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

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ABSTRACT

Two issues remain overlooked in empirical investigations of how labour share varies with technological innovation and market power. One is the risk of omitted variable bias that arises from failure to control for both innovation and market power at the same time. The second is the risk of confounding bias that arises from the possibility that innovation and market power affect each other and the labour share at the same time. I address both issues by adopting a simultaneous equations approach and using EU-KLEMS data from 1995 to 2019 on 31 OECD industries and 12 countries. The novel evidence I discover indicates that: (i) innovation always increases with market power, particularly when the latter increase from a high initial level; (ii) market power always increases with innovation, particularly when the latter is extended to include marketing and organisational innovation; (iii) market power is always more detrimental for labour share compared to innovation; and (iv) the combined effect of human capital and labour-market institutions reverses the adverse effect of innovation but it is *insufficient* to reverse the adverse effect of market power. These findings are robust to a wide range of sensitivity checks and indicate that the major driver of the decline in labour share is not technological innovation per se, but the extent of market power that enables firms to set real wages below the marginal product of labour.

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 potential determinants. The range of explanatory factors includes the weakening of labour-market institutions, globalisation/off-shoring, financialization, technological innovation, and market power. This paper aims to contribute to the literature that focuses on innovation and/or market power as potential determinants of the labour share.[1]

In one line of research, technological change spurred by falling relative prices of investment goods is the primary determinant of labour share (Karabarbounis and Neiman, 2014; Río and Lores, 2019). In another line, the focus is on the capital bias of technical change, driven by changes in preferences, markups, demographics or trade patterns (Oberfield and Raval, 2021; Alvarez-Cuadrado et al., 2018). Technological change is also associated with falling labour share when it involves automation that destroys routine jobs at faster rates than the rate of creating new tasks (Acemoglu and Restrepo, 2019; Autor and Salomons, 2018; Charalampidis, 2020). In a third 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 (Dixon and Lim, 2018; Barkai, 2020; De Loecker et al., 2020; Eggertsson et al., 2021; Gutierrez Gallardo and Philippon, 2019).

The theoretical models or frameworks that inform the empirical work in this research field mostly assume that technological change (innovation) and market power are interrelated. Nevertheless, the empirical work tends to relate labour share to technological innovation or market power only, overlooking the reciprocal relationship between the two and the need to disentangle the labour-share-effect of one from that of the other. Hence, effect-size estimates from such investigations may be biased due to misspecification or omitted variable biases.

The aim of this study is to address both sources of potential bias by proposing and estimating a set of simultaneous equation models that: (i) take account of simultaneity and reverse-causality between innovation and market power; and (ii) control for both innovation and market power as confounding factors that affect each other and the labour share at the same time; and (iii) treat innovation, market power and labour

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[1] For reviews of the debate on the roles of labour-market institutions, globalisation and financialization, see Damiani et al. (2020), Ciminelli et al. (2022), Guschanski and Onaran (2018, 2022, 2023), and Kornrich and Hicks (2015).

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share as co-evolving endogenous outcomes. The proposed empirical model draws extensively on testable predictions form theoretical Schumpeterian models of innovation (Aghion et al., 2015 and 2019a), where markups are both a driver for and an outcome of investment in innovation. However, it overcomes the limitations of the reduced-form empirical models of labour share informed either by Schumpeterian or non-Schumpeterian theoretical models.

One of our contributions is to demonstrate that it is necessary and feasible to *disentangle* the effect of innovation from that of market power and vice versa by controlling for both determinants at the same time. Controlling for determinants at the same time enables us to correct for potential omitted variable bias in both strands of the empirical literature: (i) the work that explains the fall in labour share by rising market power (markups) without controlling for the effects of innovation as an additional determinant (e.g., Dixon and Lim, 2018; Barkai, 2020; Eggertsson et al., 2021; Gutierrez Gallardo and Philippon, 2019); and (ii) the empirical work that relates the fall in labour share to technological innovation without controlling for market power (e.g., Autor et al., 2006; Goos & Manning, 2007; Goos et al., 2009; Acemoglu and Autor, 2011; Goos, 2018; Acemoglu and Restrepo, 2018).

Our work offers two further contributions. On the one hand, it reconciles the theoretical insights and the empirical stylised facts, both of which suggest that technological innovation and market power are interrelated and that innovation, market power and the labour share are coevolving outcomes that may be determined simultaneously. In this endeavour, we demonstrate that innovation increases with markups in a non-linear fashion, particularly when markups increase from a high initial level (in line with earlier work by Aghion et al., 2005). We also demonstrate that markups increase with innovation linearly, but the rate of increase is higher when innovation includes investment in organisational change, new marketing strategies and economic competenecies in addition to investment in R&D and information technology. This finding is consistent with the emerging evidence that firms/industries with higher levels of investment in intangible assets tend to have higher markups (Altomonte et al., 2021; De Ridder, 2019; Sandström, 2020).

On the other hand, our work provides novel evidence that allows for comparing the effects of technological innovation with those of market power. Here, we find that the *adverse* effect of market power on labour share is much stronger than that of technological innovation – both directly and indirectly. The discrepancy is stark enough to imply that the positive effects of labour-market institutions and human capital on labour share are *sufficient* to reverse the adverse effect from technological innovation, but they are *insufficient* to reverse the adverse effects of market power.

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. Our review indicates that empirical researchers - with notable exception of Dixon and Lim (2020) and Bellocchi and Travaglini (2023) - estimate reduced-form models where either technological innovation or market power is the determinant of falling labour share. Our review also indicates that the existing work accounts neither for the reciprocal relationship between innovation and market power or the co-evolution of innovation, market power and labour share as endogenously determined outcomes.

The theoretical justification for our simultaneous equation modeling approach is developed in Section 3, where we draw extensively on a Schumpeterian model of innovation and income distribution (Aghion et al., 2019a) to demonstrate that: (i) innovation and market power are interrelated; (ii) the labour-share is a function of both innovation and market power; and (iii) innovation, market power (markups) and the labour share are co-evolving endogenous outcomes determined simultaneously.

Section 4 presents our data and methodology. We use 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 estimation is the asymptotic distribution free (ADF) method, which is used for estimating structural equation models (SEMs) when the assumption of joint (multivariate) normality does not hold. 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 with the theoretical predictions that underpin the system of structural equations we estimate. Higher markups are always conducive to lower labour share. Moreover, the adverse effects of markups on labour share are stronger than those of technological innovation – both directly and indirectly. 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 and fairness implications.

2. Related literature

One line of research that our work is related to focuses on the implications of technological change for labour share. The theoretical models in this research line dates to induced technical change (ITC) models of the 1960s, where 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 leads to falling labour share or increasing wage disparity or both (Hicks, 1963; Kennedy, 1964; Caselli, 1999). Later on, Karabarbounis and Neiman (2014) have contributed to this line of research by demonstrating that capital deepening is spurred by falling relative prices of investment goods and it reduces labour share when the elasticity of substitution is greater than one. However, labour share can fall in technological change even if the elasticity of substitution is less than one, specifically because of capital-biased technology that reflects changes in preferences, market power, demography or trade (Oberfield and Raval, 2021; Alvarez-Cuadrado, Van Long, and Poschke, 2018). The second line of research focuses on automation and demonstrates that the labour share falls in technological change if automation destroys routine tasks at higher rates compared to the creation of new tasks (Acemoglu and Restrepo, 2018; Autor and Salomons, 2018).

A third line of related research focuses on market power as a determinant of labour share. Theoretical models in this research area acknowledge that technological innovation and market power are interrelated, but they relate the fall in labour share to rising market power and associated economic rents only. Given that the economic rents either accrue to firms with market power (Barkai, 2020; De Loecker et al., 2020) or add to "factorless income" (Karabarbounis and Neiman, 2019), labour share tends to fall with markups (See also, Dixon and Lim, 2018; Gutierrez Gallardo and Philippon, 2019; Eggertsson et al., 2021).

We identify two issues in these lines of research: (i) overlooking the

[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/

interrelation between innovation and market power; and (ii) explaining the movements in labour share with technological innovation or market power only. Yet, the interrelation between innovation and market power is either explicit or implicit in the theoretical models that underpin the empirical work. In Schumpeterian models, firms innovate to exploit excess profit opportunities and successful innovators secure higher levels of markups in high-innovation-lead industries at the same time (Aghion, 2002; Aghion et al., 2019a and 2019b; Chu and Cozzi, 2018; Jones and Kim, 2018).[3] In the SBTC models, the relationship is explicit only in the market for technology, where firms are induced to innovate with a view to exploit innovation rents that dissipate in the product market as a result of free entry and exit (Acemoglu, 1998, 2003; Bogliacino, 2014). Finally, in some of the routine-biased technical change (RBTC) models, technological innovation leads to the emergence of 'super star' firms, which are characterised by higher level of productivity, market power, and market shares (Autor et al., 2017, 2020). In others, innovation enables firms to raise the price of their innovative products and/or lower the price of their inputs (Guellec and Paunov, 2017); or to exploit the benefits of the scale economies and network effects (Bessen, 2017).

These theoretical insights are indeed compatible with the stylised facts revealed by our data. As can be observed from Fig. 1, both innovation intensity (measured as investment in knowledge assets as a ratio of value added) and markups (measured with excess profits or with the excess of price over marginal cost) have been increasing over time. On the other hand, both the wage share (i.e., the share of employee income in value added) and the labour share (i.e., the share of employees and the self-employed income in value added) have been falling over time. Despite this congruence between the theoretical insights and the data, however, the empirical work has tended to overlook the relationship between innovation and market power.

The empirical work has also failed to control for technological innovation and market power at the same time despite the positive correlation between them and the negative correlation both display with labour share. In some studies, technological change is dropped from the model because technology is assumed to be capital-augmenting and as such capital deepening is sufficient to explain the effect of technology on labour share (e.g., Karabarbounis and Neiman, 2014). Yet technical change is a determinant of labour share beyond capital deepening and this is the case in in both constant and variable elasticity of substitution production functions (see, for example Raurich et al., 2012; Bellocchi and Travaglini, 2023). Hence, the reliance on capital deepening only is a source of omitted variable bias even if market power is controlled for in the estimation. A similar risk of bias is present in Velasquez (2023), who acknowledge the role of both technological change and market power but provides estimates based on market power and capital deepening instead of technological change. A similar omitted variable issue is observed in Raurich et al. (2012), where markups are included in the model together with capital deepening but without any direct measure of technological innovation. Finally, technological innovation is also missing in empirical setups adopted in several studies that have contributed to the debate on macroeconomic consequences of market power, including the labour share (Barkai, 2020; De Loecker et al., 2020; Dixon and Lim, 2018; Gutierrez Gallardo and Philippon, 2019; Eggertsson et al., 2021).

The mirror image of the 'missing technological innovation' is the lack of control for market power when technological change or proxies thereof are controlled for. In some of these studies, market power is excluded from the empirical model directly by assuming perfect competition. This is the case in models informed by the SBTC hypothesis (Katz and Murphy, 1992; Acemoglu, 1998, 1999, 2002, 2003) as well as more recent studies drawing on production tasks or sectoral heterogeneity as potential determinants of labour share (Zhang et al., 2022; Qian et al., 2023). It is also the case in Antonelli and Tubiana (2023), who eschew the role of market power by relying on a re-interpretation of the Schumpeterian creative destruction hypothesis where breakthrough (as opposed to gradual) innovation can increase labour share, particularly if the technology is capital-saving. In some others, markups are subsumed under proxies that include but not limited to markups – for example non-technology factors that reflect labour's bargaining power (e.g., Bentolila and Saint-Paul, 2003).

To the best of our knowledge, only two studies estimate a labour share model in which both technological innovation and markups are controlled for. Dixon and Lim (2020) draw on a constant elasticity of substitution (CES) production function and demonstrate that movements in labour share are driven by changes in technology and non-technology factors that include market power. The other study is by Bellocchi and Travaglini (2023), who utilise a variable elasticity of substitution (VES) production function and allows for imperfect competition in wage setting. The authors demonstrate that the labour share always fall in markups and that technological innovation can increase or reduce labour share depending on the technology parameter that affects the magnitude of the elasticity of substitution. Although both studies are welcome steps in the right direction, we aim to complement their findings along two directions. On the one hand, we eliminate the risk of misspecification bias by allowing for a reciprocal relationship between technological innovation and market power. On the other hand, not only do we control for technological innovation and market power at the same time, but we treat the innovation, market power and the labour share as endogenous outcomes determined simultaneously.

3. The case for simultaneous equation modeling

In this section, we develop the theoretical case for a simultaneous equation approach that would enable us to address the two issues that remain overlooked in the empirical work discussed in the literature review above: (i) the risk of omitted variable bias that arises from failure to control for both innovation and market power at the same time; and (ii) the risk of confounding bias that arises from the possibility that innovation and market power affect each other and the labour share at the same time. The theoretical case is based on testable predictions from the Schumpeterian model of innovation, market power and income distribution in Aghion et al. (2019a). We will demonstrate that the causal pathways (building blocks) in the model indicate clearly that innovation and market power are interrelated; and that both affect the labour share at the same time. Our task here is to document these predictions from the theoretical Schumpeterian model and propose a simultaneous equation modeling approach that overcomes the limitations of the reduced-form models usually used in the empirical literature informed by both Schumpeterian and non-Schumpeterian perspectives.

In the Schumpeterian model of Aghion et al. (2019a), 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 (μ_H). Otherwise, its technological lead and markups are low at TL_L and μ_L, with the implication that $\mu_H > \mu_L > 1$.

Not all innovating firms would be necessarily successful. In Aghion et al. (2019a), rate of successful innovation (θ_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

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

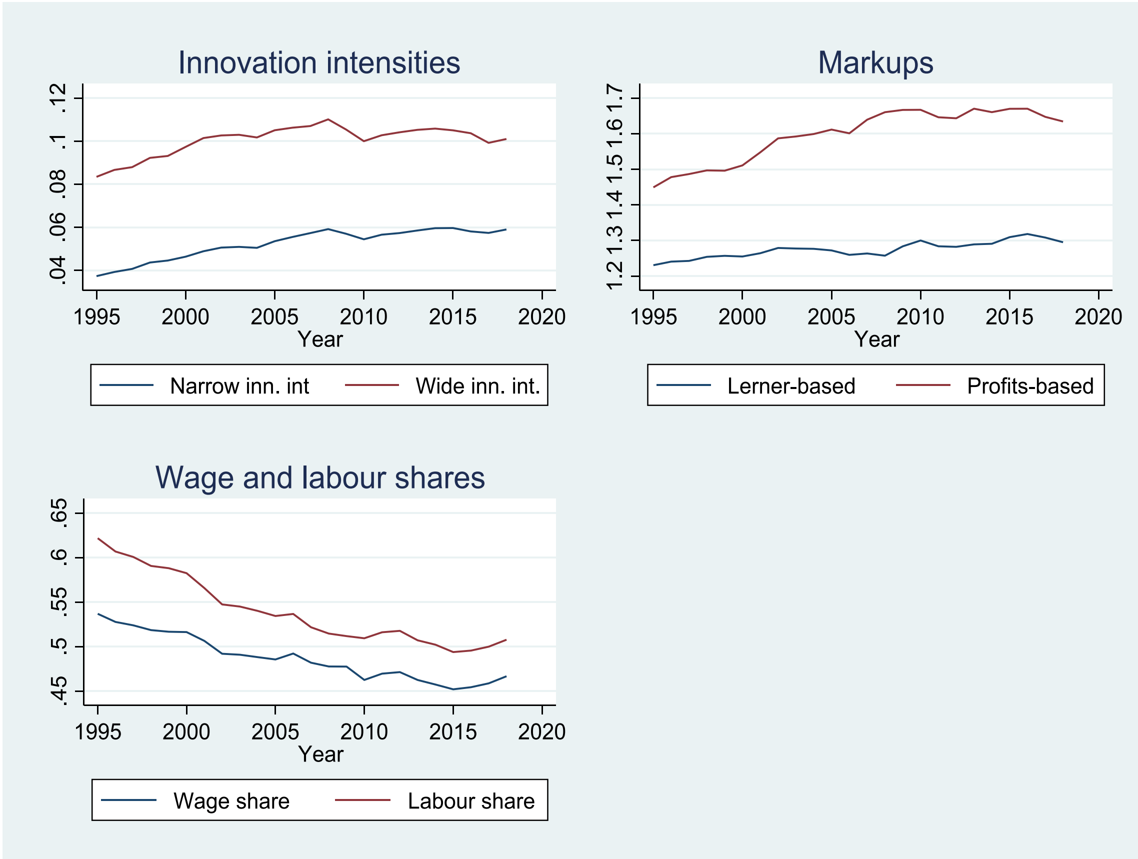

Fig. 1. Innovation, markups and labour share in OECD industries: Annual averages.
Notes: **Narrow innovation intensity** is the ratio of investment in research and development (R&D), computers and software, and other intellectual property assets to value added. **Wide innovation intensity** also includes investment in marketing innovation, organisational innovation and economic competencies. **Lerner-based markup** is the ratio of gross operating margin to total cost of labour intermediate inputs. **Profits-based markup** is the ratio of value added to the sum of capital cost, labour cost and indirect taxes on goods and services.
Wage share is the compensation of employees divided by value added; whereas **Labour share** is the compensation of employees and the self-employed divided by value added.

(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 (θ_t) in eq. (1) increases with markups in high-innovation-lead industries (μ_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 (μ_L) also increase. On the one hand, a higher μ_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 μ_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 capital and labour shares (Cap_{share} and Lab_{share}) as functions of markups and the successful rate of innovation, as indicated in 3a and 3b below.

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

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

The partial derivatives of the labour share eq. (3b) with respect to markups in high technological-lead industries (μ_H), markups in low-technological-lead industries (μ_L) and innovation rate (θ_t) are stated in 4 and 5 below.

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

$$\frac{\partial Lab_{share(t)}}{\partial \theta_t} = \frac{1}{\mu_H} - \frac{1}{\mu_L} < 0 \text{ if } \mu_H > \mu_L \tag{5}$$

Three predictions follow from the Schumpeterian model of innovation, market power and income distribution (Aghion et al. (2019a). First, the relationship between innovation and market power is bidirectional. While innovation increases in markup opportunities, successful innovators secure higher markups in both high- and low-technological-lead industries. This bidirectional relationship is not compromised by the relatively higher levels of initial markups in high-innovation-lead industries. Secondly, labour share always declines with markups, irrespective of whether markups increase in high- or low-technological lead industries (4). Third, innovation has an adverse

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 (η_i, η_c). Predicted effect signs are informed by the relevant literature discussed above and further work to be introduced below.

effect on labour share only if markups in high-technological-lead industries are higher than those in low-technological-lead industries (5).

Given the results discussed so far, we argue that reduced-form or single-equation models utilised in empirical studies are likely to be misspecified for three reasons: (i) they overlook the bidirectional relationship between innovation and market power; (ii) their reduced-form labour share models control for innovation or market power only, in contradiction with the need to control for both in accordance with predictions (4) and (5) above; and (iii) the reduced-form model does not allow for coevolution of innovation, market power and labour share as endogenous outcomes determined simultaneously. To correct for potential biases that may arise from such misspecifications, we propose to estimate a simultaneous equation model specified in 6.1–6.4 below, which allow for bidirectional relationship between innovation and markups; and control for the effects of both on labour share.

$$Innov_{ict} = \beta_{11}Markup_{ict} + \sum\nolimits_{k=1}^{K}\alpha_{1k}EP_{1kict} + \theta_{10} + \eta_{11i} + \eta_{12c} + \epsilon_{1ict} \tag{6.1}$$

$$Markup_{ict} = \beta_{21}Innov_{ict} + \sum\nolimits_{m=1}^{M}\alpha_{2m}EP_{2mict} + \theta_{20} + \eta_{21i} + \eta_{22c} + \epsilon_{2ict} \tag{6.2}$$

$$LS_{ict} = \beta_{31}Innov_{ict} + \beta_{32}Markup_{ict} + \sum\nolimits_{p=1}^{P}\alpha_{3p}EP_{pnict} + \theta_{30} + \eta_{31i} + \eta_{32c} + \epsilon_{3ict} \tag{6.3}$$

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

In the system, the β coefficients represent the direct effects of the endogenous variables on each other; whereas the α coefficients represent the direct effects of exogenous predictors (EPs) on the endogenous variables. The fixed effects at the industry level (η_i) and country level (η_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.

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),[4] where the effect of 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 increase form a high initial level – which 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 Aghion 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). 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.

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

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 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 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 from the 2021 release of the *EUKLEMS & INTANProd* database (*EU-KLEMS* thereafter).[5] 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 capitalized 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 captures the innovation investment types that have been capitalized in the System of National Accounts (SNA) and corresponds to the narrow technological innovation concept adopted in the first edition of the Oslo Manual. On the other hand, the numerator for I*nnov_int2* includes the components in *Innov_int1* and the investment in marketing (*Mark_in*), organisational change (*Org_in*) and economic competency (*Ec_comp*). This measure corresponds to the extended innovation concept that the OECD has adopted 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.

$$Innov\_int1_{ict} = \frac{R\&D_{ict} + Soft\_DB_{ict} + OIP_{ict}}{VA_{ict}} \tag{7.1}$$

$$Innov\_int2_{ict} = \frac{(R\&D_{ict} + Soft_{DB_{ict}} + OIP_{ict}) + (Org\_in_{ict} + Mark\_in_{ict} + Ec\_comp_{ict})}{VA_{ict}} \tag{7.2}$$

The two innovation measures are usually considered as complements in the relevant literature, as marketing or organisational innovation is usually undertaken to implement the product and process innovations inherent in the older innovation concept (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:

$$LS_{ict} = \frac{\left(H_{emp\,ict}/H_{empe\,ict}\right)^{*}Comp_{ict}}{VA_{ict}} \tag{8}$$

Our choice of the markup measure is informed by the debate on the measurement and economic consequences of market power (for reviews, see Basu, 2019; Syverson, 2019; Battiati et al., 2021; and Bond et al., 2021). The econometric method for obtaining markup measures has been proposed by Hall (1989, 1990) and Roeger (1995) for industry- or country-level markups; and by De Loecker et al. (2020) for firm-level markups that can be averaged to also obtain macro-or meso-level markups. The alternative approach is non-econometric and relies on accounting data to obtain either a profit-based markup that is proportional to the inverse of the economic (excess) profits (Barkai, 2020; Eggertsson et al., 2021); or a Lerner-index-based markup of prices over marginal costs (Ciapanna et al., 2022).

One advantage of the econometric methods is that they do not have to impose constant returns to scale in production – and do not require information about demand elasticity and/or marginal costs that are usually not available for the researcher. However, both approaches require correct input measurement, correct functional form for the production function, and correct estimation of the latter. Because such conditions are usually difficult to satisfy, Rovigatti (2020) reports 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 <1. Moreover, the difference between Hall (1989, 1990) and Roeger (1995) markups are too large to assuage doubts about their validity in applied research. Finally, the micro-level econometric method of De Loecker et al. (2020) yields markup measures that are model-dependent – with markups estimated from a Cobb-Douglas production function being larger than those estimated from a tanslog function.

That is why we follow Basu (2019), who observes that non-econometric methods can be used to avoid the measurement and identification problems associated with econometric methods. One of the non-econometric markups we use is based economic profits (Barkai, 2020; Eggertsson et al., 2021) whilst the other is derived from the Lerner index (Battiati et al., 2021; Ciapanna et al., 2022). Both measure have well-established micro foundations and can be estimated from observed firm-, industry- or country-level data. The profits-based markup is

[5] 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).

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. One limitation of Lerner-index-based measure is that it proxies the marginal cost that is not observed in the data with the average cost. The limitation of the profits-based markup is due to its assumption of constant returns to scale.

Basu (2019)'s assessment of the alternative measures concludes that 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 Gutierrez (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. (2021), 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.

The profits-based markup of Barkai (2020) and Eggertsson et al. (2021) relies on the share of pure profits in value added 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), we calculate the profits-based markup by industry, country, and year (μ^P_{ict}) 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, $\mu^P_{ict} > 1$ if the value added also contains excess economic profits and hence cannot be exhausted after capital and labour income and indirect taxes are deducted. Labour income is observed in the 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) compatible with perfect competition (Feenstra et al., 2015; Inklaar et al., 2019) with the net capital stock in the industry.[6]

Our Lerner-index-based markup measure 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.

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

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, μ^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.

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

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.

The levels of innovation intensity, markups and labour share in the sample have already been presented in Fig. 1 above, which indicated increasing innovation intensities and markups coupled with decreasing labour or wage shares over time. When we zoom on country-year or industry-year pairs, the evolution of the three series varies by country and/or industry. As can be observed from Figs. A1 – A3 in the Appendix,[7] 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. We can also observe that the labour share is converging towards a sample average of 0.58[8]; whereas the markup measures are converging towards a sample averages of 1.35 and 1.21. 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 to 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 one of the determinants in the innovation intensity equation – in accordance with the Schumpeterian model of Aghion et al. (2019a). 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.

[6] 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. Furthermore, the net capital stock we use for calculating capital income includes not only fixed (tangible) capital but also the knowledge assets (R&D, Soft-DB, and OIP) that have been capitalized in SNA 2008.

[7] 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 to 2010 (Vella, 2018).

4.2. Estimation methodology

We estimate the model in 6.1–6.4 above using three estimators. Of these, the three-stage least-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 a structural equation model (SEM) counterpart. 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 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 and 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 eliminate the unobserved country and industry fixed effects by demeaning the variables. Identification with demeaned variables 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 within-country-industry effect for each country-industry pair 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 <2 and hence multicollinearity is not a cause for concern in any of the equations. The variance-covariance

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 intensity 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 intensity 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 = 6553; 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 of 1.57. Secondly, the effect of innovation intensity is also positive (0.045).[11] The former is consistent with the skill-biased technical change hypothesis, where technological innovation responds to increased supply of skills (Acemoglu, 1998, 1999, 2002). The latter is consistent with the Schumpeterian model of innovation, where firms are more likely to innovate when they have higher levels of innovation productivity (Aghion et al., 2019a). The third finding indicates that product-market regulation reduces innovation - 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.

The final point to note about the innovation equation is that the *total* effects of the predictors 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.

Two further findings in the markup equation are also consistent with the justification for our simultaneous equation model. First, the *direct* and *total* effects of the product-market regulation (PMR) on markups are positive. This is consistent with evidence in Hoj et al. (2007), who report that the PMR indicator reduce competition and increase market power. Secondly, 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 share 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 the indirect effect through innovation is taken into account.

Our findings are consistent with optimising behaviour under market power (eq. 5 above), where labour share is inversely related to markups. On the one hand, market power acts 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 rents (Barkai, 2020; Eggertsson et al., 2021) or as 'factorless income' (Karabarbounis and Neiman, 2019).

Moreover, our findings enhance the quality/reliability of the existing evidence base by taking account of reciprocal relationship between innovation and markups and by disentangling effect of one from the other. The disentangled effect-size estimates indicate that effect or market power (markups) is by far the more adverse. They also indicate that the total effects of market power on labour share become more adverse when market power increases from a high initial level. This is because the increase in markups from a high initial level also increases the level of innovation that also depresses the labour share.

We make two further observations on determinants labour of share. The first is that labour share increases with human capital as expected (Park, 1997; Lundberg and Squire, 2003; Yang and Gao, 2018). 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, 2022; 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 and 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

[11] Given the logarithmic specification for human capital and the level specification for innovation productivity, the effect-size estimates imply that innovation intensity increases by 1.57 % or 4.5 % when human capital or innovation productivity increases by 1 %.

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 intensity 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 intensity	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 intensity	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	6553	6547	5965	5961	5695	5690
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 2 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.

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 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

Table 4
Markup sensitivity and implications of innovation types.

Observed effect-size patterns	12 pairwise comparisons (All estimators)	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

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 wide innovation investment measure is reported to differ from the effect on the *narrow* innovation measure (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. Comparison results are reported in Table 4 below.

Comparison results in Table 4 indicate that the wide innovation intensity that includes marketing and organisational innovation (*Innov_int2*) is more responsive to markups compared to the narrow innovation intensity (*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 for verifying 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.

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

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

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,

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 p-value: 0.000	Combined effect: −1.022 *p*-value: 0.000
2. Full sample with *Innov_int2* and no lags	Combined effect: 0.303 p-value: 0.000	Combined effect: −1.010 p-value: 0.000
3. Full sample with *Innov_int1* and two lags on exogenous predictors	Combined effect: 0.113 p-value: 0.055	Combined effect: −1.094 p-value: 0.000
4. Full sample with *Innov_int2* and two lags on exogenous predictors	Combined effect: 0.085 p-value: 0.469	Combined effect: −1.228 p-value: 0.000
5. Estimation with *Innov_int1*, excluding the crisis period	Combined effect: 0.336 p-value: 0.000	Combined effect: −1.027 p-value: 0.000
6. Estimation with *Innov_int2*, excluding the crisis period	Combined effect: 0310 p-value: 0.002	Combined effect: −0.994 p-value: 0.000

which are based on standardised coefficients to allow unit-free pooling, are reported in Table 5.

The test results indicate that any *adverse (*i.e.*, negative)* innovation effect is reversed in 5 out 6 tests, where the total effect is positive and significant. In one test, the combined effect is zero and indicates that the adverse effect of innovation on labour share is nullified by the effects of human capital and labour-market institutions. In contrast, the total effect with respect to market power remains *negative* and significant in all tests, with the implication that the combined effect of human capital and labour-market institutions remains *insufficient* either to nullify or reverse the adverse effect of the markups on labour share. Indeed, a one-standard-deviation increase in markups remains associated with an approximately one-standard-deviation decline in labour share after discounting the effects of human capital and labour-market institutions. 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 the existing empirical work on determinants of labour share overlooks two issues: (i) the risk of confounding bias that arises from the possibility that innovation and market power affect each other and the labour share at the same time; and (ii) the risk of omitted variable bias that arises from failure to control for both innovation and market power at the same time. We have addressed both issues 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. Our system of equations approach 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 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. Therefore, the sum of the effects of labour-market institutions and human capital is *sufficient* to reverse the adverse effects of technological innovation on labour share, but *insufficient* to reverse the adverse effects of market power.

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.

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 is not technological innovation per se, but the extent to which innovators are able to extract innovation rents. Therefore, we conclude with two policy recommendations that could arrest (and preferably reverse) the decline in labour share: (i) stronger labour-market institutions that would help align the real wages with the marginal product of labour; and (ii) stronger competition policy that would narrow the wedge between real wages and the marginal product of labour and protect the consumers at the same time.

Author biographical endnote.

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Declaration of competing interest

I hereby declare that I have no conflicting interest and that I have not used artificial intelligence (AI) in writing this paper. All data and codes are available on request.

Data availability

Data will be made available on request.

Appendix A. 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

(*continued on next page*)

Table A1 (*continued*)

Variable	Description	Source
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.

	Obs.	Mean	Std. Dev.	Min.	Max.
Variables in level					
Innovation intensity 1	6553	6.824	7.051	1.000	38.225
Innovation intensity 2	6536	15.655	9.372	1.192	53.600
Labour share	6553	0.597	0.174	0.163	0.927
Lerner-index-based markup	6553	1.211	0.164	1.001	2.382
Lerner-index-based markup sq.	6553	1.494	0.461	1.003	5.673
Profits-based markup	6553	1.354	0.331	0.553	3.240
Profits-based markup sq.	6553	1.942	1.128	0.306	10.498
Innovation productivity (%)	6553	0.271	1.028	−23.273	38.318
Intellectual and physical property rights index (IPRI)	6553	7.521	0.904	5.600	8.700
Human capital	6553	3.318	0.292	2.569	3.766
Trade-union density	6553	31.373	21.364	9.900	84.700
Employment protection legislation	6553	3.725	1.482	0.343	7.766
Product-market regulation	6553	1.564	0.394	0.872	2.954
Variables in logs (except %)					
Innovation intensity 1	6553	1.461	0.947	0.000	3.643
Innovation intensity 2	6536	2.562	0.645	0.175	3.982
Labour share	6553	−0.570	0.350	−1.811	−0.076
Lerner-index-based markup	6553	0.184	0.121	0.001	0.868
Lerner-index-based markup sq.	6553	0.048	0.073	0.000	0.753
Profits-based markup	6553	0.278	0.217	−0.592	1.176
Profits-based markup sq.	6553	0.124	0.181	0.000	1.382
Innovation productivity (%)	6553	0.271	1.028	−23.273	38.318
Intellectual and physical property rights index (IPRI)	6553	2.010	0.126	1.723	2.163
Human capital	6553	1.195	0.090	0.943	1.326
Trade-union density	6553	3.245	0.619	2.293	4.439
Employment protection legislation	6553	1.152	0.721	−1.069	2.050
Product-market regulation	6553	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

(*continued on next page*)

Table A3 (*continued*)

Industries	
NACE Rev. 2 Code	Description
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 intensity	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 intensity	−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	6553	6547	5965	5961	5695	5690

(*continued on next page*)

Table A4 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
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 intensity	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 intensity	−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	6553	6547	5965	5961	5695	5690
RMSE – Eq. 1	0.261	0.182	0.247	0.187	0.291	0.205
RMSE – Eq. 2	0.103	0.101	0.109	0.115	0.106	0.105
RMSE – Eq. 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

(continued on next page)

Table A6 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
	(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 intensity	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 intensity	−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	6613	6607	6067	6063	5749	5744
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

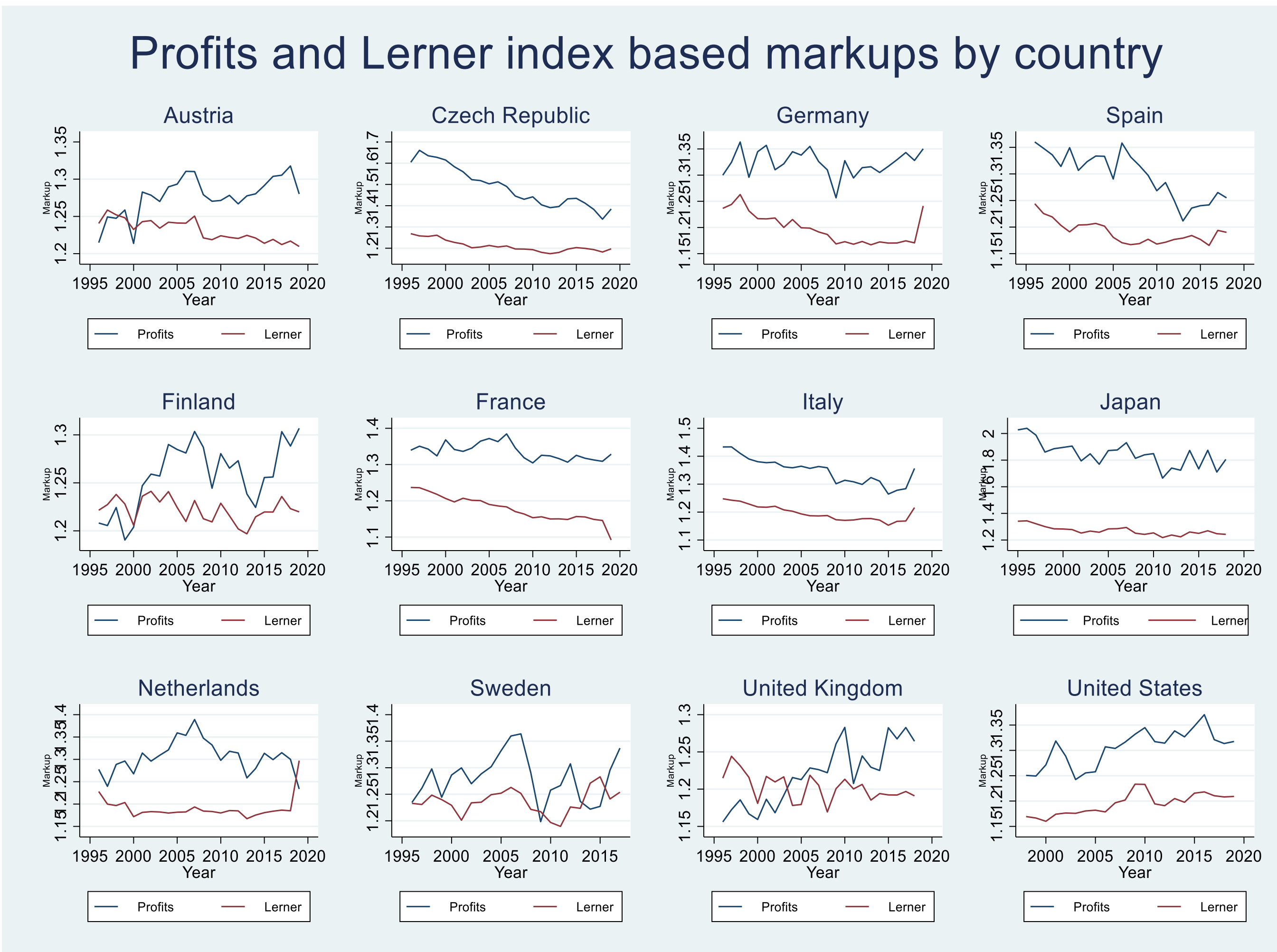

Fig. A1. Evolution of average markups by country.

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 correlated 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).

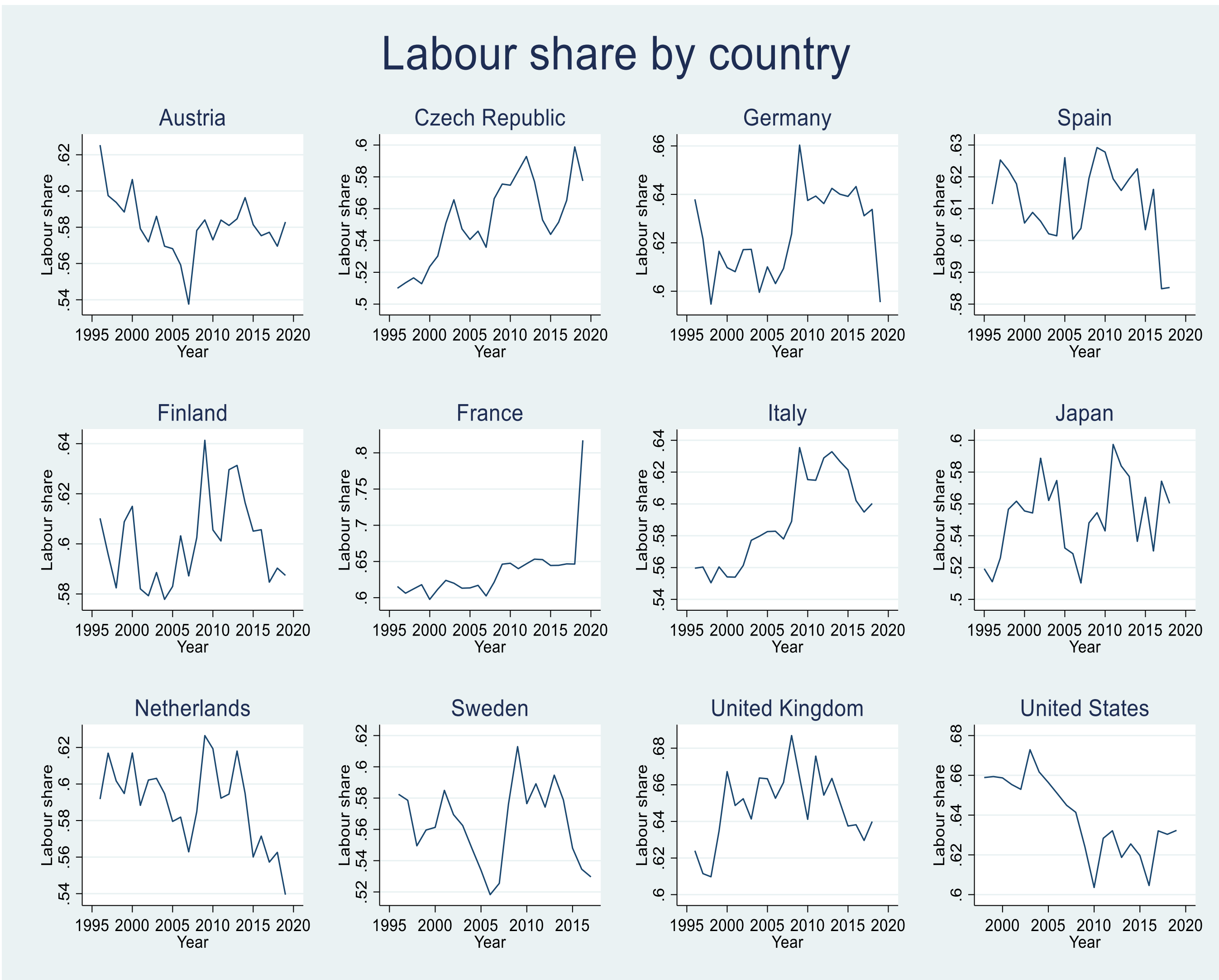

Fig. A2. Evolution of labour share by country.

The labour-share evidence from our sample also indicates heterogeneity in the level and trend of the labour share. 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 to 2009. After the crisis, the labour share continues to decline in all countries except France and Italy.

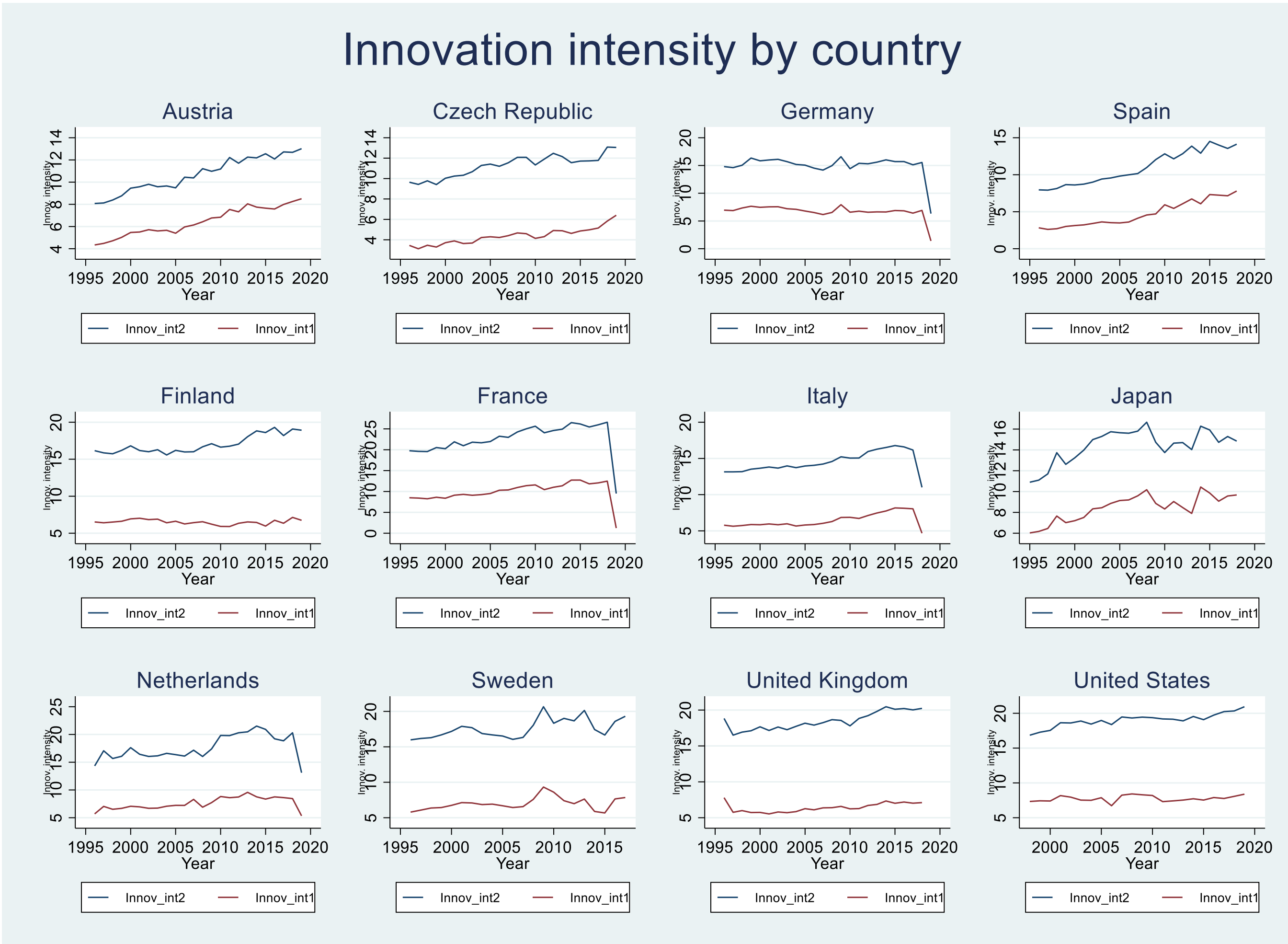

Fig. A3. Evolution of innovation intensity by country.

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 organisational 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*).

While the effect of technological innovation or markups on the decline of the labour share has been studied widely in the literature, the existing work overlooks two issues: bidirectional relationship between innovation and market power and the need to control for both in empirical estimations. We propose a simultaneous equation model where innovation, market power and the labour share are endogenous outcomes determined simultaneously. Another feature of the model is that it allows for disentangling the effect of technological innovation per se from the effect of market power that enables successful innovators to extract innovation rents.

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