# Innovation, market power and the labour share:
# Evidence from OECD industries


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## Abstract

Two issues remain overlooked in the growing research effort on the relationship between innovation, market power and labour share. One is the simultaneous determination of innovation, market power and labour share as endogenous outcomes. The second is the role of market power as a confounder that affects both innovation and labour share at the same time. We address both issues by adopting a simultaneous equations approach and using EU-KLEMS data from 1995-2019 on 31 OECD industries and 12 countries. Our findings indicate that: (i) innovation always increases with markups, particularly when the latter increase from a high initial level; (ii) market power always increase with innovation, particularly when the latter is extended to include marketing and organisational innovation; (iii) the effects of market power on labour share are always more adverse than the innovation effects; and (iv) the combined effect of labour-market institutions and human capital is not sufficient to reverse the adverse effect of market power on labour share. Our findings indicates that the major driver of the decline in labour share is not technological innovation *per se*, but the extent of market power that allows innovators to extract innovation rents.



**Keywords:** Technological innovation, markups, labour share, simultaneous equations



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## 1. Introduction

The decline in labour share in the United States and other developed countries has led to a large body of research on the roles of technological change and market power. In one line of research, the primary driver is technological change/innovation – particularly when the elasticity of substitution between capital and labour is larger than one (Karabarbounis and Neiman, 2014) or when the labour displacement effect of technological change is greater than its task creation effect (Acemoglu and Restrepo, 2018; Autor and Salomons, 2018). In another line of research, the decline in labour share is related to market power, which 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).

At the theoretical level, both lines of research acknowledge that technological change (innovation) and market power are interrelated. This theoretical recognition, however, is not reflected in the empirical models they inform. Indeed, the empirical models tend to relate labour share to technological innovation or market power only, overlooking the two-way relationship between the two and the need to disentangle the labour-share-effect of one from the other. As a result, effect-size estimates from such models may not constitute a reliable basis for evidence-based policy and practice for two reasons. First, the estimates may be subject to misspecification bias, which results from overlooking the simultaneity and reverse causality between market power and innovation. Secondly, they may also be subject to a confounding bias, which results from overlooking market power as a confounder that affects both innovation and labour share at the same time.[1]

The aim of this study is to address these sources of potential bias by proposing and estimating a simultaneous equation model where we allow for: (i) simultaneity and reverse-causality between innovation and market power; and (ii) joint determination of innovation, market power and labour share as co-evolving endogenous outcomes. Theoretically, the proposed model draws on testable predictions form Schumpeterian models of innovation (Aghion et al., 2015 and 2019a) where markups are both a driver for and an outcome of investment in

[1] A similar confounding bias is also likely if innovation affects both market power and labour share at the same time.

innovation. It is also draws on induced technological change models where profit-maximising firms substitute knowledge-intensive capital for labour when the price of the latter increases (Hicks, 1963; Kennedy, 1964; Caselli, 1999); and with skill-biased technical change (SBTC) model where technological innovation responds to the supply of skills and affects both wage inequality and the functional distribution of income. (Katz and Murphy, 1992; Acemoglu, 1998, 1999; 2002).

Using this modelling framework, we provide confirmatory evidence that both technological innovation and market power have adverse effects on labour share. Beyond this confirmatory evidence, we contribute to existing knowledge in three areas. First, we demonstrate that the adverse effect of market power on labour share is much stronger than that of technological innovation – both directly and indirectly. Secondly, we find that innovation increases with markups in a non-linear fashion, particularly when markups increase from a high initial level. Third, we find that markups increase with innovation linearly, with the rate of increase becoming higher when innovation includes investment in organisational change and new marketing strategies in addition to investment in R&D and information technology. Our fourth contribution is based on post-estimation tests, which indicate that the total effect of labour-market institutions and human capital is not sufficient to reverse the adverse effects of market power on labour share. Given that these novel findings remain consistent across various robustness checks, we argue that the major driver of the decline in labour share is not technological innovation *per se*, but the extent to which innovators are able to extract innovation rents.

The rest of the paper is organised in five sections. In section 2, we review the relevant literature on technological change (innovation) and market power as two potential determinants of falling labour share. First, we discuss the alternative measures of market power and conclude in favour of accounting-based measures that minimise the risk of model uncertainty. Then, we review the current practice of estimating reduced-form or single-equation models where either technological innovation or markups is a potential determinant of falling labour share. We conclude the literature review by arguing in favour of a simultaneous equation modelling approach, where technological innovation, market power and labour share are determined simultaneously and market power affects both innovation and labour share at the same time.

Section 4 presents our data (country-industry data for 12 OECD countries and 31 industries) from the *EUKLEMS & INTANProd* database.[2] The country-industry data is augmented with country-level data on human capital, internal rates of return on capital, physical and intellectual property rights protection, product market regulation and labour-market characteristics such as trade union density and employment protection legislation. Our preferred method for estimating the system of equations is the asymptotic distributions free (ADF) methodology used for estimating structural equation models (SEMs) when the data does not support the assumption of joint (multivariate) normality. We verify the stability/consistency of the estimates by utilising two further estimator: (i) a maximum likelihood (ML) estimator that also takes account of error correlations but assumes joint normality; and (ii) a three-stage least-squares (3SLS) estimator that takes account error correlations but assumes homoscedastic errors.

Section 5 presents our main findings, complemented with additional robustness checks in the Appendix. The main findings and the robustness checks are highly consistent and in line with the theoretical predictions that underpin the structural equations in the model. Higher markups are always conducive to lower labour share. Moreover, both direct and total adverse effects of markups on labour share are stronger than those of technological innovation. These findings remain robust across three different estimators, two markup measures and two measures for innovation intensity. Moreover, post-estimation tests indicate that the combined effect of labour-market institutions and human capital are insufficient to reverse the adverse effects of market power on labour share. Section 6 concludes with a summary of the main findings and some remarks pointing to the need for addressing market power as a major source of distortions that have both efficiency (i.e., objective) and fairness (i.e., normative) implications.

## 2. Related literature

One line of research we draw upon focuses on the measurement of market power and its economic implications at the firm, industry or country levels (for reviews, see Basu, 2019; Syverson, 2019; Battiaiti et al., 2021; and Bond et al., 2021). Work in this domain dates to

[2] The EU KLEMS & INTANProd database is available from the LUISS Lab of European Economics at LUISS University at https://euklems-intanprod-llee.luiss.it/

Hall (1989, 1990) and Roeger (1995), both of whom use econometric methods to back up country-level markups from the production function estimates. Whereas the former exploits the invariance properties of the Solow residual, the latter exploits the cost-minimisation problem of the firm as the dual of the profit-maximisation problem. For micro-level estimation, De Loecker et al. (2020) also adopts econometric approach and calculates the markup as the ratio of labour's marginal product to its share observed in the data. A third approach utilise non-econometric methods that rely on accounting data to derive two markup measures: a profit-based measure where markups are proportional to the inverse of the economic (excess) profits (Barkai, 2020; Eggertsson et al., 2021); or a Lerner-index-based measure the extent to which prices exceed marginal costs (Ciapanna et al., 2022).

One advantage of the econometric methods is that they do not impose constant returns to scale in production. Moreover, they do not require information about demand elasticity and/or marginal costs, the non-availability of which has constrained the markup estimation in the past. However, both approaches require correct input measurement, correct functional form for the production function, and correct estimation of the latter.

Replication work by Rovigatti (2020) demonstrates that the Hall (1989, 1990) method yields larger markup estimates on average, coupled with a high degree of heterogeneity where about 30% of the markup estimates are less than 1. Moreover, the difference between Hall (1989, 1990) and Roeger (1995) markups are too large to assuage doubts about their validity in applied research. Part of the reason may be due to measurement and sampling errors in the data, which affect both measures. Another may be due to the use of instruments in Hall (1989, 1990), which may provide good fit in some sectors but a poor fit in others. Moreover, the Roeger (1995) markup requires data on capital costs and the markup estimate is time-invariant.

The micro-level econometric method of De Loecker et al. (2020) follows a different route. In the first step, the output elasticity of a variable input is estimated from the production function, which can be specified as a Cobb-Douglas or as a translog function. Then the firm-level markup is estimated as the ratio of the variable input's output elasticity to the input's share in revenue. Finally, in the third stage, an industry- or country-level markup is obtained as the weighted mean of the firm-level markups using the firms' market or employment shares as weights.

In replication work, Rovigatti (2020) reports that De Loecker et al. (2020) markups estimated from a Cobb-Douglas production function are larger than those estimated from a tanslog function. Nevertheless, the distribution of the markups based on the translog function is noisier and the noise increases as the level of measurement error increases. Another issue with De Loecker markup is highlighted in Bond et al. (2021): the ratio of the variable input's output elasticity to its observed share in output is not informative about markups when firm-level revenue is used instead of output.

That is why Basu (2019) observes that non-econometric methods can be used to avoid the measurement and identification problems associated with econometric methods. The non-econometric markups are based either on economic profits (Barkai, 2020; Eggertsson et al., 2021) or on the Lerner index (Battiati et al. 2021; Ciapanna et al., 2022) - both with well-established micro foundations. Moreover, the non-econometric markups can be estimated from observed firm-, industry- or country-level data. The profits-based markup is calculated as the ratio of value added to the sum capital and labour income, whereas the Lerner-index-based markup is calculated as the ratio of gross operating margin to gross output.

Nevertheless, avoiding model uncertainty comes at the cost simplifying assumptions, one of which is constant returns to scale. This assumption is explicit in the profits-based markup of Barkai (2020) and Eggertsson et al. (2021). In the Lerner-index-based approach of Ciapanna et al., (2022), the assumption is implicit and implied by the assumption of a constant marginal cost proxied by the average cost. The second assumption is that the return on capital is known (or can be calculated) to estimate the capital income in the profit-based method. A third assumption in the Lerner-index-based approach is that the firm always satisfies the first-order conditions with respect to all inputs – i.e., the firm utilises all inputs in accordance with profit maximisation at all times. This assumption may not be satisfied if labour hiring or capital installation takes longer than purchasing intermediate inputs (Battiati et al., 2021).

Comparing the different approaches to markup estimation, Basu (2019) concludes that the econometric approaches yield markup estimates that are too large to be credible. In contrast, the non-econometric approach yields acceptable markup estimates – particularly when the underlying markup definition is profits-based. Moreover, the profits-based markup measures can be improved by taking account of indirect taxes on goods and services and by using more accurate rates of return on capital that take account of the risk-free real interest rates and the risk premium - as it is the case in Barkai (2020) and Gutiérrez (2017). Therefore, we adopt the non-econometric method to obtain two markup measures: (i) a profit-based measure that follows Barkai (2020) and Eggertsson et al. (2020), which we use as the preferred measure; and (ii) a Lerner-index-based measure that follows Battiati et al. (2021) Ciapanna et al. (2022) and we use for robustness checks.

A second strand of the literature related to our work focuses on the implications of market power and technological change for labour share. The work on technological change and labour share dates to the induced technical change (ITC) models of the 1960s, in which profit-maximising firms substitute knowledge-intensive capital for labour when the price of the latter increases relative to the former. The resulting increase in capital intensity of the production process leads to falling labour share or increasing wage disparity or both (Hicks, 1963; Kennedy, 1964; Caselli, 1999). More recent work has highlighted the elasticity of substitution between capital and labour as mediating factor. Although earlier work indicates a substitution elasticity below one (e.g., Chirinko, 2008), more recent work tends to report higher substitution elasticities and falling labour share at the same time (e.g., Karabarbounis and Neiman, 2014).

The increase in the substitution elasticity, hence the adverse effect of technological change on labour share, may be related to increased globalisation, particularly increased participation in global value chains that alter the competitive environment (Autor et al., 2017). Another explanation focuses on the change in the balance between labour displacement and task creation effects of technological innovation. In these models, labour share falls if new technologies destroy jobs at higher rates compared to the rate of new tasks they create (Acemoglu and Restrepo, 2018; Autor and Salomons, 2018).

A third line of related research acknowledges that technological innovation and market power are inter-related, but they relate the fall in labour share to rising market power. This is because, under market power, the value added includes product-market rents in addition to labour compensation and capital compensation compatible with perfect competition. Given that product-market rents accrue primarily to capital owners, labour share will tend to fall as market power (the markup rate) increases – as the evidence from the US and other countries indicates (Barkai, 2020; De Loecker et al., 2020; Battiati et al., 2021).

The increase in markups is conducive to falling labour share in Schumpeterian models of innovation too. Here, technological innovation responds to perceived markup opportunities in the industry and enables successful innovators to extract innovation rents, leading to falling labour share through two channels. On the one hand, the rate of successful innovation increases the share of capital in firm output directly by increasing the profitability of the innovative product lines. On the other hand, technological innovation affects labour share indirectly by enabling successful innovators to extract innovation rents and hence skewing the distribution of functional income in favour of capital. (Aghion, 2002; Aghion et al., 2019a and 2019b; Chu and Cozzi, 2018; Jones and Kim, 2018).[3]

The accumulated evidence so far indicates that labour share falls in both technological innovation and market power. Moreover, technological innovation and market power are inter-related. Yet, the existing empirical work does not control for both technological innovation and market power at the same time. Hence, the 'technological innovation effect' or 'market power effect' they report may suffer from omitted variable bias. Moreover, none of the studies allows for simultaneity and reverse causality between technological innovation and market power. Because either of these variables affects the other and the labour share (i.e., the dependent variable) at the same time, we are faced with an additional source potential bias in reported estimates.

The aim of this study is to use alternative measures of market power and innovation to address both issues through a system of equations approach. In the system, technological innovation increases market power by enabling successful innovators to increase their market shares (Autor et al., 2017; 2020), raise the price of their innovative products and/or lower the price of their inputs (Guellec and Paunov, 2017), or exploiting the benefits of the scale economies and network effects (Bessen, 2017). Innovation is also a driver of market power in Schumpeterian models, where the level of innovation rents is higher in high-technological-lead industries (Aghion et al., 2019a and 2019b; Jones and Kim, 2018).

In the proposed model, market power is a potential determinant of innovation effort too. This is in line both with Schumpeterian models where firms innovate in response to perceived markup opportunities (Aghion et al., 2019a); and with the "winners-take-all" perspective where

[3] An additional insight from the Schumpeterian models that innovation and rents increase the concentration of income among top earners. (Aghion et al., 2019a).

firms innovate to escape competition (Autor et al., 2017; 2020). In the former, market power increases when markups increase in high-technological-lead industries, but the effect is indeterminate if markups increase in low-technological lead industries. Overall, innovation increases with markups, but the increase is more likely when markups increase from a high initial level. In the latter, innovation initially increases due to high levels of competition (low market power), but the successful innovators (the 'super stars') enjoy both higher market power and maintain higher levels of innovation at the same time.

Beyond the two-way causality between them, technological innovation and market power also affect the labour share. The evidence from several lines of research is convergent and indicates that both technical change and market power are conducive to falling labour share. In the work informed by the "winners-take-all" model, technological innovation reduces labour share because of the reallocation of market shares toward "superstar" firms with low labour shares (Autor et al., 2017; 2020). In others, the adverse effect of technological innovation on labour share is due to falling prices of investment goods, which induce firms to substitute capital and technology for labour (Karabarbounis and Neiman, 2014; Schwellnus et al., 2018).[4]

## 3. A simultaneous equation model of innovation, market power and labour share

In developing our case for a simultaneous equation modelling approach, we draw on testable predictions from the Schumpeterian model of innovation, market power and income distribution in Aghion et al (2019a). In this model, both new entrants and incumbent firms innovate in period *t* in response to perceived markup opportunities in the industry. If a firm innovates successfully and continues to innovate in period *t+1*, it enjoys high technological lead ($TL_H$) and high markups ($\mu_H$). Otherwise, its technological lead and markups are low at $TL_L$ and $\mu_L$, with the implication that $\mu_H > \mu_L > 1$.

[4] In a third line of research, technological innovation reduces labour share by reducing the demand for labour in the execution or routinized tasks that are highly exposed to substitution by IT capital (Dao et al, 2019).

Not all innovating firms would be necessarily successful. In Aghion et al. (2019a), the rate of successful innovation ($\theta_t$) increases with the innovation effort of incumbents ($X_{It}$) and new entrants ($X_{Et}$) but decreases with the cost of entry (*z*) for new entrants – as stated in (1) below.

$$\theta_t = X_{It} + (1 - z)X_{Et} \tag{1}$$

Denoting the cost of innovation by incumbents and entrants with $C_I$ and $C_E$, Aghion et al (2019a) derive the endogenously chosen levels of innovation by incumbents ($X_I^*$) and entrants ($X_E^*$) as stated in (2a) and (2b):

$$X_I^* = \frac{\mu_H - \mu_L}{C_I} = \left(\frac{1}{\mu_L} - \frac{1}{\mu_H}\right)\frac{1}{C_I} \tag{2a}$$

$$X_E^* = \left(\mu_H - \frac{1}{L}\left[\frac{\theta_t}{\mu_H} + \frac{1-\theta_t}{\mu_L}\right]\right)\frac{1-z}{C_E} \tag{2b}$$

The equations above indicate that the successful rate of innovation ($\theta_t$) in equation (1) increases with markups in high-innovation-lead industries ($\mu_H$) and with innovation productivities (defined as $1/C_I$ and $1/C_E$). The change in successful rate of innovation is less certain when markups in low-innovation-lead industries ($\mu_L$) also increase. On the one hand, a higher $\mu_L$ increases the successful rate of innovation by inducing entrants to innovate, enter the low-technological-lead industries, and benefit from innovation rents. On the other hand, a higher $\mu_L$ provides sufficient cushion and induces incumbents to invest less in innovation. Hence, the successful rate of innovation in the industry increases with markups but the increase is more likely when markups increase in high-technology-lead industries – i.e., when markups increase from a high initial level.

Finally, Aghion et al. (2019a) derive the effect of innovation and market power (markups) on capital and labour shares ($Cap_{share}$ and $Lab_{share}$) as follows:

$$Cap_{share(t)} = \frac{\theta_t \Pi_{H,t} + (1-\theta_t)\Pi_{L,t}}{Y_t} = 1 - \frac{\theta_t}{\mu_H} - \frac{1-\theta_t}{\mu_L} \tag{3a}$$

$$Lab_{share(t)} = 1 - Cap_{share(t)} = \frac{\theta_t}{\mu_H} + \frac{1-\theta_t}{\mu_L} \tag{3b}$$

Taking the partial derivatives of the labour share equation (3b) with respect to markups in high technological-lead industries ($\mu_H$), markups in low-technological-lead industries ($\mu_L$) and innovation rate ($\theta_t$), we can state the following:

$$\frac{\partial Lab_{share(t)}}{\partial \mu_H} = -\frac{\theta_t}{\mu_H^2} < 0 \quad \text{and} \quad \frac{\partial Lab_{share(t)}}{\partial \mu_L} = -\frac{1-\theta_t}{\mu_L^2} < 0 \tag{4a}$$

$$\frac{\partial Lab_{share(t)}}{\partial \theta_t} = \frac{1}{\mu_H} - \frac{1}{\mu_L} < 0 \quad \text{if} \quad \mu_H > \mu_L \tag{4b}$$

The Schumpeterian model of Aghion et al. (2019a) allows for three predictions. First, the relationship between innovation and market power is bidirectional. On the one hand, markup opportunities provide incentives for innovation. On the other hand, successful innovation increases markups in both industry types albeit the initial level of markups in high-technological-lead industries is higher. Secondly, labour share always declines as markups increase, irrespective of whether the markups increase in high- or low-technological lead industries. Finally, labour share also declines with the rate of successful innovation, but the fall is conditional on relative markups in high- and low-technological-lead industries. The closer are the two markups, the less adverse is the effect of technological change on labour share. In the case where the two markups are equal (i.e., when $\mu_H = \mu_L$), the effect of technological change on labour share would be insignificant. Finally, when $\mu_H < \mu_L$, labour share would increase in innovation.

The negative effect of market power on labour share in the Schumpeterian model is consistent with the first-order condition in the context of a production approach to markup adopted in De Loecker et al. (2020). Under perfect competition, the first-order condition for a cost-minimising firm is to employ a variable input, say labour, until its marginal cost (i.e., the wage rate) is equal to its marginal product (i.e., the labour elasticity of output). When market power exists, however, the wage rate (hence the observed labour share in income) is no longer equal to marginal product of income. Indeed, the relationship between the two is as sated in (5) below, where $L_s$ is labour share, $w$ is the wage rate, $L$ is labour, $Y$ is output, $\alpha$ is the labour elasticity of output, and $\mu$ is the markup of price over marginal cost.

$$L_s = \frac{wL}{Y} = \frac{\alpha}{\mu} \quad (5)$$

When markups ($\mu$) are larger than 1, equation 5 indicates that the labour's share in income ($L_s$) will be less than the marginal product of labour ($\alpha$). The resulting wedge between labour share and the latter's marginal product mimics the effect of a negative productivity shock that reduces the firm's demand for labour. Indeed, the firm stops utilising labour before the latter's marginal product ($\alpha$) is equalised with the wage rate (i.e., with the observed labour share) if $\mu > 1$.

Given the results discussed so far, we argue that reduced-form or single-equation models that control for innovation or market power only; and/or those that do not account for simultaneity and reverse causality between innovation and market power would be mis-specified. To correct for miss-specification, we propose a simultaneous equation in 6.1 – 6.4 below where we allow for simultaneity and reverse causality in the relationship between innovation, markups, and labour share. In model, we have two-way causality between innovation intensity and market power, both of which determine the labour share at the same time.

$$Innov_{ict} = \beta_{11}Markup_{ict} + \textstyle\sum_{k=1}^{K}\alpha_{1k}EP_{1kict} + \theta_{10} + \eta_{11i} + \eta_{12c} + \epsilon_{1ict} \quad (6.1)$$

$$Markup_{ict} = \beta_{21}Innov_{ict} + \textstyle\sum_{m=1}^{M}\alpha_{2m}EP_{2mict} + \theta_{20} + \eta_{21i} + \eta_{22c} + \epsilon_{2ict} \quad (6.2)$$

$$LS_{ict} = \beta_{31}Innov_{ict} + \beta_{32}Markup_{ict} + \textstyle\sum_{p=1}^{P}\alpha_{3p}EP_{pnict} + \theta_{30} + \eta_{31i} + \eta_{32c} + \epsilon_{3ict} \quad (6.3)$$

$$cov(\epsilon_{1ict}, \epsilon_{2ict}) \neq 0; \;\; cov(\epsilon_{1cit}, \epsilon_{3ict}) \neq 0; \;\; (\epsilon_{2ict}, \epsilon_{3ict}) \neq 0 \quad (6.4)$$

In the system, the $\beta$ coefficients represent the direct effects of the endogenous variables on each other; whereas the $\alpha$ coefficients represent the direct effects of exogenous predictors (EPs) on the endogenous variables. The fixed effects at the industry level ($\eta_i$) and country level ($\eta_c$) take account of time-invariant unobserved heterogeneity. These unobserved effects are eliminated by using the variables as deviations from the industry/country mean. Finally, in (6.4) we allow for error correlations to take account of common time shocks and correlated measurement errors in the data. The explanatory variables in the system and the expected signs of their effects on the endogenous outcomes are listed in Table 1.

**Table 1: List of explanatory variables and expected signs of the coefficient estimates**

| Innovation intensity Equation | Markup Equation | Labour sh. Equation |
|---|---|---|
| ***Endogenous variables:*** | ***Endogenous variables:*** | ***Endogenous variables:*** |
| Markups (+) | Innovation int. (+) | Markups (-) |
| Markups sq. (+/-) | | Innovation int. (-) |
| | | |
| ***Exogenous predictors:*** | | |
| Human capital (+) | ***Exogenous predictors:*** | ***Exogenous predictors:*** |
| Invov. Prod. (+) | IPRI (-/+) | Human capital (+) |
| PMR (-) | PMR (+) | Trade union dens (+) |
| Value added (-) | Value added (+) | EPL (+) |
| | | IPRI (-/+) |
| | | Value added (-) |

Notes: All variables except those measured as growth rates (TFP growth, innovation productivity, and growth rates of capital and labour inputs) are in natural logarithms to allow for scale-free coefficient estimates. All variables are demeaned to eliminate the unobserved country and industry fixed effects ($\eta_i$, $\eta_c$). Predicted effect signs are informed by the relevant literature discussed above and further work to be introduced below.

Of the endogenous variables, markups enter the innovation intensity equation with quadratic effects. This is in accordance with Schumpeterian models of innovation (Aghion et al., 2005, 2019a)[5], where the effect of market power (or competition) on innovation is non-linear. In line with Aghion et al. (2019a), we expect the rate of innovation to increase with markups, but the increase is more likely when markups form a high initial level that is more likely in high-technology-lead industries. In contrast, innovation enters the markup equation with a linear effect, which is expected to be positive. This is consistent with the Schumpeterian model of Aghiopn et al.(2019a), where innovation, if sustained, is conducive to innovation rents irrespective of whether it takes place in high- or low-technology lead industries. Finally, both innovation and markups affect the labour share at the same time. We expect both to have an adverse effect on labour share, but we also expect the adverse effect of markups to be larger and more consistent across innovation types.

We identify a range of exogenous predictors that affect the endogenous outcomes. For example, the innovation intensity is modelled to depend on human capital, innovation productivity, and product-market regulation (*PMR*). Human capital is expected to have a positive effect on innovation intensity - in accordance with the skill-biased technical change (SBTC) hypothesis where technological change responds to the supply of skills (Acemoglu, 1998, 1999, 2002).

[5] For reviews of the debate on how competition and its absence affect innovations, see Gilbert (2006), Peneder (2012), Hashem and Ugur (2013).

The positive effect of innovation productivity is in line with the Schumpeterian model of innovation (Aghion et al., 2019a), where the innovation effort of both incumbents and new-entry firms increases with innovation productivity. In contrast, *PMR* is expected to reduce innovation because it increases entry cost and maintains the market power of the entrenched incumbents (Aghion et al., 2019a; Bassanini and Ernst, 2002).

The exogenous predictors in the markup equation consist of two institutional variables: the intellectual and physical property rights index (*IPRI*) and the *PMR*. The effect of *IPRI* on markups is uncertain – depending on whether the increase is due to higher intellectual property rights protection that may increase markups or better rule of law that may reduce markups. An increase in the *PMR* index, on the other hand, is expected to increase markups as it reflects higher levels of legal barriers to entry, protection of incumbents, and anti-trust exemptions. Indeed, a positive relationship between PMR and market power in OECD countries has already been reported by Hoj et al., (2007).

The labour share is modelled as a function of four exogenous predictors: human capital, employment protection legislation, trade union density, and *IPRI*. Labour share is expected to increase in human capital as the latter is a source of higher labour productivity and wages (Park, 1997; Lundberg and Squire, 2003; Yang and Gao, 2018). Labour share is also expected to increase in the strictness of the employment protection legislation (EPL) and the level of trade union membership. This is in accordance with the empirical findings in the bargaining power literature, where labour rights and strong unions enable workers to demand and secure higher wages (Brancaccio et al., 2018; Checchi and García-Peñalosa, 2008; Koeniger et al., 2007). However, we expect the *IPRI* to have an uncertain effect on labour share – depending on the balance between different components of the index.

Finally, it must be noted that we include value added as an additional predictor for a statistical rather than theoretical reason. By construction, value added is in the numerator of the profits-based markups and in the denominator of the innovation intensity and labour share variables. Hence, there may be a negative association between: (i) markups and innovation intensity; (ii) markups and labour share. We purge this statistical association from the causal effect by controlling for value added in all equations. This way, the markup's effect on innovation intensity or labour share is estimated after holding the value added as constant.

## 4. Data and methodology

### *4.1 Data*

Our dataset consists of 17 variables described and documented in Table A1 in the Appendix. The variables at the country-industry level are form the 2021 release of the *EUKLEMS & INTANProd* database (*EU-KLEMS* thereafter).[6] The country-industry sample consists of 12 OECD countries and 31 non-overlapping 1-digit and 2-digit industries listed in Table A3 in the Appendix. The country sample is determined by data availability for innovation productivity, measured as the contribution of knowledge capital services to value added growth. We used *EU-KLEMS'* statistical module to obtain data for gross output, value added, investment in tangible assets, capital stock, labour compensation and investment in intangible assets that have become classified as intangible capital in the System of National Accounts (SNA) in 2008. Data for investment in other intangibles that have not been capitalised in the SNA (i.e., data for investments in marketing innovation, organisational change, and economic competencies) have been obtained from the analytical module.

Hence, the data allow for constructing two measures of innovation intensity. *Innov_int1* is the sum of investment in research development (*R&D*), software and databases (*Soft-DB*), and other intellectual property assets (*OIP*) divided by value added. This measure reflects the innovation investment that has been capitalised in the SNA and corresponds to the 'technological innovation' (*Tech_in*) concept adopted by the OECD since the first edition of the Oslo Manual. On the other hand, the numerator for I*nnov_int2* includes the *Tech_in* components listed above and the investment in marketing (*Mark_in*), organisational change (*Org_in*) and economic competency (*Ec_comp*) that the OECD has added to the list of innovation activities in the third edition of the Oslo Manual in 2005. The two measures are defined formally in 7.1 and 7.2 below, where *i*, *c*, and *t* indicate industry, country, and year respectively.

$$Innov\_int1_{ict} = \frac{Tech\_in_{ict}}{VA_{ict}} = \frac{R\&D_{ict} + Soft\_DB_{ict} + OIP_{ict}}{VA_{ict}} \qquad (7.1)$$

[6] 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).

$$Innov\_int2_{ict} = \frac{Tech\_in_{ict} + (Org\_in_{ict} + Mark\_in_{ict} + Ec\_comp_{ict})}{VA_{ict}} \quad (7.1)$$

The relevant literature tends to consider the two innovation types as complements, particularly because the marketing-organisational innovation is usually undertaken to implement the product and process innovations inherent in the technological innovation (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 both the narrow and the extended measures to verify if: (i) the two-way relationship between innovation and market power differs by innovation type; and (ii) the effect of innovation and market power on labour share differs between innovation types.

We use a labour share measure that takes account of the self-employed (mostly owners-managers of small firms) in addition to employees on the payroll, assuming that the hourly wage of the self-employed is equal to mean hourly wage of the employees (Battiati et al., 2021; Ciapanna et al., 2022). Using *LS* for labour share; $H_{emp}$ for the number of hours worked by the total labour force; $H_{empe}$ for the number of hours worked by employees; *Comp* for compensation of employees; and *VA* for value added; the labour share is calculated as follows:

$$LS_{ict} = \frac{\left(Hemp_{ict}/Hempe_{ict}\right) * Comp_{ict}}{VA_{ict}} \quad (8)$$

In the light of the review in section 2, we adopt an accounting-based (non-econometric) approach to measuring market power. Our preferred measure is that of Barkai (2020) and Eggertsson et al. (2021), which we denote as the profits-based markup. The measure relies on the pure profit share that remains after capital and labour are awarded their income shares under the assumption of perfect competition and constant returns to scale. Taking account of the indirect taxes on goods and services as recommended by Barkai (2020) and Basu (2019), the profits-based markup by industry, country, and year ($\mu^P_{ict}$) is calculated in accordance with (15) below, where $PS_{ict}$ is the share of economic profits in value added after labour and capital income are accounted for.

$$\mu^P_{ict} = \frac{1}{1 - PS_{ict}} = \frac{1}{1 - \frac{VA_{ict} - Lab_{inc_{ict}} - Cap_{inc_{ict}} - Ind\_tax_{ict}}{VA_{ict}}} = \frac{VA_{ict}}{Lab\_inc_{ict} + Cap\_inc_{ict} + Ind\_tax_{ict}} \quad (9)$$

The profit-based markup is 1 if value added is exhausted when labour income, capital income and indirect taxes are accounted for. 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 in accordance with the numerator in (8) above to take account of 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.

Our second markup measure is Lerner-index-based and draws on Battiati et al. (2021) and Ciapanna et al. (2022). For this measure, we begin with an industry-level Lerner index defined as the markup of prices over marginal costs, as indicated in 10.1 below.

$$L_{ict} = \frac{P_{ict} - MC_{it}}{P_{ict}} \cong \frac{(P_{ict} - AC_{it})Q_{ict}}{P_{ict}Q_{ict}} = \frac{Y_{ict} - TAC_{ict}}{Y_{ict}} \qquad (10.1)$$

Because the marginal cost is not observed/available in the data, the Lerner index is calculated by assuming that the marginal cost is constant and equals to average cost (*AC*). Based on this assumption, the numerator and denominator of 10.1 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 10.2 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.

$$\mu_{ict}^{L} = \frac{1}{1 - L_{ict}} = \frac{1}{1 - \frac{Y_{ict} - TAC_{ict}}{Y_{ict}}} = \frac{Y_{ict}}{TAC_{ict}} = \frac{Y_{ict}}{II_{ict} + Lab\_Cost_{ict}} \qquad (10.2)$$

We have trimmed the top and bottom 1% of the observations for markup, labour share and innovation measures. The trimming reduces the noise due to potential mismeasurement in the underlying data and the risk of outlier influence. 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.

Figures A1 – A3 in the Appendix present the evolution of markups, innovation intensity, and labour share by country using the estimation sample. The evolution of markups and labour share differs between countries.[7] On the one hand, 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 o *increase* in countries with below average values to start with. The profits-based markups are usually larger than the Lerner-index-based markups, but both measures are correlated within each country (correlation coefficients ranging from 0.15 to 0.72). Moreover, the markups tend to decrease in countries with high initial level, but they tend to increase in countries with low levels at the beginning of the estimation period. These tendencies indicate a convergence towards the sample averages of 1.35 and 1.21 for the profits- and Lerner-index-based markups respectively. A similar trend is observed for labour share, which is converging towards the sample average of 0.58.[8] Another trend that emerges from the data is that markups are procyclical - i.e., they increase during boom periods and fall during recessions.[9] In contrast, the labour share is counter-cyclical in that it tends to increase during crisis periods – particularly during the global financial crisis from 2007-2010.[10] 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.

We use eight exogenous regressors that predict innovation, market power and labour share as discussed above. Of these, innovation productivity (*Innov_prod*) is measured at the country-industry level and taken directly from *EU-KLEMS*. This variable measures the contribution of intangible capital services (not investment) to the growth of value added. It is a determinant of

[7] The evolution differs by industry too. The industry-levels graphs are not reported here to save space, but they can be provided on request.
[8] A notable country exception is the US, where markups always increase, and labour share always falls over time.
[9] 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.
[10] 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).

the innovation intensity equation. The remaining exogenous predictors are measured at the country level and consist of: internal rates of return on capital, indirect taxes as percent of GDP, human capital, intellectual and physical property protection index, product-market regulation index, trade union density and strictness of the employment protection legislation. Sources and descriptions of these variables are given in Table A1 in the Appendix.

### *4.2 Estimation methodology*

We estimate the model in 6.1 – 6.4 above using three estimators. Of these, the three-stage leaste-squares (3SLS) estimators is used for estimating a system of simultaneous equations whereas the asymptotic distribution free (ADF) and the maximum likelihood (ML) estimators are used to estimate structural equation models. The 3SLS is an efficient estimator that yields coefficient estimates after taking account of error correlations between equations (Zellner and Theil, 1992) and takes account endogeneity by using the predicted values of the endogenous variables. Nevertheless, the 3SLS estimator assumes homoscedastic errors and does not provide estimates for both direct and indirect effects of the variables in the system.

Hence, we also use two structural equation model (SEM) estimators that allow for addressing both issues, but with different assumptions about the distribution of the variables and the error terms. Whereas the ML estimator assumes joint normality, the ADF estimator does not. To choose between ADF and ML, we test for multivariate normality using the Doornik–Hansen omnibus test (Doornik and Hansen, 2008). Because the test rejects the null hypothesis of multivariate normality in all equations, we use the ADF estimator as our preferred estimator and report estimates from the ML and 3SLS estimators as robustness checks.

Beyond estimating both direct and indirect effects, the ADF methodology offers three additional advantages: (i) it produces more efficient estimates than ML when the joint normality assumption is not satisfied; (ii) it generates heteroskedasticity-robust standard errors; and (iii) it is a generalised method of moments (GMM) estimator that takes account of endogeneity that arises from simultaneity and correlated disturbances.

A recent simulation study (Maydeu-Olivares, et al, 2018) reports that the ADF method yields acceptable levels of relative bias for the parameter estimates and good coverage of the 95% confidence intervals even with small sample sizes between 100-500. The ADF performance across different scenarios is as good as or better than the performance of the ML method even with larger sample sizes. These findings are in line with similar findings in earlier studies (e.g., Muthén, 1989; Finch et al., 1997; Lei and Lomax, 2005).

We report several model fit statistics to verify if the estimated model fits the sample data satisfactorily. Some of the fit statistics are more reliable when the joint normality assumption is satisfied. These include: (i) the root mean square error of approximation (RMSEA) proposed by Steiger (1990); (ii) the comparative fit index (CFI) of Bentler (1990); and (iii) the Tucker–Lewis index (TLI) of Bentler and Bonett (1980). In contrast, the standardised root mean of the squared residuals (SRMR) does not require joint normality. We follow best-practice guidelines (Hu and Bentler, 1999; West et al., 2012) and report four fit statistics: RMSEA, CFI, TLI ,and SRMR. The RMSEA and SRMR take values between 0 and 1, with values closer to zero representing better model fit. To indicate good fit, the RMSEA and SRMR should be 0.05 or less. The CFI and TLI also take values between 0 and 1, with values closer to 1 representing better fit. The recommended threshold is 0.95 for CFI and 0.90 for TLI.

In our estimations, we take account of potential correlation between the regressors and the unobserved country-industry fixed effects by demeaning the variables and thus eliminating the panel-specific fixed effects. This identification strategy requires less stringent assumptions than pooled OLS, where the panel-specific fixed effects are assumed the same across panels (Brüderl and Ludwig, 2015; McArdle and Nesselroade, 2014). Moreover, demeaning enables us to identify the causal effects within country-industry pairs after eliminating the confounding effects of the unobserved and time-invariant variables (Kropko and Kubinec, 2020).

A second source of endogeneity is due to potential correlation between the regressors and the idiosyncratic errors. All the estimators discussed above address this issue for the endogenous variables (innovation intensity, markups, and labour share) by using their estimated values from the first stage of the estimation. Indeed, the ADF method is based on a GMM estimator that takes account of correlated disturbances between models and simultaneity between endogenous variables at the same time. We assume that the country-level exogenous predictors are orthogonal to the idiosyncratic error, but we also use two-year lags as robustness checks that reduce the risk of correlation due to reverse causality.

Before estimation, we check for multicollinearity by obtaining variance inflation factor (VIF) statistics for each equation. We also obtain the standardised variance-covariance matrix across all equations. Both checks indicate that the VIF statistic is less than 2 and hence multicollinearity is not a cause for concern in any of the equations. The variance-covariance estimates, on the other hand, indicate high correlation (around 0.74) only between product-market regulation (PMR) and trade-union density that do not take place in the same equation.

We also check model stability, using the Bentler and Freeman (1983) procedure that calculates eigenvalue stability indices. These indices are based on the coefficients on endogenous variables predicting other endogenous variables; and indicate that the model is stable if all the eigenvalues lie inside the unit circle. We also check if the model in 6.1. – 6.4 is identified, using the procedure proposed by Baum (2007) for simultaneous equation models. Test results from both tests indicate that the proposed SEM is both stable and identified.

## 5. Estimation results and robustness checks

The first set of estimation results is presented in Table 2, which reports the direct, indirect, and total effect-size estimates for the regressors in the innovation, markup, and labour share equations. The estimates are based on the ADF estimator, which yields robust standard errors and does not require joint normality. The coefficient estimates are unit-free elasticities and comparable across variables, except for innovation productivity that is measured in % change.

In the light of the fit criteria recommended in Hu and Bentler (1999), the model fit statistics given at the bottom of the table indicate good fit. The RMSEA of 0.032 and SRMR of 0.030 are well below the cut-off value of 0.05. Also, the CFI of 0.977 and TLI of 0.910 are above the minimum thresholds of 0.95 and 0.90, respectively. Given the model fit and the fact that the model is both stable and identified in the pre-estimation tests, we conclude that the model is well specified to replicate the variance-covariance structure of the data.

Starting with the innovation intensity equation, we observe that the *direct* effect of market power on innovation intensity is insignificant in the linear term but positive and significant in the quadratic term. This finding indicates that innovation increases with markups when the latter increases from a high initial level – as predicted by the Schumpeterian model of innovation (Aghion et al., 2019a). The increase in markup from a high initial level is more likely to occur in high-technology-lead industries with higher markup opportunities that induce innovative new entry and provide added incentives for the incumbents to innovate. In contrast, when markups increase from a low initial level, the increase may or may not induce higher innovation. The result would depend on the extent to which the incumbents are entrenched and on whether new entry is deterred by higher entry costs relative to markup opportunities.

Three further findings in the innovation equation enhances our confidence in the ability of the model to yield consistent estimates. First, human capital enters with a positive coefficient, indicating that a 1% increase in the human capital index is associated with a 1.57% increase in innovation intensity. This is consistent with the skill-biased technical change hypothesis, where technological innovation responds to increased supply of skills (Acemoglu, 1998, 1999, 2002). Secondly, innovation intensity increases by 4% when innovation productivity increases by one unit – in line with the Schumpeterian model where firms are more likely to innovate when they are more successful in converting innovation inputs into profitable product lines (Aghion et al., 2019a). The third finding indicates that product-market regulation reduces innovation. This is in line with OECD evidence reported in Bassanini and Ernst (2002) – and with predictions from the Schumpeterian model where entrenched incumbents and higher entry costs reduce innovation.

An additional point to note is that the *total* effects of the predictors in the innovation equation have the same signs as the *direct* effects but are slightly larger in magnitude. This is due to reinforcing *indirect* effects that result from interdependence between innovation and markups. Although the indirect effects are statistically insignificant, their linear combination with the direct effect yields statistically significant total effects, which are larger in magnitude compared to the direct effects.

Results in the markup equation indicate that innovation intensity leads to higher markups. A 1% increase in innovation intensity is associated with an increase of 0.124% in average markups. This finding is consistent with the emerging evidence that firms/industries with higher levels of investment in knowledge (intangible) assets tend to have higher markups (Altomonte et al., 2021; De Ridder, 2019; Sandström, 2020). It is also consistent the Schumpeterian model of innovation in Aghion et al. (2019a), where markups increase with innovation if successful innovators continue with their innovation effort.

**Table 2: Innovation, markups, and labour share:**
**Direct, indirect, and total effects**

| | Direct effect | Indirect effect | Total effect |
|---|---|---|---|
| **Innovation intensity1 equation** | | | |
| Profits-based markup | 2.7832 | 1.4740 | 4.2572 |
| | (1.7134) | (2.3288) | (4.0324) |
| Profits-based markup sq | 0.1791** | 0.0948 | 0.2739*** |
| | (0.0850) | (0.0674) | (0.0898) |
| Human capital | 1.5719*** | 0.8325 | 2.4043*** |
| | (0.5479) | (0.5282) | (0.1526) |
| Innovation productivity | 0.0447*** | 0.0237 | 0.0684*** |
| | (0.0159) | (0.0150) | (0.0051) |
| Product-market regulation | -0.3439*** | 0.1398 | -0.2040*** |
| | (0.1015) | (0.0934) | (0.0254) |
| Value added | -0.0035 | 0.0024 | -0.0011 |
| | (0.0027) | (0.0021) | (0.0013) |
| Intel. and physical property rights index | | -0.2047** | -0.2047** |
| | | (0.0806) | (0.0806) |
| **Profits-based markup equation** | | | |
| Innovation in tensity 1 | 0.1244*** | 0.0659 | 0.1903** |
| | (0.0180) | (0.0673) | (0.0761) |
| Human capital | | 0.2991*** | 0.2991*** |
| | | (0.0432) | (0.0432) |
| Innovation productivity | | 0.0085*** | 0.0085*** |
| | | (0.0010) | (0.0010) |
| Product-market regulation | 0.0756*** | -0.0254*** | 0.0502*** |
| | (0.0113) | (0.0052) | (0.0081) |
| Value added | 0.0010* | -0.0001 | 0.0009 |
| | (0.0006) | (0.0002) | (0.0005) |
| Intel. and physical property rights index | -0.0481 | -0.0255** | -0.0735** |
| | (0.0330) | (0.0107) | (0.0289) |
| **Labour share equation** | | | |
| Innovation in tensity 1 | 0.0126 | -0.2983*** | -0.2857** |
| | (0.0146) | (0.1104) | (0.1121) |
| Profits-based markup | -1.6029*** | -0.7952 | -2.3981*** |
| | (0.1194) | (0.7714) | (0.7607) |
| Profits-based markup sq | | -0.0512*** | -0.0512*** |
| | | (0.0173) | (0.0173) |
| Human capital | 0.3759*** | -0.4491*** | -0.0732 |
| | (0.0502) | (0.0632) | (0.0622) |
| Innovation productivity | | -0.0128*** | -0.0128*** |
| | | (0.0016) | (0.0016) |
| Product-market regulation | | -0.0831*** | -0.0831*** |
| | | (0.0114) | (0.0114) |
| Value added | 0.0021*** | -0.0014 | 0.0007 |
| | (0.0005) | (0.0009) | (0.0006) |
| Intel. and physical property rights index | -0.0617** | 0.1153** | 0.0536 |
| | (0.0274) | (0.0479) | (0.0333) |
| Trade union density | 0.0752*** | | 0.0752*** |
| | (0.0072) | | (0.0072) |
| Employment protection legislation | 0.1296*** | | 0.1296*** |
| | (0.0101) | | (0.0101) |

*N = 6,553; RMSEA = 0.032; SRMR = 0.030; CFI = 0.977; TFI = 0.910*

Notes: All variables in natural logarithm and demeaned to purge country-industry fixed effects. Innovation intensity is measured as the ratio of the investment in capitalized knowledge assets to value added. Exogenous predictors enter with contemporaneous values. Asymptotic distribution free (ADF) estimates with robust standard errors. Empty cells indicate absence of direct-effect paths in the model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Two further findings in the markup equation are also consistent with the theoretical predictions that underpin our simultaneous equation model. On the one hand, the positive *direct* and *total* effects of the product-market regulation (PMR) on markups are in line with findings in Hoj et al., (2007), who report that the set of rules and regulations (e.g., entry costs, incumbent protection, exemptions from anti-trust regulations, etc.) captured by the PMR indicator reduce competition and increase market power. On the other hand, the positive indirect and total effects of innovation productivity on markups are also consistent with the Schumpeterian model of innovation, which predicts that innovation productivity increases the innovation effort that is necessary to extract higher markups. The effect of the intellectual and physical property rights index (IPRI) on markups is negative but insignificant – and this is in line with our prediction in Table 1 above.

In the labour share equation, we observe that innovation intensity has a small but insignificant direct effect on labour share. However, the indirect effect is negative and significant. Both yield a negative and significant total effect of -0.286. In contrast, the markup has a large and negative direct effect of -1.602, which is worsened to a total effect of -2.398. Moreover, the indirect effect of the quadratic markup term is also negative (-0.051), indicating that the total effect of markups on labour becomes more adverse when markups increase from a high initial level. Hence, the effect of markups on labour share is: (a) more adverse than that of innovation; and (b) the decline in labour share is steeper when markups increase from a high initial level.

Our findings are consistent with optimising behaviour under market power (eq. 10 above), where labour share is inversely related to markups. It is also consistent with the extant literature that reports adverse markup effects on labour share, including Autor et al. (2020), Barkai (2020), De Loecker et al. (2020), Eggertsson et al. (2021) and Pak and Schwellnus (2019).[11] Markups can cause declining labour share for two reasons. On the one hand, they act like a negative productivity shock that reduces the demand for labour and hence the wage bill (Baqaee and Farhi, 2020). On the other hand, markups drive a wedge between the marginal product of labour and its observed share in income. As a result, the demand for labour remains below optimum and the product-market rents are appropriated as pure profits (rents) (Barkai, 2020; Eggertsson et al., 2021) or as 'factorless income' (Karabarbounis and Neiman, 2019).

[11] For reviews, see Battiati et al. (2021) and Paul and Oishi (2018).

However, our findings also extend the existing evidence base. On the one hand, they separate the effect of innovation on labour share from the effect of market power that enables successful innovations to extract innovation rents. Our findings indicate that the latter effect is by far the more adverse. On the other hand, we demonstrate that the total effects of market power on labour share become more adverse at when market power increases from a high initial level.

We make two further observations on determinants labour of share. The first is that labour share increases with human capital as expected. An increase in human capital is expected to increase the marginal product of labour and thereby increase the labour's share in come. Secondly, labour share increases with trade union density and employment protection legislation – in line with findings in bargaining power literature (Brancaccio et al., 2018; Checchi and García-Peñalosa, 2008; Guschanski and Onaran, 2021; Koeniger et al., 2007). These findings enhance our confidence in the predictive capacity of the proposed SEM as it delivers estimates that are consistent with the underlying theoretical/analytical framework with the wider empirical literature.

We have conducted a wide range of robustness checks reported in Table 3 below and Tables A4-A6 in the Appendix. In Table 3, we check whether the coefficient estimates from the ADF estimator remain robust to different samples, innovation measures, and lag specifications. Then, Tables A4 and A5 in the Appendix repeat the same check with two different estimators – a maximum likelihood (ML) estimator in Table A4 and a 3SLS estimator in Table A5. Finally, an additional set of ADF-based results are presented in Table A6, where we use the Lerner-index-based markup measure instead of the profits-based measure.

The direct-effect estimates in column 1 of Table 3 are copied from column (1) of Table 1 discussed above. These are compared with estimates from five robustness checks reported in in columns 2-5. In column 2, we keep the same sample as Table 1, but we use *Innov_int2* as our innovation intensity measure. The aim here is to verify whether we have sign and statistical significance consistency when the innovation measure changes. In columns (3) and (4), we use two-year-lagged exogenous predictors and repeat the estimation with both *Innov_int1* and *Innov_int2*, respectively. Here, the aim is to verify consistency across different lag specifications. Finally, in columns (5) and (6), we verify whether our results in columns (1) and (2) are affected by the downturn in the business cycle. This is done by excluding the crisis period (the 2007-2009 period) from the estimation sample.

Table 3: ADF estimation of innovation, markups and labour share equations: Evidence from different samples, innovation measures, and lag specifications

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Innovation intensity1 equation | | | | | | |
| Profits-based markup | 2.7832 | 4.0656*** | 5.5250*** | 4.3016*** | 2.9177* | 3.2826*** |
| | (1.7134) | (0.0851) | (0.3071) | (0.0633) | (1.6158) | (0.0598) |
| Profits-based markup sq | 0.1791** | 0.0237* | 0.0483 | 0.0269** | 0.0879 | 0.0172** |
| | (0.0850) | (0.0131) | (0.0412) | (0.0112) | (0.0624) | (0.0080) |
| Human capital | 1.5719*** | 0.2200** | 0.7859*** | 0.2528*** | 1.3196** | 0.2242*** |
| | (0.5479) | (0.1111) | (0.2623) | (0.0774) | (0.6414) | (0.0804) |
| Innovation productivity | 0.0447*** | 0.0040* | 0.0175*** | 0.0031*** | 0.0496** | 0.0053*** |
| | (0.0159) | (0.0021) | (0.0060) | (0.0009) | (0.0241) | (0.0020) |
| Product-market regulation | -0.3439*** | -0.4461*** | -0.4610*** | -0.4306*** | -0.3894*** | -0.4492*** |
| | (0.1015) | (0.0330) | (0.0541) | (0.0341) | (0.1167) | (0.0278) |
| Value added | -0.0035 | -0.0048* | -0.0120*** | -0.0087*** | -0.0039 | -0.0046* |
| | (0.0027) | (0.0028) | (0.0040) | (0.0032) | (0.0029) | (0.0026) |
| Profits-based markup equation | | | | | | |
| Innovation in tensity | 0.1244*** | 0.2170*** | 0.1246*** | 0.2009*** | 0.1553*** | 0.2665*** |
| | (0.0180) | (0.0114) | (0.0144) | (0.0075) | (0.0202) | (0.0101) |
| Product-market regulation | 0.0756*** | 0.1039*** | 0.0748*** | 0.0946*** | 0.0947*** | 0.1287*** |
| | (0.0113) | (0.0086) | (0.0093) | (0.0078) | (0.0125) | (0.0087) |
| Value added | 0.0010* | 0.0011* | 0.0019*** | 0.0019*** | 0.0011* | 0.0013* |
| | (0.0006) | (0.0007) | (0.0007) | (0.0007) | (0.0007) | (0.0007) |
| Property rights index | -0.0481 | -0.0096* | -0.0115** | -0.0098*** | -0.0457 | -0.0128*** |
| | (0.0330) | (0.0049) | (0.0058) | (0.0032) | (0.0362) | (0.0047) |
| Labour share equation | | | | | | |
| Innovation in tensity | 0.0126 | -0.0147 | -0.0781*** | -0.1678*** | 0.0065 | -0.0269 |
| | (0.0146) | (0.0222) | (0.0191) | (0.0316) | (0.0154) | (0.0229) |
| Profits-based markup | -1.6029*** | -1.5777*** | -1.6542*** | -1.8787*** | -1.5887*** | -1.5904*** |
| | (0.1194) | (0.0936) | (0.1255) | (0.1263) | (0.1018) | (0.0835) |
| Human capital | 0.3759*** | 0.4770*** | 0.5897*** | 0.8162*** | 0.3937*** | 0.5111*** |
| | (0.0502) | (0.0654) | (0.0628) | (0.0878) | (0.0538) | (0.0677) |
| Value added | 0.0021*** | 0.0021*** | 0.0011** | 0.0010* | 0.0020*** | 0.0019*** |
| | (0.0005) | (0.0004) | (0.0005) | (0.0006) | (0.0005) | (0.0005) |
| Property rights index | -0.0617** | -0.0631*** | -0.0062 | -0.0749*** | -0.0879*** | -0.1024*** |
| | (0.0274) | (0.0202) | (0.0238) | (0.0278) | (0.0278) | (0.0216) |
| Trade union density | 0.0752*** | 0.0732*** | 0.0623*** | 0.0626*** | 0.0728*** | 0.0705*** |
| | (0.0072) | (0.0072) | (0.0073) | (0.0072) | (0.0074) | (0.0074) |
| Emp. protection legislation | 0.1296*** | 0.1316*** | 0.0811*** | 0.0782*** | 0.1362*** | 0.1381*** |
| | (0.0101) | (0.0101) | (0.0097) | (0.0096) | (0.0108) | (0.0107) |
| *N* | 6,553 | 6,547 | 5,965 | 5,961 | 5,695 | 5,690 |
| RMSEA | 0.032 | 0.031 | 0.024 | 0.031 | 0.031 | 0.031 |
| SRMR | 0.030 | 0.030 | 0.014 | 0.014 | 0.032 | 0.032 |
| CFI | 0.977 | 0.983 | 0.984 | 0.980 | 0.980 | 0.985 |
| TFI | 0.910 | 0.935 | 0.937 | 0.925 | 0.924 | 0.941 |

Notes: All results are based on ADF estimator. (1) Full sample with innovation intensity1 and no lags; (2) Full sample with innovation intensity2 and no lags; (3) Full sample with innovation intensity1 and two lags on exogenous predictors; (4) Full sample with innovation intensity2 and two lags on exogenous predictors; (5) Full sample with innovation intensity1, excluding the crisis period (2007-2009);(6) Full sample with innovation intensity2, excluding the crisis period (2007-2009). For other notes, see Table 2 above. Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Reading across columns, we observe a high degree of sign and significance consistency for the coefficient estimates in all equations. The two exceptions are: (i) the effect of the linear markup term on innovation intensity; and (ii) the effect of innovation intensity on labour share. These inconsistencies, however, are in line with theoretical predictions from the Schumpeterian model of innovation. On the one hand, the estimates for the linear and quadratic markup terms indicate that the effect of markups on innovation is uncertain when markups increase from a low initial level, but the effect is positive when markups increase from a high initial level. On the other hand, the small and variable effect of innovation on labour share is compatible with Schumpeterian model prediction when markups in high- and low-technology-lead industries are close to each other.

We arrive at similar conclusions when we compare the results in Table 3 with further robustness checks reported in Tables A4 – A6 in the Appendix. The degree of sign and significance consistency is very high (between 70% - 100%) across all estimation results. Moreover, the fit statistics are as good as or better than the those discussed in the context of Table 2. Hence, we have sufficient evidence to conclude that the proposed model fits the data well; and yields estimates that remain consistent across different samples, innovation measures and estimators. The findings from the model enable us to report the following: (i) innovation tends to increase with markups and the increase is larger when markups increase form a high initial level; (ii) markups always increase with innovation intensity; and (iii) the effect of innovation on labour share is small and unstable across columns, but the adverse effect of markups is consistently larger in magnitude and stable across estimations.

We now compare the coefficient estimates to verify if their magnitudes vary between innovation type (i.e., between *Innov_int1* and *Innov_int2*). This is pertinent because the effect of market structure on the combined innovation investment (i.e., investment in 'technological' and 'marketing-organisational' innovation) is reported to differ from the effect on 'technological' innovation only (Schubert, 2010). The results in Table 3 and Tables A4-A6 in the Appendix allows for 12 pairwise comparisons between innovation *Innov_int1* and *Innov_int2*. The number of pairwise comparison is six when we focus on ADF results in Tables 3 and A6 only. The comparison results are reported in Table 4 below.

**Table 4: Markup sensitivity and implications of innovation types**

| Observed magnitude patterns | Times observed in 12 pairwise comparisons (All estimators) | Times observed in 6 pairwise comparisons (ADF only) |
|---|---|---|
| Effect of markups on *Innov_int2* is *larger* than the effect on *Innov_int1* | 7 | 5 |
| Effect of *Innov_int2* on markups is *larger* than the effect of *Innov_int1* | 10 | 6 |
| Effect of human capital on *Innov_int2* is *smaller* than the effect on *Innov_int1* | 10 | 6 |
| Effect of innovation productivity on *Innov_int2* is *smaller* than the effect on *Innov_int1* | 10 | 6 |
| Effect of *Innov_int2* on labour share is *more adverse* compared to the effect of *Innov_int1* | 9 | 4 |

Comparison results in Table 4 indicate that the innovation intensity that includes both 'technological' and 'marketing-organisational' innovation (*Innov_int2*) is more responsive to markups compared to innovation *Innov_int1*. Perhaps because of this higher markup sensitivity, *Innov_int2* is less sensitive to a given increase in innovation productivity or human capital in all estimations based on the preferred ADF estimator. Secondly, the rate of increase in market power (markups) is usually higher for a given increase in *Innov_int2* compared to the same rate of increase in *Innov_int1*. The third pattern is that *Innov_int2* is more likely to have a more adverse effects on labour share compared to *Innov_int1* – both directly and indirectly through its stronger effect on markups. These findings indicate that the OECD's extended definition includes innovation activities that: (a) tend to increase market power at higher rates; and (b) have more adverse effects on labour share at the same time. Given these patterns, a more critical assessment of the drivers and consequences of the increasing levels of investment in new marketing strategies and organisational change is called for.

The final set of evidence we present relates to two post-estimations tests we conduct to verify if the effects of innovation or markups on labour share are reversed by the combined effects of three policy-related variables we control for: human capital, trade union density and employment protection legislation. Recalling the specification of the labour share equation in 6.3 above, the null hypotheses for the two tests are stated below.

$H_{10}$: $\widehat{\beta_{31}} + \widehat{\alpha_{31}} + \widehat{\alpha_{32}} + \widehat{\alpha_{33}} = 0$ (*Test 1*)

$H_{20}$: $\widehat{\beta_{32}} + \widehat{\alpha_{31}} + \widehat{\alpha_{32}} + \widehat{\alpha_{33}} = 0$ (*Test 2*)

In *Test 1*, we test if the negative effect of innovation, $\widehat{\beta_{31}}$, is reversed by the sum of the estimated effects of human capital ($\widehat{\alpha_{31}}$), trade union density ($\widehat{\alpha_{32}}$), and employment protection legislation ($\widehat{\alpha_{33}}$) - all of which tend to increase labour share. In *Test 2*, we follow the same procedure for the negative effect of market power, $\widehat{\beta_{32}}$ and the three effect-size estimates for human capital and labour market institutions. The results, which are based on standardised coefficients to allow unit-free pooling, are reported in Table 5.

**Table 5: Adverse effects of innovation and markups on labour share: Are they reversed by the effects of human capital and labour-market institutions?**

| **Specifications in Table 3, columns 1 – 6** | **Test 1: Innovation intensity combined with human capital and labour-market institutions** | **Test 2: Market power combined with human capital and labour-market institutions** |
|---|---|---|
| 1. Full sample with *Innov_int1* and no lags | Combined effect: 0.593<br>p-value: 0.000 | Combined effect: -1.022<br>p-value: 0.000 |
| 2. Full sample with *Innov_int2* and no lags | Combined effect: 0.303<br>p-value: 0.000 | Combined effect: -1.010<br>p-value: 0.000 |
| 3. Full sample with *Innov_int1* and two lags on exogenous predictors | Combined effect: 0.113<br>p-value: 0.055 | Combined effect: -1.094<br>p-value: 0.000 |
| 4. Full sample with *Innov_int2* and two lags on exogenous predictors | Combined effect: 0.085<br>p-value: 0.469 | Combined effect: -1.228<br>p-value: 0.000 |
| 5. Estimation with *Innov_int1*, excluding the crisis period | Combined effect: 0.336<br>p-value: 0.000 | Combined effect: -1.027<br>p-value: 0.000 |
| 6. Estimation with *Innov_int2*, excluding the crisis period | Combined effect: 0310<br>p-value: 0.002 | Combined effect: -0.994<br>p-value: 0.000 |

The test results indicate that the combined effect of human capital and labour-market institutions is sufficient to nullify the adverse effect of innovation in one estimation and to reverse it in 5 estimations. In contrast, the combined effect of human capital and labour-market institutions is insufficient either to nullify or reverse the adverse effect of the markups on labour share in any of the specifications. After discounting the effects of human capital and labour-market institutions, a one-standard-deviation increase in markups remains associated with an approximately one-standard-deviation decline in labour share. Hence, we conclude that the extent to which innovators can extract innovation rents is by far a more significant determinant of labour share compared to innovation *per se*.

## 6. Conclusions

Our point of departure in this paper has been the observation that technological innovation and market power are interrelated theoretically, but the relationship between the two is not accounted for in empirical work. The existing empirical models tend to relate labour share to technological innovation or market power only, overlooking the two-way relationship between the two. This oversight is a potential source of model specification and confounding biases that undermine the reliability of the existing evidence and prevent researchers from disentangling the effect of market power on labour share from that innovation or vice versa.

We have addressed this oversight by proposing and estimating a simultaneous equation model that allows for: (i) simultaneity and reverse-causality between innovation and market power; and (ii) joint determination of innovation, market power and labour share as co-evolving endogenous outcomes. The system of equations in the model is informed by testable predictions form Schumpeterian models of innovation (Aghion et al., 2015 and 2019a) where markups are both a driver for and an outcome of investment in innovation. It is also compatible with predictions from induced technological change and skill-biased technical change models, where technological innovation responds to labour cost and the supply of skills, respectively.

Using a panel dataset for 31 non-overlapping industries in 12 OECD countries, we provide confirmatory evidence that both technological innovation and market power have adverse effects on labour share. Beyond this confirmatory evidence, we have contributed to the existing evidence base in two ways.

First, we have established that there is reverse causality between technological innovation and market power, which are endogenous outcomes determined simultaneously. On the one hand, markups always increase with innovation linearly and the rate of increase is higher when innovation includes investment in organisational change and new marketing strategies in addition to investment in R&D and information technology. On the other hand, innovation is related to market power in a non-linear fashion. The effect of markups on innovation is uncertain when markups increase from a low initial level, but it is always positive when markups increase from a high initial level. These findings are consistent with testable predictions from Schumpeterian models. More importantly, however, they also indicate that the effect of innovation or market power on labour share can be estimated correctly only if both are included in the empirical model and if the latter allows for simultaneous determination of innovation, market power and labour share as endogenous outcomes.

Secondly, we were able to disentangle the effects of technological innovation on labour share from that of market power; and have demonstrated that the adverse effect of market power on labour share is much stronger than that of technological innovation – both directly and indirectly.

Our third contribution is to demonstrate that innovation type matters for both the inter-connection between innovation and market power and for the effects of both on labour share. Our findings indicate that the inter-connection between innovation and markups is stronger and the effects of both on labour share labour is more adverse as firms invest more in marketing innovation and organisational change strategies. Our fourth contribution is to demonstrate that the total effect of labour-market institutions and human capital is not sufficient to reverse the adverse effects of market power on labour share.

Given that these novel findings remain consistent across various robustness checks, we argue that both technological innovation and market power are conducive to decline in labour share. However, the major driver of the decline in labour share is not technological innovation *per se*, but the extent to which innovators are able to extract innovation rents. Therefore, in addition to stronger labour-market institutions, a stronger competition policy is necessary for arresting and perhaps reversing the decline in labour share.

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**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: “Innovation, market power and the labour share: Evidence from OECD industries”. 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 estimators, samples, innovation intensity measures, markup measures, and lag specifications.

## Table A1: Variable description and documentation

| Variable | Description | Source |
|---|---|---|
| | **Variables at the industry-country level** | |
| Innovation intensity 1 | The ratio of investment in research and development (R&D), computers and software, and other intellectual property assets to value added. | EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/ |
| Innovation intensity 2 | Innovation investment in (1) plus investment in marketing innovation, organisational innovation and economic competencies divided by value added. | 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 adjusted for labour time by the self-employed (or owner-manager) labour divided by value added. | EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/ |
| Innovation productivity | The contribution of knowledge assets to value added growth (%) | EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/ |
| Value added | Gross value added, current prices, millions. | EU-KLEMS&INTANProd database, https://euklems-intanprod-llee.luiss.it/ |
| | **Variables at the country level** | |
| Human capital | An index based on average years of schooling and an assumed rate of return for primary, secondary, and tertiary education. | Penn World Tables, https://www.rug.nl/ggdc/productivity/pwt/?lang=en |
| Intellectual and Physical Property Rights index (*IPRI*) | An index from 1 to 10, based on simple average of the scores for legal and political environment (LP); physical property rights (PPR) protection; and intellectual property rights (IPR) protection. | Montanari, L., & Levy-Carcienter, S. (2020). International Property Rights Index 2020. Property Rights Alliance, https://news.fiar.me/wp-content/uploads/2021/03/IPRI_2020-Full_Report.pdf |
| Product market regulation (*PMR*) | An economy-wide index of competition-restrictive regulation in product markets, ranging from 0 (least restrictive) to 6 (most restrictive). | https://www.oecd.org/economy/reform/indicators-of-product-market-regulation// . See also Koske et al. (2015). |
| Trade union density | Employees with trade union membership as percentage of total employees (%). | OECD statistical databases https://stats.oecd.org/Index.aspx?DataSetCode=TUD |
| 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 |
| Internal rates of return on capital (*IRR*) | The internal rates of return on capital compatible with perfect competition (%). | Penn World Tables (PWT): https://www.rug.nl/ggdc/productivity/pwt/?lang=en |
| Indirect taxes on goods and services | The rate of indirect taxes on goods and services as percentage of GDP (%). | OECD Global Revenue Statistics Database at https://stats.oecd.org/Index.aspx?DataSetCode=RS_GBL |

## Table A2: 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 A3: 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 A4: Maximum likelihood estimation of innovation, markup and labour share equations: Robustness checks with different samples, innovation measures, and lag specifications**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Innovation intensity equation | | | | | | |
| Profits-based markup | 2.5910$^{*}$ | 4.1095$^{***}$ | 5.3625$^{***}$ | -1.2560$^{***}$ | 3.4352$^{*}$ | 3.0411$^{***}$ |
| | (1.4812) | (0.8036) | (1.2019) | (0.0712) | (1.7913) | (0.5766) |
| Profits-based markup sq | 0.0540 | 0.0638 | 0.0452 | 0.2340$^{***}$ | -0.0517 | 0.0215 |
| | (0.0690) | (0.0457) | (0.0402) | (0.0558) | (0.0492) | (0.0227) |
| Human capital | 1.7833$^{***}$ | 0.6929$^{*}$ | 0.7758 | 2.5810$^{***}$ | 1.1226 | 0.5556 |
| | (0.4698) | (0.4068) | (0.5630) | (0.1173) | (0.7391) | (0.3727) |
| Innovation productivity | 0.0518$^{***}$ | 0.0126$^{*}$ | 0.0172 | 0.0295$^{***}$ | 0.0427 | 0.0128 |
| | (0.0132) | (0.0074) | (0.0125) | (0.0021) | (0.0280) | (0.0086) |
| Product-market regulation | -0.3181$^{***}$ | -0.4032$^{***}$ | -0.4850$^{***}$ | -0.0434$^{**}$ | -0.4328$^{***}$ | -0.4165$^{***}$ |
| | (0.0905) | (0.0706) | (0.1021) | (0.0177) | (0.1367) | (0.0632) |
| Value added | -0.0073$^{**}$ | -0.0094$^{***}$ | -0.0128$^{***}$ | -0.0024$^{***}$ | -0.0095$^{**}$ | -0.0084$^{***}$ |
| | (0.0035) | (0.0031) | (0.0040) | (0.0008) | (0.0045) | (0.0026) |
| Profits-based markup equation | | | | | | |
| Innovation in tensity | 0.1104$^{***}$ | 0.1576$^{***}$ | 0.1294$^{***}$ | 0.2245$^{***}$ | 0.1565$^{***}$ | 0.2333$^{***}$ |
| | (0.0198) | (0.0317) | (0.0238) | (0.0475) | (0.0224) | (0.0363) |
| Product-market regulation | 0.0711$^{***}$ | 0.0820$^{***}$ | 0.0815$^{***}$ | 0.1115$^{***}$ | 0.0984$^{***}$ | 0.1183$^{***}$ |
| | (0.0123) | (0.0158) | (0.0133) | (0.0215) | (0.0141) | (0.0180) |
| Value added | 0.0021$^{***}$ | 0.0021$^{***}$ | 0.0021$^{***}$ | 0.0022$^{***}$ | 0.0024$^{***}$ | 0.0025$^{***}$ |
| | (0.0006) | (0.0006) | (0.0006) | (0.0007) | (0.0007) | (0.0007) |
| Property rights index | -0.0629$^{*}$ | -0.0297 | -0.0128 | 0.0378 | -0.0394 | -0.0317 |
| | (0.0346) | (0.0206) | (0.0116) | (0.0481) | (0.0386) | (0.0241) |
| Labour share equation | | | | | | |
| Innovation in tensity | -0.0391$^{***}$ | -0.0099 | -0.0728$^{***}$ | -0.1698$^{***}$ | 0.0083 | -0.0966$^{***}$ |
| | (0.0083) | (0.0215) | (0.0196) | (0.0343) | (0.0161) | (0.0175) |
| Profits-based markup | -1.1042$^{***}$ | -1.6446$^{***}$ | -1.5912$^{***}$ | -1.6076$^{***}$ | -1.5335$^{***}$ | -1.1685$^{***}$ |
| | (0.0263) | (0.1444) | (0.1307) | (0.1107) | (0.1075) | (0.0258) |
| Human capital | 0.4799$^{***}$ | 0.4488$^{***}$ | 0.5744$^{***}$ | 0.8118$^{***}$ | 0.3763$^{***}$ | 0.6076$^{***}$ |
| | (0.0410) | (0.0583) | (0.0648) | (0.0947) | (0.0508) | (0.0591) |
| Value added | 0.0015$^{***}$ | 0.0025$^{***}$ | 0.0011$^{**}$ | 0.0008$^{*}$ | 0.0024$^{***}$ | 0.0014$^{***}$ |
| | (0.0003) | (0.0005) | (0.0005) | (0.0005) | (0.0005) | (0.0003) |
| Property rights index | -0.0176 | -0.0646$^{***}$ | -0.0075 | 0.0469$^{**}$ | -0.0756$^{***}$ | -0.0632$^{***}$ |
| | (0.0179) | (0.0242) | (0.0225) | (0.0219) | (0.0265) | (0.0204) |
| Trade union density | 0.0573$^{***}$ | 0.0746$^{***}$ | 0.0641$^{***}$ | 0.0638$^{***}$ | 0.0717$^{***}$ | 0.0504$^{***}$ |
| | (0.0057) | (0.0069) | (0.0071) | (0.0071) | (0.0072) | (0.0061) |
| Emp. protection legislation | 0.1190$^{***}$ | 0.1313$^{***}$ | 0.0813$^{***}$ | 0.0810$^{***}$ | 0.1347$^{***}$ | 0.1250$^{***}$ |
| | (0.0092) | (0.0095) | (0.0095) | (0.0095) | (0.0102) | (0.0100) |
| *N* | 6,553 | 6,547 | 5,965 | 5,961 | 5,695 | 5,690 |
| RMSEA | 0.064 | 0.065 | 0.027 | 0.050 | 0.070 | 0.068 |
| SRMR | 0.028 | 0.028 | 0.010 | 0.013 | 0.030 | 0.030 |
| CFI | 0.987 | 0.982 | 0.997 | 0.991 | 0.983 | 0.983 |
| TFI | 0.950 | 0.939 | 0.998 | 0.968 | 0.930 | 0.942 |

Notes: Results based on maximum likelihood estimator. (1) Full sample with innovation intensity1 and no lags; (2) Full sample with innovation intensity2 and no lags; (3) Full sample with innovation intensity1 and two lags on exogenous predictors; (4) Full sample with innovation intensity2 and two lags on exogenous predictors; (5) Full sample with innovation intensity1, excluding the crisis period (2007-2009);(6) Full sample with innovation intensity2, excluding the crisis period (2007-2009). Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table A5: 3SLS estimation of innovation, markup and labour share equations: Robustness checks with different samples, innovation measures, and lag specifications**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Innovation intensity equation | | | | | | |
| Profits-based markup | 0.4331 | 0.3670 | 0.0302 | 0.4601$^{**}$ | 1.0414$^{**}$ | 0.7071$^{***}$ |
| | (0.3983) | (0.2319) | (0.4280) | (0.2283) | (0.4378) | (0.2629) |
| Profits-based markup sq | 0.5168$^{**}$ | 0.5070$^{***}$ | 0.1349 | 0.1594$^{***}$ | 0.4788$^{**}$ | 0.4368$^{***}$ |
| | (0.2036) | (0.1108) | (0.1008) | (0.0549) | (0.2359) | (0.1311) |
| Human capital | 2.4270$^{***}$ | 2.1151$^{***}$ | 2.6721$^{***}$ | 1.8695$^{***}$ | 2.2399$^{***}$ | 1.9451$^{***}$ |
| | (0.2456) | (0.1486) | (0.2460) | (0.1445) | (0.2839) | (0.1792) |
| Innovation productivity | 0.0729$^{***}$ | 0.0361$^{***}$ | 0.0570$^{***}$ | 0.0208$^{***}$ | 0.0884$^{***}$ | 0.0433$^{***}$ |
| | (0.0044) | (0.0026) | (0.0048) | (0.0024) | (0.0071) | (0.0042) |
| Product-market regulation | -0.1948$^{***}$ | -0.1558$^{***}$ | -0.1273$^{***}$ | -0.1702$^{***}$ | -0.2370$^{***}$ | -0.1905$^{***}$ |
| | (0.0409) | (0.0244) | (0.0407) | (0.0235) | (0.0483) | (0.0300) |
| Value added | -0.0025$^{*}$ | -0.0025$^{***}$ | -0.0052$^{***}$ | -0.0046$^{***}$ | -0.0038$^{**}$ | -0.0036$^{***}$ |
| | (0.0014) | (0.0009) | (0.0015) | (0.0009) | (0.0016) | (0.0011) |
| Profits-based markup equation | | | | | | |
| Innovation in tensity | 0.0498$^{***}$ | 0.0329 | 0.1240$^{***}$ | 0.1981$^{***}$ | 0.0810$^{***}$ | 0.0760$^{***}$ |
| | (0.0159) | (0.0245) | (0.0236) | (0.0394) | (0.0171) | (0.0270) |
| Property rights index | -0.1046$^{***}$ | -0.1816$^{***}$ | -0.0411 | -0.1171$^{***}$ | -0.1115$^{***}$ | -0.1854$^{***}$ |
| | (0.0312) | (0.0300) | (0.0366) | (0.0371) | (0.0311) | (0.0298) |
| Product-market regulation | 0.0393$^{***}$ | 0.0226$^{*}$ | 0.0796$^{***}$ | 0.0959$^{***}$ | 0.0578$^{***}$ | 0.0441$^{***}$ |
| | (0.0105) | (0.0126) | (0.0131) | (0.0179) | (0.0112) | (0.0139) |
| Value added | 0.0019$^{***}$ | 0.0017$^{***}$ | 0.0020$^{***}$ | 0.0019$^{***}$ | 0.0022$^{***}$ | 0.0020$^{***}$ |
| | (0.0006) | (0.0006) | (0.0006) | (0.0007) | (0.0006) | (0.0006) |
| Labour share equation | | | | | | |
| Innovation in tensity | -0.0285$^{***}$ | -0.0539$^{***}$ | -0.0919$^{***}$ | -0.1917$^{***}$ | -0.0359$^{***}$ | -0.0671$^{***}$ |
| | (0.0095) | (0.0172) | (0.0251) | (0.0490) | (0.0101) | (0.0185) |
| Profits-based markup | -1.2179$^{***}$ | -1.2965$^{***}$ | -1.4094$^{***}$ | -1.6004$^{***}$ | -1.2597$^{***}$ | -1.3668$^{***}$ |
| | (0.0408) | (0.0460) | (0.2096) | (0.2249) | (0.0390) | (0.0435) |
| Human capital | 0.4668$^{***}$ | 0.5335$^{***}$ | 0.6026$^{***}$ | 0.8750$^{***}$ | 0.4842$^{***}$ | 0.5677$^{***}$ |
| | (0.0415) | (0.0561) | (0.0637) | (0.1121) | (0.0433) | (0.0590) |
| Trade union density | 0.0649$^{***}$ | 0.0670$^{***}$ | 0.0513$^{***}$ | 0.0464$^{**}$ | 0.0622$^{***}$ | 0.0647$^{***}$ |
| | (0.0068) | (0.0070) | (0.0184) | (0.0192) | (0.0069) | (0.0072) |
| Emp. protection legislation | 0.1218$^{***}$ | 0.1250$^{***}$ | 0.0834$^{***}$ | 0.0983$^{***}$ | 0.1267$^{***}$ | 0.1300$^{***}$ |
| | (0.0094) | (0.0094) | (0.0100) | (0.0125) | (0.0100) | (0.0100) |
| Property rights index | -0.0227 | -0.0335$^{*}$ | 0.0065 | -0.1118$^{***}$ | -0.0518$^{***}$ | -0.0731$^{***}$ |
| | (0.0178) | (0.0190) | (0.0256) | (0.0319) | (0.0190) | (0.0206) |
| Value added | 0.0018$^{***}$ | 0.0018$^{***}$ | 0.0008 | 0.0004 | 0.0018$^{***}$ | 0.0018$^{***}$ |
| | (0.0003) | (0.0003) | (0.0006) | (0.0007) | (0.0003) | (0.0004) |
| *N* | 6,553 | 6,547 | 5,965 | 5,961 | 5,695 | 5,690 |
| RMSE – Equation 1 | 0.261 | 0.182 | 0.247 | 0.187 | 0.291 | 0.205 |
| RMSE – Equation 2 | 0.103 | 0.101 | 0.109 | 0.115 | 0.106 | 0.105 |
| RMSE – Equation 3 | 0.057 | 0.059 | 0.062 | 0.070 | 0.059 | 0.062 |

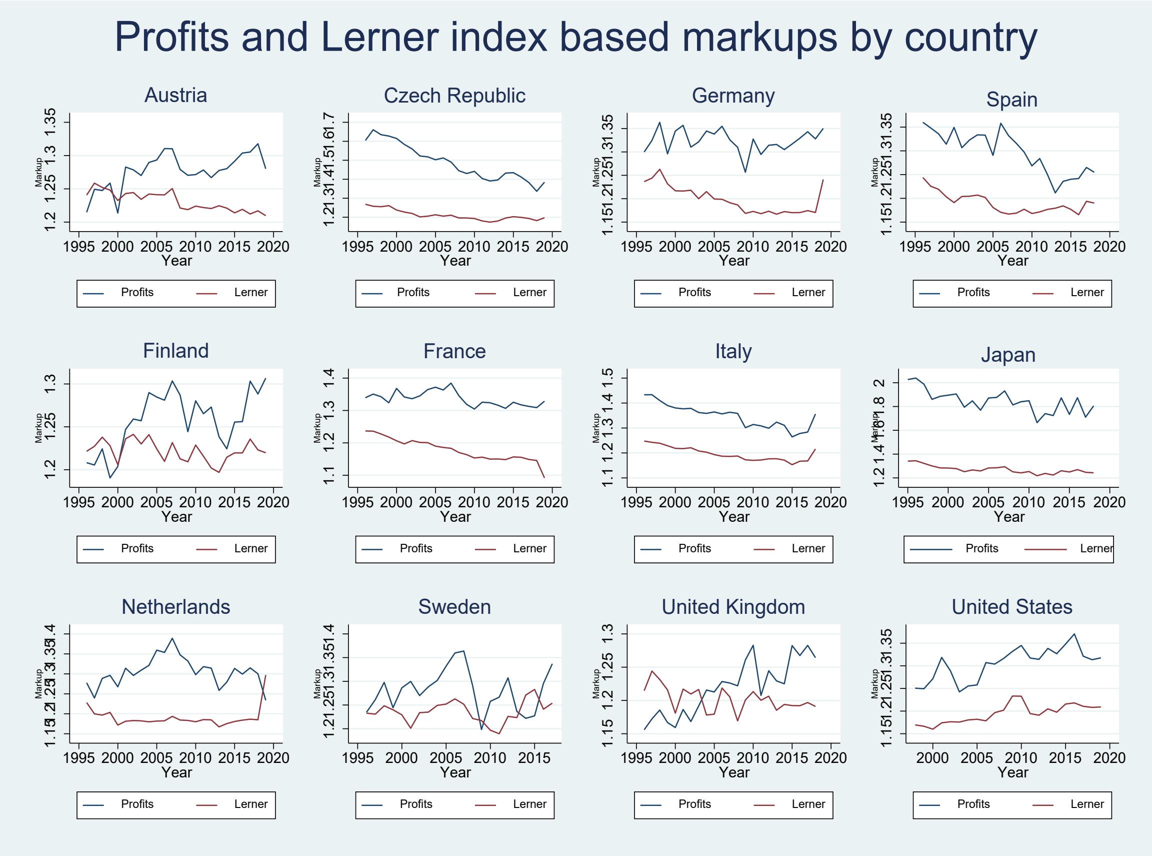
Notes: 3SLS estimation. (1) Full sample with innovation intensity1 and no lags; (2) Full sample with innovation intensity2 and no lags; (3) Full sample with innovation intensity1 and two lags on exogenous predictors; (4) Full sample with innovation intensity2 and two lags on exogenous predictors; (5) Full sample with innovation intensity1, excluding the crisis period (2007-2009);(6) Full sample with innovation intensity2, excluding the crisis period (2007-2009). Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Table A6: ADF estimation of innovation, markups and labour share equations: Robustness checks with Lerner-index-based markups**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Innovation intensity equation | | | | | | |
| Lerner-index-based markup | 5.1727** | 7.0691*** | 3.7994** | 5.6581*** | 6.8199** | 8.5721*** |
| | (2.2849) | (1.7222) | (1.6512) | (1.4849) | (3.1021) | (3.2151) |
| Lerner-index-based markup sq | 1.6328*** | 0.6006* | -0.6476 | -0.2441 | 1.0386** | 0.1618 |
| | (0.5332) | (0.3338) | (0.5194) | (0.2039) | (0.4883) | (0.2302) |
| Human capital | 1.7564*** | 1.1664*** | 1.9061*** | 0.9457*** | 1.3115*** | 0.4220 |
| | (0.2494) | (0.2635) | (0.2864) | (0.3013) | (0.4076) | (0.5012) |
| Innovation productivity | 0.0634*** | 0.0261*** | 0.0431*** | 0.0138*** | 0.0624*** | 0.0137 |
| | (0.0082) | (0.0056) | (0.0055) | (0.0041) | (0.0186) | (0.0162) |
| Product-market regulation | -0.5281*** | -0.6134*** | -0.3837*** | -0.5156*** | -0.6809*** | -0.7999*** |
| | (0.1406) | (0.1106) | (0.1038) | (0.0965) | (0.2073) | (0.2224) |
| Value added | -0.0057** | -0.0069** | -0.0101*** | -0.0113*** | -0.0079** | -0.0092** |
| | (0.0026) | (0.0028) | (0.0027) | (0.0029) | (0.0034) | (0.0038) |
| Lerner-index-based markup eq. | | | | | | |
| Innovation in tensity | 0.0349*** | 0.0463*** | 0.0444*** | 0.0744*** | 0.0550*** | 0.0860*** |
| | (0.0073) | (0.0139) | (0.0111) | (0.0186) | (0.0089) | (0.0153) |
| Product-market regulation | 0.0646*** | 0.0661*** | 0.0610*** | 0.0698*** | 0.0768*** | 0.0859*** |
| | (0.0047) | (0.0068) | (0.0060) | (0.0083) | (0.0055) | (0.0076) |
| Value added | 0.0007*** | 0.0008** | 0.0013*** | 0.0014*** | 0.0009*** | 0.0010*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Property rights index | -0.0384*** | -0.0342*** | -0.0548*** | -0.0399** | -0.0275* | -0.0124 |
| | (0.0143) | (0.0122) | (0.0156) | (0.0172) | (0.0162) | (0.0179) |
| Labour share equation | | | | | | |
| Innovation in tensity | -0.0638*** | -0.1032*** | -0.0516* | -0.0848* | -0.0566*** | -0.0887*** |
| | (0.0161) | (0.0288) | (0.0270) | (0.0440) | (0.0199) | (0.0321) |
| Lerner-index-based markup | -1.6067*** | -1.7606*** | -1.6329*** | -1.7572*** | -1.7202*** | -1.8664*** |
| | (0.1723) | (0.1847) | (0.2153) | (0.2365) | (0.1534) | (0.1586) |
| Human capital | -0.0946 | -0.0433 | -0.0576 | -0.0355 | -0.1475** | -0.1177 |
| | (0.0665) | (0.0805) | (0.0903) | (0.1062) | (0.0723) | (0.0851) |
| Value added | -0.0006 | -0.0003 | -0.0008 | -0.0005 | -0.0008 | -0.0003 |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Property rights index | -0.0884*** | -0.1129*** | -0.0741** | -0.0891** | -0.1042*** | -0.1245*** |
| | (0.0299) | (0.0319) | (0.0358) | (0.0417) | (0.0306) | (0.0328) |
| Trade union density | -0.0212* | -0.0146 | -0.0191* | -0.0183* | -0.0228** | -0.0168 |
| | (0.0111) | (0.0107) | (0.0115) | (0.0111) | (0.0112) | (0.0108) |
| Emp. protection legislation | 0.1011*** | 0.0993*** | 0.0925*** | 0.0866*** | 0.1053*** | 0.1025*** |
| | (0.0144) | (0.0141) | (0.0144) | (0.0139) | (0.0153) | (0.0150) |
| *N* | 6,613 | 6,607 | 6,067 | 6,063 | 5,749 | 5,744 |
| RMSEA | 0.030 | 0.035 | 0.024 | 0.033 | 0.035 | 0.041 |
| SRMR | 0.012 | 0.013 | 0.010 | 0.012 | 0.014 | 0.015 |
| CFI | 0.980 | 0.978 | 0.986 | 0.978 | 0.976 | 0.973 |
| TFI | 0.921 | 0.914 | 0.947 | 0.916 | 0.908 | 0.894 |

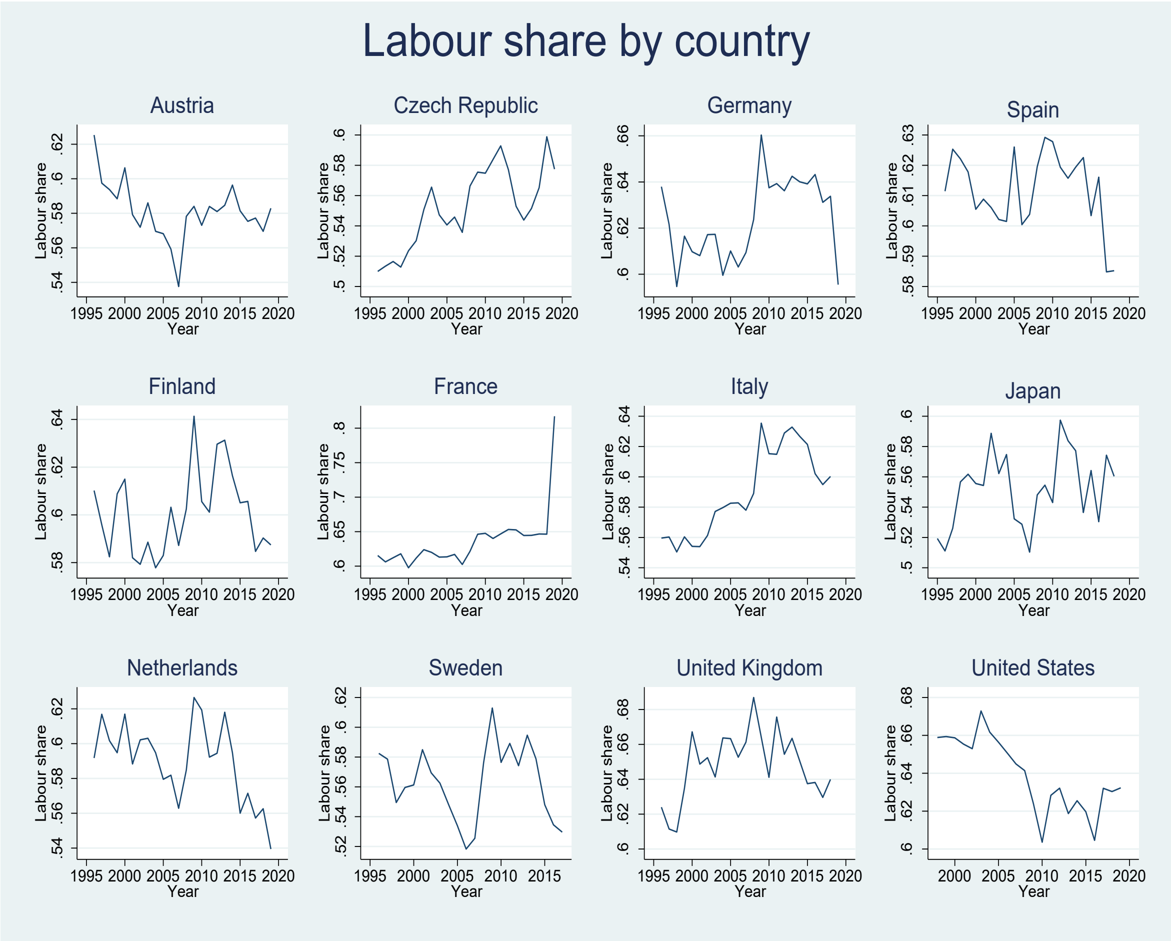
Notes: All estimations are based on ADF methodology. (1) Full sample with innovation intensity1 and no lags; (2) Full sample with innovation intensity2 and no lags; (3) Full sample with innovation intensity1 and two lags on exogenous predictors; (4) Full sample with innovation intensity2 and two lags on exogenous predictors; (5) Full sample with innovation intensity1, excluding the crisis period (2007-2009);(6) Full sample with innovation intensity2, excluding the crisis period (2007-2009). Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Figure A1: Evolution of average markups by country**



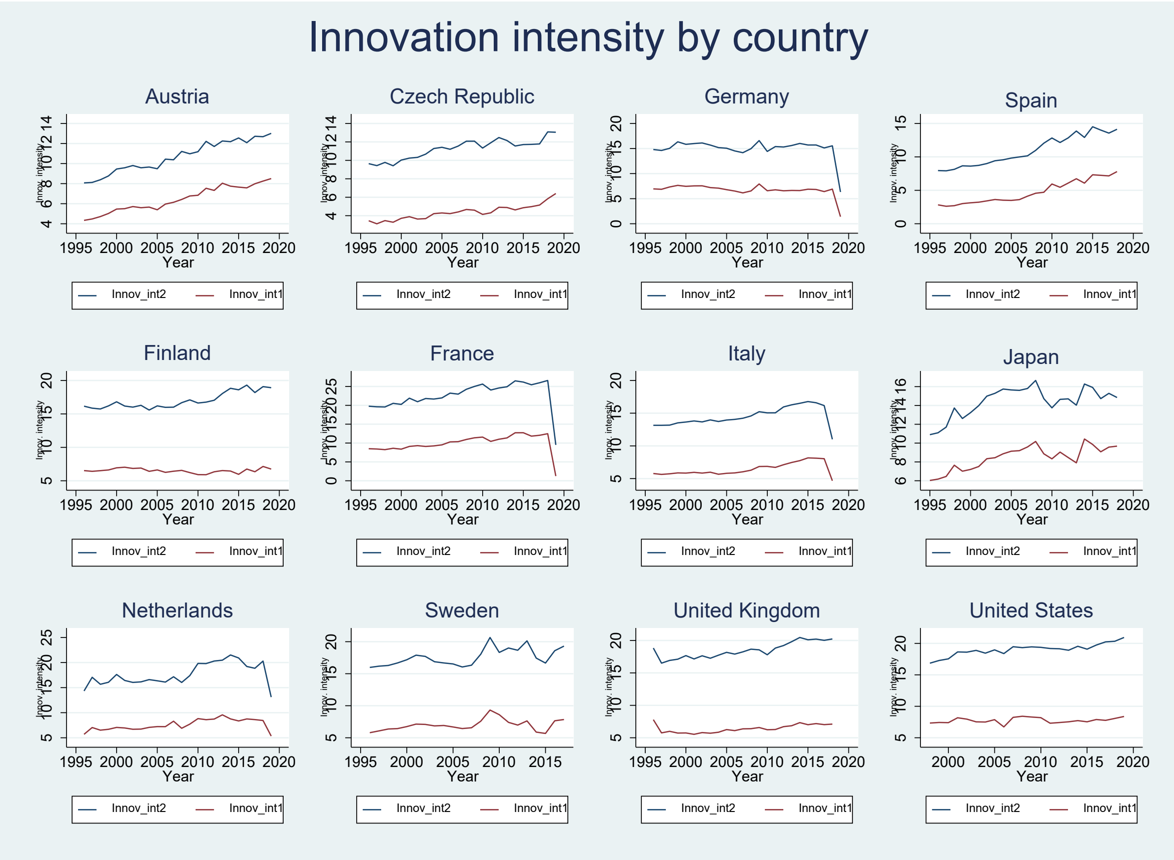

The profits-based markup is informed by Barkai (2020) and Eggertsson et al. (2021); whereas the Lerner-index-based markup is based on Ciapanna et al. (2020). One conclusion supported by the evidence is that the two markups differ in magnitude – with the profits-based markup remaining higher than the Lerner-index-based markup. However, both markups are corelated within each country, with the within-country correlation ranging from 0.15 in Austria to 0.53 in Spain and the US and 0.72 in Japan. Secondly, the markups vary over time – 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). Third, the within-country 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 evidence from our sample indicates that heterogeneity in the level and trend of the labour share in value added. One conclusion that can be derived from the evidence is that the 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). Finally, 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.

**Figure A3: Evolution of innovation intensity by country**




*Innov_int1* includes innovation investment in the following knowledge assets: research and development (*R&D*); computers, software, and databases (*COMP_Soft_DB*); and other intellectual property assets (*Other_IP*). *Innov_int2*, on the other hand, includes innovation investment in a wider set of assets that includes the former plus organizational innovation (*Org_in*), marketing innovation (*Mark_in*), and economic competencies (*Ec_Comp*). Both are measured as ratios of the relevant innovation investment to value added. The sample evidence indicates that innovation intensity 1 and 2 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). It also indicates the intensity of the investment in non-capitalized knowledge assets (*Org_in*, *Mark-in*, and *Ec_Comp*) is higher than (usually twice) the intensity of the investment in capitalized knowledge assets (*R&D, COMP_Soft_DB,* and *Other_IP*).