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Are Firms Hiring Enough Workers?

FIRM-LEVEL EVIDENCE FROM FINLAND'S MANUFACTURING AND SERVICE INDUSTRIES

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Abstract

Microeconomic theory posits that in competitive markets, wages are determined by the marginal revenue product of labor. This study empirically tests this theoretical prediction using comprehensive firm-level register data from Finland's manufacturing and service industries in years 2000–2022. We estimate the marginal products of labor based on production functions estimated using both parametric and nonparametric methods, including convex expectile regression and its control function extension. We then compare the estimated marginal products with estimated marginal costs of labor. The estimated marginal products systematically exceed the marginal costs in all industries, which suggests that most Finnish firms are understaffed, employing less than profit-maximization in a competitive market would require. We find that marginal products are most closely aligned with marginal costs in traditional service sectors. In contrast, the marginal products exceed the marginal costs most notably in capital and knowledge-intensive manufacturing industries, such as pharmaceuticals, metal industries, and information services. Our findings reveal persistent and heterogeneous wage-productivity gaps in Finland despite the fact that Finland has strong unions and labor market institutions.

Tiivistelmä

Palkkaavatko yritykset tarpeeksi työvoimaa? Suomen teollisuus- ja palvelualojen yritystason tarkastelu

Mikrotalousteorian mukaan kilpailullisilla markkinoilla palkat määräytyvät työn rajatuotoksen perusteella. Tässä tutkimuksessa testaamme tätä teoreettista tulosta empiirisesti hyödyntämällä kattavia yritystason rekisteriaineistoja Suomen teollisuus- ja palvelualoilta vuosilta 2000–2022. Työn rajatuotos estimoidaan tuotantofunktioiden avulla käyttäen sekä parametrisia että ei-parametrisia menetelmiä kuten konveksi ekspektiiliregressio ja sen kontrollifunktiolaajennus. Tämän jälkeen estimoituja rajatuotoksia verrataan työn rajakustannuksiin. Tulosten perusteella rajatuotos ylittää rajakustannuksen kaikilla toimialoilla, mikä viittaa siihen, että yritykset eivät työllistä niin paljon kuin olisi kilpailullisilla markkinoilla kannattavaa yksityisen voiton maksimoinnin näkökulmasta. Rajakustannukset ovat kaikkein lähimpänä rajatuotosta perinteisillä palvelualoilla, kun taas erot ovat suurimmillaan pääoma- ja tietointensiivisillä teollisuuden aloilla, kuten lääketeollisuudessa, metalliteollisuudessa ja tietopalveluissa. Tulostemme perusteella bruttopalkat poikkeavat systemaattisesti rajatuotoksesta huolimatta siitä, että Suomessa ammattiliitot ja työmarkkinainstituutiot ovat perinteisesti vahvat.

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Keywords: Convex expectile regression, Labor compensation, Wage-productivity gap, Marginal product of labor, Manufacturing, Service industries, Finland

Asiasanat: Konveksi ekspektiiliregressio, Työvoiman korvaus, Korvaus–tuottavuus-kuilu, Työn rajatuotos, Teollisuus, Palvelualat, Suomi

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1 Introduction

The neoclassical marginal revenue productivity theory of wages posits that in competitive markets, wages are determined by the marginal revenue product of labor (Clark, 1899). This close link between the real wage and marginal product of labor remains practically important, for example, in computable general equilibrium (CGE) models. It also forms the foundation of the growth accounting approach to measure total factor productivity growth. However, growing empirical evidence has challenged this theory.

At the macro level, the growth of real wages has been slower than labor productivity growth in many OECD countries, including those with strong labor market institutions (OECD, 2021; International Labour Organization, 2020). This divergence of labor productivity and wage growth has been referred to as the *great decoupling* (Brynjolfsson and McAfee, 2013), the *wage-productivity gap* (Elgin and Kuzubas, 2013), or the *productivity-pay gap* (Bivens and Mishel, 2015). Stansbury and Summers (2017) show that the divergence is associated with a declining share of labor in the national income. Elgin and Kuzubas (2013) find that the wage-productivity gap is positively associated with unemployment and negatively associated with unionization.

At the industry level, Berlingieri et al. (2024) provide evidence on the increasing wages and productivity dispersion using harmonized micro-aggregated register-based data for 12 OECD countries over 2001–2012. Their results indicate that the increasing dispersion was mainly driven by the bottom deciles of the wage and productivity distributions. They also show that between-firm wage dispersion increased more in sectors that experienced an increase in productivity dispersion. Berlingieri et al. (2024) also found that globalization and digitalization have further strengthened the link between productivity and wage dispersion.

At the level of individual employees, Frank (1984) compared productivity and pay in specific sales occupations (such as real estate and automobile sales persons), in which the wages and productivity can be directly observed for each worker. He found that the wage rates varied far less than individual productivity, and as a result, the most productive employees were paid substantially less than their marginal products, while the least productive employees were paid substantially more. Frank (1984) explained these findings by such considerations as status, equity, and fairness.

Thus far, there is little direct evidence on the productivity-pay gap at the firm level. One notable exception is Deb et al. (2022), who used establishment data of the US Census Bureau in years 1997–2016 to show that both monopoly and monopsony power contributed to the decoupling of productivity and wage growth, with the rising monopoly power being the primary determinant. The empirical objective of this study is to provide further cross-sectional firm-level evidence on the wage-productivity gaps in the manufacturing and service industries. The analysis uses comprehensive register-based data covering virtually the entire population of firms in Finland. We compare the relative wage-productivity gaps in 16 industries in the years 2000–2022, of which eight are manufacturing industries and the other eight are service industries.

Neither marginal cost nor marginal revenue products are directly observable at the firm level. The estimation of marginal products is challenging due to well-known endogeneity problems in the empirical estimation of production functions. Further, restrictive functional form assumptions can cause bias in the marginal product estimates. To avoid restrictive parametric assumptions, this study applies a data-driven nonparametric method called *convex expectile regression* (CER) (Kuosmanen and Zhou, 2021; Dai et al., 2024), which only requires the production functions to be monotonic increasing and concave. While CER is less sensitive to the endogeneity bias than the conventional parametric method, we also apply its control function extension (CER-CF) to further alleviate endogeneity (Dai et al., 2025). For comparison, we also report the standard fixed effects estimates using the classic Cobb–Douglas production function.

The remainder of the paper is organized as follows. Section 2 presents the neoclassical microeconomic argument of why the wage rate equals marginal revenue product for firms that operate in a competitive market environment, and introduces the relative pay gap as an indicator of how well the wages align with the marginal revenue product. Section 3 discusses two alternative approaches to estimate the marginal cost of labor. Section 4 outlines three alternative methods to estimate the marginal revenue product of labor. Section 5 presents an empirical study of eight manufacturing and eight service industries in Finland, using comprehensive firm-level register-based data. Section 6 presents our concluding remarks.

2 Relative pay gap and the theory of the firm

This section briefly reiterates the neoclassical microeconomic argument as to why the wage rate should equal the marginal revenue product of labor in competitive markets. We then introduce the notion of the relative pay gap.

Consider a profit-maximizing firm under monopolistic competition. The optimal demand of labor L is found by solving the following unconstrained optimization problem:

$$\max_{L} \ \pi = pf(L, K) - wL - rK, \tag{1}$$

where p is the output price, f is a monotonic increasing and concave production function, L and K are labor and capital inputs, respectively, w is the wage rate, and r denotes the return on capital. In competitive labor and capital markets, the firm takes input prices w and r as given. In monopolistic competition, however, the output price p is not exogenously given, but depends on such factors as the degree of product differentiation and competition as well as the market power of the firm.

Differentiating equation (1) with respect to labor L, and reorganizing terms, we have the familiar first-order condition:

$$MRP = p\frac{\partial f(L, K)}{\partial L} = w = MC. \tag{2}$$

Equation (2) formally states the neoclassical marginal revenue productivity theory of wages. On the left-hand side of equation (2), we have the marginal revenue product (MRP), which is the product of the marginal revenue (price p) and the marginal product of labor (the partial derivative of the production function f). The wage rate w on the right-hand side of equation (2) is the marginal cost (MC) of labor. In other words, the profit-maximizing firm will demand labor input until the marginal increase in revenue equals the wage rate, which is the marginal cost of labor in competitive labor markets.

The main objective of this study is to empirically assess whether the first-order condition (2) holds, at least approximately. To this end, we use the *relative pay gap* (RPG) to quantify possible deviations from equation (2):

$$RPG = \frac{MC}{MRP}. \tag{3}$$

An RPG equal to one indicates perfect alignment between wages and the marginal revenue product (MRP), as predicted by the neoclassical microeconomic theory. An RPG greater than one indicates over-compensation, meaning that wages exceed workers' marginal contributions. Conversely, an RPG less than one suggests under-compensation, where wages fall short of the MRP.

In the real world, empirical estimates of RPG can temporarily deviate from the benchmark value of one due to various sources of heterogeneity. Production functions f can differ across firms due to different rates of technology adoption, vintage of capital stock, or differences in operational efficiency. Output prices p can also differ across firms due to quality differences, differentiated products, and market power, even in a relatively narrowly defined industry. Wage rates w can also differ due to heterogeneity of workers' skills, education, and experience, even within the same firm. Further, the wage rate of workers currently employed may differ from that of potential new hires available in the job market.

However, if one can adjust for these sources of heterogeneity, in competitive markets, RPG is expected to be approximately equal to one for each firm. Further, when the firm-level RPG ratios are aggregated to the industry level, random deviations due to heterogeneity should effectively cancel out, so one would expect the RPG ratios to align more closely with one at the industry level. Systematic deviations from unity could therefore serve as useful indicators of monopoly or monopsony power (cf. Deb et al., 2022), excessive bargaining power of labor unions, or sector-specific frictions in the labor market.

3 Estimating the marginal cost of labor

In the previous section, we took the wage rate w as the marginal cost of labor, acknowledging that wage rates can differ due to heterogeneity in workers' skills, education, and experience, even within the same firm. When wage rates are observed for individual employees, they must be aggregated to the firm level to compute the RPG of a firm. However, the wage rate of currently employed workers may differ from that of potential new hires. To address these complications, we rely on two complementary approaches to estimate the marginal cost of labor, referred to as top-down and bottom-up approaches.

3.1 Top-down approach

Given a panel data of firms, a common approach to estimate the marginal cost of labor at the industry level is to resort to a two-way fixed-effects model:

$$W_{it} = \beta_L L_{it} + \gamma_t + \delta_i + \varepsilon_{it}, \tag{4}$$

where W_{it} is the gross wage bill of firm i in year t ($i = 1, \ldots, N$, $t = 1, \ldots, T$), L_{it} is the number of employees, coefficients γ_t and δ_i are the year and firm fixed effects, respectively, and ε_{it} is the random error term with zero mean and finite variance. Coefficient β_L represents the marginal cost (MC) of labor.

Equation (4) can be estimated separately for each industry to allow β_L to differ across industries. However, this approach ignores firm-level heterogeneity as well as intertemporal changes in marginal costs. In essence, regression model (4) estimates the conditional mean of the marginal costs of firms that operate in the same industry. In other words, the coefficient β_L can be interpreted as the industry average of the marginal cost of labor during the given study period.

3.2 Bottom-up approach

Another possibility is to start from the firm level and approximate the wage rate by the gross wage per worker (GWW):

$$GWW_{it} = \frac{W_{it}}{L_{it}}. \tag{5}$$

GWW indicates the average wage rate of workers currently employed, and it is widely used as a measure of between-firm wage differentials (cf. Yeh et al., 2022; Berlingieri et al., 2024). Although GWW does not necessarily equal the marginal cost of labor, it can serve as a reasonable proxy if a firm can marginally increase its labor input using the current wage rate, either by hiring new workers or by increasing the hours of existing workers.

Combining equations (4) and (5), the expected value of GWW can be stated as

$$\mathbb{E}(GWW_{it}) = \beta_L + \frac{\gamma_t + \delta_i}{L_{it}}. \tag{6}$$

Equation (6) presents an explicit link between the top-down and bottom-up approaches. For the reference firm in the reference year (for which $\delta_i = 0$ and $\gamma_t = 0$ by construction), the expected GWW equals the marginal cost β_L. Significant firm- or year-specific fixed effects can cause bias in the firm-specific GWW indicators; however, such biases tend to cancel out when the firm-specific GWW are aggregated to the industry level.

It is worth emphasizing that averaging is unavoidable; the question is merely at which stage of analysis we choose to average. In the top-down approach, we first average over firms and years and then compare the industry-level averages of marginal costs and marginal products. In the bottom-up approach, we can first compare the firm- and year-specific marginal costs and marginal products and then average them to obtain industry-level estimates. The key advantage of the firm- and year-specific GWW is that it allows for a direct comparison with the firm- and year-specific marginal product estimates, to be introduced in the next section.

4 Estimating the marginal revenue product of labor

The marginal revenue product of labor cannot be directly observed either, except in some specific professions.[1] In general, empirical estimation of the marginal product requires estimation of the production function (see equation (2)). To this end, we first introduce value added y as a function of labor and capital inputs, defined as

$$y = pf(L, K) - M = g(L, K), \tag{7}$$

where M denotes the intermediate inputs. Assuming that p and M are independent of L and K, the value added production function g is a linear transformation of the volume-based production function f. Note further that

$$MRP = p\frac{\partial f(L, K)}{\partial L} = \frac{\partial g(L, K)}{\partial L}. \tag{8}$$

Thus, we can use the value added production function g to estimate the marginal revenue product (MRP).

To empirically estimate MRP using firm-level panel data, we posit the following two-way fixed-effects model in logs:

$$\ln y_{it} = \ln g(L_{it}, K_{it}) + \theta_t + \delta_i + \varepsilon_{it}, \tag{9}$$

[1] Frank (1984) compared pay and productivity of real estate and automobile sales persons, whose productivity can be reasonably proxied at the level of an individual employee. In more complex production processes, the contribution of an individual employee cannot be directly observed.

where θ_t is a year fixed effect, δ_i is a firm fixed effect, and ε_{it} is a random error term with zero mean and finite variance. To estimate model (9), we consider both the parametric Cobb–Douglas specification of g as well as a nonparametric approach, which does not depend on an arbitrary functional form specification of g.

4.1 Cobb–Douglas specification

The Cobb–Douglas production function remains the most standard parametric specification of the production function. In terms of the panel data regression (9), the Cobb–Douglas production function can be stated in the log-linear form as follows:

$$\ln g(L_{it}, K_{it}) = \beta_L \ln L_{it} + \beta_K \ln K_{it}, \tag{10}$$

where β_L and β_K are the output elasticities of labor and capital, respectively. Note that β_L is not generally equal to the MRP, but the MRP can differ across firm-year observations.

Having estimated the coefficient β_L, we obtain the MRP as

$$MRP_{it} = \beta_L \frac{Y_{it}}{L_{it}}. \tag{11}$$

This firm- and year-specific MRP estimate can be directly compared with GWW in the bottom-up approach. In the top-down approach, the MC estimate is an industry-specific constant, so we use the median value to aggregate the firm-level MRP estimates to the industry level.

4.2 Convex expectile regression (CER)

While the Cobb–Douglas specification remains widely used, it is restrictive to assume that the output elasticities are constant across all firms in the same industry and all years in the study period. Further, the substitution elasticity of labor and capital is always equal to one in the Cobb–Douglas specification by construction. To avoid such restrictive parametric assumptions, we also consider a fully nonparametric approach called convex expectile regression (CER), introduced by Kuosmanen et al. (2015).

In the convex regression, the production function g is assumed to be monotonically increasing and globally concave, but no particular functional form assumptions are needed. Building on the famous Afriat theorem in the theory of revealed preference, Kuosmanen

(2008) showed that the shape-constrained g can be characterized by a piecewise linear function subject to a system of Afriat inequalities:[2]

$$\begin{aligned} & g(L_{it}, K_{it}) = \alpha_{it} + \beta_{L,it} L_{it} + \beta_{K,it} K_{it}, \\ & g(L_{it}, K_{it}) \leq \alpha_{hs} + \beta_{L,hs} L_{it} + \beta_{K,hs} K_{it}, \quad \forall i, h, \ \forall t, s, \\ & \qquad \beta_{L,it} \geq 0, \quad \beta_{K,it} \geq 0. \end{aligned} \tag{12}$$

It is important to emphasize that the Afriat coefficients $\beta_{L,it}$ are specific to each firm-year observation, whereas the Cobb–Douglas coefficients β_L are constant. In essence, the coefficients $\alpha_{it}, \beta_{L,it}, \beta_{K,it}$ characterize the estimator $\hat{g}(L, K)$ as a piecewise linear function, which satisfies concavity due to the Afriat inequalities, and monotonicity due to the constraints $\beta_{L,it} \geq 0$, $\beta_{K,it} \geq 0$. However, the true production function $g(L, K)$ does not need to be piecewise linear; see Kuosmanen (2008) for further details.

CER generalizes the convex regression by minimizing the following asymmetric quadratic loss function:

$$\tau \sum_{t=1}^{T} \sum_{i=1}^{n} (\varepsilon_{it}^{+})^2 + (1-\tau) \sum_{t=1}^{T} \sum_{i=1}^{n} (\varepsilon_{it}^{-})^2, \tag{13}$$

where the parameter $\tau \in (0, 1)$ defines the expectile (set by the user) and the error term $\varepsilon_{it} = \varepsilon_{it}^{+} - \varepsilon_{it}^{-}$ consists of a positive error component $\varepsilon_{it}^{+} \geq 0$ and a negative one $\varepsilon_{it}^{-} \geq 0$. Note that the usual least-squares loss function is a special case obtained by setting $\tau = 0.5$.

Following Kuosmanen and Zhou (2021), we estimate a grid of ten expectiles by setting $\tau = 0.05, 0.15, \ldots, 0.95$, and then find the nearest expectile τ to each firm-year observation. Our MRP estimate is then obtained as

$$MRP_{L,it} = \hat{\beta}_{L,it}^{\tau}, \tag{14}$$

where $\hat{\beta}_{L,it}^{\tau}$ is the CER coefficient corresponding to the nearest expectile τ to firm i in year t. The purpose of using the nearest expectile is to allow MRP to depend on productivity — intuitively, high-productivity firms have a higher MRP of labor than low-productivity firms. Further, the productivity of a firm can increase or decrease over time, so the nearest τ can change during the study period.

[2] The fundamental difference between the revealed preference tests and the convex regression is that the former one empirically tests if the observed data satisfy the theoretical constraints, whereas the latter one imposes the theoretical constraints to fit a well-behaved function to data.

We apply the CER separately to each industry using firm-level panel data. The CER estimation is implemented in Python using the `pyStoNED` package (see Dai et al., 2024). In the bottom-up approach, the firm- and year-specific MRP estimate is directly compared with GWW. In the top-down approach, we use the median values of the firm-level MRP estimates as the industry-level aggregates.

4.3 CER with a control function (CER-CF)

Empirical estimation of the production function is considered challenging due to the well-known endogeneity problem: a firm’s demand for labor and capital inputs depends on its productivity, and hence L and K are likely correlated with the error term ε. To alleviate endogeneity bias, Olley and Pakes (1996) introduced the so-called control function approach, where they used investment as a state variable, which can be seen as a proxy for unobserved productivity shocks. However, since many firms invest periodically, making zero investments in some years, Levinsohn and Petrin (2003) suggested using intermediate inputs as the state variable (see also Ackerberg et al., 2015).

Recently, Rødseth et al. (2025) introduced the control function approach to the convex regression. Dai et al. (2025) further showed that the convex regression is less sensitive to endogeneity bias, but using the control function can help to further alleviate the bias. Although it remains unclear how the endogeneity bias affects the CER estimator introduced in the previous subsection, to alleviate potential bias, we incorporate the control function into our CER estimations.

Following Levinsohn and Petrin (2003), we use the intermediate inputs as the state variable. In contrast to Rødseth et al. (2025), who introduced a nonparametric control function, in this study we utilize a semi-nonparametric specification that combines a nonparametric production function with a parametric specification of the control function (cf. Johnson and Kuosmanen, 2011). In practice, the regression equation (9) is extended as

$$\ln y_{it} = \ln g(L_{it}, K_{it}) + \gamma M_{it} + \theta_t + \delta_i + \varepsilon_{it}. \tag{15}$$

Note that in this specification, the intermediate inputs M are not part of the nonparametric production function g, which is subject to equations (12). If the demand for M correlates with unobserved productivity, as Levinsohn and Petrin (2003) suggest, then introducing M

explicitly into the regression equation helps alleviate the correlation between inputs L, K, and the error term ε.

5 Application to Finnish manufacturing and service industries

5.1 Data and industry coverage

We use firm-level panel data from the *Financial Statement Data Panel* of Statistics Finland covering the period 2000–2022. This register-based dataset includes nearly all operating firms in Finland, enabling a comprehensive analysis of the wage–productivity gap across industries. The Financial Statement Data Panel is highly representative of the Finnish private sector, covering firms of all sizes, from small enterprises to large corporations. The dataset excludes self-employed individuals and public sector organizations, which fall outside the scope of this study. This comprehensive coverage of private-sector firms makes the data particularly well suited for analyzing wage–productivity gaps at both the firm and industry levels.

To alleviate heterogeneity, we focus on industries defined at the 2–5 digit level of the NACE 2008 classification that produce relatively homogeneous products and include a sufficient number of firms. Based on these criteria, the sample covers eight manufacturing and eight service industries. Table 1 presents a full list of the sixteen industries considered and the number of firm-year observations (N) for each industry. Our final dataset includes in total 8,507 firms and 65,055 firm-year observations.

The main variables used in the analysis are value added, fixed assets, operating surplus, full-time equivalent (FTE) employment, and intermediate inputs (defined as turnover minus value added). All monetary variables have been deflated to the constant price level of year 2015 using 2-digit industry-level price deflators from the National Accounts. The gross wage bill is calculated as the value added minus the operating surplus. Further, the gross wage per worker (GWW) is obtained as the gross wage bill divided by the number of employees.

Table 1. Selected industries.

NACE code	Industry description	N
Manufacturing industries:		
C10	Manufacture of food products	7,387
C161	Sawmilling and planing of wood	2,008
C17	Manufacture of paper and paper products	1,681
C20	Manufacture of chemicals and chemical products	2,162
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	322
C24	Manufacture of basic metals	1,259
C26	Manufacture of computer, electronic and optical products	3,118
C31	Manufacture of furniture	3,324
Service industries:		
G45201	Maintenance and repair of motor vehicles	3,539
H4941	Freight transport by road	15,577
H52	Warehousing and support activities for transportation	5,604
I55101	Accommodation	3,181
J6201	Computer programming activities	8,863
J63	Information service activities	1,233
M69	Legal and accounting activities	4,702
M72	Scientific research and development	1,095

5.2 Estimated marginal costs and marginal revenue products

Before turning to relative pay gaps, we first compare the levels of observed wages, estimated marginal costs, and marginal revenue products of labor across industries. Table 2 reports the industry-level averages of gross wage per worker, estimated marginal cost, and the estimated marginal revenue products of labor for the period 2000–2022. The gross wage per worker (GWW) provides a firm-level proxy of the marginal cost, as discussed in Section 3.2. The econometric estimate of the marginal cost of labor ($\mathrm{MC}_{\mathrm{FE}}$) is obtained from the two-way fixed-effects regression as discussed in Section 3.1. Marginal revenue products of labor (MRP) are estimated using three approaches: the Cobb–Douglas specification ($\mathrm{MRP}_{\mathrm{CD}}$, Section 4.1), convex expectile regression ($\mathrm{MRP}_{\mathrm{CER}}$, Section 4.2), and convex expectile regression with a control function ($\mathrm{MRP}_{\mathrm{CER\text{-}CF}}$, Section 4.3).

Interestingly, the average GWW is higher than the fixed effects estimate of MC in seven out of eight manufacturing industries but only five out of eight service industries. The average GWW is notably higher than the estimated MC in sawmilling, paper manufacturing and the basic metals industries. In contrast, the fixed effects MC estimate exceeds GWW considerably in the scientific R&D sector, and to a lesser extent also in computer programming and vehicle repair services.

The average MRP estimates depend on the estimation method. The parametric Cobb–Douglas specification yields the lowest mean MRP in six out of eight manufacturing industries and the seven out of eight service industries. The nonparametric CER yields the lowest mean MRP only for the basic metals industry, CER augmented with the control function yields the lowest mean MRP in the chemicals manufacturing and computer programming. Introducing the control function to the CER estimation yields a lower mean MRP in twelve out of sixteen industries.

Table 2. Gross wage per worker, marginal cost, and marginal product estimates of labor by industry (€ prices of 2015, industry averages 2000–2022).

Industry	GWW	MC_{FE}	MRP_{CD}	MRP_{CER}	$MRP_{CER\text{-}CF}$
C10 Food manufacturing	45,393	41,724	56,275	83,129	74,300
C161 Sawmilling	38,606	23,949	61,695	67,667	68,718
C17 Paper manufacturing	52,232	30,393	64,434	125,318	155,997
C20 Chemicals manufacturing	59,813	54,057	126,925	140,975	123,386
C21 Pharmaceuticals	50,553	37,799	231,401	285,752	470,751
C24 Basic metals	46,173	26,900	87,012	84,713	86,725
C26 Electronics	45,922	45,931	83,913	116,159	99,470
C31 Furniture manufacturing	40,962	39,792	51,798	62,761	55,584
G45201 Vehicle repair	44,604	47,684	52,785	66,866	63,507
H49410 Road transport	46,292	43,118	50,233	59,035	56,467
H52 Warehousing/support	47,045	45,714	57,829	71,187	67,279
I55101 Accommodation	34,018	30,752	41,662	57,454	44,323
J62010 Computer programming	65,863	67,844	93,157	162,640	88,972
J63 Information services	64,492	58,804	127,831	182,949	174,889
M69 Legal/accounting	54,883	50,695	71,201	124,793	105,449
M72 Scientific R&D	67,930	81,546	103,985	142,021	121,214

Note: GWW = gross wage per worker (value added minus operating surplus per employee). MC_{FE} = marginal cost of labor estimated from the fixed-effects regression (equation 4). MRP_{CD}, MRP_{CER}, and $MRP_{CER\text{-}CF}$ = marginal revenue product estimates based on the Cobb–Douglas specification (equation 10), convex expectile regression (equation 13), and convex expectile regression with a control function (equation 15), respectively.

Perhaps the most striking observation from Table 2 is that whichever method is used for estimating the average MC and MRP, for all industries, both alternative MC estimates fall on average considerably below all three alternative estimates of MRP. To gain further insight, we next compare the relative pay gaps (RPGs) obtained using the bottom-up and top-down approaches.

5.3 Relative pay gaps (RPGs)

In Section 2, we introduced the relative pay gap (RPG), defined as the ratio of MC and MRP, as a measure of misalignment from the neoclassical marginal revenue productivity theory of wages. Figure 1 presents the industry averages of RPGs obtained using the top-down approach, based on the ratio of the econometric marginal cost estimates (MC_{FE}) and the three alternative MRP estimates reported in Table 2.

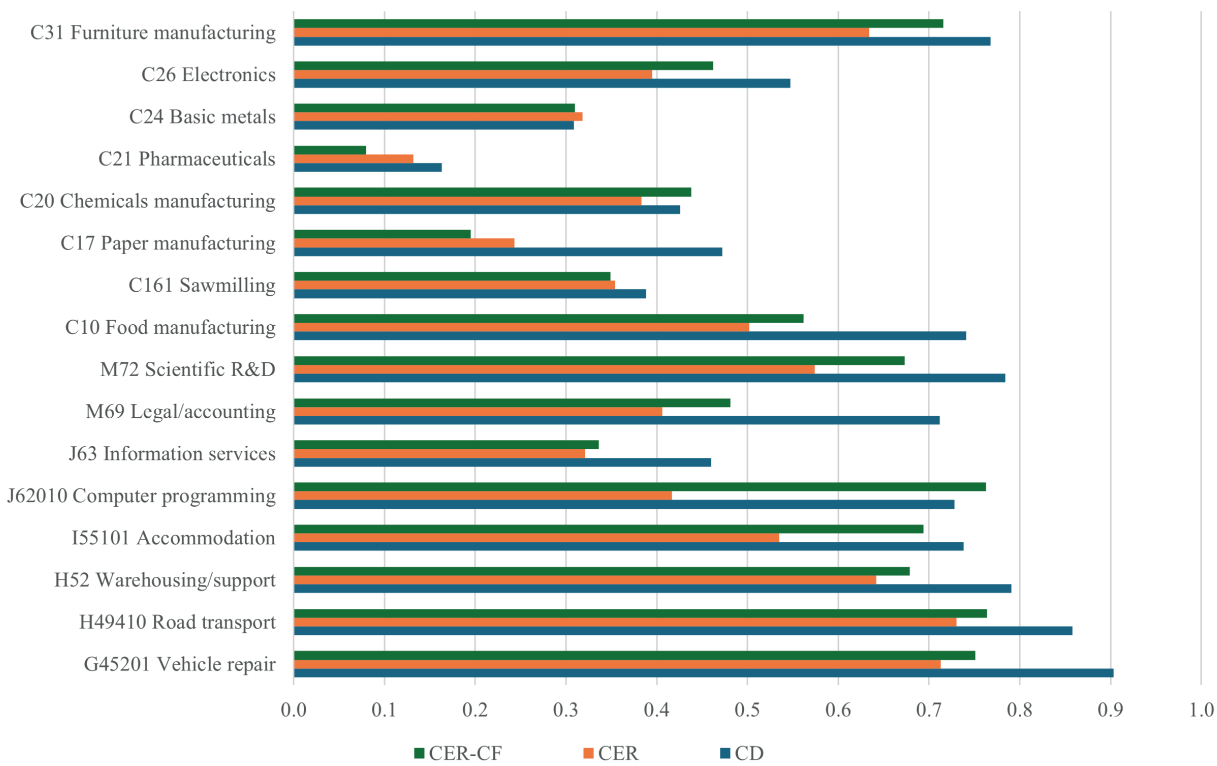


Fig. 1. Relative pay gap (RPG) according to the top-down approach, defined as the ratio of the fixed-effects estimate of the marginal cost of labor (MC_{FE}) and the industry averages of $MRP_{CER\text{-}CF}$, MRP_{CER}, and MRP_{CD}, respectively.

In all 16 industries considered, the average RPG ratio is notably lower than one, which points towards widespread understaffing, that is, firms employ less than profit maximization would require. The size of the RPG ratio depends on the estimation method: for all industries except basic metals the Cobb–Douglas specification produces the highest average RPG ratio, whereas the nonparametric CER and CER-CF approaches yield somewhat smaller RPG ratios.

Figure 1 also reveals substantial heterogeneity between industries. In traditional service sectors, such as vehicle repair (G45201), road transport (H49410), warehousing (H52), accommodation (I55101), and furniture manufacturing (C31), the RPG ratios are relatively high. In contrast, in capital-intensive manufacturing (C17 Paper, C20 Chemicals, C21 Pharmaceuticals) and knowledge-intensive services (J63 Information services, M72 Scientific R&D), the RPG ratios are rather low. For example, in pharmaceuticals, the average RPG ratio is close to 0.1, which means that the estimated marginal cost is only ten percent of the estimated marginal product.

For comparison, Figure 2 reports the RPGs based on the bottom-up approach, based on the gross wage per worker (GWW). We first compute the RPG ratio for each firm-year observation separately, and report the median value for each the industry; the median is more robust than the average to extremely large or small values of the firm-specific ratios. Thus, the median values of the firm-year specific RPG ratios do not necessarily coincide with the ratio of the average GWW and MRP estimates reported in Table 2.

The bottom-up approach yields generally higher RPG ratios than the top-down approach for all industries; the only exception is the scientific R&D, for which the RPG ratio is slightly lower when using the CER method. Still, most bottom-up RPG estimates remain below the unity. For only four out of sixteen industries, the median value of the RPG ratio based on the Cobb–Douglas estimate of MRP exceeds the benchmark level of one. When the nonparametric CER or CER-CF estimators are used, the median RPG ratio remains below one for all industries. The patterns between the three alternative MRP estimation methods remains similar in the top-down and bottom-up approaches. On average, the bottom up-approach increases the RPG ratio compared to the top-down approach by 0.22 when using the CER-CF method, 0.24 when using the CER method, and 0.27 when using the parametric Cobb–Douglas specification.

The bottom-up approach alleviates heterogeneity across industries to some extent. For pharmaceuticals (C21), for example, the top-down RPG ratio based on the CER-CF method was less than 0.1, but the corresponding bottom-up RPG ratio exceeds 0.4. For this industry, the RPG ratio is most sensitive to the choice between the top-down or bottom-up approach. In contrast, for vehicle repair (G45201), the RPG ratios remain almost the same both in the top-down and bottom-up approaches.

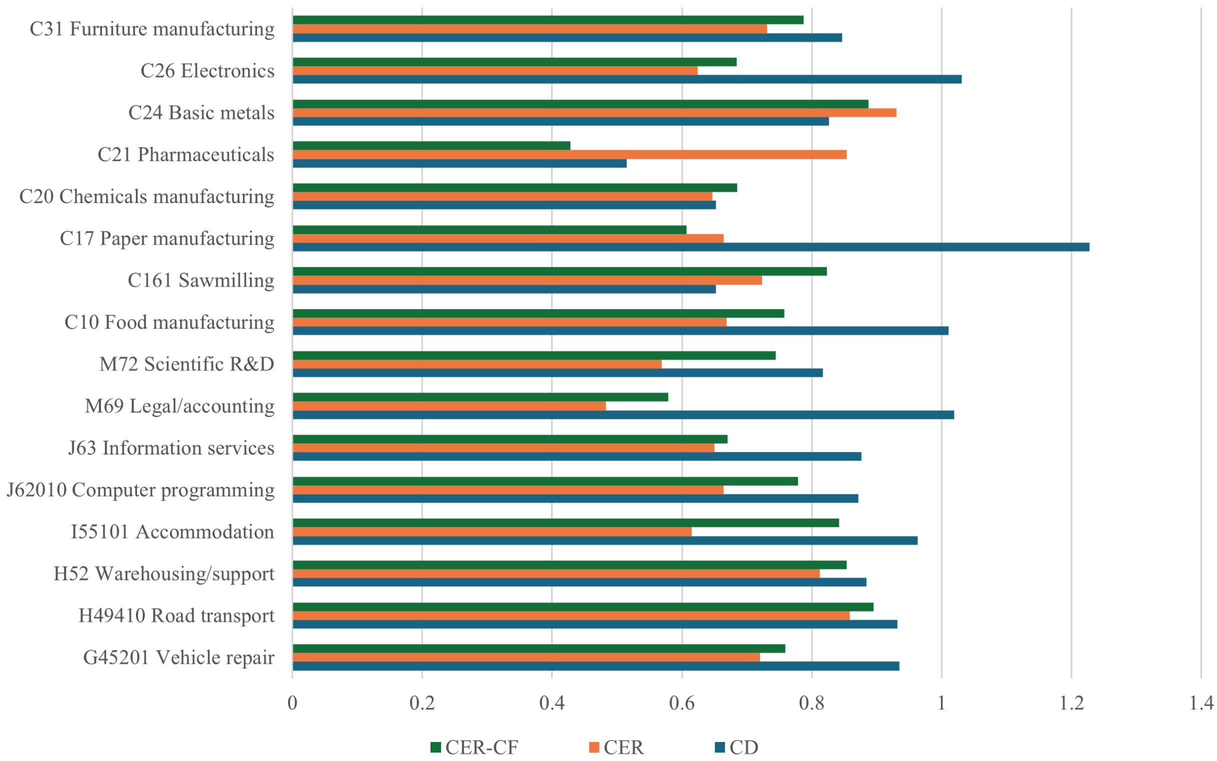


Fig. 2. Relative pay gap (RPG) according to the bottom-up approach, defined as the median of the firm-specific ratio between the gross wage per worker (GWW) and the $MRP_{CER\text{-}CF}$, MRP_{CER}, and MRP_{CD}, respectively.

5.4 Dispersion of RPG

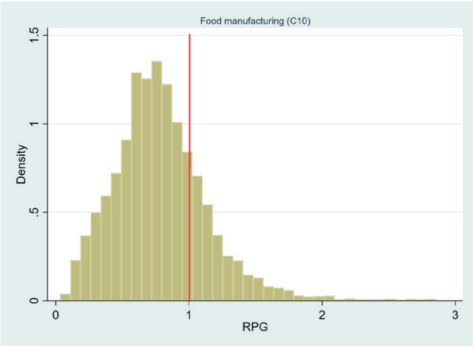
Thus far, we have compared the average and median values of RPG ratios across industries. In this subsection, we turn to the dispersion of RPG across firms within the same industry. Figure 3 presents histograms of firm-level RPGs for the eight manufacturing industries, calculated as the ratio of the gross wage per worker (GWW) to the marginal revenue product of labor estimated using our preferred estimation method: nonparametric CER-CF.

Figure 3 reveals that firm-level heterogeneity can be substantial, even within narrowly defined industries. In all manufacturing industries, some firms have RPG ratios above unity, which suggests overstaffing, whereas the majority of firms have RPG ratios below unity, indicating understaffing. The distributions are highly skewed to the left especially in paper manufacturing (Figure 3c), pharmaceuticals (Figure 3e), and electronics (Figure 3g). Basic metals (Figure 3f) also exhibit wide variation. In contrast, the empirical distribution of RPG is most symmetric in furniture manufacturing (Figure 3h).

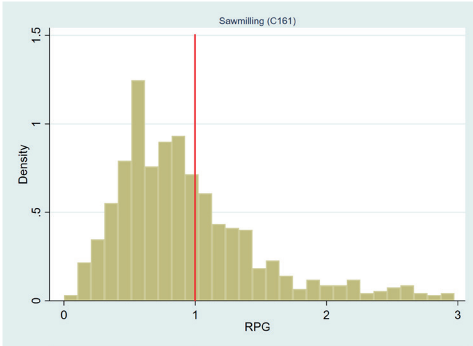
Figure 4 shows the corresponding histograms for the eight service industries. Compared to manufacturing, dispersion is lower, and distributions are more symmetric. In road transport (Figure 4b), for example, the distribution is tightly concentrated around unity, suggesting a closer alignment between wages and the marginal revenue product of labor. Other traditional services, such as vehicle repair (Figure 4a) and accommodation (Figure 4d), also display a relatively narrow spread.

Taken together, Figures 3 and 4 suggest that RPG heterogeneity is greatest in industries characterized by digitalization, such as computer programming (Figure 4e) and information services (Figure 4f), as well as in export-oriented manufacturing, including sawmilling (Figure 3b), paper manufacturing (Figure 3c), and pharmaceuticals (Figure 3e). In contrast, the lowest dispersion is found in domestic services, especially road transport (Figure 4b). These patterns conform with Berlingieri et al. (2024), who documented that globalization and digitalization are associated with greater dispersion in wages and productivity. Our results suggest that similar mechanisms may play a role in the Finnish manufacturing and service industries.

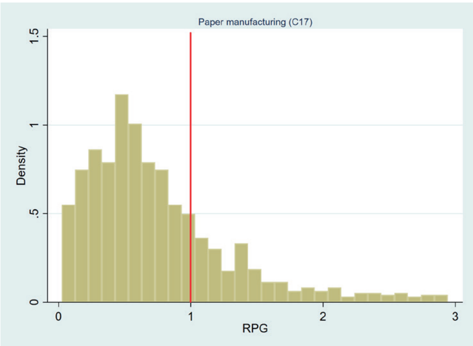
Considering both industry and firm level comparisons, our results indicate that understaffing is widespread, but very heterogeneous across industries. The degree of understaffing is most severe in the capital- and knowledge-intensive sectors, whereas traditional service industries are closer aligned with the marginal revenue productivity theory of wages.



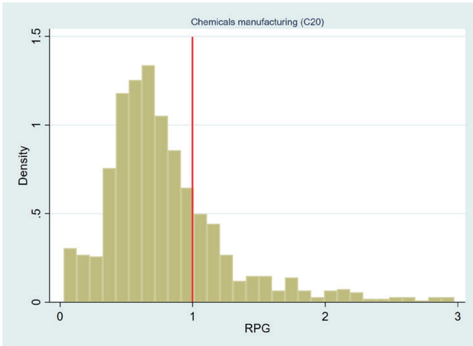
(a) Food manufacturing (C10)



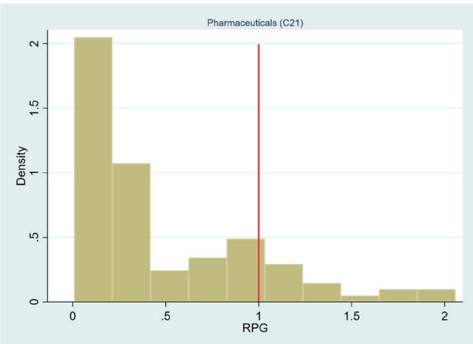
(b) Sawmilling (C161)



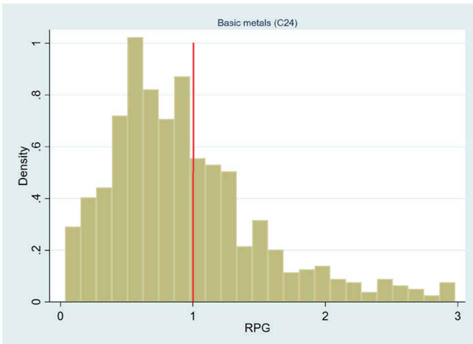
(c) Paper manufacturing (C17)



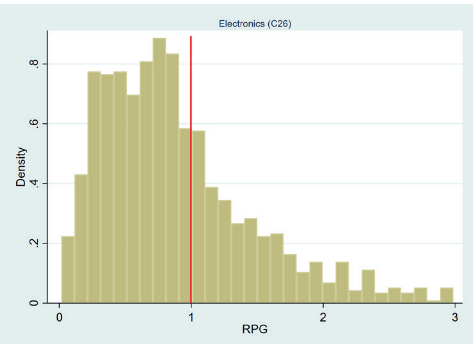
(d) Chemicals manufacturing (C20)



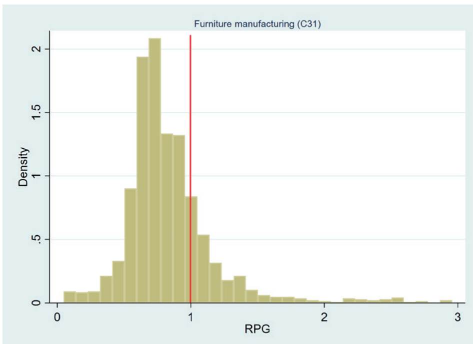
(e) Pharmaceuticals (C21)



(f) Basic metals (C24)

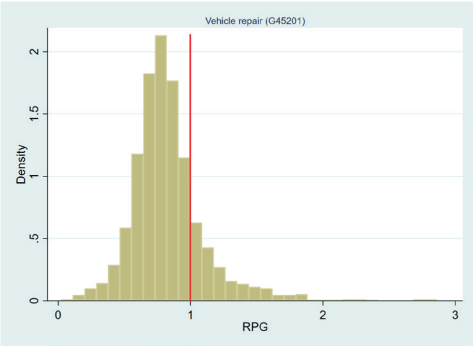


(g) Electronics (C26)

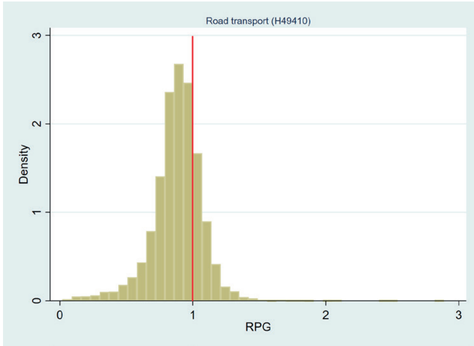


(h) Furniture manufacturing (C31)

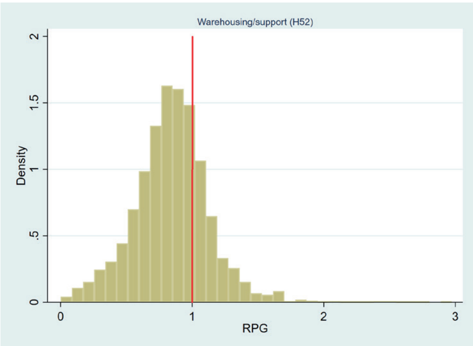
Fig. 3. Histograms of RPGs in the eight manufacturing industries, defined as the ratio of GWW to the marginal revenue product of labor estimated using CER-CF.



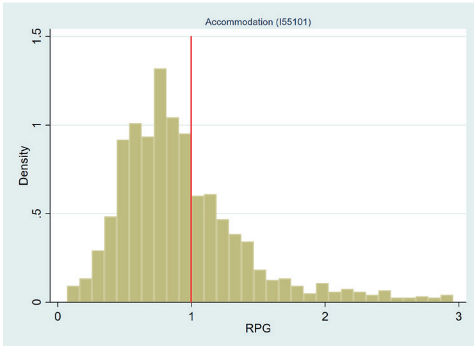
(a) Vehicle repair (G45201)



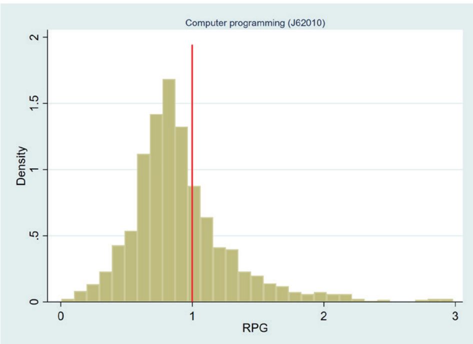
(b) Road transport (H49410)



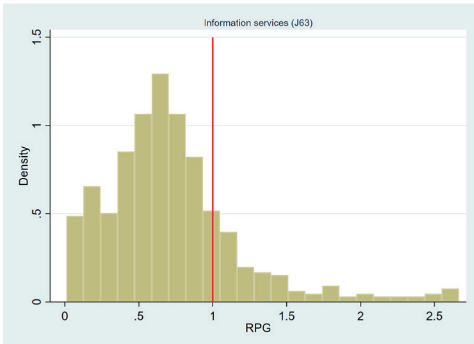
(c) Warehousing/support (H52)



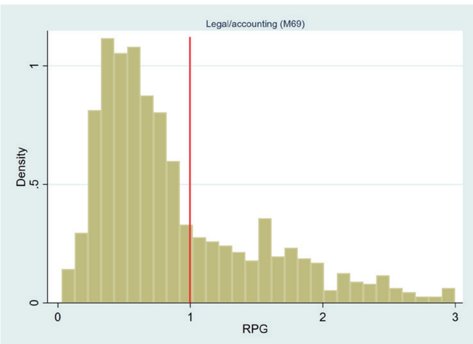
(d) Accommodation (I55101)



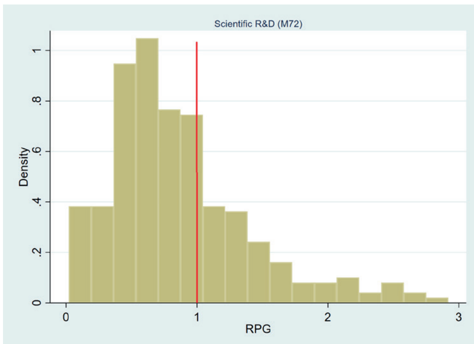
(e) Computer programming (J62010)



(f) Information services (J63)



(g) Legal/accounting (M69)



(h) Scientific R&D (M72)

Fig. 4. Histograms of RPGs in the eight service industries, defined as the ratio of GWW to the marginal revenue product of labor estimated using CER-CF.

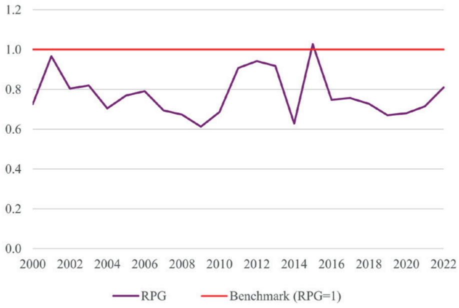
5.5 Development of RPG over time

In this subsection we consider the intertemporal development of RPGs to assess whether the misalignment between gross labor compensation and the marginal revenue product of labor has changed during the time period of 2000–2022. Figures 5 and 6 plot the yearly averages of the RPGs for the manufacturing and service industries, respectively. The red horizontal line marks the benchmark value of one, which corresponds to perfect alignment between labor compensation and the marginal revenue product of labor. The purple line shows the observed yearly averages of RPGs, calculated as the ratio of the gross wage per worker (GWW) to the marginal revenue product estimated using the CER-CF method. Values below unity indicate understaffing, whereas values above unity indicate overstaffing.

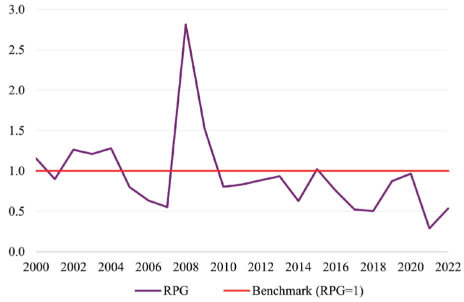
In manufacturing industries (Figure 5), several industries display temporary spikes or drops in RPGs around the years of major economic crises. Large deviations are visible in sawmilling (Figure 5b) and pharmaceuticals (Figure 5e) during the financial crisis in 2008–2009 and the subsequent European debt crisis. Additional fluctuations appear around the Covid-19 shock in 2020–2021 for the same industries; however, these shifts are short-lived and do not alter the overall pattern. Overall, the RPG ratios remain persistently below unity, without any obvious upward or downward trend.

In the service industries (Figure 6), the intertemporal patterns are less affected by the macroeconomic shocks such as the great recession or Covid-19. Some temporary deviations occurred during 2008–2009 and 2020–2021, but they did not persist for a long time. Traditional services, such as road transport (Figure 6b), vehicle repair (Figure 6a), and warehousing (Figure 6c), show RPG ratios close to unity throughout the time period considered, with limited volatility. Knowledge-intensive services, such as information services (Figure 6f), computer programming (Figure 6e), and scientific R&D (Figure 6h), display somewhat wider fluctuations, but without systematic intertemporal trends.

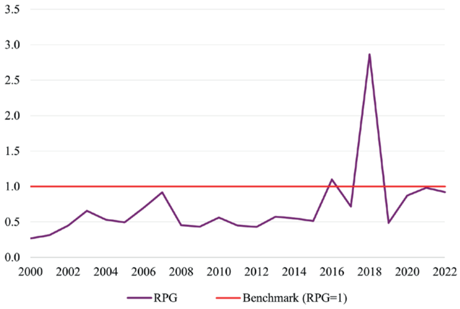
Overall, the evidence suggests that while RPGs fluctuate in response to macroeconomic shocks, there is no indication of a long-term growth trend or decline over the two-decade study period. This finding contrasts with Berlingieri et al. (2024), who documented increasing wage-productivity dispersion at the industry level across OECD countries. In Finland, understaffing appears structural and persistent, with only short-term fluctuations during the years of global crises.



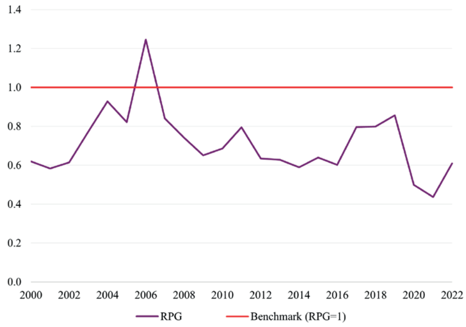
(a) Food manufacturing (C10)



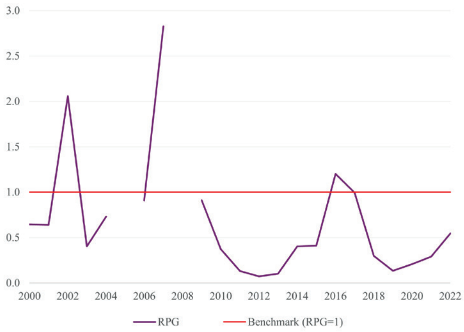
(b) Sawmilling (C161)



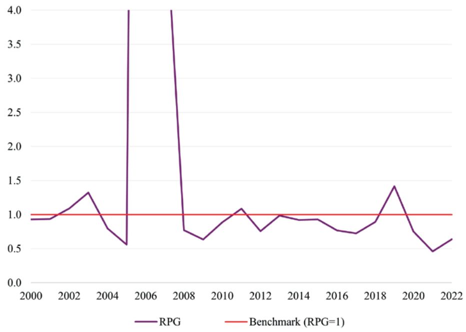
(c) Paper manufacturing (C17)



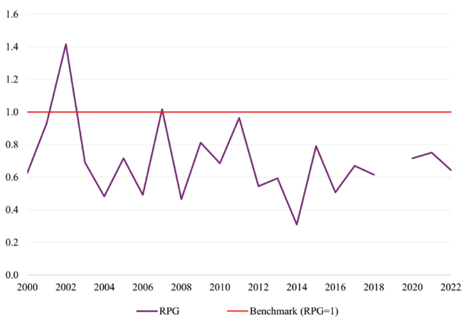
(d) Chemicals manufacturing (C20)



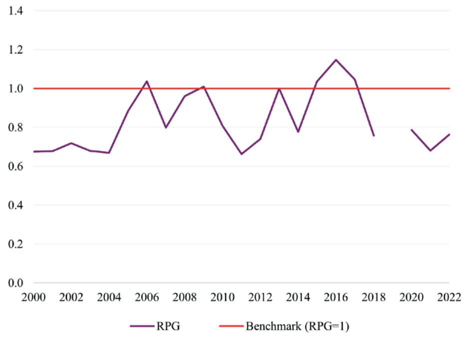
(e) Pharmaceuticals (C21)



(f) Basic metals (C24)

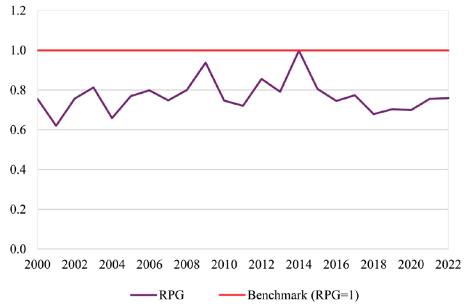


(g) Electronics (C26)

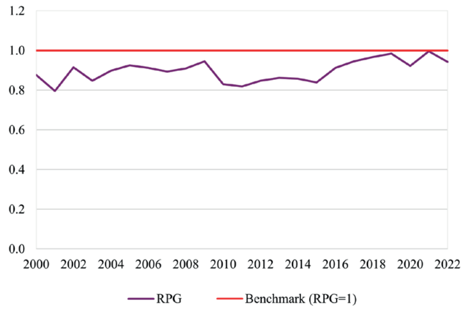


(h) Furniture manufacturing (C31)

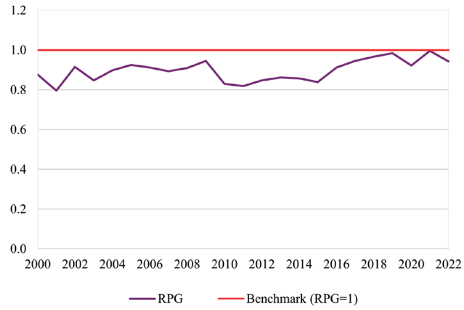
Fig. 5. Intertemporal development of the average yearly RPG in eight manufacturing industries, 2000–2022. Benchmark line indicates RPG = 1.



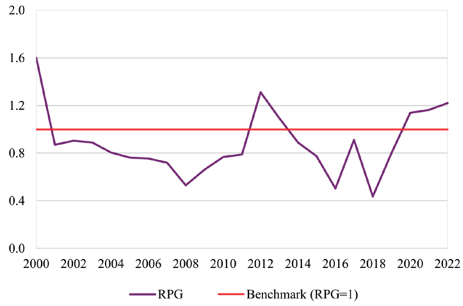
(a) Vehicle repair (G45201)



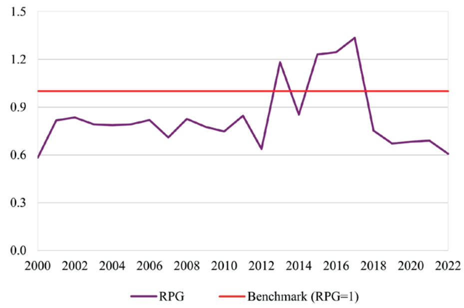
(b) Road transport (H49410)



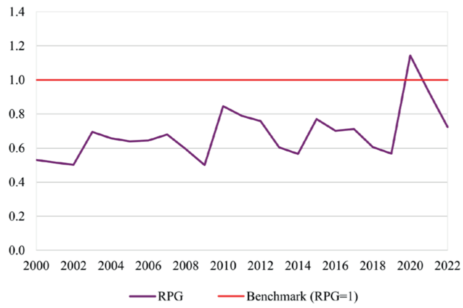
(c) Warehousing/support (H52)



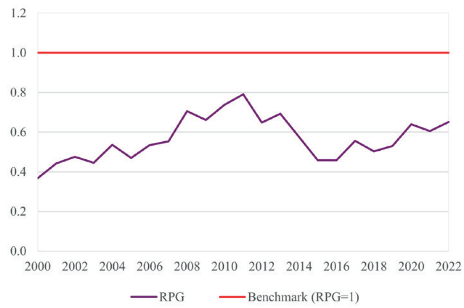
(d) Accommodation (I55101)



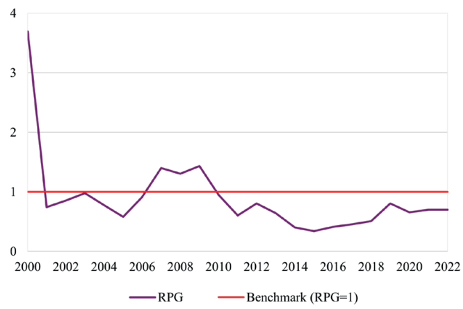
(e) Computer programming (J62010)



(f) Information services (J63)



(g) Legal/accounting (M69)



(h) Scientific R&D (M72)

Fig. 6. Intertemporal development of the average yearly RPG in eight service industries, 2000–2022. Benchmark line indicates RPG = 1.

6 Discussion and conclusions

This study is among the first to conduct a systematic firm-level test of the marginal revenue productivity theory of wages using comprehensive register-based data. Examining eight manufacturing and eight service industries in Finland from 2000 to 2022, we find evidence of widespread understaffing. In other words, across all estimation methods, the average gross wage fell short of the marginal revenue product of labor. The persistence of such gaps is notable: a profit-maximizing firm in a competitive market would normally hire workers until the wage equals the marginal revenue product, yet Finnish firms, on average, did not reach that point.

Our results also reveal substantial variation in the size of this relative pay gap across industries. Manufacturing industries, especially pharmaceuticals, paper, and basic metals, show the largest deviations from marginal productivity theory, with wages covering only a small fraction of the estimated marginal product of labor. In more traditional service sectors, such as road transport and vehicle repair, wages are much closer to alignment with marginal products. In contrast, knowledge-intensive services such as information technology and legal/accounting, as well as high-tech manufacturing, exhibit wider gaps, similar to those in capital-intensive manufacturing. These patterns indicate that understaffing is most severe in capital- and knowledge-intensive sectors, whereas many conventional services are closer to the benchmark of wage–product equality.

A comparison of labor cost measures suggests that using the simple gross wage per worker understates the degree of understaffing. We found that relative pay gaps based on gross wages are somewhat smaller (i.e., closer to parity) than those based on our econometric estimates of the marginal cost of labor. This implies that firm-level comparisons using only average wages may underestimate the true wage–productivity misalignment. At the same time, there is considerable variation across firms, even within narrowly defined industries. Some firms pay wages above their estimated marginal product (overstaffing), but the majority display wages well below the marginal product. This within-industry dispersion means that industry-level gaps mask even greater heterogeneity at the firm level. Thus, the distribution of returns to labor is highly uneven across firms.

Despite Finland's strong labor market institutions, understaffing appears to be systematic in both manufacturing and services. Our evidence challenges the assumption that coordinated institutions alone can ensure that wages align with marginal productivity. Collective bargaining and centralized wage settings may compress wage differences within industries, but sector-specific dynamics and firm-level heterogeneity still generate persistent gaps. In the Finnish context, institutional frameworks cannot fully offset misalignment when technological intensity, market structure, and productivity dispersion vary significantly across sectors.

An important question is why firms do not hire more labor or bid up wages to close these gaps. One explanation is that many firms face labor supply constraints. If companies cannot find enough workers with the requisite skills, they are unable to expand employment even when additional workers' output would far exceed their cost. In such cases, the firm operates below its profit-maximizing employment level because suitable labor is simply not available. Finland's highly regulated education system, in which the government controls the number of study places in various fields, can contribute to this problem by limiting the supply of graduates in high-demand professions. A shortage of skilled workers, whether due to education bottlenecks, demographic trends, or other skill mismatches, means that even substantial wage increases may not immediately bring in the required labor. Geographic and occupational mismatches in the labor market further exacerbate this issue: productive jobs may go unfilled because potential workers are in different regions or lack specific qualifications, allowing a wage–productivity gap to persist despite what appear to be profit opportunities for firms.

Another contributing factor could be labor market frictions and regulations. Finland's strict employment protection laws make laying off workers difficult, which may inadvertently discourage firms from hiring up to the point where wages equal marginal products. Risk-averse managers, who are wary of future downturns or the costs of reducing staff, might deliberately employ fewer workers than the short-run profit maximum. In practice, this means that firms accept some lost output (and profit) in exchange for avoiding potential firing costs later. Additionally, Finland's coordinated wage-setting system, characterized by strong labor unions and collective agreements, tends to compress wage differentials across firms and industries. While such coordination promotes fairness and wage stability, it can prevent wages in high-productivity sectors or regions from rising sufficiently to attract more workers.

In a fully competitive labor market, acute labor shortages would drive wages sharply upward to lure workers into those sectors or locations. However, under centralized bargaining, wage increases are constrained and homogenized across sectors. This institutional rigidity can thus leave certain high-productivity firms persistently understaffed relative to what a flexible market would dictate, and their workers pay below what their marginal output would justify.

A third potential driver of the wage–productivity gap is market power. If employers have monopsony power in hiring, for instance, if workers have few alternative job options in a region or occupation, firms can profitably set wages below workers' marginal revenue products and hire fewer workers than in competitive equilibrium. Monopsony thus creates a direct wedge between wages and productivity, exactly the pattern we observe. Likewise, monopoly power on the product market side might allow firms to capture a greater share of the value added without commensurate pressure to raise wages. Recent empirical studies support this interpretation. For example, (Deb et al., 2022) find that both rising labor market concentration (monopsony) and product market concentration (monopoly) contribute to the decoupling of wages from productivity growth in advanced economies. In Finland, industries with less competition (either for labor or in output markets) may thus be more prone to underpaying workers relative to their marginal product. In sum, a combination of skill shortages, labor market frictions, institutional wage setting, and monopsony/monopoly power could help explain why wages remain below marginal productivity in a sustained way.

Our contribution in this study is to document the existence and breadth of this wage–productivity gap; determining the exact mix of underlying causes lies beyond our scope and remains an important avenue for future research. The range of plausible explanations outlined above suggests that no single policy lever will fully close this gap. Instead, a multifaceted approach is required to better align wages with productivity. From a policy perspective, addressing the persistent understaffing calls for attention to all these mechanisms. Education and training policies may need to be adjusted to alleviate skill bottlenecks in high-productivity fields. Labor market policy could seek a balance between worker protection and flexibility so that firms are less hesitant to hire. Simultaneously, reinforcing competition in both the product and labor markets, for instance, through anti-monopoly regulations or measures to boost worker mobility and bargaining power, can help curtail the excess market power that enables wage suppression. Additionally, ensuring that productivity gains are shared more equitably within industries (e.g., via firm-level incentives or broader wage agreement frameworks that reward productivity increases) contributes to narrowing the pay gap. Achieving a closer alignment of wages with marginal products will likely require coordinated adjustments at both the sectoral and firm levels tailored to the specific conditions of each industry.

Finally, accumulating empirical evidence against the strict marginal productivity theory of wages has wider implications for economic analysis and policy. If observed wages systematically understate workers' marginal products, conventional growth accounting will undervalue labor's contribution to output and productivity growth. In other words, some improvements in output currently attributed to total factor productivity (technology) might in fact reflect labor's unmeasured contributions. This could bias the measured technological progress downward and lead to an incomplete or distorted understanding of the sources of economic growth. Notably, the extent of this bias may differ across industries: it would be most pronounced in capital- and knowledge-intensive sectors, where the wage–marginal product gap is widest. A deeper investigation of how the growing wage–productivity gap affects measured total factor productivity is therefore an important topic for future research, as it may influence both academic perspectives on productivity dynamics and the design of policies aimed at fostering equitable growth.

Acknowledgments

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