Technological innovation, markups, and the labour market: Direct and mediating effects on employment and the labour share in OECD industries

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Abstract

Empirical models of employment and labour share do not take account of technological innovation and market power at the same time. Nevertheless, this is in contradiction with the first-order conditions from production functions with imperfect competition and constant or variable elasticity of substitution. Predictions from the first-order conditions indicate that labour share or employment always falls in markups, whereas the effects of technological innovation depend on the elasticity of substitution. We test these predictions with EU-KLEMS data on 32 industries in 12 OECD countries observed from 1995-2019. We report the following findings: (i) the effect of market power on employment and labour share is always negative and large; (ii) the effect of innovation is positive but small; and (iii) the mediating effect is negative, indicating that the job-creating effects of innovation is gradually reversed as market power increases. These findings remain robust across different innovation and markup measures and between different samples. Hence, we conclude that the main driver of the decline in employment and/or labour share is not technological innovation as such but the level of rents that innovating firms are able to extract.

Keywords: Technological change, markups, labour share, elasticity of substitution

1. Introduction

The debate on employment effects of technological innovation has a long history. Since the Luddite riots of the early 19th century in Britain, workers and their unions have emphasized the risks of technological unemployment. At the opposite end, policy makers and business representatives tended to argue that technological change is essential for growth and job creation. In between, economists have highlighted several factors that may tilt the balance between the job-creating and job-destroying effects of technological innovation. In the compensation framework, the overall effect depends on the extent to which the job-destroying effects of technological change are counterbalanced by compensation mechanisms that create jobs through lower prices/wages, higher investment, or new product lines etc. (for recent reviews, see Calvino and Virgillitto, 2018; Hötte et al., 2022; Mondolo, 2022). In the substitution framework, the overall effect depends on whether the elasticity of substitution between capital and labour is greater than one (the skill-biased technical change hypothesis) or on the extent to which task creation exceeds automation (the routine-biased technical change hypothesis) (Katz and Murphy, 1992; Acemoglu, 1998, 1999, 2002, 2003; Acemoglu and Autor, 2011; Goos, 2018; Acemoglu and Restrepo, 2018).

A common thread in both lines of research so far has been the neglect of market power as an additional determinant with direct and mediating effects on employment. This has remained the case even though 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; Aghion et al., 2019a).

In another line of research, the decline in the labour share is related to increasing market power (Barkai, 2020; De Loecker et al., 2020; Eggertsson et al., 2021; Gutiérrez and Philippon, 2019). Here labour share falls in market power because the latter enables firms to maximise profits before the optimal level of employment is reached. The oversight here is the mirror image of the one in the literature on technological change and employment: the effect of market power on labour share is modeled and estimated without controlling for the direct or mediating effects of technological innovation.

The separation of technological innovation and market power in empirical models of employment or labour share is not warranted – either theoretically or empirically. This is because technological innovation and market power are related in Schumpeterian models of innovation (Aghion et al., 2005; Peneder, 2012; Hashem and Ugur, 2013) and in the literature on the economic consequences of market power (Autor et al., 2017, 2020; Barkai, 2020; Battiati et al., 2021; De Loecker et al., 2020). Moreover, profit-maximising behaviour under imperfect competition implies that the effect of technological change on employment and labour share is intertwined with the effect of market power – irrespective of whether the elasticity of substitution is constant or variable (Raurich et at., 2012; Bellocchi and Travaglini, 2023; Di Pace and Villa, 2016; Velasquez, 2023).

Hence, the aim of this paper is to account for the direct and mediating effects of technological innovation and markups on two labour-market outcomes - the labour share and the level of employment. To do this, we allow for imperfect competition and draw on first-order conditions from both constant and variable elasticities of substitution (CES and VES) production functions. We demonstrate that profit-maximisation under imperfect competition leads to sub-optimal levels of employment and labour share. Moreover, employment and the labour share always fall in market-power, whereas the effects of technological innovation depend on the elasticity of substitution. Thirdly, the adverse effects of markups are exacerbated when innovation increases and the small but positive effects of technological innovation are attenuated and eventually reversed as market power increases.

The rest of this paper is organised as follows. In section 2, we review the relevant literature with a view to highlight the continued separation of technological innovation and market power in labour-share and employment models. We conclude this section by arguing that such separation is not warranted theoretically or empirically and is likely to be a source of misspecification bias. In section 3, we draw on the first-order conditions in constant and variable elasticity of substitution (CES and VES) production functions and demonstrate that empirical models should control for both technological innovation and market power and their interactive effects at the same time. Comparative-static results in section 3 suggest that markups are always conducive to lower levels of employment or labour share, whereas the effects of technological change depend on the elasticity of substitutions. These direct effects are exacerbated or moderated through indirect effects that results from the interaction between technological innovation and market power.

In section 4, we introduce our estimations strategy and the industry-level measures of innovation and markups we use for estimation. Drawing on EU-KLEMS data for 32 industries in 12 OECD countries observed from 1995-2019, we calculate two measures of market power. One of the measures depends on the Lerner index (Ciapanna et al., 2022) and the other on excess economic profits (Barkai, 2020; Eggertsson et al., 2021). We use four innovation measures, which reflect both broad and narrow measures of innovation intensity defined as investment in intangible (knowledge) assets relative to both industry value added and total investment in the industry. For estimation, we use a multi-way fixed-effect estimator (Correira, 2016) that enables us to take account of unobserved effects at the country and industry levels and over time. Section 5 presents the estimation results for the direct and interactive effects of both technological innovation and markups, after taking account of additional factors such as the capital-labour ratio, the wage level, the level of value added, and the strength of employment protection legislation. The estimations results lend consistent support to our analytical predictions derived in section 3. We conclude in section 6 by distilling the main findings and arguing that the main driver of the movements in employment and the labour share in OECD countries-industries over more than two decades (1998-2019) is not technological change per se, but the level of market power than enables innovating firms/industries to extract rents.

2. Relevant literature on employment and labour-share: Separate treatment of innovation and markups as potential determinants

We can distinguish between two analytical frameworks within which the relationship between technological innovation and employment has been investigated: (i) the compensation framework that focuses on the compensation mechanisms that may reverse the job-destroying effects of technical change; and (ii) the substitution framework that investigates how skill- or routine-biased technical change affect the demand for and wages of different job categories. As will be demonstrated below, work within both frameworks focuses on the role technological change only even though the market power lurks at the background as an additional factor that affects both labour compensation and employment.

The compensation framework dates to Freeman et al. (1982), Pianta (2005), and Vivarelli (1995), followed by more recent contributions by Vivarelli (2014), Calvino and Virgillito (2018) and Dosi et al. (2021). In this framework, the debate centres around the extent to which compensation mechanisms (e.g., new investment, falling product prices or wages, increases in income or product variety, etc. that may follow innovation) can reverse the adverse effects of technological change on employment. Although the scope for compensation is envisaged to be higher at the industry or country level analyses, the work has drawn attention to the factors that may complicate or hinder the functioning of the compensation mechanisms. These conditioning factors include macroeconomic/cyclical conditions and labour-market institutions (Vivarelli, 2014; Calvino & Virgillito, 2018; Dosi et al., 2021) as well as product-market competition (Bogliacino & Vivarelli, 2012). In a recent review of this debate, Mondolo (2020) concludes that it is difficult to predict whether the compensation mechanisms compensate for the labour-saving effects of technological change.

Work within the substitution framework focuses on the employment and/or wage effects of technological change on different labour categories. Earlier work around the skill-biased technological change (SBTC) hypothesis (Katz and Murphy, 1992) has drawn attention to increasing wage/employment share of skilled labour despite the increase in the supply of university graduates in the 1980s. The apparent inconsistency is explained by the nature of the technological change, which has been responding to the increased supply of skilled labour by complementing rather than replacing it. The SBTC framework has been studied widely both in terms of theoretical modeling (Acemoglu, 1998, 1999, 2002, 2003; Acemoglu and Autor, 2011) and with respect to empirical investigations (Acemoglu and Autor, 2011; Goldin and Katz, 2008; Goos, 2018).

Reviewers of the SBTC literature acknowledge that the work has been capable of capturing the employment/wage trends in the 1980s and 1990s, but they also draw attention to several weaknesses. For example, Bogliacino (2014) indicates that the work treats technology as the only source of change in the labour market, overlooking the effects of other determinants such as labour-market institutions or market power. On the other hand, Mondolo (2020) concludes that the SBTC framework cannot explain the more recent trends that reflect a fall in the employment of medium-skilled labour together with an increase in the employment of low-skilled labour.

Such criticism has led to mutation of the SBTC hypothesis into a routine-biased technical change (RBTC) version. The latter focuses on tasks, rather than on labour skills. It postulates that new technologies complement non-routine tasks, leading to polarized job growth (Autor et al., 2006; Goos & Manning, 2007; Goos et al., 2009). Because non-routine tasks are performed by both high- and low-skilled labour, the routine-biased technical change complements labour at both ends of the skill distribution, leading to lower demand for the medium-skilled labour that performs mostly routine-intensive tasks.

The shift of focus from skills to tasks has enabled Acemoglu and Restrepo (2018) to develop the RBTC hypothesis further and analyse the likely impacts of automation on employment, wages and labour share. The automation model assumes two types of technological change: (i) automation that allows firms to substitute capital for tasks previously performed by labour; and (ii) the creation of new tasks that replaces old tasks by new variants with higher labour productivity. The static version of the model predicts that automation always reduces the labour share and employment and may even reduce wages. In contrast, the fully endogenized version predicts two possible outcomes – depending on whether automation is followed by the creation of new tasks. If automation is followed by the creation of new tasks, we have stability in the labour share and employment. If, however, automation is easier/cheaper relative to the creation of new tasks, task creation may not be sufficient, and the economy will tend toward lower levels of employment and labour share.

One take-away from the brief review above is that both compensation and substitution frameworks have identified nuanced causal channels and arrived at less alarming conclusions compared to some empirical work that predicts that almost half of US jobs (including service/white-collar/cognitive jobs) could be automated over the next decade or two (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017). Nevertheless, work within both frameworks remain oblivious to the question of whether market-power should be part of the story too. The risk of model misspecification bias that may result from this oversight must be addressed for three reasons.

First, both RBTC and SBTC models assume that entry to the innovation market is free, but innovation enhances the innovators' market power. This market power is eliminated in the model through perfect competition in the product markets (Acemoglu, 1998, 2003; for a critique, see Bogliacino 2014). If product markets are characterised by imperfect competition, the effect of technological change on employment or wages in the SBTC models will depend not only on the elasticity of substitution between capital and labour as the model would suggest but also on the level of markups in the industry.

Secondly, 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; Aghion et al., 2019a). 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).

The third reason against the separation of innovation and market power in employment and labour share models is the proliferation of the evidence on rising market power and its adverse economic consequences at the firm, industry and country levels (for reviews, see Basu, 2019; Syverson, 2019; Battiaiti et al., 2021; and Bond et al., 2021). Evidence from one line of research in this area indicates that labour share tends to fall as the level of markups increases. The adverse effect has been reported with profit-based measures where markups are proportional to the inverse of the economic (excess) profits (Barkai, 2020; Eggertsson et al., 2021) and with Lerner-index-based measures where the markup is the wedge between prices and marginal costs approximated with average costs (Ciapanna et al., 2022).

Although the focus on markups as an additional determinants of labour share is a step in the right direction, the market-power literature remains silent about whether the labour-share models should also control for technological innovation. It also remains silent about whether markups affect the level of employment in addition to labour share. Stated differently, the potential specification bias in the literature on markups and the labour-market outcomes is a mirror image of the potential bias in the literature that investigates the effects of technological innovation on labour-market outcomes. To address these potential specification biases, we draw on profit-maximising behaviour in both constant and variable elasticity of substitution production functions. As we demonstrate in section 3 below, the effect of technological innovation on employment or labour share is intertwined with the effect of market power

(Raurich et at., 2012; Bellocchi and Travaglini, 2023; Di Pace and Villa, 2016; Velasquez, 2023).

3. Direct and mediating effects of innovation and markups in employment and labour-share models

In this section, we draw on the first-order condition in a constant or variable elasticity of substitution production function to demonstrate that equilibrium labour share of employment depends on both market power and technological innovation at the same time. First, we draw on Raurich et al. (2012) to derive the industry-level labour share (LS) and employment (L) equations under imperfect competition and constant elasticity of substitution (CES).[1] Denoting the industry output (value added) with Y_t, the industry-level capital stock with K_t, the level of employment with L_t, the CES production function can be stated as follows:

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

In (1), A_t is labour-augmenting technological change and $A_t L_t$ is labour in efficiency units; α and 1- α are capital and labour weights in the CES production technology; 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 is equal to the real wage (W_t) multiplied by the markup of prices over marginal costs. Denoting markups with μ_t and noting that the marginal product of labour is the partial derivative of the output in (1) with respect to labour, the first-order condition for profit maximisation is:

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

[1] The minor difference here is the addition of the capital-augmenting technology (A_t) to the CES production function.

Combining (1) and (2) and moving the markups (μ_t) to the right, the labour share (LS) compatible with profit maximising behaviour can be written as follows:

$$LS_t = \frac{W_t L_t}{Y_t} = \frac{1-\alpha}{\mu_t}\left(\frac{Y_t}{A_t L_t}\right)^{\frac{1-\sigma}{\sigma}}. \qquad (2a)$$

Here the average labour productivity is given by (2b) below:

$$\left(\frac{Y_t}{A_t L_t}\right)^{\frac{1-\sigma}{\sigma}} = \frac{1}{\alpha\left(\frac{K_t}{A_t L_t}\right)^{\frac{\sigma-1}{\sigma}}+(1-\alpha)} \qquad (2b)$$

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

It is immediately clear that the labour share is a decreasing function of markups as the latter drives a wedge between the real wage (W_t) and the marginal product of labour $(1-\alpha)$. 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).

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

Three immediate conclusions follow from the profit-maximising levels of labour share and employment in (3) and (4) above. First, the equilibrium labour share or employment depend on both markups (μ_t) and the rate of technological innovation (A_t) defined as labour-augmenting technical change. Secondly, the equilibrium levels of labour share in (3) and employment in (4) always fall with markups – irrespective of whether the elasticity of substitution (σ) is greater or smaller than one. In contrast, the effects of technological innovation on the labour share or employment depend on the elasticity of substitution. At a given level of markups, employment and labour share decrease with innovation if $\sigma > 1$ but increase with innovation if $\sigma < 1$. Finally, the effects of technological innovation on labour share or employment are mediated by the effects or market power and *vice versa*.

These implications can be spelled out formally by taking the partial derivatives of equations (3) and (4) with respect to markups or technical change. Starting with the partial derivatives with respect to markups, we can write:

$$\frac{\partial LS_t}{\partial \mu_t} = -\frac{1}{\mu_t^2}\left[\frac{1-\alpha}{\alpha\left(\frac{K_t}{A_t L_t}\right)^{\frac{\sigma-1}{\sigma}}+(1-\alpha)}\right] < 0 \tag{5a}$$

$$\frac{\partial L_t}{\partial \mu_t} = -\frac{1}{\mu_t^2}\frac{Y_t}{W_t}\left[\frac{1-\alpha}{\alpha\left(\frac{K_t}{A_t L_t}\right)^{\frac{\sigma-1}{\sigma}}+(1-\alpha)}\right] < 0 \tag{5b}$$

The comparative-static equations indicate that the empirical models for estimating the effect of markups on labour share or employment must control for innovation too as the latter features at the right-hand side of both equations 5a and 5b. The empirical models must also control for how innovation mediates the effect of market power on either labour share or employment. This is because the effect of market power depends on the product (ii.e., interaction) of both terms.

Similarly, the comparative-static equations for the effect of innovation on labour share (5b) or on employment (6b) indicate that the empirical models must control for market power as the latter features in both equations. Moreover, the empirical models must also control for mediating (interactive) effects of both determinants too. This is because the effect of either innovation or market power depends on the product (ii.e., interaction) of both terms. Thirdly, both labour share and employment models should control for the capital-labour ratio ($\frac{K_t}{L_t}$), which appear on the right-hand side the partial derivatives for both outcomes. The final observation is that the employment model should additionally control for industry-level real value added (Y_t) and industry-level average wage (W_t).

$$\frac{\partial LS_t}{\partial(A_t)} = -\frac{1}{\mu_t}\frac{\alpha\left(\frac{\sigma-1}{\sigma}\right)(1-\alpha)}{\left[\alpha+(1-\alpha)\left(\frac{K_t}{A_tL_t}\right)^{\frac{\sigma-1}{\sigma}}\right]^2} < 0 \quad only\ if\ \sigma > 1 \qquad (5b)$$

Similarly, the partial derivatives of the employment equation with respect to markups and technological change are stated in 6a and 6b below.

$$\frac{\partial L_t}{\partial \mu_t} = -\frac{1}{\mu_t^2}\frac{Y_t}{W_t}\left[\frac{1-\alpha}{\alpha\left(\frac{K_t}{A_tL_t}\right)^{\frac{\sigma-1}{\sigma}}+(1-\alpha)}\right] < 0 \qquad (6a)$$

And

$$\frac{\partial L_t}{\partial(A_t)} = -\frac{1}{\mu_t}\frac{Y_t}{W_t}\frac{\alpha\left(\frac{\sigma-1}{\sigma}\right)(1-\alpha)}{\left[\alpha+(1-\alpha)\left(\frac{K_t}{A_tL_t}\right)^{\frac{\sigma-1}{\sigma}}\right]^2} < 0 \quad only\ if\ \sigma > 1 \qquad (6b)$$

Keeping technological innovation (A_t) and the ratio of capital to labour ($\frac{K_t}{L_t}$) constant, equations (5a) and (6a) imply that the labour share (*LS*) and the level of employment (*L*) always fall in markups irrespective of the magnitude of the elasticity of substitution, σ.

On the other hand, keeping markups and the capital-labour ratio ($\frac{K_t}{L_t}$) constant, equations (5b) and (6b) imply that the effect of technological innovation (A_t) on *LS* or *L* would be conditional on the magnitude of the elasticity of substitution, σ. If $\sigma < 1$, the *LS* and *L* would increase with technological innovation. If $\sigma > 1$, the *LS* and *L* would decrease in technological innovation. If $\sigma = 1$, the production function is Cobb-Douglas, and the *LS* and *L* would be determined by the labour weight $(1-\alpha)$ only.

Focusing on the direct and interactive effects of technical change and markups in equations 5a –6b above, the first-order condition in the CES production allows for seven conclusions listed in Table 1 below.

Table 1: Predictions from the first-order condition in the CES production function

CES1:	*Labour share or employment **always falls** with markups – irrespective of the magnitude of the elasticity of substitution, σ (5a and 6a).*
CES2:	*The labour share or employment **falls** in technical change (A_t/B_t) **only if** $\sigma > 1$ (5b and 6b).*
CES3:	*The labour share or employment **increases** in technical change (A_t/B_t) **only if** $\sigma < 1$ (5b and 6b).*
CES4:	*The **adverse effects of markups** on labour share and employment are **exacerbated** by technical change **if $\boldsymbol{\sigma < 1}$** (5a and 6a).*
CES5:	*The **adverse effects of markups** on labour share and employment are **attenuated** by technical change **if $\boldsymbol{\sigma > 1}$** (5a and 6a).*
CES6:	*The positive effect of technical change on employment that obtains when $\sigma < 1$ is **attenuated** if market power increases (5b and 6b)*
CES7:	*The adverse effect of technical change on employment that obtains when $\sigma > 1$ is **exacerbated** if market power increases (5b and 6b)*

One question that arises from the analysis so far is whether the comparative static results above would hold if the elasticity of substitution was variable. To address this question, we draw on Bellocchi and Travaglini (2023) who allow the elasticity of substitution to vary with capital accumulation (i.e., with the capital-labour ratio) and two technology parameters, *b* and *c*. The proposed VES production function and the specification of the additional parameters are given in 7a, 7ab and 7c below.

$$Y_t = F(K_t, L_t) = \left[\alpha K_t^{\frac{\sigma_k - 1}{\sigma_k}} + (1-\alpha) k_t^{-c(1+\frac{1-\sigma_k}{\sigma_k})} (\eta A_t L_t)^{\frac{\sigma_k - 1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k - 1}} \tag{7a}$$

$$\sigma_k = \frac{b}{1 - c\left(1 + \frac{MRTS_{K,L}}{k_t}\right)} \tag{7b}$$

$$\eta = \frac{1-b}{1-b-c} \tag{7c}$$

In (7a), Y_t, K_t, L_t are industry-level output (value added), capital and labour; α and $1-\alpha$ are distribution parameters (factor weights); A_t is labour-augmenting technology; $k_t = \frac{K_t}{L_t}$ is the capital-labour ratio that captures the rate of capital accumulation; σ_k is the variable elasticity of substitution (VES); and b and c are technology parameters that affect the relationship between the VES (σ_k) and the rate of capital accumulation (k_t). Bellocchi and Travaglini (2023) demonstrate that the VES (σ_k) depends on the technology coefficients (*b, c*) and the marginal rate of technical substitution (MRTS) between capital and labour (7b). In (7c), the composite parameter η deviates from 1 if $c \neq 0$. If $c \neq 0$, the VES in (7a) increases with the capital-labour ratio when (*b*+*c*) < 1, but decreases with the capital-labour ratio when (*b*+*c*) > 1. In either case, the composite parameter η is different than one and the production function remains a VES production function. However, if $c = 0$, the composite parameter (η) is equal to 1 and the elasticity of substitution (σ_k) is equal to *b*. In this case, the production function reverts to a CES production function.

Under imperfect competition, Bellocchi and Travaglini (2023) demonstrate that the labour share compatible with the first-order condition from the VES production function can be written as follows:

$$ln\left(\frac{W_t L_t}{Y_t}\right) = bln(1-\alpha) + (\mathrm{b}-1)\ln(A_t) + (1-b)lnW_t - clnk_t - bln\mu_t \quad (8a)$$

On the other hand, the level of employment compatible with the first-order condition can be stated by moving the wage and output variables to the right and obtaining equation (8b) below.

$$lnL_t = bln(1-\alpha) + (\mathrm{b}-1)\ln(A_t) - blnW_t - clnk_t - bln\mu_t + lnY_t \quad (8b)$$

The labour share in (8a) and the level of employment in (8b) always fall in markups (μ_t) because the technology parameter *b* is non-negative. This is similar to the comparative-static result from the CES production function, where the effects or markups on labour share or employment are always negative. The difference here is that the effect of markups on labour share or employment is *more adverse* when technology parameter *b* is larger. In (7b), a larger *b* is associated with a higher elasticity of substitution – *ceteris paribus*. Therefore, the first comparative-static result from the VES production function can be stated as follows:

> *VES1. The labour share and the level of employment* ***always fall*** *in markups, but the adverse effects of markups are exacerbated as the variable elasticity of substitution increases.*

In contrast, the labour share or the employment will fall in technological change (A_t) only if *b* < *1* – i.e., when the variable elasticity of substitution is more likely to increase with capital accumulation. This is also similar (but not identical) to the comparative-static result from the

CES production function, where the effects of technological change on labour share and employment is adverse when the elasticity of substitution is greater than one. The difference in the VES context is that what matters is not the magnitude of the elasticity of substitution across or within industries, but the extent to which the elasticity of substitution increases or decreases with capital accumulation. Drawing on this framework, Bellocchi and Travaglini (2023) demonstrate that the labour share has fallen in their sample of OECD countries even though the estimated elasticity of substitution is below one in five out of six countries. Hence, we state the second comparative-static result from the VES production function can be stated as follows:

VES2. *The labour share or employment falls (increases) in technological innovation* ***only if*** *the variable elasticity of substitution increases (does not increase) with capital accumulation.*

In section 4 below we specify our empirical models in accordance with the conclusions above and discuss the estimation method for and the measurement of key variables in the models.

4. Methodology and data

One prediction from the analysis above is that markups always have adverse effects on both employment and the labour share in both CES and VES production frameworks. In contrast, the effects of technological innovation on employment or labour share are conditional on the magnitude of the elasticity of substitution (in the CES framework) or on whether the elasticity of substitution increases with capital accumulation (in the VES framework). A third prediction is that innovation and market power are substitutes in that they exacerbate (attenuate) each other's effect when these effects are negative (positive). The fourth prediction is that both employment and labour-share models should control for capital-labour ratio as standard. The fifth prediction is that the employment model should control for wages and output (value added) in addition to the standard set of covariates that enter both models.

To test these predictions, we utilise country-industry-year data from the 2021 release of the *EUKLEMS & INTANProd* database (*EU-KLEMS* thereafter).[2] The country-industry sample consists of 12 OECD countries and 32 non-overlapping 1-digit and 2-digit industries listed in

[2] 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).

Table A1 in the Appendix. Given this data structure, the empirical model should control for unobserved heterogeneity at the country (c), industry (i) and year (t) levels.

In the light of the above, we state the empirical models for employment (*L*) and labour share (*LS*) as follows:

$$L_{cit} = \alpha_{11} + \beta_{11} I_{cit} + \beta_{12} M_{cit} + \beta_{13} (I * M)_{cit} + \beta_{1p} \sum_{p=4}^{P} CV_{pcit} + v_{1c} + v_{1i} + \delta_{1t} + \varepsilon_{1cit} \quad (9a)$$

$$LS_{cit} = \alpha_{21} + \beta_{21} I_{cit} + \beta_{22} M_{cit} + \beta_{23} (I * M)_{cit} + \beta_{2p} \sum_{p=4}^{P} CV_{pcit} + v_{2c} + v_{2i} + \delta_{2t} + \varepsilon_{2cit} \quad (9b)$$

Innovation (*I*), markups (*M*) and their interaction (*I*M*) are common to both employment and labour-share equations in accordance with conclusions from the first-order conditions in the *CES/VES* production functions. The set of control variables (*CV*) in both models includes the capital-labour ratio in accordance with the *CES/VES* production function framework and the strictness of the employment protection legislation as a measure of labour-market institutions. The *CV* set in the employment model includes two additional variables - wages and output (value added) – in line with the first-order conditions from the *CES/VES* production functions. The expected effects of the covariates in both models are summarised in Table 2 below.

Table 2: Expected effects in the employment and labour-share models

Covariate	**Employment model**	**Labour share model**
Innovation intensity	+[#]	+[#]
Markup	-	-
Innovation *x* markup interaction	-	-
Real wage	-	n.a.
Capital-labour ratio	-	-
Employment protection legislation	+/-	+
Value added[##]	+	-

Notes: [#] The coefficient estimates for innovation intensity are expected to be positive in line with with meta-analysis findings in Havranek et al. (2019) and Knoblach et al (2016), where the CES is significantly smaller than one after correcting for selection bias. [##] Valued added is in constant (2015) prices in the employment model but in current prices in the labour share model.

The expected effects of market power, its interaction with innovation, and that of the capital-labour ratio on both employment and the labour share are informed by predictions form the first-order conditions in the CES/VES productions function discussed above. The effect of innovation is also informed by the same analytical framework, but it is subject to the assumption that the constant elasticity of substitution is less than one. This is assumption is justified in the light of meta-analysis findings that the CES is much less than one after correcting for publication selection bias (Havranek et al., 2019; Knoblach et al., 2016). The negative effect of real wages and the positive effect of output on employment are also informed by the first-order conditions from the CES/VES production functions – and are in line with predictions form derived labour demand models (Chennels and Van Reenen, 2002; Van Reenen, 1997; Ugur et al, 2018). The positive effect of real value added (output) on employment is line with the prediction from the first-order condition for employment in the CES production function.

The strength of the employment protection legislation (*EPL*) is obtained from the OECD statistical database. It is an index that ranges from 0 to 6 and captures employee protection with respect to dismissal of workers on regular contracts and the hiring of workers on temporary contracts. Its positive effect on labour share and its uncertain effect on employment are informed by findings in the empirical literature on labour-market institutions n employment and wages (Brancaccio et al., 2018; Checchi and García-Peñalosa, 2008; Koeniger et al., 2007).

The nominal value added is included in the labour-share model to take account of the negative statistical association between markups (where value added appears in the numerator) and labour share (where value added appears in the denominator). Its inclusion ensures that the coefficient on markups is estimated by keeping the value-added constant across industries. As such, the coefficient on markups is determined by the variations in rents (excess profits) rather than the variations in value added.

We take account of time-invariant heterogeneity at the country and industry levels through v_c and v_i, respectively to eliminate bias due to unobservables that differs between countries/industries but remain constant over time. Finally, we take account of time-fixed-effects through δ_t to eliminate bias from unobservables that change over time but remain constant over countries and industries in each time period. This specification implies a three-way fixed-effect model in which we control for unobserved heterogeneity at three levels: countries, industries, and years.

We estimate the models using a multi-way fixed effects estimator proposed by Correira (2016). The estimator enhances the scope for causal inference by eliminating the unobserved factors and ensuring zero covariance between the regressors and the unit- and time-specific errors captured by v_c, v_i, and δ_t. To minimise the risk of endogeneity due to simultaneity or reverse causality, we use the two-year-forward value of the dependent variables (employment or labour share).[3]

The three-way fixed-effect estimator is similar in structure to the two-way fixed-effect estimator, where the fixed effect components capture unobservables related to one cross-section and one time-period dimension. In our specification, we allow for unobservables along two cross-section dimensions (country and industry) and one time dimension (years). Wooldridge (2021) demonstrates that the two-way fixed-effect estimator can be used for identifying the causal effect in intervention analysis. However, this finding is challenged on the grounds that the assumption of constant treatment in the two-way fixed-effect model may not be satisfied. Because the multi-way fixed-effect estimator we utilise does not assume a constant treatment (i.e., because innovation and markups are time varying), the identification issues highlighted by Chaisemartin and d'Haultfoeuille (2020, 2022) do not arise. The three-way control for unobservables allows for identifying causal effects within country-industry pairs after eliminating the time effects (Kropko and Kubinec, 2020).

The variables in the model are based on data from the *EU-KLEMS* database.[4] We use *EU-KLEMS' statistical module* to obtain data for gross output, value added, investment, capital stock, employment, labour compensation etc. and investment in intangible (knowledge) assets such as research and development (R&D), software and databases and other intellectual property assets that have been *capitalised* in the System of National Accounts (SNA) in 2008. We use the *analytical module* for data on investment in other intangible (knowledge) assets that include marketing innovation, organisational change, and economic competencies, but have not been capitalised in the SNA 2008.

The data on intangible (knowledge) assets allow for constructing four measures of innovation intensity. Of the two *narrow* measures, *Innov_int1a* is the sum of investment in research

[3] We also use one-year forward and contemporaneous values of the dependent variables for robustness checks. The estimation results remain unchanged in 90% of the robustness checks.
[4] 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).

development (*I_R&D*), software and databases (*I_Soft-DB*), and other intellectual property assets (*I_OIP*) as percentage of value added. In the second narrow measure, *Innov_int1b*, the numerator is the same as *Innov_int1a* but the denominator is the sum of investment in tangible and capitalised intangible assets (*I_TAN* + *I_INTAN*) instead of value added. These narrow measures are closely related to the original innovation concept adopted by the OECD in the first edition of the Oslo Manual in 1992.

In the *wider* measures of *Innov_2a* and *Innov_2b*, the numerator consists of investment in marketing (*I_Mark*), organisational change (*I_Org*) and economic competency (*I_Ec_comp*) - in addition to investment in research development (*I_R&D*), software and databases (*I_Soft-DB*), and other intellectual property assets (*I_OIP*). The denominator is the value added in *Innov_2a*, but the sum of investment in tangible and capitalised intangible assets (*I_TAN* + *I_INTAN*). As such, *Innov_Int2a* and *Innov_Int2b* are closely related to the wider technological innovation definition that the OECD has adopted after the third edition of the Oslo Manual in 2005.

The four innovation measures are defined formally in 10a – 10d below, where *c*, *i*, and *t* indicate country, industry, and year respectively.

$$Innov\_int1a_{ict} = \frac{I\_R\&D_{ict} + I\_Soft\_DB_{ict} + I\_OIP_{ict}}{VA_{ict}} \tag{10a}$$

$$Innov\_int1b_{ict} = \frac{I\_R\&D_{ict} + I\_Soft\_DB_{ict} + I\_OIP_{ict}}{I\_TAN_{ict} + I\_INTAN_{ict}} \tag{10a}$$

$$Innov\_int2a_{ict} = \frac{(I\_R\&D_{ict} + I\_SOFT\_DB_{ict} + I\_OIP_{ict}) + (I\_Org_{ict} + Mark_{ict} + I\_Ec\_comp_{ict})}{VA_{ict}} \tag{10c}$$

$$Innov\_int2b_{ict} = \frac{(I\_R\&D_{ict} + I\_SOFT\_DB_{ict} + I\_OIP_{ict}) + (I\_Org_{ict} + Mark_{ict} + I\_Ec\_comp_{ict})}{I\_TAN_{ict} + I\_INTAN_{ict}} \tag{10d}$$

The related literature tends to consider the narrow and wide innovation measures as complements, particularly because the marketing-organisational innovation is usually undertaken to implement the product and process innovations inherent in technological change (Schubert, 2010; Galindo-Rueda, 2013). Moreover, there is evidence that the relationship 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, we use the four innovation measures to verify whether the effects of innovation on employment or labour-share differs between: (i) the breadth of the innovation measures; and (ii) the flow and stock measures of innovation.

We 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 (Hall, 1988, 1989; Roeger, 1995; De Loecker et al., 2020), and non-econometric measures of market power. The conclusion in Basu (2019) is that non-econometric methods can be used to avoid the measurement and identification problems associated with econometric methods, which 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 measure is defined in (11) below. It draws on Barkai (2020) and Eggertsson et al. (2021), where the markup measures the share of pure (economic) profits that remains after capital and labour are awarded their income shares under the twin assumptions of perfect competition and constant returns to scale. defined in (11) below.

$$\mu_{ict}^{P} = \frac{1}{1-PS_{ict}} = \frac{1}{1-\frac{VA_{ict}-Lab_{inc_{ict}}-Cap_{inc_{ict}}-Ind\_tax_{ict}}{VA_{ict}}} = \frac{VA_{ict}}{Lab\_inc_{ict}+Cap\_inc_{ict}+Ind\_tax_{ict}} \quad (11)$$

The profit-based markup is 1 if the value added is exhausted by labour income, capital income and indirect taxes. On the other hand, $\mu_{ict}^{P} > 1$ 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 data – and it is adjusted for the self-employed. Capital income, however, is not observable. To derive it, we multiply the 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. Our use of the country-level IRRs for calculating capital income at the industry-country level relies on the assumption that the IRRs are equalised across industries within each country. Here, it must be noted that the net capital stock we use for calculating capital income includes the capitalised knowledge assets (*R&D*, *Soft-DB*, and *OIP*) indicated above.

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 (12a).

$$LI_{ict} = \frac{P_{ict} - MC_{it}}{P_{ict}} \cong \frac{(P_{ict} - AC_{it})Q_{ict}}{P_{ict}Q_{ict}} = \frac{Y_{ict} - TAC_{ict}}{Y_{ict}} \tag{12a}$$

The numerator and denominator of 12a can be multiplied with output quantity to obtain the Lerner index as the difference between gross output (Y_{ict}) and total average costs (TAC_{ict}) divided by the gross output. Using this measure, the Lerner-index-based markup, $\mu^{L},$ is obtained in accordance with 12b below, where the total average cost (TAC_{ict}) is the sum of intermediate input cost (II_{ict}) and labour cost (Lab_Cost_{ict}) adjusted for self-employment.

$$\mu^{L}_{ict} = \frac{1}{1 - L_{ict}} = \frac{1}{1 - \frac{Y_{ict} - TAC_{ict}}{Y_{ict}}} = \frac{Y_{ict}}{TAC_{ict}} = \frac{Y_{ict}}{II_{ict} + Lab\_Cost_{ict}} \tag{12b}$$

Of the remaining covariates, output and real wage in the employment model are measured as industry-level value added in 2015 prices and average wage per employee in 2015 prices, respectively. In the labour-share model, value added is controlled for to take account of the negative association between labour share and both markup definitions. Because the variables used for measuring markups are all in current prices, the value added in the labour-share models is included in current prices too. Finally, of the outcome variables, employment (L) is measured as the number of employees in thousands and as such it excludes the self-employed. The labour-share variable (LS) is the compensation of employees as a percentage of value added.[5]

We have trimmed the top and bottom 1% of the observations for markup, labour share and innovation measures. The trimming reduces the risk of outlier influence and attenuates the level of noise due to potential measurement errors. We have checked whether the trimming of the outliers alters the estimation results. The checks indicate that the sign and significance of the coefficient estimates with and without trimming are similar, but the precision is higher when the outliers are trimmed.

[5] We have checked if the estimation results remain the same when employment and labour share take account of the self-employed. For this purpose, we have constructed alternative measures of employment and labour share, assuming that the average wage for the self-employed is the same as the average wage for employees. 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.

Figures A1 – A3 in the Appendix present the evolution of markups, innovation intensity, and labour share by country.[6] Both markups and the labour share tend to *fall* in countries with above average values at the beginning of the analysis period, but they tend to *increase* in countries with below average values to start with. Hence, we observe 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 is converging towards the sample average of 0.58.[7] Another observation from the data is that markups are procyclical - i.e., they increase during boom periods and fall during recessions.[8] In contrast, the labour share is counter-cyclical – particularly so during 2007-2010.[9] Finally, the trend for both measures of innovation intensity is similar across countries, indicating an increasing level of investment in knowledge assets 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.

5. Results

We have estimated models 9a and 9b with a three-way fixed-effect estimator using four alternative innovation intensity measures (*Innov_int1a, Innov_int2a*, *Innov_int1b, Innov_int2b*); two markup measures (*profits- and Lerner-based markup*s); and two samples (the *full sample* of 12 OECD countries and 32 industries and the *Euro area sample* of 6 countries and 32 industries). Hence, we present 16 (= 4 x 2 x 2) estimation results for each model, of which four results are presented in the main text and the remaining 12 are presented in the Appendix as robustness checks. The main estimation results for the employment model (eq. 9a) are presented in Table 3 below, followed by those of the labour-share model in Table 4. Robustness checks for the employment model are presented in Tables 3A – 3C in the Appendix, followed by those for the labour-share model in Tables 4A – 4C.

[6] The evolution by industry is not reported here to save space, but it can be provided on request.
[7] A notable country exception is the US, where markups always increase, and labour share always falls over time.
[8] The pro-cyclicality of markups we observe in the *EU-KLEMS* data is in line with recent findings in Braun and Raddatz (2016) and Nekarda and Ramey (2020), who report similar findings at the firm level. In this line research, 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.
[9] The counter-cyclicality of the labour share is usually 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).

Results in columns 1 and 2 of Table 3 are based on the narrow definition of innovation intensity, which consists of investment in R&D, software and databases and other intellectual property assets relative to value added. In columns 3 and 4, we use the wider measure that includes investment in organisational change, marketing, and economic competencies in addition to the narrow set of innovation proxies. The markup measure is Lerner-based in columns 1 and 3 and profits-based in columns 2 and 4. Finally, column 5 reports the consistency of the coefficient estimates with predictions from the first-order conditions in the *CES/VES* production functions, as summarised in Table 2 above. Similar consistency information is also provided for the robustness checks in Tables 3A – 3C in the Appendix.

One observation from Table 3 is that the model fits the data very well, explaining 87% – 93% of the within and around 99% of the overall variation in the observed value of the employment variable. The predictive power of the model is high across both narrow and wide measures of innovation, but the fit statistics indicate the that the level of within variation explained is higher when the profits-based markup (Barkai, 2020; Eggertsson et al., 2021) is used (columns 2 and 4). This finding lends support to Basu's (2019) conclusion that the profits-based markup yields more reliable estimates for market power – compared to both Lerner-based markups (Ciapanna et al., 2022) as well as econometrically estimated markups of Hall (1988, 1989), Roeger (1995) and De Loecker et al. (2020). Therefore, we report results based on both Lerner- and profits-based markup measures, but we rely on the profits-based measure for post-estimation exercises.

Table 3: Direct and indirect effects of innovation and markups on employment: Full sample

Dependent variable: Employment	(1) Innovation Int_1a Lerner-based markup	(2) Innovation Int_1a Profits-based markup	(3) Innovation Int_2a Lerner-based markup	(4) Innovation Int_2a Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	0.0685^{***}	0.0515^{***}	0.1474^{***}	0.0878^{***}	$100^{\#}$
	(0.0082)	(0.0045)	(0.0091)	(0.0058)	
Markup	-1.1797^{***}	-0.8042^{***}	-0.6978^{***}	-0.7807^{***}	100
	(0.0423)	(0.0182)	(0.0505)	(0.0340)	
Innovation-markup interaction	-0.1293^{***}	-0.0424^{***}	-0.3035^{***}	-0.0351^{***}	100
	(0.0270)	(0.0087)	(0.0233)	(0.0127)	
Capital-labour ratio	-0.1328^{***}	-0.2652^{***}	-0.1214^{***}	-0.2358^{***}	100
	(0.0070)	(0.0061)	(0.0056)	(0.0044)	
Real wage	-0.8553^{***}	-0.8751^{***}	-0.8943^{***}	-0.8842^{***}	100
	(0.0120)	(0.0070)	(0.0095)	(0.0067)	
Employment protection legislation	0.0609^{**}	0.1253^{***}	0.0602^{***}	0.1075^{***}	100
	(0.0252)	(0.0227)	(0.0226)	(0.0170)	
Value added (constant 2015 prices)	0.9011^{***}	0.9412^{***}	0.9324^{***}	0.9450^{***}	100
	(0.0081)	(0.0037)	(0.0048)	(0.0037)	
Constant	6.3954^{***}	6.8579^{***}	6.2082^{***}	6.6501^{***}	n.a.
	(0.1056)	(0.0811)	(0.1057)	(0.0746)	
Observations	8586	8937	8442	8765	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.9912	0.9938	0.9919	0.9953	
R^2 (within)	0.8724	0.9085	0.8795	0.9282	
Log likelihood	3164.5408	4873.7007	3619.8617	6094.6851	
RMSE	0.1681	0.1409	0.1583	0.1213	

Notes: Innovation intensities 1a and 2a are investment in tangible (knowledge) assets as % of value added (equations 10a and 10b in section 4 above). The Lerner- and profit-based markups are as defined in equations 11 and 12a. Three-way fixed-effect estimation with control for country, industry, and time fixed effects. All variables are in natural logarithms. The dependent variable is the two-year-forward value of employment. Results based on one-year forward and contemporaneous values of employment are consistent. These are not reported to save space but can be provided on request. Robust standard errors are in parentheses. # The level of consistency for the innovation coefficient assumes that the constant elasticity of substitution is less than one – in line with meta-analysis findings in Havranek et al. (2019) and Knoblach et al (2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Returning to coefficient estimates in the top panel, we observe that innovation intensity is associated with a positive but small increase in employment. Relying on the profits-based markup that ensures a better fit with the data, the effect is between 0.05% – 0.08% increase in employment when technological innovation increases by 1%. The small and positive effect indicate that the constant elasticity of substitution between capital and labour is below one and/or the variable elasticity of substitution is not increasing with capital accumulation. This implied complementarity between capital and labour is consistent with meta-analysis evidence that the constant elasticity of substitution is below one after accounting for publication selection bias (Havranek et al., 2019; Knoblach et al., 2016). As such, the coefficient estimates for technological innovation reflect 100% consistency with predictions in Table 2 above.

The coefficient estimates for the markups are also fully consistent with the predictions in Table 2. A one-percent increase in markups is associated with an adverse effect of 0.70 - 1.15 percent on employment - about 8-10 times of the innovation effects. Similar consistency is observed with respect to the interaction (indirect) effects of innovation and markups. The negative and significant coefficient estimates 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 eventually reversed when market power increases at a given level of market power.

How do these findings compare with robustness checks reported in Tables 3A – 3C in the Appendix? The coefficient estimates for technological innovation are 100% consistent in Table 3A, where innovation intensity is relative to value added and the sample consists of Eurozone countries only. However, the level of consistency declines (50% in Table 3B) and eventually disappears (0% in Table 3C) when innovation intensity is measured relative to total (tangible + intangible) investment. These findings indicate that the effect of innovation on employment is usually positive, but the estimate may vary depending on how technological innovation is measured. Our findings are in line with review evidence, which indicate that the job-creating effects of technological innovation are more likely to dominate the job-destroying effects; but the multiplicity of innovation proxies used pose a challenge to the consistency of the reported estimates (Calvino and Virgilito, 2018; Hötte et al., 2022; Mondolo, 2022).

In contrast, the coefficient estimates for the market power are always negative, larger in magnitude and remain statistically significant across all robustness checks. Similar results are observed with respect to the interaction between market power and technological innovation.

The coefficient estimates for the interaction terms are always negative across robustness checks and remain 88% consistent in terms of significance. The findings with respect to the market power effects are consistent with the predictions form the first-order conditions in the CES/VES production functions. They are also novel because, to the best of our knowledge, they constitute the first set of evidence on the employment effects of market power after Wiess (1998), who has reported that the equilibrium level of industry employment and the speed of labour adjustment fall with market power in the US manufacturing industries.

The finding of negative coefficient estimates for the interaction term is equally important and novel. On the one hand, it indicates 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, Specifically, job creation would be less likely when increased innovation is accompanied with increasing market power. On the other hand, it enriches the scant evidence on job-destroying effects of market power by demonstrating that increased innovation in industries with high markups would exacerbate the job-destroying effects of market power.

Estimation results for the labour share model are reported in Table 4. The effect of technological innovation on labour share is positive but small – both in Table 4 and in the robustness checks reported in Tables 4A – 4C in the Appendix. This finding is consistent with the increasing evidence that technological innovation tends to be associated with a small or moderate increase in labour share when the elasticity of substitution is smaller than one (Ripotto, 2001; Guerriero, 2012; Meng and Wang, 2021; Cheng et al., 2022). It is also consistent with the finding in O'Mahony et al. (2021) who draw on the EU-KLEMS data we use here and report a small but positive technological innovation effect on labour share.[10] Finally, the complementarity between capital and labour implied by the positive innovation effect on labour share is consistent with meta-analysis evidence that the constant elasticity of substitution is below one after accounting for publication selection bias (Havranek et al., 2019; Knoblach et al., 2016).

[10] In O'Mahony et al (2021) the positive effect of technological innovation is due to two factors: an elasticity of substitution less than one and a job-creating effect due to R&D investments outweighing the job-destroying effect of the investment in information and communication technologies (ICT).

Table 4: Direct and indirect effects of innovation and markups on labour share: Full sample

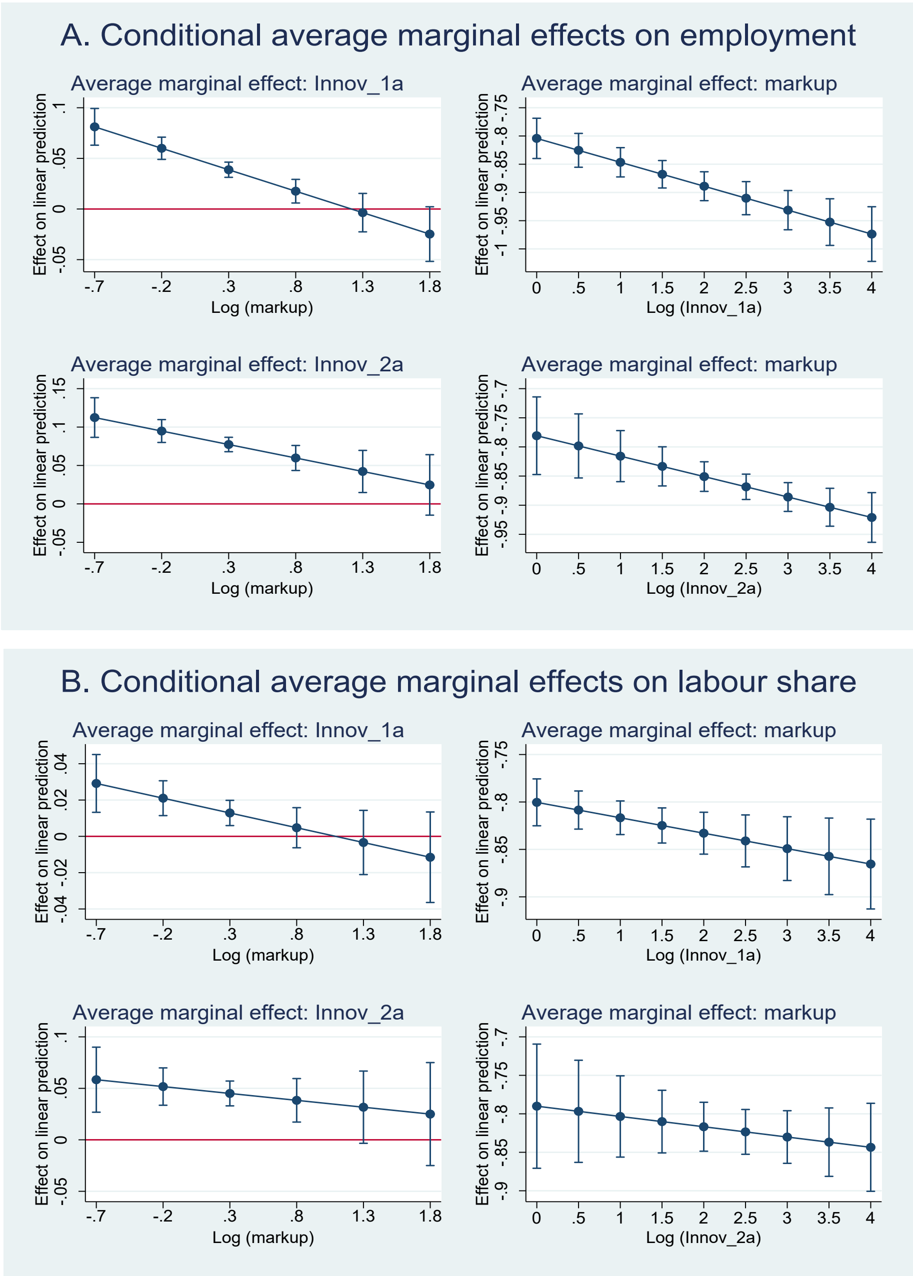
Dependent variable: Labour share	(1) Innovation Int_1a Lerner-based markup	(2) Innovation Int_1a Profits-based markup	(3) Innovation Int_2a Lerner-based markup	(4) Innovation Int_2a Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	0.0487***	0.0178***	0.1043***	0.0491***	100
	(0.0084)	(0.0040)	(0.0102)	(0.0051)	
Markup	-1.1426***	-0.8004***	-0.8275***	-0.7901***	100
	(0.0542)	(0.0126)	(0.0586)	(0.0236)	
Innovation-markup interaction	-0.1121***	-0.0163**	-0.2329***	-0.0134	75
	(0.0277)	(0.0078)	(0.0242)	(0.0096)	
Capital-labour ratio	-0.1317***	-0.2348***	-0.1260***	-0.2298***	100
	(0.0068)	(0.0038)	(0.0059)	(0.0036)	
Employment protection legislation	0.1203***	0.1350***	0.1063***	0.1340***	100
	(0.0271)	(0.0196)	(0.0263)	(0.0192)	
Value added (current prices)	-0.0605***	-0.0258***	-0.0437***	-0.0243***	100
	(0.0067)	(0.0034)	(0.0057)	(0.0034)	
Constant	0.7000***	0.9069***	0.3446***	0.7855***	n.a.
	(0.0821)	(0.0409)	(0.0685)	(0.0429)	
Observations	8697	8949	8559	8804	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.8735	0.9174	0.8605	0.9048	
R^2 (within)	0.4824	0.6308	0.4937	0.6393	
Log likelihood	2222.8451	4132.1288	2393.4330	4282.6196	
RMSE	0.1882	0.1531	0.1838	0.1494	

Notes: The dependent variable is two-year-forward value of labour share. Results based on one-year forward and contemporaneous values of employment are consistent. These are not reported to save space but can be provided on request. For other notes, see Table 3.

The coefficient estimates for market power are consistent with the predictions from the first-order conditions in the CES/VES production functions and across all robustness checks. In the case of the interaction term between innovation and market power, however, the level of consistency across robustness checks is 75% only. The labour share always falls with markups and this adverse effect is exacerbated when innovation increases in industries with market power. The adverse effect of market power we establish is also consistent with the increasing evidence on macroeconomic consequences of market power. In this line of research, market power is a major cause of declining labour share because it enables firms to maximise profits at lower levels of labour utilisation compared to perfect competition (Barkai, 2020; De Loecker et al., 2020; Eggertsson et al., 2021; Gutiérrez and Philippon, 2019). What we add to the extant literature is to demonstrate that this effect is not necessarily linear. Our findings indicate that the adverse effect of market power on labour share is exacerbated as the level of innovation increases in the industry.

The coefficient estimates for the remaining covariates in Tables 3 and 4 are also consistent with the theoretical and empirical literature. For example, capital deepening (i.e., a higher capital/labour ratio) is always associated with a negative effect on employment and labour share. This is consistent with the predictions from the first-order conditions in the CES/VES production functions and with empirical evidence in Bellocchi and Travaglini (2023), who report that capital deepening, together with markup and technological change, are significant determinants of labour share and employment. In the employment model (Table 3), real wages are always associated with a fall in employment – in line with predictions from the derived labour demand models (Chenneles and Van Reenen, 2002; Van Reenen, 1997). In both Table 3 and Table 4, employment protection legislation (EPL) is always associated with an increase in employment and labour share, respectively. The positive effect of EPL on employment is consistent with meta-analysis evidence in Heimberger (2021), who report that EPL in OECD countries is less likely to increase unemployment compared to EPL measures for other countries. The positive effect of EPL on labour share, on the other hand, is consistent with empirical 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). Finally, higher real value added is conducive to higher employment in Table 3 but a higher value added in current prices is a source of falling labour share in Table 4. The positive effect of real value added on employment is consistent with the predictions from the first-order conditions in the CES.VES production func and with the derived labour demand models (Chenneles and Van Reenen, 2002; Van Reenen, 1997). The negative relationship between valued added in current prices and labour share (Table 4) captures the inbuilt negative association between value added and labour share measure, where value added in current prices appears in the denominator.

Figure 1: Conditional average marginal effects of innovation and markups on employment and labour share



We conclude the discussion on the estimation results by examining the average marginal effects (AMEs) of innovation and markups on employment and labour share after taking account of the indirect (interaction) effects in Figure 1. The AMEs on employment are depicted in panel A, followed by the AMEs on labour share in Panel B. Also, the AMEs of technological innovation (*I*) on both outcomes are depicted in the left half, followed by the AMEs of markups (*M*) in the right half of Figure 1. The AMEs are predicted in accordance with the partial derivatives of the employment (*L*) and labour share (*LS*) models (equations 9a and 9b above) with respect to innovation and employment – as stated below.

AMEs on employment in Panel A $\quad \frac{\partial L}{\partial I} = \beta_{11} + \beta_{13}(M) \quad \frac{\partial L}{\partial M} = \beta_{12} + \beta_{13}(I)$

AMEs on employment in Panel B $\quad \frac{\partial LS}{\partial I} = \beta_{21} + \beta_{23}(M) \quad \frac{\partial LS}{\partial M} = \beta_{22} + \beta_{23}(I)$

Focusing on AMEs in the left half of Figure 1, we observe that the small but positive effect of technological innovation on both employment and labour share declines as the level of market power increases. The AMEs become statistically and/or practically insignificant when the markup is at or beyond the 75th percentile of the markup distribution in the sample. In the right half of Figure 1, markups always have a negative and large effect on both employment and labour share; and the adverse effect is exacerbated as innovation increases in the industry. Given the level of consistency in the robustness checks, one conclusion we derive is that market power is the main driver of the decline in employment and/or labour share in OECD and Eurozone industries. The second conclusion is that the estimates for employment and/or labour-share effects of technological innovation or markups would be biased if the estimated models fail to control for the direct and indirect effects of both determinants.

Conclusions

In this paper, we have identified an oversight 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 tends to neglect market power as an additional determinant with direct and mediating effects on employment. 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; Aghion et al., 2019a). On the other hand, the effect of market power on employment or labour share is modeled and estimated without controlling for the direct or mediating effects of technological innovation (Barkai, 2020; De Loecker et al., 2020; Eggertsson et al., 2021; Gutiérrez and Philippon, 2019).

Drawing on first-order conditions in the constant and variable elasticity of substitution (CES/VES) production functions, we have demonstrated that the separation of technological innovation and market power in empirical models of employment or labour share is not warranted. Indeed, profit-maximising behaviour under imperfect competition implies that the effects of technological change and market power on employment and labour share are intertwined (Raurich et at., 2012; Bellocchi and Travaglini, 2023; Di Pace and Villa, 2016; Velasquez, 2023).

Drawing on country-industry data for 32 industries in 12 OECD countries and empirical models that control for markups, innovation, and their interaction effects, we obtained two novel findings. Compared to technological innovation, higher levels of market power are by far the more important source of lower employment and labour share in OECD/European industries. Secondly, the effects of market power and technological innovation on employment or labour share are substitutes: the increase in one determinant reduces the positive effect or exacerbates the negative effect of the other determinant on both employment and labour share. Therefore, we 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.

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Appendix

Appendix

This Appendix contains descriptive information on the sample and several robustness checks for the estimations reported in the main text of the paper titled: "Technological innovation, markups, and the labour market: Direct and mediating effects on employment and the labour share". The descriptive information consists of variable description and documentation, summary statistics, and evolution or markups, labour share and innovation by country. The robustness checks consist of estimation results based on different samples and innovation intensity measures.

Table A1.1: Variable description and documentation

Variable	Description	Source
	Variables at the industry-country level	
Innovation intensity 1a and 1b	**1a:** The ratio of investment in research and development (R&D), computers and software, and other intellectual property assets to value added. **1a:** The ratio of investment in research and development (R&D), computers and software, and other intellectual property assets to total investment.	EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/
Innovation intensity 2a and 2b	2a: Innovation investment in (1) plus investment in marketing innovation, organisational innovation and economic competencies divided by value added. 2b: Innovation investment in (1) plus investment in marketing innovation, organisational innovation and economic competencies divided by total investment.	EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/
Markup - Ciapanna et al. (2020)	A Lerner index-based markup, calculated as the ratio of gross operating margin to the sum intermediates cost and labour cost.	Own calculation, using necessary data from EU-KLEMS&INTANProd database at https://euklems-intanprod-llee.luiss.it/
Markup - Barkai (2020)	A profit-based markup, calculated as the ratio of value added to the sum of capital cost, labour cost and indirect taxes on goods and services.	Own calculation, using data from EU-KLEMS&INTANProd database at https://euklems-intanprod-llee.luiss.it/ and from OECD Global Revenue Statistics database at https://stats.oecd.org/Index.aspx?DataSetCode=RS_GBL
Labour share	Compensation of employees divided by value added.	EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/
Value added (current)	Gross value added, current prices, millions.	EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/
Value added (constant)	Gross value added, constant 2015 prices, millions.	EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/
Wage (real)	Average wage per employee in 2015 constant prices	
	Variables at the country level	
Employment protection legislation (*EPL*)	An index of employment protection through regulations on the dismissal of workers on regular contracts and the hiring of workers on temporary contracts (between 0 and 6)	OECD statistical databases https://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm

Table A1.2: Summary statistics

Variables in level	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Innovation intensity 1	6,553	6.824	7.051	1.000	38.225
Innovation intensity 2	6,536	15.655	9.372	1.192	53.600
Labour share	6,553	0.597	0.174	0.163	0.927
Lerner-index-based markup	6,553	1.211	0.164	1.001	2.382
Lerner-index-based markup sq.	6,553	1.494	0.461	1.003	5.673
Profits-based markup	6,553	1.354	0.331	0.553	3.240
Profits-based markup sq.	6,553	1.942	1.128	0.306	10.498
Innovation productivity (%)	6,553	0.271	1.028	-23.273	38.318
Intellectual and physical property rights index (IPRI)	6,553	7.521	0.904	5.600	8.700
Human capital	6,553	3.318	0.292	2.569	3.766
Trade-union density	6,553	31.373	21.364	9.900	84.700
Employment protection legislation	6,553	3.725	1.482	0.343	7.766
Product-market regulation	6,553	1.564	0.394	0.872	2.954
Variables in logs (except %)	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Innovation intensity 1	6,553	1.461	0.947	0.000	3.643
Innovation intensity 2	6,536	2.562	0.645	0.175	3.982
Labour share	6,553	-0.570	0.350	-1.811	-0.076
Lerner-index-based markup	6,553	0.184	0.121	0.001	0.868
Lerner-index-based markup sq.	6,553	0.048	0.073	0.000	0.753
Profits-based markup	6,553	0.278	0.217	-0.592	1.176
Profits-based markup sq.	6,553	0.124	0.181	0.000	1.382
Innovation productivity (%)	6,553	0.271	1.028	-23.273	38.318
Intellectual and physical property rights index (IPRI)	6,553	2.010	0.126	1.723	2.163
Human capital	6,553	1.195	0.090	0.943	1.326
Trade-union density	6,553	3.245	0.619	2.293	4.439
Employment protection legislation	6,553	1.152	0.721	-1.069	2.050
Product-market regulation	6,553	0.418	0.240	-0.137	1.083

Table A2: Industries and countries in the estimation sample

	Industries
NACE Rev. 2 Code	**Description**
B	Mining and quarrying
C10-C12	Manufacture of food products; beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel, leather and related products
C16-C18	Manufacture of wood, paper, printing and reproduction
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22-C23	Manufacture of rubber and plastic products and other non-metallic mineral products
C24-C25	Manufacture of basic metals and fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29-C30	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment
C31-C33	Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	Accommodation and food service activities
J58-J60	Publishing, motion picture, video, television programme production; sound recording, programming and broadcasting activities
J61	Telecommunications
J62-J63	Computer programming, consultancy, and information service activities
M	Professional, scientific and technical activities
N	Administrative and support service activities

	Countries
Code	**Name**
AT	Austria
CZ	Czech Republic
DE	Germany
ES	Spain
FI	Finland
FR	France
IT	Italy
JP	Japan
NL	The Netherlands
SE	Sweden
UK	United Kingdom
US	United States

Table 3A: Innovation and markups: Direct and indirect effects on **employment** in the **Euro-area sample**

Dependent variable: Employment	(1) Innovation Int_1a Lerner-based markup	(2) Innovation Int_1a Profits-based markup	(3) Innovation Int_2a Lerner-based markup	(4) Innovation Int_2a Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	0.0413***	0.0285***	0.1546***	0.0917***	100#
	(0.0129)	(0.0066)	(0.0173)	(0.0090)	
Markup	-1.2771***	-0.7408***	-0.6732***	-0.5329***	100
	(0.0787)	(0.0269)	(0.1313)	(0.0444)	
Innovation-markup interaction	-0.1245***	-0.0498***	-0.3040***	-0.1108***	100
	(0.0451)	(0.0143)	(0.0517)	(0.0179)	
Capital-labour ratio	-0.1055***	-0.2834***	-0.1138***	-0.2525***	100
	(0.0115)	(0.0090)	(0.0090)	(0.0065)	
Real wage	-0.8281***	-0.8732***	-0.8857***	-0.8894***	100
	(0.0219)	(0.0112)	(0.0157)	(0.0101)	
Employment protection legislation	-0.0945**	0.0267	-0.0718*	0.0442	100
	(0.0458)	(0.0416)	(0.0391)	(0.0269)	
Value added (constant 2015 prices)	0.8950***	0.9509***	0.9431***	0.9631***	100
	(0.0169)	(0.0066)	(0.0085)	(0.0060)	
Constant	6.1612***	6.7460***	6.0373***	6.4809***	n.a.
	(0.1675)	(0.1205)	(0.1717)	(0.0972)	
Observations	3747	3750	3648	3633	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.9891	0.9919	0.9903	0.9944	
R^2 (within)	0.8440	0.8887	0.8631	0.9211	
Log likelihood	1300.7819	1909.8802	1573.8522	2562.4928	
RMSE	0.1726	0.1468	0.1587	0.1207	

Notes: Innovation intensities 1a and 2a are investment in tangible (knowledge) assets as % of value added (equations 10a and 10b in section 4 above). The Lerner- and profit-based markups are as defined in equations 11 and 12a. Three-way fixed-effect estimation with control for country, industry, and time fixed effects. All variables are in natural logarithms. The dependent variable is the two-year-forward value of employment. Results based on one-year forward and contemporaneous values of employment are consistent. These are not reported to save space but can be provided on request. Robust standard errors are in parentheses. # The level of consistency for the innovation coefficient assumes that the constant elasticity of substitution is less than one – in line with meta-analysis findings in Havranek et al. (2019) and Knoblach et al (2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3B: Innovation intensity relative to total investment and markups: Direct and indirect effects on **employment** in the **full sample**

Dependent variable: Employment	(1) Innovation Int_1b Lerner-based markup	(2) Innovation Int_1b Profits-based markup	(3) Innovation Int_2b Lerner-based markup	(4) Innovation Int_2b Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	0.0100	0.0074**	0.0009	0.0161***	50#
	(0.0067)	(0.0036)	(0.0073)	(0.0050)	
Markup	-1.1824***	-0.7436***	-1.1128***	-0.5625***	100
	(0.0526)	(0.0227)	(0.0573)	(0.0455)	
Innovation-markup interaction	-0.0693***	-0.0552***	-0.0711***	-0.0869***	100
	(0.0192)	(0.0074)	(0.0150)	(0.0112)	
Capital-labour ratio	-0.1158***	-0.2488***	-0.1218***	-0.2471***	100
	(0.0067)	(0.0055)	(0.0067)	(0.0060)	
Real wage	-0.8292***	-0.8731***	-0.8273***	-0.8709***	100
	(0.0156)	(0.0073)	(0.0154)	(0.0074)	
Employment protection legislation	0.0316	0.1032***	0.0308	0.0993***	100
	(0.0258)	(0.0227)	(0.0260)	(0.0226)	
Value added (constant 2015 prices)	0.8800***	0.9417***	0.8794***	0.9416***	100
	(0.0147)	(0.0038)	(0.0145)	(0.0041)	
Constant	6.3025***	6.8154***	6.3503***	6.7468***	n.a.
	(0.1054)	(0.0814)	(0.1056)	(0.0840)	
Observations	8676	9022	8676	9022	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.9900	0.9937	0.9900	0.9937	
R^2 (within)	0.8558	0.9076	0.8562	0.9086	
Log likelihood	2625.8716	4847.9328	2639.2899	4898.1077	
RMSE	0.1796	0.1420	0.1793	0.1412	

Notes: See Table 3A above.

Table 3C: Innovation intensity relative to total investment and markups: Direct and indirect effects on **employment** in the **Euro-area sample**

Dependent variable: Employment	(1) Innovation Int_1b Lerner-based markup	(2) Innovation Int_1b Profits-based markup	(3) Innovation Int_2b Lerner-based markup	(4) Innovation Int_2b Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	-0.0135	-0.0069	-0.0242*	-0.0208**	0$^{\#}$
	(0.0109)	(0.0047)	(0.0124)	(0.0082)	
Markup	-1.3243***	-0.6749***	-1.3077***	-0.4638***	100
	(0.1037)	(0.0339)	(0.1413)	(0.0761)	
Innovation-markup interaction	-0.0218	-0.0555***	-0.0174	-0.0922***	50
	(0.0345)	(0.0105)	(0.0346)	(0.0186)	
Capital-labour ratio	-0.1052***	-0.2749***	-0.1153***	-0.2875***	100
	(0.0113)	(0.0084)	(0.0117)	(0.0096)	
Real wage	-0.7756***	-0.8710***	-0.7735***	-0.8668***	100
	(0.0318)	(0.0113)	(0.0320)	(0.0119)	
Employment protection legislation	-0.1040**	0.0148	-0.0994**	0.0222	100
	(0.0467)	(0.0413)	(0.0470)	(0.0405)	
Value added (constant 2015 prices)	0.8411***	0.9465***	0.8379***	0.9428***	100
	(0.0327)	(0.0071)	(0.0330)	(0.0078)	
Constant	6.1534***	6.7961***	6.2607***	6.9051***	n.a.
	(0.1649)	(0.1199)	(0.1629)	(0.1257)	
Observations	3795	3794	3795	3794	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.9868	0.9919	0.9868	0.9921	
R^2 (within)	0.8114	0.8894	0.8116	0.8913	
Log likelihood	941.2382	1946.3400	943.7080	1978.0432	
RMSE	0.1906	0.1462	0.1904	0.1450	

Notes: See Table 3A above.

Table 4A: Innovation intensity relative to value added and markups: Direct and indirect effects on **labour share** in the **Euro-area sample**

Dependent variable: Labour share	(1) Innovation Int_1a Lerner-based markup	(2) Innovation Int_1a Profits-based markup	(3) Innovation Int_2a Lerner-based markup	(4) Innovation Int_2a Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	0.0442***	0.0121**	0.0903***	0.0454***	100
	(0.0123)	(0.0058)	(0.0169)	(0.0119)	
Markup	-0.9409***	-0.6759***	-0.6244***	-0.5319***	100
	(0.1022)	(0.0198)	(0.1254)	(0.0548)	
Innovation-markup interaction	-0.2141***	-0.0739***	-0.2700***	-0.1034***	100
	(0.0465)	(0.0126)	(0.0486)	(0.0237)	
Capital-labour ratio	-0.1009***	-0.2269***	-0.1088***	-0.2299***	100
	(0.0101)	(0.0062)	(0.0091)	(0.0067)	
Employment protection legislation	0.0156	0.0957***	0.0191	0.1226***	100
	(0.0442)	(0.0320)	(0.0423)	(0.0322)	
Value added (current prices)	-0.0286***	-0.0029	-0.0257***	-0.0020	50
	(0.0108)	(0.0056)	(0.0083)	(0.0074)	
Constant	0.1640	0.4148***	0.0255	0.3131***	
	(0.1334)	(0.0687)	(0.1038)	(0.0843)	
Observations	3760	3738	3666	3647	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.8666	0.9220	0.8369	0.9025	
R^2 (within)	0.3605	0.5655	0.3796	0.5796	
Log likelihood	1130.1820	1882.1257	1201.8506	1925.9018	
RMSE	0.1808	0.1476	0.1760	0.1440	

Notes: The dependent variable is two-year-forward value of labour share. Results based on one-year forward and contemporaneous values of employment are consistent. These are not reported to save space but can be provided on request. For other notes, see Table 3.

Table 4B: Innovation intensity relative to total investment and markups: Direct and indirect effects on **labour share** in the **full sample**

Dependent variable: Labour share	(1) Innovation Int_1b Lerner-based markup	(2) Innovation Int_1b Profits-based markup	(3) Innovation Int_2b Lerner-based markup	(4) Innovation Int_2b Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	0.0147**	0.0087**	0.0046	0.0308***	100#
	(0.0065)	(0.0038)	(0.0068)	(0.0050)	
Markup	-1.0328***	-0.7228***	-1.0714***	-0.6066***	100
	(0.0620)	(0.0214)	(0.0591)	(0.0392)	
Innovation-markup interaction	-0.1215***	-0.0468***	-0.0704***	-0.0631***	100
	(0.0211)	(0.0075)	(0.0140)	(0.0095)	
Capital-labour ratio	-0.1163***	-0.2263***	-0.1224***	-0.2195***	100
	(0.0060)	(0.0046)	(0.0064)	(0.0049)	
Employment protection legislation	0.1046***	0.1232***	0.1023***	0.1137***	100
	(0.0268)	(0.0203)	(0.0271)	(0.0204)	
Value added (current prices)	-0.0546***	-0.0240***	-0.0577***	-0.0226***	100
	(0.0066)	(0.0046)	(0.0066)	(0.0047)	
Constant	0.5995***	0.8621***	0.6900***	0.7225***	n.a.
	(0.0816)	(0.0561)	(0.0862)	(0.0640)	
Observations	8786	9034	8786	9034	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.8721	0.9165	0.8713	0.9171	
R^2 (within)	0.4820	0.6303	0.4786	0.6330	
Log likelihood	2224.6594	4146.6765	2195.7150	4180.0212	
RMSE	0.1887	0.1536	0.1893	0.1530	

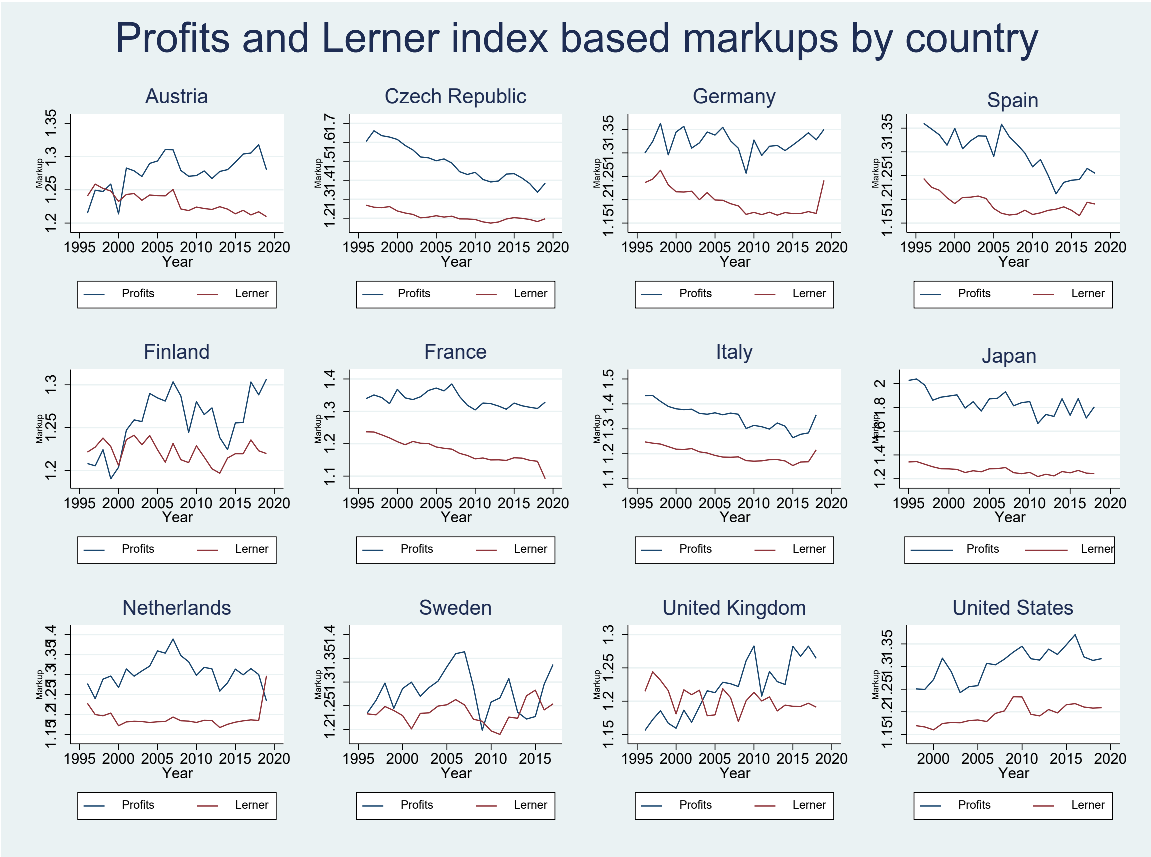
Notes: The dependent variable is two-year-forward value of labour share. Results based on one-year forward and contemporaneous values of employment are consistent. These are not reported to save space but can be provided on request. For other notes, see Table 3.

Table 4C: Innovation intensity relative to total investment and markups: Direct and indirect effects on **labour share** in the **Euro-area sample**

Dependent variable: Labour share	(1) Innovation Int_1b Lerner-based markup	(2) Innovation Int_1b Profits-based markup	(3) Innovation Int_2b Lerner-based markup	(4) Innovation Int_2b Profits-based markup	(5) Consistency with predictions in Table 2 (%)
Innovation intensity	0.0210**	0.0050	0.0018	0.0083	100$^{\#}$
	(0.0098)	(0.0056)	(0.0111)	(0.0077)	
Markup	-0.8353***	-0.5768***	-0.8868***	-0.3848***	100
	(0.1192)	(0.0341)	(0.1544)	(0.0596)	
Innovation-markup interaction	-0.1675***	-0.0836***	-0.0891***	-0.1057***	100
	(0.0365)	(0.0114)	(0.0324)	(0.0149)	
Capital-labour ratio	-0.0960***	-0.2212***	-0.1027***	-0.2260***	100
	(0.0092)	(0.0065)	(0.0101)	(0.0071)	
Employment protection legislation	0.0125	0.0897***	0.0092	0.0902***	50
	(0.0436)	(0.0330)	(0.0445)	(0.0332)	
Value added (current prices)	-0.0219**	-0.0001	-0.0248**	-0.0014	50
	(0.0104)	(0.0074)	(0.0105)	(0.0074)	
Constant	0.0940	0.3856***	0.1996	0.4029***	n.a.
	(0.1343)	(0.0834)	(0.1390)	(0.0940)	
Observations	3806	3781	3806	3781	
Prob > F	0.0000	0.0000	0.0000	0.0000	
R^2 (adjusted)	0.8654	0.9221	0.8633	0.9223	
R^2 (within)	0.3578	0.5683	0.3476	0.5693	
Log likelihood	1145.7996	1923.5198	1115.7260	1927.9317	
RMSE	0.1807	0.1468	0.1821	0.1466	

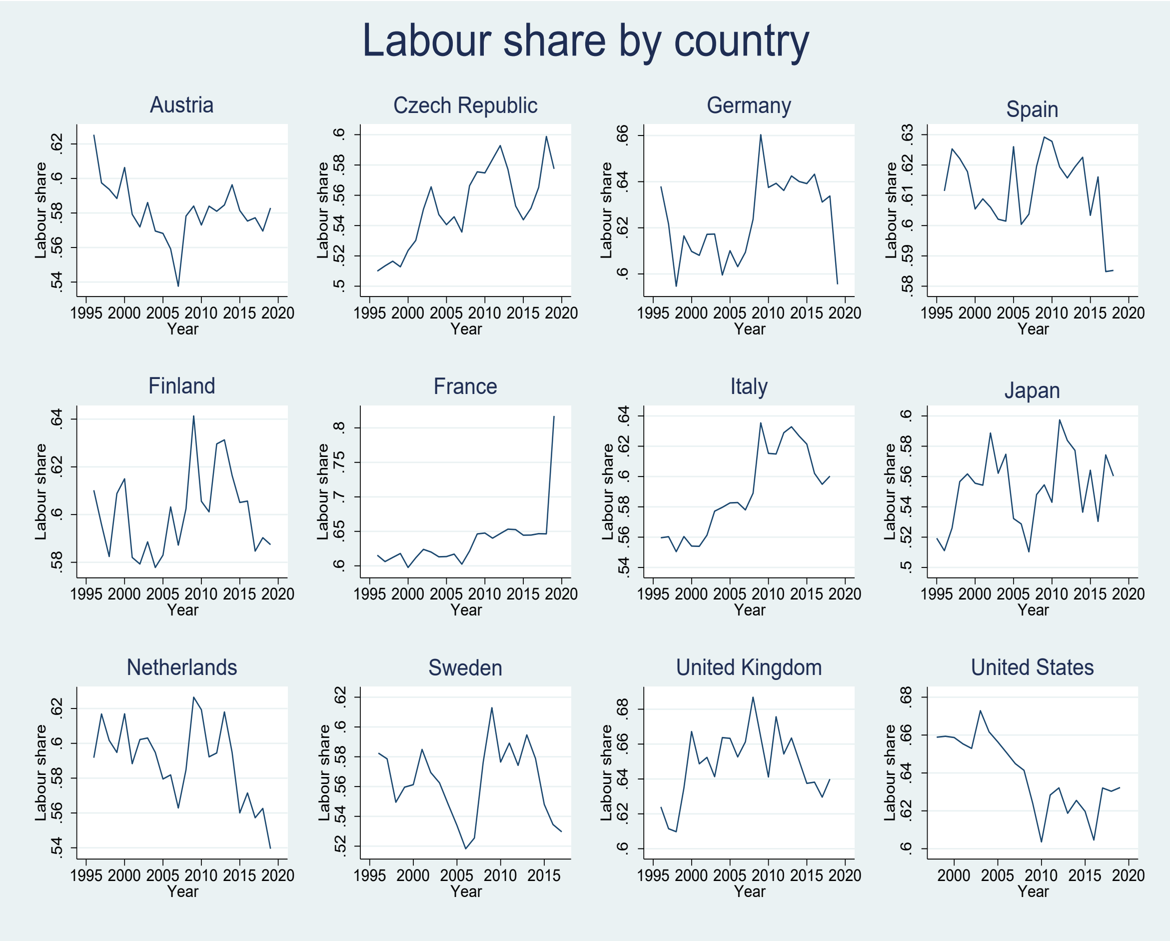
Notes: The dependent variable is two-year-forward value of labour share. Results based on one-year forward and contemporaneous values of employment are consistent. These are not reported to save space but can be provided on request. For other notes, see Table 3.

Figure A1: Evolution of average markups by country



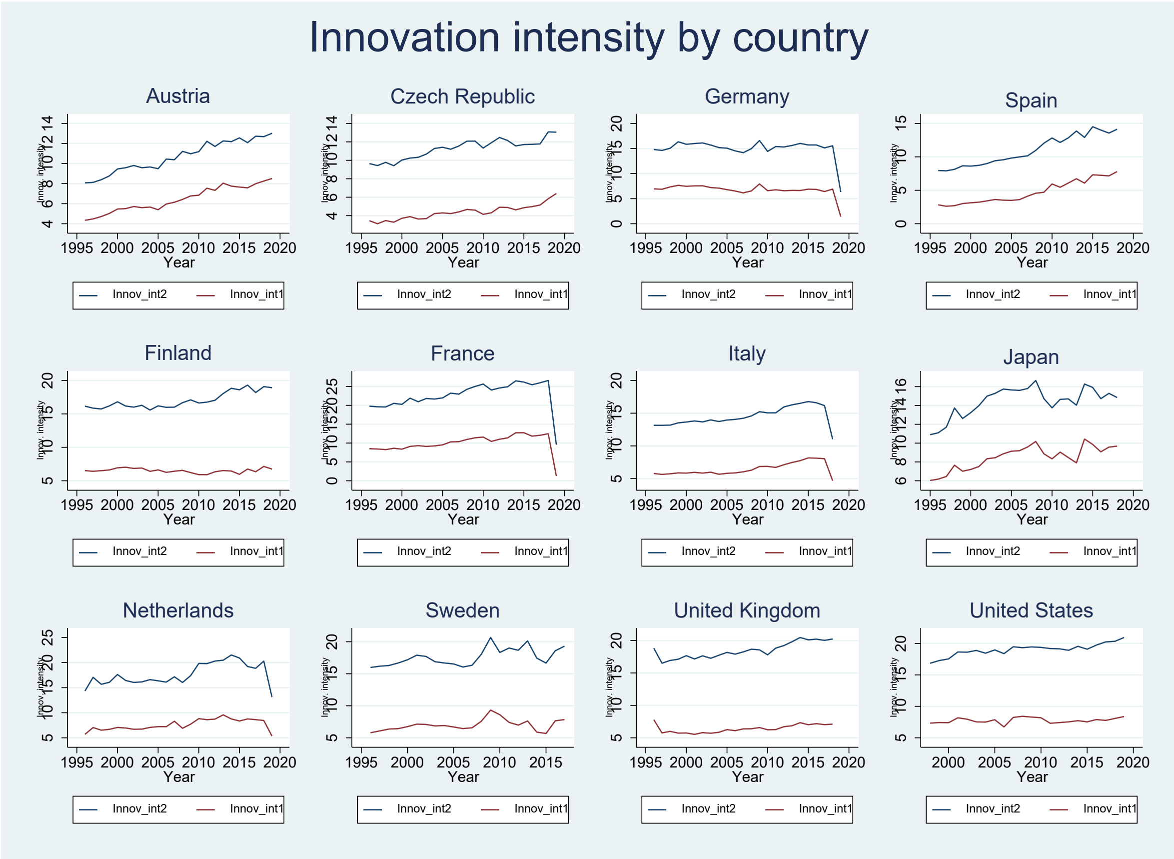
We draw on Barkai (2020) and Eggertsson et al. (2021) for the profits-based markups and on Ciapanna et al. (2020) for the Lerner-index-based markup. The two markups differ in magnitude, but they are corelated within each country - with a within-country correlation ranging from 0.15 in Austria to 0.53 in Spain and the US and 0.72 in Japan. The markups vary over time but with evident decline during the global financial crisis. This is in line with the procyclicality of markups reported in Braun and Raddatz (2016) and Nekarda and Ramey (2020). Finally, the country-level markups are converging towards a sample average of approximately 1.20. The convergence is driven by falling markups in countries with above-average markups at the beginning of the period (e.g., the Czech Republic, Japan, Italy) but by increasing markups in countries with below-average markups at the beginning of the analysis period (e.g., Finland, United Kingdom, United States).

Figure A2: Evolution of labour share by country



The country-level labour share is converging towards an average around 0.58. This convergence is driven by falling labour share in countries with above-average labour share at the beginning of the period (e.g., Austria, Germany, Spain, Netherlands, United States) but by increasing labor share in countries with below-average labour share at the beginning of the analysis period (e.g., the Czech Republic, France, Italy, United Kingdom). There is evidence of counter cyclicality in labour share as it tends to increase over the 3-year period from 2007-2009. After the crisis, the labour share continues to decline in all countries except France and Italy. The counter-cyclicality of labour share has been discussed around the issue of labour hoarding during the crisis period from 2007-2010 (Vella, 2018).

Figure A3: Evolution of innovation intensity by country



Innov_int1 corresponds to the narrow definition of innovation. It consists of investment in research and development (*R&D*), computers, software, and databases (*COMP_Soft_DB*), and other intellectual property assets (*Other_IP*) as percentage of value added. *Innov_int2*, on the other hand, corresponds to the wide definition and includes innovation investment in organizational innovation (*Org_in*), marketing innovation (*Mark_in*), and economic competencies (*Ec_Comp*) in addition to the innovation investment components included in the narrow definition. Both innovation intensities exhibit an increasing trend over time until 2017, after which both measures fall sharply in some countries with higher-than-average innovation intensity to start with (e.g., Germany, France, Italy, and The Netherlands).