optimal level of employment is reached (see for example Barkai, 2020; De Loecker et al., 2020; Eggertsson et al., 2021). Although the increased attention to the effects of market power on labour share is a welcome step, the literature tends to overlook the question of whether labour share depends on both market power and technological innovation at the same time.

The main argument in this paper is that the one-sided focus in

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empirical models of employment and labour share is not warranted. One reason is that innovation and market power are inter-related. This is the case both in Schumpeterian models of innovation (Aghion et al., 2005; Peneder, 2012; Hashem and Ugur, 2013) and in the literature on economic consequences of market power (Autor et al., 2017; D. 2020; Barkai, 2020; Battiati et al., 2021; De Loecker et al., 2020). Secondly, in both constant and variable elasticity of substitution production functions under imperfect competition, the effect of innovation on employment or labour share is *intertwined* with that of market power (see, for example Raurich et at., 2012; Bellocchi and Travaglini, 2023; Di Pace and Villa, 2016; Velasquez, 2023).

Given such theoretical priors, a single focus on either innovation or market power would be a source of bias in the estimation of employment or labour-share models for two reasons. First, the omission of innovation or market power would lead to confounding bias as both regressors are inter-related and affect employment and labour share at the same time. Secondly, the omission of the interactive effect would lead to a model misspecification bias that distorts the direct-effect estimates and prevents researchers from investigating whether innovation and market are complements or substitutes.

To address both issues, I first provide an overview of the relevant literature in Section 2. Here, I trace the evolution of the theoretical and empirical debate and highlight the lack of attention to both innovation and market power as joint determinants of both employment and labour share.

This overview sets the stage for Section 3, where I draw on the first-order conditions in constant elasticity of substitution (CES) production functions to demonstrate that it is theoretically necessary to control for both innovation and market power in empirical models of employment and labour share.[1] The analysis in Section 3 leads to two testable inferences: (i) higher markups are always conducive to lower levels of employment or labour share, whereas the effects of technological change depend on the elasticity of substitutions; and (ii) innovation and market power are substitutes in that an increase in one determinant is sufficient to exacerbate the total adverse effect on employment or labour share when the other determinant is kept constant.

Section 4 introduces the industry-level measures of innovation and market power and discusses the estimation strategy. To measure market power, I draw on 1995–2019 EU-KLEMS data for 32 industries in 12 OECD countries and calculate two markup measures: a Lerner-index-based measure proposed by Ciapanna et al. (2022) and an excess-profits-based measure used in Barkai (2020) and Eggertsson et al. (2021) among others. I also calculate four innovation measures, which reflect both broad and narrow measures of innovation adopted by the OECD.

For estimation, I use a general method of moments (GMM) estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) where the lagged dependent variable (employment or labour share) is treated as pre-determined; and the technological innovation and market power, the interaction of the latter, real wages, the value added and the capital-labour ratio are treated as endogenous. I check the robustness of the results from the system GMM estimator with estimations based on a two-year-forward value of the dependent variable, using two fixed-effect estimators: (i) a multi-way fixed-effect estimator (Correia, 2016) that takes account of unobserved heterogeneity by absorbing the fixed effects at the country, industry and year levels; and (ii) a within estimator that eliminates the time-invariant heterogeneity by demeaning the variables and absorbs the time effects through year dummies.

Section 5 presents the estimates for direct and interactive effects of both technological innovation and markups, after taking account of additional factors such as capital-labour ratio, wage level, value added, and the strength of employment protection legislation. The results from both GMM and fixed-effect (within) estimators are highly consistent with the theoretical predictions derived from the analysis in Section 3. Finally, Section 6 distils the main findings and concludes that the main driver of the change in employment and the labour share in OECD countries-industries between 1995 and 2019 is not technological change per se, but the level of market power that allows for extraction of innovation rents at the industry level.

This paper is closely related to emerging work on the implications of markups for optimising behaviour in constant or variable elasticity of substitutions (CES / VES) production functions (Raurich et al., 2012; Dixon and Lim, 2020; and Bellocchi and Travaglini, 2023). It is also related to three recent studies that control for both innovation and market power in the estimation of an employment model (Lim and Lee, 2019) and labour share models (Moreira, 2022; Ugur, 2024). In line with this literature, it confirms that the direct effect of market power on employment or labour share is always negative whereas that of innovation depends on whether the elasticity of substitution between capital and labour is smaller or larger than one. It extends this emergent literature by demonstrating that innovation and market power: (i) have both direct and indirect effects on employment or labour share; and (ii) are substitutes in that an increase in innovation exacerbates the adverse effect of market power whereas an increase in market power attenuates and eventually reverses the small but positive effect of innovation.

2. An overview of the literature: key insights and the persistence of one-sided model specification

In this section, I provide an overview of the extant literature on how innovation or market power affects the level of employment or labour share. One aim is to trace the evolution of the research field and identify the key insights from the evolving research effort. The other is to verify the extent to which researchers have tended to adopt a one-sided focus that relates employment or labour share to either innovation or market power only – without controlling for *both direct* and *indirect effects* from both determinants.

In a recent review of the literature, Montobbio et al. (2023) identify three waves of studies, distinguished by innovation proxies used in the analysis: studies that investigate the effects of process and product innovation (wave 1); those that investigate the effects of robotisation and automation (wave 2); and those that rely on mapped patent-task trees and artificial intelligence as preferred proxies of technological change (wave 3). The review also identifies two clusters characterised by the outcome variable investigated: studies focusing on the *level of employment* that reflects the balance between the job-creating and job-destroying effects of innovation (cluster 1); and those focusing on the *quality of work* to capture the transformative effects of innovation on jobs and tasks (cluster 2).

Beyond these patterns, my reading of the literature also suggests that the empirical work has been informed by two theoretical/analytical frameworks. On the one hand, the *compensation mechanisms framework* has informed investigations into whether the job-destroying effect of technological change are mitigated or reversed by job-creating effects of the compensation mechanisms that work through lower prices and/or higher output and investment after innovation. Since its modern articulation by Freeman et al. (1982) and Vivarelli (1995), this analytical framework has been invoked to verify whether the job-creating or job-destroying effects of innovation dominate (e.g., Pianta, 2005; Vivarelli, 2014; Calvino and Virgillito, 2018; Dosi et al., 2021). Researchers in this field have been cognizant of the factors that may complicate or hinder the functioning of the compensation mechanisms, particularly macroeconomic/cyclical conditions, and labour-market institutions (Vivarelli, 2014; Calvino and Virgillito, 2018; Dosi et al., 2021) as well as product-market competition (Bogliacino and Vivarelli, 2012). Recent reviews (e.g., Barbieri et al., 2020; Mondolo, 2022;

[1] In the appendix, I also demonstrate that the theoretical case for joint control remains valid when the optimal levels of employment and labour share are determined within a variable elasticity of substitution (VES) production function framework.

Montobbio et al., 2023) document and confirm the role of these intervening factors, which include the innovation type (e.g., product vs. process innovation), the level of aggregation (e.g., firm vs. industry level), knowledge intensity of the industry, and the effectiveness of the compensation mechanism through price decreases after innovation.

The second draws framework on the concept of *biased technical change* to investigate how skill- or routine-biased technical change (SBTC / RBTC) affects the demand for labour and the wage structure of different job/skill categories. In the original SBTC model (Katz and Murphy, 1992), technological change complements the increased supply of skilled labour, leading to an increase in the latter's share in employment and/or total wage bill. This framework has remained dominant in the research field thanks to extensions to the model (Acemoglu, 1998, 1999, 2002, 2003; Acemoglu and Autor, 2011) and new evidence from empirical applications (Acemoglu and Autor, 2011; Goldin and Katz, 2008; Goos, 2018).

In the new Millennium, however, this research agenda had to address a challenge posed by change in observed employment trends: increase in the employment of both *low-skilled* and *high-skilled* labour at the expense of *medium-skilled* labour (Bogliacino, 2014). This empirical challenge has led to the development of routine-biased technological change (RBTC) models, where new technologies complement non-routine tasks instead of skilled labour, leading to polarized job growth (Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2009). Because non-routine tasks are performed by both high- and low-skilled labour, RBTC complements labour at both ends of the skill distribution, leading to lower demand for the medium-skilled labour that performs mostly routine-intensive tasks (Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2009).

Existing reviews (Barbieri et al., 2020; Mondolo, 2022; Montobbio et al., 2023) indicate that the reported employment effects are heterogenous in the RBTC literature too. The heterogeneity is driven mainly by the type of tasks and occupations as well as firm/sector variation. While routinised tasks are more vulnerable to automation, non-routinised tasks tend be complementary to new technologies, particularly artificial intelligence (AI).

These conclusions are in line with evidence from recent studies. For example, Balsmeier and Woerter (2019) draws on firm-level Swiss data and report that increased investment in digitalization is associated with a small positive net effect on employment, which reflects the balance between a job-creating effect on high-skilled workers and a job-destroying effect on low-skilled workers. Damioli et al. (2023) investigate the effects of AI technologies on employment in sectors that supply AI products. Using patent statistics (PatStat) data from the European Patent Office (EPO) and firm data from the BvD-ORBIS database the authors report a positive employment effect of AI when firms are suppliers of AI technologies. This finding is similar to the positive effect of product innovation reported in the first wave of studies that compared the effects of product and process innovation.

Dauth et al. (2021) draw on administrative data to industrial robots in Germany. They estimate a measure of robot exposure and report that the latter is associated with job destruction in manufacturing. However, these job-destroying effects are offset by new jobs in services. The effect varies also by worker types. While the job-destroying effect are heavily felt by young workers, automation tend to be associated with more stable employment for incumbents. The study also reports that the new jobs for incumbents tend to be of higher quality. Finally, the findings indicate that industrial robots have benefited workers in occupations with complementary tasks, such as managers or technical scientists. A contemporaneous study by Koch et al. (2021) reports even larger positive effects. Using a treatment effect estimation methodology, the authors report that robot-adopting firms increase overall employment by around 10% within four years of adoption; and the increase applies to both low- and high-skilled workers.

The evidence pointing to job creation following robot adoption may be reflecting a market-stealing effect that increases the market share of leading robot adopters at the expense of laggards. Evidence provided by Webb (2020) lends support to this conjecture. Using a new measure of exposure to different technologies (software and robots; and AI), this study reports that AI effects are more varied across different kinds of occupations and workers, compared to the effects of software and robots that tend to be negative on average. This study also cautions that the effects of AI on employment will be dependent on future changes in the supply of labour and future patterns of human capital investment.

As it can be observed from the overview above, the existing literature has made significant contributions to knowledge about how the employment effect of technological innovation may vary over time, across technology types and by the level of analysis. However, these contributions should not detract from the fact that the extant literature has remained oblivious to the question of whether market power can also affect the level of employment – either directly or as a moderating variable that adds to the heterogeneity of the findings reported so far. This has remained the case despite increasing evidence on the level/persistence of market power and its economic consequences in terms of investment, productivity and business dynamism (see, for example, De Loecker et al., 2020; Diez et al., 2018; Basu, 2019; Syverson, 2019). It has also remained the case even though some contributors to the innovation-employment debate informed by the SBTC/RBTC framework have accepted the adverse effect of market power on labour share (e.g., Autor et al., 2020).

A mirror image of the one-sided focus that characterises the innovation-employment literature is observed among studies that investigate the effect of market power on labour share. On the one hand, these studies contribute to knowledge by demonstrating that market power affects not only investment and business dynamism (for reviews, see Basu, 2019; Syverson, 2019; Battiaiti et al., 2021; and Bond et al., 2021), but also the labour share. An adverse effect has been reported with profit-based markups that are proportional to the inverse of the economic (excess) profits (Barkai, 2020; Eggertsson et al., 2021) and with Lerner-index-based markups that reflect the wedge between prices and marginal costs (Ciapanna et al., 2022). Although the focus on markups as a determinant of labour share is a step in the right direction, the market-power literature remains silent about whether it is also necessary to control for technological innovation too. It also remains silent about whether market power is detrimental not only the labour share but also for the level of employment.

Yet, the one-sided focus on innovation or market power in employment or labour-share models is not warranted or several reasons. On the one hand, the effect of innovation on employment depends on the extent to which firms lower their post-innovation prices in accordance with the likely fall in post-innovation marginal costs. This is evident in the workhorse model of Harrison et al. (2008, 2014), which has informed a rich literature on the roles of process and product innovations within the compensation mechanisms framework. The assumption in this model is that the fall in post-innovation prices would be proportional (but not necessarily equal) to the fall in post-innovation marginal costs (see also and Diaz et al., 2020). It inevitably follows that the estimated innovation effect will be contaminated with the effect of the markup rates if firms maintain a wedge between prices and marginal costs after innovation. Moreover, this confounding bias will be larger the higher is the firms' markup to start with and the stronger is the relationship between innovation and market power.

Secondly, both RBTC and SBTC models of innovation and employment allow for excess profits opportunities (markups) in the innovation market but assume that these markups are eventually eliminated in the product market due to free entry and exit (Acemoglu, 1998, 2003; for a critique, see Bogliacino 2014). Given that this assumption may not hold in the face of mounting evidence on the prevalence and persistence of market power (see, for example, De Loecker et al., 2020; Diez et al., 2018; Basu, 2019; Syverson, 2019), the level of employment or labour share would depend not only on technological change and the elasticity of substitution but also on the level of markups opportunities that enable innovating firms/industries to drive a wedge between wages and the marginal product of labour. Therefore, the share of different skills in total employment and/or the evolution of wage shares will differ not only skill type but also by the level of market power in the industry.

The third reason is that market power and technological innovation are interrelated in several lines of research. For example, Schumpeterian models of innovation demonstrate that technological innovation is both a cause and consequence of economic profit (markup) opportunities (Aghion et al., 2005, 2019). In these models, firms innovate either to escape competition or to maintain market power. Innovation and markups are also related in the literature on technological innovation, super-star firms and labour income (Autor et al. 2020). Finally, innovation and markups are also interrelated in the literature on market power and innovation in the digital markets (Calvano and Polo, 2021).

Given that innovation and market power are inter-related and that both affect the outcome variable (employment or labour share), the exclusion of one or the other from either employment or labour-share models will be conducive to a *confounding bias*. Hence, the estimated effects will not capture a 'true effect' of innovation or market power but a 'contaminated effect' that can be attenuated or exacerbated by that of the omitted confounder.

My review of the literature suggests that there are only a handful of studies that avoid the risk of confounding bias by controlling for both innovation and market power in their employment or labour share models.[2] Of these, Lim and Lee (2019) investigate the employment effects of process and product innovations among South Korean firms. The authors estimate an employment model with interaction terms between innovation and market power. They report that process innovation has a more adverse effect on employment among firms in more monopolistic markets.[3]

Moreira (2022) investigates the determinants of falling labour share in US industries, using a model where technological change and market power affects labour share and structural change simultaneously. The author reports that increasing market power accounts for about two-thirds of the decline in the labour share, whereas technical change accounts for the remaining one-third. A third study by Ugur (2024) draws on a Schumpeterian model of innovation and income distribution (Aghion et al., 2019) and adopts a structural equation modelling (SEM) approach to labour-share estimation. The study reports that both market power and technological innovation affect the labour share even though the former is the main driver of the fall in labour share.

The remaining two studies utilise constant and variables elasticity of substitution (CES and VES) production functions to make the case for relating labour share to innovation and market power at the same time. Of these, Dixon and Lim (2020) draw on a CES production function and demonstrate that the labour share depends on changes in technology and non-technology factors that include market power. Bellocchi and Travaglini (2023), on the other hand, utilise a VES production function and allows for imperfect competition in wage setting. The authors demonstrate that the labour share always fall in markups and that technological innovation can increase or reduce labour share depending on the elasticity of substitution.

This paper is related to and aims to make two contributions to this emerging literature. First, it demonstrates that innovation and market power affect both the labour share and the level of employment *directly* and *indirectly*. Secondly, it demonstrates that innovation and market power are *substitutes* in their effects on employment or labour share: an increase in one determinant is sufficient to exacerbate the fall in employment or labour share when the other determinant is kept constant. Beyond these contributions, this study confirms the recent findings from the CES production analysis, which indicate that the direct effect of market power on employment or labour share is always negative and large whereas that of innovation is small and can be positive or negative depending on whether the elasticity of substitution between capital and labour is larger or smaller than one.

3. Innovation and markups: direct and indirect effects on employment and labour share

In this section, I draw on a constant elasticity of substitution (CES) production function under imperfect competition to address three concerns raised about the neoclassical production function (Cobb and Douglas, 1928; Solow, 1956) as a basis for estimating factor shares and/or total factor productivity (TFP) growth. As pointed out in Shaikh (1974), Labini (1995), Pasinetti (2000), and Felipe and McCombie (2014), the first concern is about whether factors (particularly labour) are rewarded in accordance with their marginal products. This is followed by questioning the extent to which each factor of production can be fully employed thanks to its infinite possibilities of substitution with other factors. The third concern is about whether the labour share is constant as predicted by the Cobb-Douglas production function or it varies by the level of development or over time.

The CES production function under market power alleviates such concerns by relaxing the twin assumptions of perfect competition and unitary elasticity of substitution between capital and labour. As a result, the CES production function framework allows three conclusions that stand in contrast to those implied by the Cobb-Douglas production function. First, it implies that labour is not necessarily employed or rewarded in accordance with its marginal productivity because market power enables firms to drive a wedge between real wages and the marginal product of labour. Secondly, it implies that the labour share is not necessarily constant as the markup in imperfectly competitive markets/industries is time-varying. Thirdly, the changes in employment or labour share under technological innovation depends not only on the elasticity of substitution between capital and labour but also on market power.

In what follows, I utilise a CES production function similar to Raurich et al. (2012) and demonstrate that: (i) market power does indeed drive a wedge between the marginal product of labour and real wages; (ii) the equilibrium levels of labour share or employment depend on both market power and technological innovation at the same time; (iii) market power is more likely to have an adverse effect on employment or labour share compared to technological innovation; and (iv) market power and innovation are substitutes in that market power attenuates and eventually reverses the job-creating effect of innovation that obtains when the elasticity of substitution is greater than one.[4]

Denoting the industry-level value added with Y_t, capital stock with K_t, and employment with L_t, the CES production function can be stated as follows:

$$Y_t = F(K_t, A_tL_t) = \left[\alpha K_t^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(A_tL_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

In (1), A_t is labour-augmenting technological change and A_tL_t is effective labour or labour in efficiency units; α and 1- α are positive

[2] Two other studies also control for both market power and 'technical change' proxies, captured by investment good prices (Karabarbounis and Nieman, 2014) and by the capital-labour ratio (Raurich et al., 2012). Both studies report that the model performs better when both 'technical change' proxies and markups are included. The issue here is that the 'technical change' proxies used have more to do with the capital-labour ratio rather than input or output measures of innovation widely used in the literature.

[3] Controlling for interaction between innovation and market power is a welcome step in the right direction. The limitation in Lim and Lee (2019), however, is that the authors do not control for direct market power effect in their models.

[4] A similar conclusion can be derived from a variable elasticity of substitution (VES) production function, and this is presented in Box A1 in the Appendix.

fractions that reflect the capital and labour weights in the CES production; and σ is the elasticity of substitution between capital and labour.

If market power exists in the industry, profit maximisation is achieved when the marginal product of labour (i.e., the partial derivative of the CES production function with respect to labour) is equal to the real wage multiplied by the markup of prices over marginal costs. Denoting markups with μ_t and the real wage with W_t, the first-order condition for profit maximisation and the equilibrium wage are stated in (2a) and (2b), respectively:

$$\mu_t W_t = F_L(K_t, A_t L_t) = (1-\alpha)\left[\alpha K_t^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(A_t L_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (A_t L_t)^{\frac{-1}{\sigma}} A_t \tag{2a}$$

$$W_t = F_L(K_t, A_t L_t) = \frac{1}{\mu_t}\left\{(1-\alpha)\left[\alpha K_t^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(A_t L_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (A_t L_t)^{\frac{-1}{\sigma}} A_t\right\} \tag{2b}$$

It is immediately clear from (2b) that market power drives a wedge between the observed real wage (W_t) and the marginal product of labour in the curled brackets. When market power exists (i.e., when $\mu_t > 1$), the marginal product of labour is higher than the observed wage by the markup rate. This result obtains because firms in imperfectly competitive industries stop hiring before the marginal product of labour is equalised with the average wage.

Defining labour share as the ratio of wage bill to value added[5] and following the steps in *Box A1 in the Appendix*, we can write the profit-maximising levels of labour share as a function of markups (μ_t) and labour-augmenting technology (A_t) as follows:

$$LS_t = \frac{W_t L_t}{Y_t} = \frac{\frac{1-\alpha}{\mu_t}}{\left[\alpha\left(\frac{K_t}{L_t}\right)^{\frac{\sigma-1}{\sigma}} (A_t)^{\frac{1-\sigma}{\sigma}}\right] + (1-\alpha)} \tag{3}$$

Using the labour share equation in (3) we can also derive the level of employment (labour demand) compatible with profit maximisation, which is stated in (4).

$$L_t = LS_t \frac{Y_t}{W_t} = \frac{\frac{1-\alpha}{\mu_t}}{\left[\alpha\left(\frac{K_t}{L_t}\right)^{\frac{\sigma-1}{\sigma}} (A_t)^{\frac{1-\sigma}{\sigma}}\right] + (1-\alpha)} \frac{Y_t}{W_t} \tag{4}$$

It is clear from (3) and (4) that employment (L) or labour share (LS) always fall in markups (μ_t) because the increase in markup reduces the value of the numerator in both equations. In contrast, the effect of increased technological innovation depends on the magnitude of the elasticity of substitution (σ). If $\sigma > 1$, the value of the terms within the squared bracket in the denominator falls as innovation increases. As a result, the value of the quotients in (3) or (4) increases. In contrast, both labour share and employment fall in innovation if $\sigma < 1$.

The formal derivation of the direct and interactive effects of innovation and markups on both employment and labour share is presented in *Box A1 in the Appendix*, where we state the first-order and cross partial derivatives of the labour share and employment equations. The analysis above and the results in Box A1 allow for several conclusions.[6]

First, both labour share and employment always fall in markups – irrespective of whether the elasticity of substitution (σ) is smaller or greater than one. *Secondly*, the labour share and employment increase (fall) in technological innovation if the elasticity of substitution is greater (smaller) than one. When $\sigma > 1$, the labour-augmenting technological change induces firms to substitute the more productive labour for capital at more than proportionate rates, leading to lower capital-labour ratio and higher levels of employment and labour share. When $\sigma < 1$, however, the rate of substitution between capital and labour is less than proportionate and hence both labour share and employment falls in technological innovation.[7]

The *third* conclusion is that labour share and employment depend on *both* innovation and markups as both terms appear on the right-hand side of both equations. The implication for empirical modelling is straightforward: a labour share or employment model to be estimated must control for both determinants even if its main interest is in the effect of either market power or innovation only. Moreover, Eqs. (3) and (4) above indicate that empirical labour share models must control for capital-labour ratio (K_t / L_t); whereas employment models must also control for real output and real wages (Y_t and W_t) in addition to the capital-labour ratio.

The *fourth* conclusion relates to the effects of capital-labour ratio, output and real wages. Both labour share and employment fall (increase) in capital-labour ratio (K_t / L_t) if the elasticity of substitution is greater (smaller) than one. On the other hand, employment increases in output (Y_t) but falls in real wages (W_t). These conclusions are also consistent with employment or labour share models derived from the CES production function framework (see, for example, Van Reenen, 1997; Karabarbounis and Nieman, 2014).

The first-order partial derivatives in *Box A1* (equations A7a - A7d) and the cross partial derivatives in A8a and A8b allow for two further conclusions on how innovation mediates the effect of markups and vice versa. Hence, the *fifth* conclusion is that the effects of market power on labour share or employment *are mediated* through technological innovation whereas the effects of technological innovation are mediated by market power. The implication for empirical specification is that it is necessary to control for the interaction between market power and innovation.

The *sixth* conclusion relates to whether innovation or market power exacerbates or attenuates the effect of its counterpart. From equations A8a and A8b in the Appendix, we observe that technological innovation *exacerbates* the adverse effect of market power on labour share or employment irrespective of whether the constant elasticity of substitution is smaller or greater than one. This is because the increase in innovation when firms already enjoy monopoly power will reduce the levels of employment and labour share through two channels: (i) *lower output* levels due to setting of real wages below the marginal productivity of labour; and (ii) a *higher capital/labour ratio* that reflects the increased gap between post-innovation capital and labour. A similar result obtains for the indirect effect of markups, which attenuates any positive innovation effect or exacerbates any adverse innovation effect, depending on the elasticity of substitution. The conclusions so far are

[5] It must be noted here that the labour share in this specification is the share of wage income in value added. As such, it does not include the share of self-employed, who tend to be owners-managers of small firms. We prefer this specification because the average wage for employees is observed but the average 'wage' for the self-employed is not observed in the data.

[6] It must be indicated here that this paper does not address the effect of market power on the skill composition or wage structure of the labour force. However, the CES framework is flexible enough to capture the effect of innovation or market power on the employment and/or wage share of *different labour categories* too. This can be done by modelling the different labour categories as separate labour inputs in a CES production function under imperfect competition.

[7] For similar results from the CES production functions, see Van Reenen (1997) who derives the labour demand equation and Karabarbounis and Nieman (2014) who derive a labour-share equation.

Table 1
Conclusions from the first-order condition in the CES production function.

C1:	Labour share or employment always falls in markups – irrespective of the magnitude of the elasticity of substitution.
C2:	Labour share or employment falls in technological innovation only if $\sigma < 1$; otherwise, both increase in technological innovation.
C3:	Labour share or employment always depends on both innovation and markups at the same time.
C4:	Both labour share and employment fall in capital-labour ratio (K_t/L_t) if the elasticity of substitution is greater than one; whereas employment falls in real wages (W_t) and increases with output (Y_t)
C5:	The effects of innovation and market power on labour share or employment are non-monotonic in that technological innovation mediates the effects of market power and the latter mediates the effects of technical change.
C6:	Technological innovation and market power act as substitutes in that an increase in innovation exacerbates the adverse effects of market power; whereas an increase in market power attenuates and may eventually reverse the positive effect of innovation when the elasticity of substitution is greater than 1.

summarised in Table 1 to facilitate tractability.[8]

4. Methodology and data

We test the validity of the conclusions in Table 1 with country-industry-year data from the 2021 release of the *EUKLEMS & INTAN-Prod* database (*EU-KLEMS* thereafter).[9] The sample consists of 12 OECD countries and 32 non-overlapping 1-digit and 2-digit industries listed in *Table A1 in the Appendix*. Drawing on insights from the CES production function analysis above, the models for estimation are stated in 5a and 5b below. In the models, i denotes industry, c denotes country, t indicates year, v_{1ic} and v_{2ic} are time-invariant unobserved heterogeneity (fixed effects) at the industry-country level, and δ_{1t} and δ_{2t} are time fixed effects.

$$L_{ict} = \alpha_{11} + \alpha_{12}L_{ict-1} + \beta_{11}I_{ict} + \beta_{12}M_{ict} + \beta_{13}(I*M)_{ict} + \beta_{14}(K\_L)_{ict} + \beta_{1p}\sum_{p=5}^{P} CV_{pict} + v_{1ic} + \delta_{1t} + \varepsilon_{1ict} \tag{5a}$$

$$LS_{ict} = \alpha_{21} + \alpha_{22}LS_{ict-1} + \beta_{21}I_{ict} + \beta_{22}M_{ict} + \beta_{23}(I*M)_{ict} + \beta_{24}(K\_L)_{ict} + \beta_{2q}\sum_{q=5}^{Q} CV_{qict} + v_{2ic} + \delta_{2t} + \varepsilon_{2ict} \tag{5b}$$

Of the dependent variables, employment (L_{ict}) is measured as the number of *employees* in thousands; whereas labour share (LS_{ict}) is the compensation of *employees* as a fraction of value added.[10] The lagged dependent variables, $L_{ict-1}$and LS_{ict-1}, account for potential persistence in both series. Innovation (I_{ict}), markups (M_{ict}), the interaction between the two ($I*M_{ict}$), and the capital-labour ratio (K_L_{ict}) are common to both employment and labour-share equations in accordance with the first-order conditions from the CES production function. The control variables in CV_{pict} consist of real wage and value added in 2015 prices (W_r_{ict} and VA_cons_{ict}) and the strictness of employment protection legislation (EPL_{ict}); whereas those in CV_{qict} consist of EPL_{ict} and value added in current prices (VA_cur_{ict}).

I estimate the two models with a generalised method of moments (GMM) estimator, using a full set of year dummies captured by δ_{1t} and δ_{2t}. Given that the employment and labour-share series are highly persistent, I have opted for the system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998). Unlike the difference GMM, the system approach is better suited to addresses the poor instrument problem by adding the equation in levels to the system and instrumenting the level variables with the lags of their first differences, leading to additional moment conditions and efficiency. In estimation, I specify the lagged dependent variable (employment or labour share) as pre-determined; and the technological innovation and market power, the interaction of the latter, real wages, the value added and the capital-labour ratio as endogenous. The employment protection legislation (EPL), which is a country-level variable, is treated as exogenous.

Several issues may arise when system GMM is used to estimate dynamic models such as 5a and 5b. First, the system is prone to generate too many moments (and thus too many instruments) as the number of endogenous variables in the model and the time dimension of the data increase. The second issue arises if the initial conditions assumption that does not hold - i.e., if the first-differences of the dependent variable used as instruments in the level equations are correlated with the panel-specific 'fixed' effects (v_{1ic} and v_{2ic}). The first issue is addressed by reducing the number of instruments through collapsing and/or principal component analysis (Roodman, 2009). The second is addressed through difference-in-Hansen test on the instruments for the level model (Kripfganz, 2019; Blundell and Bond, 2023).

Nevertheless, Kiviet et al. (2017) report additional issues that may challenge the accuracy and efficiency of the GMM estimators. For example, the performance of all GMM estimators deteriorates when the effect-noise-ratio is large. Secondly, inaccuracies in the estimated variances of the estimates can be mitigated by a Windmeijer correction, but the positive or negative bias in coefficient estimates is often more serious than the negative bias in the variance estimate. A third issue is that limiting the number of instruments usually reduces bias, but this gain may be obtained at the potential cost of power loss. Finally, the number of instruments should be reduced to mitigate size problems of the Sargan-Hansen overidentification tests, but the rejection probability of these tests tends to direct researchers towards accurate yet inconsistent estimates.

Given such issues, I also estimate static versions of the employment and labour-share models using two types of fixed-effect estimators: (i) a conventional two-way fixed-effect (within) estimator with year dummies that eliminates the time-invariant individual heterogeneity by demeaning the variables; and (ii) a three-way fixed effect estimator (Correia, 2016; Kropko and Kubinec, 2020) that absorbs the fixed effects at the industry, country, and year levels. Although results from these estimators do not take account of auto-regressive errors, they can be used for comparison with the GMM results on two grounds.

First, they mitigate the risk of simultaneity and reverse causality by focusing on the two-year-forward value of the dependant variable. Secondly, they eliminate the risk of endogeneity that may arise from correlation between the regressors and unobserved heterogeneity at the country, industry, and year levels. The three-way fixed-effect estimator is similar to the two-way counterpart, which Wooldridge (2021) considers as a valid estimator for causal effects in intervention analysis. Although these estimators are faced with identification problems when the treatment is constant over time (De Chaisemartin and

[8] It is also necessary to indicate that these conclusions hold if one relies on first-order conditions from a variable elasticity of substitution (VES) production function too – as can be seen in Box A2 in the Appendix.

[9] The 2021 release is provided by the Luiss Lab of European Economics at Luiss University in Rome, Italy. The release is documented in: The EUKLEMS & INTANProd productivity database: Methods and data description. Further information on previous releases is available in O'Mahony and Timmer (2009) and Stehrer et al. (2019).

[10] The employment and labour share measures do not include the self-employed as wage data for the latter is not available. Nevertheless, I have checked if the estimation results differ when the self-employed are added and assigned the average wage in the industry. The results remain more than 90% consistent across different innovation/markup definitions and samples. These results are not reported here to save space but can be supplied on request.

Table 2
Expected effects on labour share and employment.

Dependant variable	Employment	Labour share
Effect of:		
Innovation intensity (I_{ict})	$\pm^{\#}$	$\pm^{\#}$
Markup (M_{ict})	–	–
Innovation * markup interaction $(I*M)_{ict}$	–	–
Capital-labour ratio $(K\_L)_{ict}$	–	–
Real wage (W_r_{ict})	–	n.a.
Real output (VA_cons_{ict})	+	n.a.

Notes: # The coefficient on innovation intensity can be positive or negative, depending on the value of the elasticity of substitution (σ). The coefficient is predicted to be positive [negative] if $\sigma > 1$ [$\sigma < 1$].

d'Haultfoeuille, 2020, 2022), such limitations do not apply to the case in this paper because the treatment (i.e., innovation and markups as determinants of interest) are time varying. Given the strength and weaknesses of the alternative estimators, I will base my inference on the level of consistency between the system GMM results based on (5a) and (5b) and the battery of fixed-effect estimation results (based on equations A11a and A11b in the Appendix) and reported in the Appendix Tables A5 – A12.[11]

The key regressors in both models and the expected signs of their effects are presented in Table 2. The negative effects of market power (M_{ict}), its interaction with innovation $(I*M)_{ict}$, and that of capital-labour ratio $(K\_L)_{ict}$ reflect the predictions form the first-order conditions in the CES production function. The coefficient on innovation intensity (I_{ict}) can be either negative or positive, depending on whether the elasticity of substitution is smaller or greater than one. Finally, the negative effect of real wages (W_r_{ict}) and the positive effect of output (VA_cons_{ict}) on employment also reflect the first-order conditions from the CES production functions – and are in line with predictions form derived labour demand models (Chennells and Van Reenen, 2002; Van Reenen, 1997; Ugur et al., 2018).

Of the key variables common to both equations, innovation intensity is measured as the percentage share of intangibles investment in value added (I_{1ict} and I_{2ict}) or in total investment (I_{3ict} and I_{4ict}), as defined in equations 6a – 6d below.

$$I_{1ict} = \frac{I\_R\&D_{ict} + I\_Soft\_DB_{ict} + I\_OIP_{ict}}{VA_{ict}} \tag{6a}$$

$$I_{2ict} = \frac{(I\_R\&D_{ict} + I\_SOFT\_DB_{ict} + I\_OIP_{ict}) + (I\_Org_{ict} + Mark_{ict} + I\_Ec.comp_{ict})}{VA_{ict}} \tag{6b}$$

$$I_{3ict} = \frac{I\_R\&D_{ict} + I\_Soft\_DB_{ict} + I\_OIP_{ict}}{I\_TAN_{ict} + I\_INTAN_{ict}} \tag{6c}$$

$$I_{4ict} = \frac{(I\_R\&D_{ict} + I\_SOFT\_DB_{ict} + I\_OIP_{ict}) + (I\_Org_{ict} + Mark_{ict} + I\_Ec.comp_{ict})}{I\_TAN_{ict} + I\_INTAN_{ict}} \tag{6d}$$

Innovation intensity in I_{1ict} and I_{3ict} is based on investment in intangible (knowledge) assets that have been *capitalised* in the System of National Accounts (SNA) in 2008. This "narrow" measure includes investment in research development (*I_R&D*), software and databases (*I_Soft-DB*), and other intellectual property assets (*I_OIP*). It captures the original OECD measure adopted in the *Oslo Manual* of 1992 (OECD/Eurostat 1992). Whereas I_{1ict} measure innovation intensity as a percentage of value added (VA_{ict}), I_{3ict} measures it as a percentage of total investment in tangible and intangible assets $(I_{TANict} + I_{INTAN_{ict}})$.

On the other hand, I_{2ict} and I_{4ict} measure innovation intensity augmented with non-capitalised investment in knowledge assets. This "wide" measure reflects the revised innovation definition in the 4th edition of the *Oslo Manual* (OECD/Eurostat, 2018), which additionally includes *non-capitalised* knowledge assets such as marketing (*I_Mark*), organisational change (*I_Org*) and economic competency (*I_Ec_comp*). The related literature tends to consider the "narrow" and "wide" measures of innovation as complementary (Schubert, 2010; Galindo-Rueda, 2013). Moreover, there is evidence that the interaction between market structure and innovation differs depending on whether the firm is engaged in one or both types of innovation at the same time (Schubert, 2010). Given this debate, I use both measures to verify whether the effects of innovation on employment or labour-share differs between "narrow" and "wide" innovation measures and their interactions with market power.

I use two accounting-based (non-econometric) measures of market power: a profit-based measure where markups are proportional to the inverse of the economic (excess) profits (Barkai, 2020; Eggertsson et al., 2021); and a Lerner-index-based measure based on the extent to which prices exceed marginal costs (Ciapanna et al., 2022). This decision is informed by a review of the literature (Basu, 2019) on econometric and non-econometric measures of market power, which concludes that non-econometric methods can be used to avoid the measurement and identification problems associated with econometric methods (e.g., Hall, 1988, 1989; Roeger, 1995; De Loecker et al., 2020), The latter tend to yield higher levels of market power on average and higher levels of noise in the upper end of the markup distribution (see also, Rovigatti 2020).

The profits-based markup, μ^P_{ict}, measures the share of pure (economic) profits that remains after capital and labour are awarded their income shares, assuming perfect competition and constant returns to scale.

$$\mu^P_{ict} = \frac{1}{1 - PS_{ict}} = \frac{1}{1 - \frac{VA_{ict} - Lab_{inc\,ict} - Cap_{inc\,ict} - Ind\_tax_{ict}}{VA_{ict}}} = \frac{VA_{ict}}{Lab\_inc_{ict} + Cap\_inc_{ict} + Ind\_tax_{ict}} \tag{7}$$

$\mu^P_{ict} = 1$ if the value added is exhausted by labour income, capital income and indirect taxes. On the other hand, $\mu^P_{ict} > 1$ if the value added also contains excess economic profits and hence cannot be exhausted after capital and labour income and indirect taxes are deducted. Labour income is observed in the *EU-KLEMS* data – and it is adjusted for the self-employed. Capital income, however, is not available. It is obtained by multiplying the country-level internal rates of return on capital (IRR) from the Penn World Tables (Feenstra et a., 2015; Inklaar et al., 2019) with the net capital stock in the industry. I use country-level IRRs to calculate capital income, assuming that IRRs are equalised across industries within each country.[12]

The Lerner-index-based measure draws on Battiati et al. (2021) and Ciapanna et al. (2022). First, we define an industry-level Lerner index using average costs as a proxy for marginal costs (8a).

$$LI_{ict} = \frac{P_{ict} - MC_{it}}{P_{ict}} \cong \frac{(P_{ict} - AC_{it})Q_{ict}}{P_{ict}Q_{ict}} = \frac{Y_{ict} - TC_{ict}}{Y_{ict}} \tag{8a}$$

The numerator and denominator of 8a can be multiplied with output quantity to obtain the Lerner index as the difference between gross output (Y_{ict}) and total costs (TC_{ict}) divided by the gross output. Using this measure, the Lerner-index-based markup, μ^L_{ict}, is obtained in accordance with 8b below, where total cost (TC_{ict}) is the sum of intermediate input cost (II_{ict}) and labour cost (Lab_Cost_{ict}) adjusted for self-employment.

[11] As will be observed in the results section, sign and significance consistency of the estimates from GMM and fixed-effect estimators remains high – between 75% - 100%.

[12] It must be noted that the net capital stock I use for calculating capital income includes the tangible assets and the capitalised intangible assets (R&D, Soft-DB, and OIP) mentioned above.

$$\mu^L_{ict} = \frac{1}{1 - L_{ict}} = \frac{1}{1 - \frac{Y_{ict} - TC_{ict}}{Y_{ict}}} = \frac{Y_{ict}}{TC_{ict}} = \frac{Y_{ict}}{II_{ict} + Lab\_Cost_{ict}} \tag{8b}$$

In both models, the set of controls (*CV*) include the real wage in 2015 prices (*W_r*) and the strictness of employment protection legislation (*EPL*). While *W_r* is controlled for in accordance with the first-order conditions from the CES production function, EPL is controlled for in accordance with the bargaining power literature where labour rights affect wage and employment levels (Brancaccio et al., 2018; Checchi and García-Peñalosa, 2008; Koeniger et al., 2007). In the employment model (Eq. (5a)), I control for value added in 2015 prices (*VA_cons*) in accordance with predictions from the CES production functions and derived labour demand models (Chennells and Van Reenen, 2002; Van Reenen, 1997). In the labour share model (Eq. (5b)), however, I control for value added in current prices (*VA*). This is to take account of the negative association between markups and the labour share that may arise from measurement of the variables.[13]

Finally, I transform all the variables into natural logarithms to ensure coherence in functional form and ameliorate the high level of skewness in the distribution of the innovation intensities (I_{1ict} - I_{4ict}) when measured as percentages.[14]

The evolution of the key variables in the estimation sample is charted in Fig. 1, where both narrow and wide measures of innovation intensities (measured as% of value added) and both measures of markups have been increasing over time. In contrast, the wage share (i.e., the share of employee compensation in value added) and that of the labour share (i.e., the share of total employed compensation in value added) have been falling over time. The upward trend in employment (measured as the number of FTE employees in thousand) is punctuated with two dips during the burst of the *dot.com* bubble in the early 2000s and the global financial crisis from 2007–2009. These trends suggest that labour share is negatively associated with markups and innovation, whereas the association between employment and markups or innovation is not clear-cut.

The trends are more heterogenous when we focus on single countries or industries – as reported in Ugur (2024). A visual inspection of Figures A1 – A3 in Ugur (2024) indicates that both markups tend to *increase* in countries/industries with below average values at the beginning of the analysis period, but they tend to *fall* in countries/industries with above average values to start with. Hence, there seems to be a convergence towards the sample averages of 1.35 and 1.21 for the profits- and Lerner-index-based markups, respectively. Similarly, the labour share seems to be converging towards the sample average of 0.58.[15] Moreover, markups are procyclical - increasing during boom periods and falling during recessions.[16] In contrast, the labour share is counter-cyclical – particularly so during 2007–2010.[17] In contrast, both measures of innovation intensity tend to increase over time. A notable exception to this trend is observed from 2017 onwards, when innovation intensity records a sharp decline in countries with above-average level throughout the period (i.e., France, Germany, Italy and the Netherlands).[18]

5. Results

I estimate models 5a and 5b with a system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), treating the lagged employment as pre-determined, and the technological innovation, markups, the innovation-markup interaction, the capital-labour ratio, the real wage and value added as endogenous. Results for the employment model are presented in Table 3, where estimates based on the narrow definition of innovation intensity (I_1) are reported in columns 1 and 2 and those based on the wider definition (I_2) in columns 3 and 4. The markup measure is Lerner-index-based in columns 1 and 3 and profits-based in columns 2 and 4. To ensure consistency in functional form and minimise the level of skewness in the distribution of the innovation intensity measures, all variables are transformed into natural logarithms. Finally, column 5 reports the level of sign and significance consistency of the coefficients with predictions from the first-order conditions in the *CES* production functions summarised in Table 2 above.

Across innovation and markup measures, the coefficient estimates for innovation are consistent with predictions in Table 2 and indicate that innovation intensity is usually associated with a positive but small increase in employment. The effect is relatively larger in the case of wide innovation (I_2), which includes investment in *non-capitalised* knowledge assets that consist of organisational innovation, marketing innovation, and investment in economic competencies. Given the predictions from the CES production function (Raurich et al., 2012), the small yet positive innovation effect implies that the elasticity of substitution between capital and labour is greater than one. The level of consistency is 75% in the case of market power effects, as the coefficient estimate remains insignificant in column 3 where the markup measure is Lerner-based. Compared to innovation, the market power effects are adverse and much larger in magnitude – as implied by the first-order conditions in the CES production function.

The negative and significant coefficient estimates for the interaction term indicate that the adverse effects of markups on employment are exacerbated when innovation increases; and the small but positive effects of technological innovation are attenuated and may be eventually reversed when market power increases. The estimates are 75% consistent with predictions in Table 2 and indicate that innovation and market power are substitute sources of decline in labour share or employment. Focusing on findings in columns 3 and 4 only, we observe that the *interaction effects* of market power and innovation are *more adverse* when innovation is defined widely to include non-capitalised knowledge assets.

[13] In the estimation sample, the correlation between labour share and the profits- and Lerner-index-based markups is −0.27 and −0.84, respectively – as can be seen in column 2 of Table A1.3 in the Appendix. In the case of profits-based markup (μ^{p}), the negative association may be driven by the fact that value added in current prices (VA) appears in the numerator of the markup measure and in the denominator of the labour share. In the case of profits-based markup (μ^{p}), on the other hand, the output in current prices (Y) appears in the numerator of the Lerner-index-based markup measure (μ^{L}); and it is highly correlated with VA (with a correlation coefficient of 0.98). Therefore, I control for VA as a potential confounder that is related to profit-based or Lerner-index-based markups as explanatory variables and to labour share as the outcome variable.

[14] Results based on innovation intensities in percentages (%) instead of natural logarithms are consistent in terms of sign and significance but less precise. These results are not presented here but can be provided on request.

[15] A notable exception is the US, where markups always increase, and labour share always falls over time.

[16] The pro-cyclicality of markups observed here is in line with recent findings in Braun and Raddatz (2016) and Nekarda and Ramey (2020), who report that the procyclicality of the markups is due to changes in the demand elasticity and financial constraints faced by the firm at different stages of the business cycle.

[17] The counter-cyclicality of the labour share is explained by hiring and firing costs, which cause firms to hire and fire at lower speeds compared to the speed of change in output. A particular variant of this explanation has been discussed around the issue of labour hoarding during the recent crisis period from 2007-2010 (Vella, 2018).

[18] Given the dip in the innovation intensity in France, Germany, Italy, and the Netherlands from 2017 onwards, I have estimated the models with data for the pre-2017 period. The sign and significance of the coefficient estimates remain the same. These results are not reported here but can be provided on request.

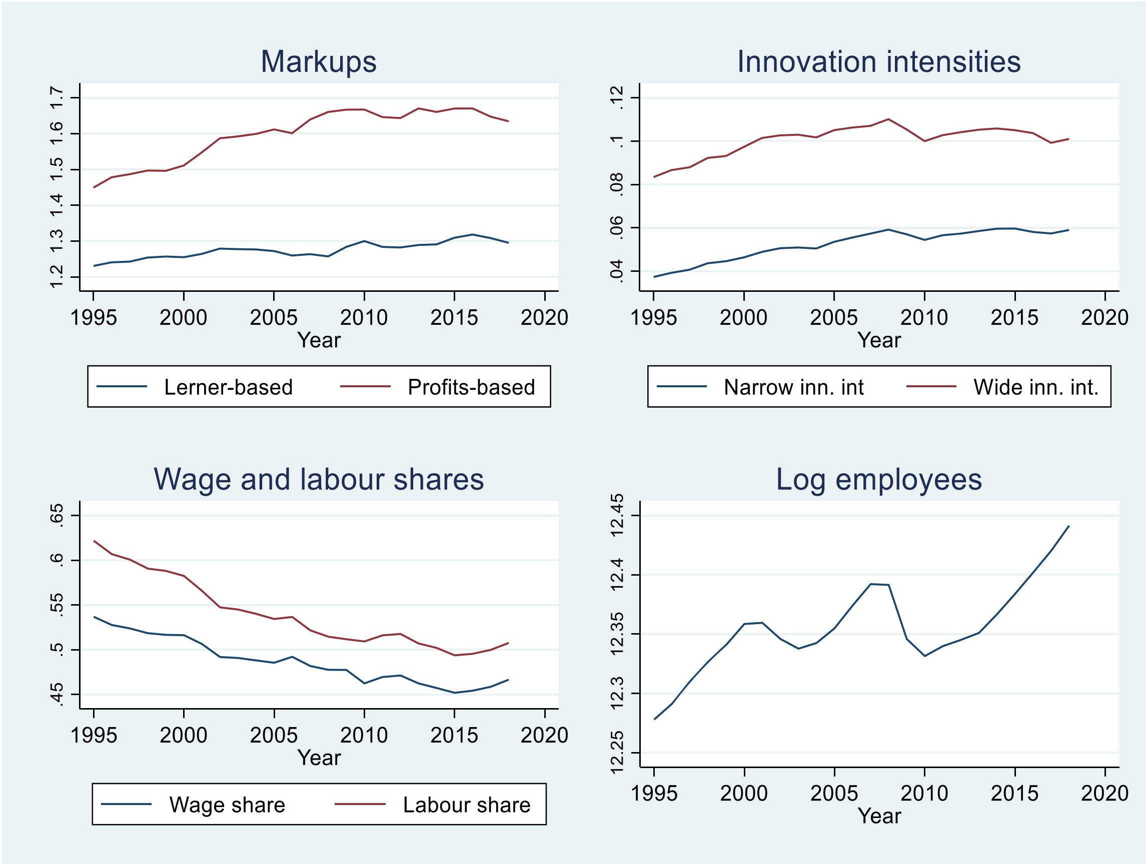

Fig. 1. Evolution of innovation, markups, labour share and employment: 1995–2019.

Only two earlier studies have reported findings that indicate an adverse market power effect on employment. Of these, Wiess (1998) has reported that the equilibrium level of industry employment and the speed of labour adjustment fall as market power increases in US manufacturing industries. On the other hand, Lim and Lee (2019) estimate an employment model with indirect (interactive) market power effects and report that process innovation has a more adverse effect on employment amongst firms in more monopolistic markets. My findings are related to but complement these earlier findings by: (i) providing a theoretical underpinning for both *direct* and *indirect* effects of market power on employment; and (ii) demonstrating that market power has both direct and indirect effects on employment. The findings above also enhance the existing knowledge base by demonstrating that the effect of technological innovation on employment differs not only by innovation type, the level of aggregation and the effectiveness of the compensation mechanisms as suggested by the existing reviews (Calvino and Virgilito, 2018; Hötte et al., 2022; Mondolo, 2022); but also, by the level of market power in the industry.

The inferences above are supported by highly consistent evidence from several robustness checks. On the one hand, the results in Table 3 are highly consistent with the GMM estimation results based on innovation intensity measured as percentage of total investment (I_3 and I_4) reported in Table A3 in the Appendix. The level of consistency is 100% for the innovation and markup coefficients; and 75% for the coefficient on the innovation-markup interaction. On the other hand, both sets of GMM results remain highly consistent (with 75% - 100% consistency) with the results from a battery of robustness checks based on fixed-effect estimators and reported in Tables A5 – A12 in the Appendix.

Estimation results for the labour share are reported in Table 4. The effect of technological innovation on labour share is positive but small. This finding is consistent with widely reported evidence that technological innovation is associated with a small or moderate increase in labour share when the elasticity of substitution is greater than one (Van Reenen, 1997; Ripotto, 2001; Guerriero, 2012; Meng and Wang, 2021; O'Mahony et al., 2021; Chen et al., 2022). The effect of market power on labour share, however, is overwhelmingly adverse. In 3 out 4 estimations, labour share falls with markups and the latter's adverse effects on labour share are larger in magnitude compared to the positive but small effects of innovation. Moreover, the adverse effect of market power is exacerbated when innovation increases in industries with market power. The adverse effect of market power we establish is consistent with emerging evidence on labour share (Bellocchi and Travaglini, 2023; Dixon and Lim, 2020; Moreira, 2022; and Ugur, 2024). It is also in line with increasing evidence on adverse macroeconomic consequences of market power (Barkai, 2020; De Loecker et al., 2020; Eggertsson et al., 2021).

Our findings contribute to the evolving research field along two paths. On the one hand, the negative and significant coefficient estimates for the interaction term indicate that the innovation's small but positive effect on labour share diminishes and may be reversed as market power increases. Similarly, the adverse effect of market power is exacerbated when innovation increases in industries with market power. Our second contribution is to demonstrate that the indirect effects of innovation or market power are more adverse when innovation intensity includes investment in non-capitalised knowledge assets such as marketing or organisation innovation or investment in economic competences. The GMM results remain consistent when the model is estimated with innovation intensity as percentage of total investment (as can be observed in Table A4 in the Appendix). They also remain 75% - 100% consistent with results from robustness checks with fixed-effect estimators, reported in Tables A5 – A12 in the Appendix.

Focusing on remaining covariates, we observe that a higher capital/

Table 3
Innovation, markups, and EMPLOYMENT: INNOVATION AS% OF VALUE ADDED - GMM results.

Dependent *variable: Employment*	(1) Innovation int. I_1 Lerner-based markup	(2) Innovation int. I_1 Profits-based markup	(3) Innovation int. I_2 Lerner-based markup	(4) Innovation int. I_2 Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Employment lag1	0.8929***	0.6916***	0.8179***	0.4868***	
	(0.1090)	(0.0463)	(0.1175)	(0.0942)	
Employment lag2	−0.1704**		−0.1583*	0.0553	
	(0.0777)		(0.0848)	(0.0915)	
Employment lag3			0.0272		
			(0.0601)		
Innovation intensity	0.0239*	0.0137	0.0936***	0.0640***	100#
	(0.0142)	(0.0085)	(0.0306)	(0.0231)	
Markup	−0.2569**	−0.2747***	−0.2084	−0.1997*	75
	(0.1141)	(0.0605)	(0.2016)	(0.1105)	
Innovation-markup interaction	−0.1547***	0.0116	−0.2115***	−0.0757*	75
	(0.0400)	(0.0205)	(0.0785)	(0.0440)	
Capital-labour ratio	−0.0378**	−0.0941***	−0.0518***	−0.1122***	100
	(0.0158)	(0.0160)	(0.0155)	(0.0168)	
Real wage	−0.2653***	−0.2357***	−0.3070***	−0.3501***	100
	(0.0481)	(0.0369)	(0.0562)	(0.0509)	
Employment protection legislation	−0.0029	−0.0016	−0.0034	0.0044	n.a.
	(0.0114)	(0.0076)	(0.0111)	(0.0109)	
Value added (constant 2015 prices)	0.2799***	0.3064***	0.3375***	0.4346***	100
	(0.0512)	(0.0451)	(0.0596)	(0.0554)	
Constant	1.8168***	1.6640***	1.9046***	2.2871***	
	(0.3276)	(0.2567)	(0.3496)	(0.3140)	
Observations	8580	9247	8425	8371	
Number of instruments	141	147	141	134	
AR(1) p-value	0.0000	0.0000	0.0000	0.0069	
AR(2) p-value	0.1980	0.1894	0.4198	0.4512	
Hansen test of over-identification restriction (p-value)	0.1124	0.2014	0.1279	0.2185	
Difference-in-Hansen tests for exogeneity of instruments	0.384	0.149	0.305	0.812	

Notes: The dependent variable is the number of employees in thousands. All variables are in natural logarithms. I_1 and I_2 are the narrow and wide measures of innovation intensity as% of value added (Eqs. (6a) and 6b in Section 4). The Lerner- and profit-based markups are as defined in Eqs. (7) and 8b. *Endogenous variables* are lagged employment, technological innovation, markups, innovation-markup interactions, capital-labour ratio, the real wage and value added; whereas the lagged dependent variable is treated as pre-determined. Consistency indicates sign and significance congruence with predictions from the CES production function summarized in Table 2. # The coefficient on innovation intensity can be positive, zero or negative - depending on whether the elasticity of substitution is greater than, equal to or smaller than one. n.a. indicates not applicable. Robust standard errors in parentheses. * $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

labour ratio is always associated with a negative effect on employment in Table 3 and labour share in Table 4. This is consistent with predictions from the CES production function in Table 2, and with empirical evidence in Bellocchi and Travaglini (2023) who report that capital deepening is a significant determinant of labour share and employment. We also observe that higher real wages are always associated with lower employment (Table 3), in line with predictions from the CES production function in Table 2 and from derived labour demand models (Chennells and Van Reenen, 2002; Van Reenen, 1997). Thirdly, higher value added in constant 2015 prices is conducive to higher employment in Table 3, in line with predictions from the CES production function in Table. The results so far remain 75% - 100% consistent with evidence from robustness checks reported in Tables A4 – A12 in the Appendix. The final observation relates to coefficient estimates for employment protection legislation (EPL), which are mixed in GMM estimations but remain positive in several fixed-effect estimations reported in Tables A5 – A12 in the Appendix.[19]

In what follows, I present post-estimation evidence concerning the conditional marginal effects (CMEs) of innovation and markups on employment and the labour share, taking account of both direct and indirect (interaction) effects in the models. The CMEs are obtained from the system GMM estimations in accordance with 9a and 9b below, where L_{ict} is employment, LS_{ict} is labour share, I_{ict} is innovation intensity, and M_{ict} is market power in the employment and labour share equations (Eq. (5a) and 5b).

$$\text{CMEs on employment } \frac{\partial L_{ict}}{\partial I_{ict}} = \beta_{11} + \beta_{13}(M_{ict}) \; \frac{\partial L_{ict}}{\partial M_{ict}} = \beta_{12} + \beta_{13}(I_{ict}) \tag{9a}$$

$$\text{CMEs on labour share } \frac{\partial LS_{ict}}{\partial I_{ict}} = \beta_{21} + \beta_{23}(M_{ict}) \; \frac{\partial LS_{ict}}{\partial M_{ict}} = \beta_{22} + \beta_{23}(I_{ict}) \tag{9b}$$

In Fig. 2, I chart the CMEs for innovation against increasing values of markup in the left panel, where the CMEs of innovation on employment are in the top left and the CMEs of innovation on labour-share are in the bottom left section. The CMEs for markups are charted against increasing levels of innovation intensity, with CMEs on employment in the top and CMEs on labour share in the bottom section.

In the top left panel of Fig. 2, it can be observed that the small but positive CMEs of innovation are declining and eventually becoming either insignificant or negative as the profits-based markup increases. This is the case for both innovation types, but the CMEs of widely defined innovation intensity (I_2) are attenuated and eventually reversed

[19] The fixed-effect results are consistent with earlier findings in the bargaining power literature, where labour rights enable workers to demand and secure higher wages (Brancaccio et al., 2018; Checchi and García-Peñalosa, 2008; Koeniger et al., 2007).

Table 4
Innovation, markups, and the LABOUR SHARE: INNOVATION AS% OF VALUE ADDED - GMM results.

Dependant variable: Labour share	(1) Innovation int. I_1 Lerner-based markup	(2) Innovation int. I_1 Profits-based markup	(3) Innovation int. I_2 Lerner-based markup	(4) Innovation int. I_2 Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Labour share lag1	0.2394***	0.1696***	0.3384***	0.0621	
	(0.0729)	(0.0303)	(0.0790)	(0.0541)	
Innovation intensity	0.1045*	0.0090	0.1922***	0.1828***	100[#]
	(0.0541)	(0.0122)	(0.0666)	(0.0552)	
Markup	−0.8437***	−0.9196***	−0.6267**	−0.3387	75
	(0.1689)	(0.0479)	(0.2825)	(0.2889)	
Innovation-markup interaction	−0.2341*	−0.0800***	−0.3349**	−0.2691**	100
	(0.1261)	(0.0234)	(0.1397)	(0.1230)	
Capital-labour ratio	−0.0647***	−0.1202***	−0.0282***	−0.1161***	100
	(0.0157)	(0.0084)	(0.0090)	(0.0146)	
Employment protection legislation	−0.0247	0.0320**	−0.0073	0.0477**	n.a.
	(0.0209)	(0.0139)	(0.0178)	(0.0224)	
Value added (current prices)	0.0130**	0.0583***	0.0070	0.0632***	n.a.
	(0.0065)	(0.0049)	(0.0060)	(0.0075)	
Constant	−0.1701*	−0.2693***	−0.5586***	−0.8406***	
	(0.0907)	(0.0537)	(0.1751)	(0.1408)	
Observations	8988	9241	8839	9085	
Number of instruments	122.0000	122.0000	104.0000	118.0000	
AR(1) p-value	0.0017	0.0000	0.0019	0.0363	
AR(2) p-value	0.4094	0.3958	0.8187	0.3268	
Hansen test of over-identification restriction (p-value)	0.1108	0.1145	0.1201	0.1321	
Difference-in-Hansen tests for exogeneity of instruments	0.111	0.243	0.118	0.279	

Notes: Notes: The dependant variable is the share of employee compensation in value added. *Endogenous variables* are lagged labour share, technological innovation, markups, innovation-markup interactions, capital-labour ratio, the real wage and value added; whereas the lagged dependant variable is treated as pre-determined. For other notes, see Table 3 above.

at faster rates as the markup increases. A similar pattern is observable in the right top panel, where the CMEs of markups becomes more adverse as innovation increases. The adverse CMEs of market power are estimated more precisely when innovation is defined widely to include non-capitalised knowledge assets. In the bottom panel of Fig. 2, the CMEs of innovation and markup exhibit a similar pattern. On the one hand, the CMEs of innovation on labour share decline and eventually become negative as markup increases. On the other hand, the CMEs of markup on labour share becomes more adverse as innovation increases. Again, the adverse CMEs of market power are estimated more precisely when innovation is defined widely. A further observation from Fig. 2 is the following: the small but positive effect of the *wide* innovation measure falls *quicker* and eventually becomes negative when the level of markup is above 1.25 (when log markup > 0.3). In contrast, the small but positive effect of the n*arrow* innovation measure falls at a *slower* rate and eventually becomes negative when the level of markup is above 1.65 (log markup > 0.5).

6. Conclusions

I have drawn attention to a one-sided focus in modelling and estimating the effects of technological innovation or market power on employment or labour share. On the one hand, the work that examines the effect of innovation on employment of labour share tends to neglect market power as an additional determinant with direct and mediating effects. This oversight has persisted despite the fact the skill-biased technical change models assume monopoly power in the production of technology (Acemoglu, 1998, 2003; Bogliacino 2014) and Schumpeterian models of innovation allow for imperfect competition in both product and technology markets (Aghion et al., 2005, 2019). On the other hand, the work that investigates the effect of market power on employment or labour share tends to overlook the direct and mediating effects of technological innovation (see, for example, Barkai, 2020; De Loecker et al., 2020; Eggertsson et al., 2021). This lop-sided approach has persisted even innovation and market power are inter-related and both affect labour share and employment at the same time.

Drawing on first-order conditions in the constant and variable elasticity of substitution (CES/VES) production functions (Raurich et at., 2012; Bellocchi and Travaglini, 2023; Di Pace and Villa, 2016; Velasquez, 2023), I have provided a theoretical underpinning for modelling employment or labour share as functions of both innovation and market power at the same time. Then, I have tested the derived models with country-industry data for 32 industries in 12 OECD countries, allowing for both direct and indirect effects on employment and labour share. My findings are consistent with the predictions form optimising behaviour in a CES production function with imperfect competition; and offer three contributions to the existing evidence base.

Compared to technological innovation, higher levels of market power are by far the more important source of lower employment and labour share in OECD countries/industries. Secondly, market power and technological innovation act as substitutes in their effects on employment or labour share: an increase in one determinant is sufficient to exacerbate the fall in both employment and the labour share. Thirdly, increasing markups attenuate and eventually reverse the small but positive effect of innovation on employment or labour share at faster rates and in a more precise pattern when innovation is measured widely to include investment in marketing strategies, organisational change, and economic competencies.

Given these findings, I conclude that the main driver of falling labour share or employment is not the level of technological innovation as such but the level of market power that enables successful innovators to extract innovation rents. An evidence-based policy implication of this research is that a stronger competition policy that would reduce the price wedge and stronger labour-market institutions that would enable

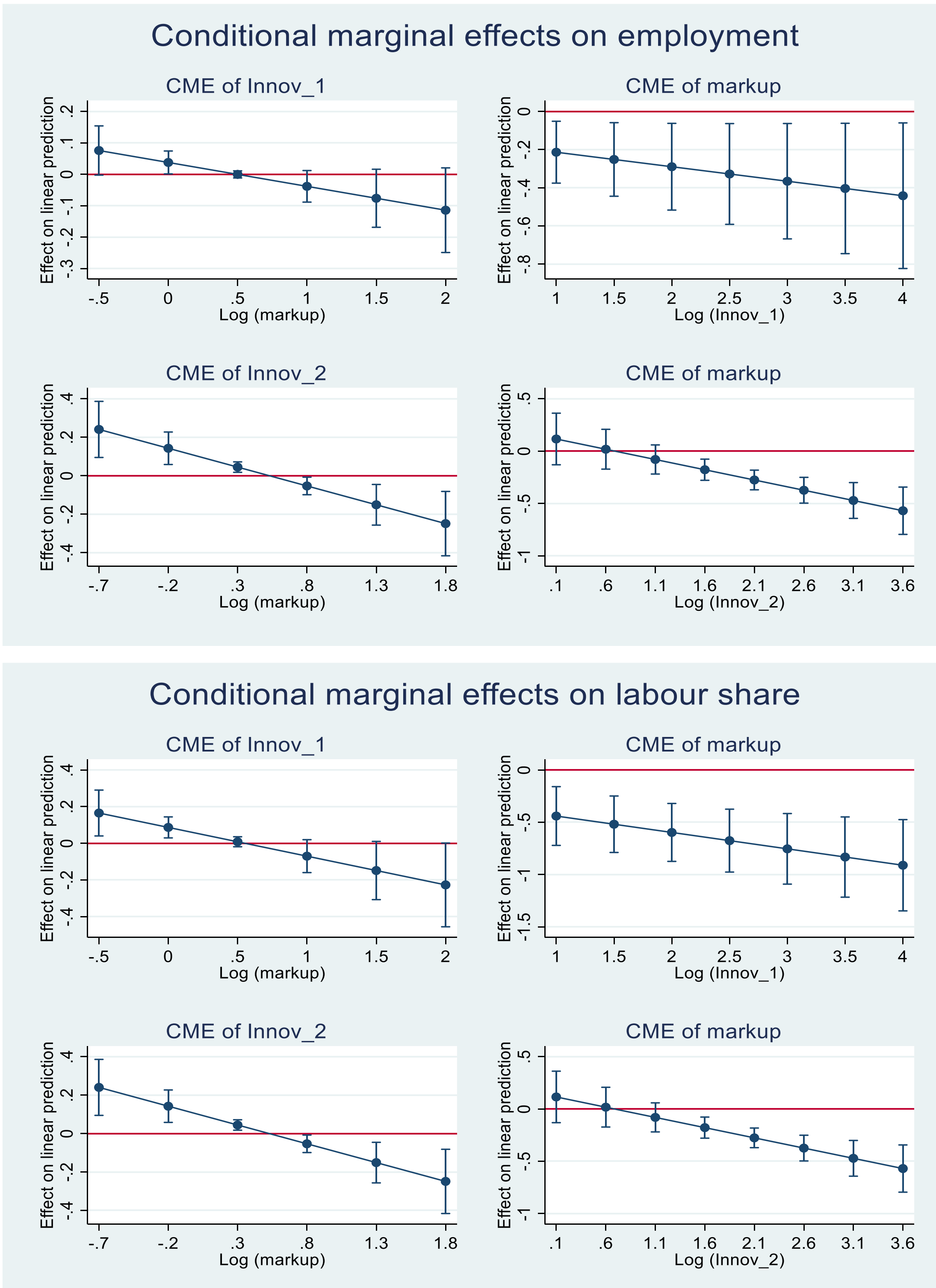

Fig. 2. Conditional marginal effects (CMEs) of innovation and markups.
Notes: The AMEs are based on GMM estimations of the employment and labour share models with narrow and wide innovation intensities (I_1 and I_2), using profits-based markups.

workers to reduce the wedge between real wages and the marginal product of labour would improve static efficiency and reduce inequality at the same time.

CRediT authorship contribution statement

Mehmet Ugur: Writing – review & editing.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.strueco.2024.07.011.

References

Acemoglu, D., 1998. Why do new technologies complement skills? Directed technical change and wage inequality. Q. J. Econ. 113, 1055–1089.
Acemoglu, D., 1999. Changes in unemployment and wage inequality: an alternative theory and some evidence. Am. Econ. Rev. 89, 1259–1278.
Acemoglu, D., 2002. Technical change, inequality and the labor market. J. Econ. Lit. 40, 7–22.
Acemoglu, D., 2003. Patterns of skill premia. Rev. Econ. Stud. 70, 231–251.
Acemoglu, D., Autor, D., 2011. Skills, tasks and technologies: implications for employment and earnings. In: Handbook of Labor Economics, 4. Elsevier, pp. 1043–1171.
Acemoglu, D., Restrepo, P., 2018. The race between man and machine: implications of technology for growth, factor shares, and employment. Am. Econ. Rev. 108 (6), 1488–1542.
Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. J. Econ. Perspect. 33 (2), 3–30.
Acemoglu, D., Restrepo, P., 2020. Robots and jobs: evidence from US labor markets'. J. Political Economy 128 (6), 2188–2244.
Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and innovation: an inverted-U relationship. Q. J. Econ. 120 (2), 701–728.
Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., Hémous, D., 2019. Innovation and top income inequality. Rev. Econ. Stud. 86 (1), 1–45.
Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econom. 68 (1), 29–51.
Autor, D.H., Katz, L.F., Kearney, M.S., 2006. The polarization of the US labor market. Am. Econ. Rev. 96 (2), 189–194.
Autor, D., David, D., Lawrence, F.K., Patterson, C., Van Reenen, J., 2017. Concentrating on the fall of the labor share. Am. Econ. Rev. 107 (5), 180–185.
Autor, D., Dorn, D., Katz, L.F., Patterson, C., Van Reenen, J., 2020. The fall of the labor share and the rise of superstar firms. Q. J. Econ. 135 (2), 645–709.
Balsmeier, B.Woerter.M, 2019. Is this time different How digitalization influences job creation and destruction. Res. Policy. 48 (8), 1–10. https://doi.org/10.1016/j.respol.2019.03.010.
Barbieri, Laura, Mussida, Chiara, Piva, Mariacristina, Vivarelli, Marco, 2020. Testing the employment and skill impact of new technologies. In: Zimmermann, Klaus F. (Ed.), Handbook of Labor, Human Resources and Population Economics. Springer, Cham, pp. 1–27. https://doi.org/10.1007/978-3-319-57365-6_1-1.
Barkai, S., 2020. Declining labor and capital shares. J. Finance 75 (5), 2421–2463.
Basu, S., 2019. Are price-cost markups rising in the United States? A discussion of the evidence. J. Econ. Perspect. 33 (3), 3–22.
Battiati, C., Jona-Lasinio, C., Marvasi, E., Sopranzetti, S., 2021. Market power and productivity trends in the European economies. Luiss School Eur. Political Economy. *WP no.* 1/2021.
Bellocchi, A., Travaglini, G., 2023. Can variable elasticity of substitution explain changes in labor shares? J. Macroecon. 76, 103518.
Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econom. 87 (1), 115–143.
Blundell, R., Bond, S., 2023. Initial conditions and Blundell–Bond estimators. J. Econom. 234, 101–110.
Bogliacino, F., 2014. A critical review of the technology-inequality debate. Suma De Negocios 5 (12), 124–135.
Bogliacino, F., Vivarelli, M., 2012. The job creation effect of R&D expenditures. Aust. Econ. Pap. 51 (2), 96–113.
Bond, S., Hashemi, A., Kaplan, G., Zoch, P., 2021. Some unpleasant markup arithmetic: production function elasticities and their estimation from production data. J. Monet. Econ. 121, 1–14. https://doi.org/10.1016/j.jmoneco.2021.05.004.
Brancaccio, E., Garbellini, N., Giammetti, R., 2018. Structural labour market reforms, GDP growth and the functional distribution of income. Struct. Chang. Econ. Dyn. 44 (March), 34–45.
Braun, M., Raddatz, C., 2016. Liquidity constraints, competition, and markup cyclicality. Financ. Manage 45 (3), 769–802.
Calvano, E., Polo, M., 2021. Market power, competition and innovation in digital markets: a survey. Inf. Econ. Policy 54, 100853.
Calvino, F., Virgillito, M.E., 2018. The innovation-employment nexus: a critical survey of theory and empirics. J. Econ. Surv. 32 (1), 83–117.
Checchi, D., García-Peñalosa, C., 2008. Labour market institutions and income inequality. Econ. Policy. 23 (56), 602–649.
Chen, N., Sun, D., Chen, J., 2022. Digital transformation, labour share, and industrial heterogeneity. J. Innov. Knowl. 7 (2), 100173.
Chennells, L., van Reenen, J., 2002. Technical change and the structure of employment and wages: a survey of the microeconometric evidence. In: Greenan, N., L'Horty, Y., Mairesse, J. (Eds.), Productivity, Inequality and the Digital Economy. MIT Press, Cambridge, MA, pp. 175–223.
Ciapanna, E., Formai, S., Linarello, A., Rovigatti, G., 2022. Measuring market power: macro and micro evidence from Italy. Bank Italy Occasional Paper (672).
Correia, S., 2016. A Feasible Estimator For Linear Models With Multi-Way Fixed Effects. Duke University Working Paper. *http://scorreia.com/research/hdfe.pdf*.
Damioli, G., Van Roy, V., Vertesy, V., Vivarelli, M, 2023. AI technologies and employment. Micro evidence from the supply side. Appl. Econ. Lett. 30 (6), 816–821.
Dauth, W., Findeisen, S.Südekum.J., Woessner, N, 2021. The adjustment of labor markets to robots. J. Eur. Econ. Assoc. 19 (6), 3104–3153.
De Chaisemartin, C., d'Haultfoeuille, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. Am. Econ. Rev. 110 (9), 2964–2996.
De Chaisemartin, C., d'Haultfoeuille, X., 2022. *Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey* (No. w29691). Natl. Bureau Econ. Res.
De Loecker, J., Eeckhout, J., Unger, G., 2020. The rise of market power and the macroeconomic implications. Q. J. Econ. 135 (2), 561–644.
Di Pace, F., Villa, S., 2016. Factor complementarity and labour market dynamics. Eur. Econ. Rev. 82, 70–112.
Diaz, G.A., Barge-Gil, A., Heijs, J., 2020. The effect of innovation on skilled and unskilled workers during bad times. Struct. Chang. Econ. Dyn. 52, 141–158.
Diez, M.F., Leigh, M.D., Tambunlertchai, S., 2018. Global Market Power and Its Macroeconomic Implications. International Monetary Fund. *IMF Working Papers*, no WP 18/137.
Dixon, R., Lim, G.C., 2020. Is the decline in labour's share in the US driven by changes in technology and/or market power? An empirical analysis. Appl. Econ. 52 (59), 6400–6415.
Dosi, G., Piva, M., Virgillito, M.E., Vivarelli, M., 2021. Embodied and disembodied technological change: the sectoral patterns of job-creation and job-destruction. Res. Policy. 50 (4), 104199.
Eggertsson, G.B., Robbins, J.A., Wold, E.G., 2021. Kaldor and Piketty's facts: the rise of monopoly power in the United States. J. Monet. Econ. 124, S19–S38.
Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the Penn World Table. Am. Econ. Rev. 105 (10), 3150–3182.
Freeman, C., Clark, J., Soete, L., 1982. Unemployment and Technical Innovation. Pinter Publisher.
Galindo-Rueda, F., 2013. The OECD measurement agenda for innovation. In: Gault, Fred (Ed.), Handbook of Innovation Indicators and Measurement. Edward Elgar, Cheltenham, pp. 217–246.
Goldin, C., Katz, L.F., 2008. The Race Between Education and Technology. Harvard University Press, Belknap.
Goos, M., 2018. The impact of technological progress on labour markets: policy challenges. Oxf. Rev. Econ. Policy. 34 (3), 349–361.
Goos, M., Manning, A., 2007. Lousy and lovely jobs: the rising polarization of work in Britain. Rev. Econ. Stat. 89 (1), 118–133.
Goos, M., Manning, A., Salomons, A., 2009. Job polarization in Europe. Am. Econ. Rev. 99 (2), 58–63.
Guerriero, M., Sen, K., 2012. What determines the share of labour in national income? *A Cross-Country Analysis* (No. 6643). Institute of Labor Economics (IZA).
Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2008. *Does Innovation Stimulate Employment? A Firm-Level Analysis Using Comparable Micro-Data From Four European Countries*. No. 08-111, 2008. ZEW-Leibniz Centre for European Economic Research.
Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2014. Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. Int. J. Ind. Organ. 35, 29–43.
Hall, R.E., 1988. The relation between price and marginal cost in US industry. J. Political Economy 96 (5), 921–947.
Hall, R.E., 1989. Invariance properties of Solow's productivity residual. Harper, University of Chicago Press 225–302. https://doi.org/10.3386/W3034.
Hashem, N., Ugur, M., 2013. Corporate governance and innovation in US-listed firms: the mediating effects of market concentration. In: Ugur, M. (Ed.), Governance, Regulation and Innovation. Edward Elgar, Cheltenham, pp. 86–121.
Hötte, K., Somers, M., and Theodorakopoulos, A. (2022). Technology and jobs: a systematic literature review. *arXiv* preprint, https://arxiv.org/pdf/2204.01296.pdf.
Inklaar, R., Albarrán, D.G., Woltjer, P., 2019. The composition of capital and cross-country productivity comparisons. Int. Productivity Monitor 36 (36), 34–52.
Karabarbounis, L., Neiman, B., 2014. The global decline of the labor share. Q. J. Econ. 129 (1), 61–103.
Katz, L.F., Murphy, K.M., 1992. Changes in relative wages, 1963–1987: supply and demand factors. Q. J. Econ. 107 (1), 35–78.
Kiviet, J.F., Pleus, M., Poldermans, R.W., 2017. Accuracy and efficiency of various GMM inference techniques in dynamic micro panel data models. Econometrics 5 (1), 14.
Koch, M., Manuylov, I., Smolka, M., 2021. Robots and firms'. Econ. J. 131 (638), 553–2584.

Koeniger, W., Leonardi, M., Nunziata, L., 2007. Labor market institutions and wage inequality. ILR Rev. 60 (3), 340–356.
Kripfganz, S., 2019. Generalized method of moments estimation of linear dynamic panel data models. In: *London Stata Conference*, 5 September 2019. https://www.stata.com/meeting/uk19/slides/uk19_kripfganz.pdf.
Kropko, J., Kubinec, R., 2020. Interpretation and identification of within-unit and cross-sectional variation in panel data models. PLoS. One 15 (4), e0231349.
Lim, J., Lee, K., 2019. Employment effect of innovation under different market structures: findings from Korean manufacturing firms. Technol. Forecast. Soc. Change 146 (September), 606–615.
Meng, F., Wang, W., 2021. The influence of factor-biased technological progress on the share of labour income in the digital economy. Technol. Anal. Strateg. Manage 1–16. https://doi.org/10.1080/09537325.2021.1998431.
Mondolo, J., 2022. The composite link between technological change and employment: a survey of the literature. J. Econ. Surv. 36 (4), 1027–1068.
Moreira, S.F., 2022. Inside the decline of the labor share: technical change, market power, and structural change. J. Econ. Dyn. Control 145, 104566.
Nekarda, C.J., Ramey, V.A., 2020. The cyclical behavior of the price-cost markup. J. Money Credit Bank. 52 (S2), 319–353.
OECD/Eurostat, 1992. Oslo manual: Proposed Guidelines For Collecting and Interpreting Technological Innovation Data. OECD. https://www.oecd-ilibrary.org/docserver/9789264192263-en.pdf?expires=1710593442&id=id&accname=guest&checksum=3C988B6FE1AD9F28BA6C6E152452B5C5.
OECD/Eurostat, 2018. *Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data On Innovation, 4th Edition, The Measurement of Scientific, Technological and Innovation Activities*. OECD. https://doi.org/10.1787/9789264304604-en.
O'Mahony, M., Timmer, M.P., 2009. Output, input and productivity measures at the industry level: the EU KLEMS database. Econ. J. 119 (538), F374–F403.
O'Mahony, M., Vecchi, M., Venturini, F., 2021. Capital heterogeneity and the decline of the labour share. Economica 88 (350), 271–296.
Peneder, M., 2012. Competition and innovation: revisiting the inverted-U relationship. J. Industry Comp. Trade 12, 1–5. https://doi.org/10.1007/s10842-011-0123-4.
Pianta, M., 2005. Innovation and employment. In: Fagerberg, D.M.J., Nelson, R.R. (Eds.), The Oxford Handbook of Innovation. Oxford University Press, pp. 568–598.
Montobbio, F., Staccioli, J., Virgillito, M.E., Vivarelli, M., 2023. The empirics of technology, employment and occupations: Lessons learned and challenges ahead. J. Econ. Surv. 1–34.
Raurich, X., Sala, H., Sorolla, V., 2012. Factor shares, the price markup, and the elasticity of substitution between capital and labor. J. Macroecon. 34 (1), 181–198.
Roeger, W., 1995. Can imperfect competition explain the difference between primal and dual productivity measures? Estimates for US manufacturing. J. Political Economy 103 (2), 316–330.
Roodman, D., 2009b. A note on the theme of too many instruments. Oxf. Bull. Econ. Stat. 71 (1), 135–158.
Schubert, T., 2010. Marketing and organisational innovations in entrepreneurial innovation processes and their relation to market structure and firm characteristics. Rev. Ind. Organ. 36 (2), 189–212.
Stehrer, R., Bykova, A., Jäger, K., Reiter, O., Schwarzhappel, M., 2019. Industry Level Growth and Productivity Data With Special Focus On Intangible assets: Report on Methodologies and Data Construction For the EU KLEMS Release 2019. Vienna Institute for International Economic Studies.
Syverson, C., 2019. Macroeconomics and market power: context, implications, and open questions. J. Econ. Perspect. 33 (3), 23–43.
gur, M., 2024. Innovation, market power and the labour share: evidence from OECD industries. Technol. Forecast. Soc. Change 203, 123388.
Ugur, M., Awaworyi Churchill, S., Solomon, E, 2018. Technological innovation and employment in derived labour demand models: a hierarchical meta-regression analysis. J. Econ. Surv. 32 (1), 50–82.
Van Reenen, J., 1997. Employment and technological innovation: evidence from UK manufacturing firms. J. Labor. Econ. 15 (2), 255–284.
Velasquez, A. (2023). Production technology, market power, and the decline of the labor share. IMF Working Papers no WP/23/32.
Vella, M., 2018. Employment and labour hoarding: a production function approach. J. Econ. Finance Admin. Sci. 23 (46), 230–246.
Vivarelli, M., 1995. The Economics of Technology and employment: Theory and Empirical Evidence. Edward Elgar.
Vivarelli, M., 2014. Innovation, employment and skills in advanced and developing countries: a survey of economic literature. J. Econ. Issues. 48 (1), 123–154.
Webb, M. (2020). The impact of artificial intelligence on the labor market. Available at SSRN: https://ssrn.com/abstract=3482150 or https://doi.org/10.2139/ssrn.3482150.
Wooldridge, J.M. (.2021). Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators. *Available at SSRN 3906345*.