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Non-Compete Agreements, Tacit Knowledge and Market Imperfections*

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Abstract: This paper provides evidence from a natural experiment on the importance of tacit knowledge that workers have about firms' intangible assets for competition in product and labor markets. First, evidence is presented on product and labor market imperfections across firms in manufacturing and services industries in the Netherlands. Price-cost markups and wage markups are both shown to be positively related to intangible intensity at the firm level. A model is developed of the processes of intangible investment and wage bargaining of heterogeneous firms, providing a mechanism that relates workers' tacit knowledge to product and labor market imperfections at the firm level. The model also incorporates a role for non-compete agreements (NCAs) limiting worker mobility. Our main empirical contribution comes from using linked employer-employee panel data with information on NCAs and changes in enforceability of these agreements. Using an event-study framework, we demonstrate that the removal of NCAs leads to higher wages and worker mobility and that the effect is stronger for workers employed in intangible-intensive firms. We find that NCAs affect workers across the skill distribution and across industries. The causal findings from changes in the legality of NCAs correspond with the mechanism described in the model.

Keywords: Price-cost markups, rent sharing, technology, tacit knowledge, non-compete agreements.

JEL classification: J41, L10, M52.

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1 Introduction

By now, it is widely recognized that most contemporary product and labor markets are characterized by some degree of imperfect competition.[1] Recent empirical evidence has not only shown the prevalence of product and labor market imperfections but also their co-movement, with price-cost markups and wage markups often showing up together (Damoah, 2021; Mertens and Mottironi, 2023; Dobbelaere and Wiersma, 2024). What is lacking, though, is a micro-foundation for the co-movement of pricing rules in both markets and an empirical test to validate this micro-founded mechanism. Establishing such micro-foundation is valuable as it can inform us on the origins of the observed market imperfections and guide policy interventions to address them, such as implementing changes in minimum wages or legal restrictions on worker mobility.

Using firm panel data in the Netherlands for 37,084 firms over the period 2000-2020, we document that the vast majority of employers in manufacturing and services industries set prices above the marginal cost of production and pay workers above their marginal revenue product. At the same time, we show that both price-cost markups and wage markups are positively related to intangible intensity at the firm level, that is, the degree to which firms rely on non-physical assets that contribute to production. Motivated by these observed patterns, this paper assesses the role of tacit knowledge embedded in specific technologies in driving the co-movement of product and labor market imperfections. To this end, we model the processes of intangible investment and wage bargaining of heterogeneous firms. This provides a mechanism relating workers' tacit knowledge to firms' price-cost markups and wage markups. The intuition is that knowledge is a critical asset for firms, enabling them to operate physical capital more efficiently and, thereby, gaining a competitive edge. However, the effective ownership of knowledge by a firm is inherently imperfect, especially when it resides exclusively with key employees and remains tacit in nature. Since employees are free to change employers, their departure could result in the loss of this valuable tacit knowledge, leading to a hold-up problem (Coase, 2000). To ensure continued investment in the accumulation of tacit knowledge and to secure the returns from it, firms find it profitable to share a portion of these returns with their employees, resulting in higher compensation and a reduced likelihood of employees leaving. We then validate the model with a natural experiment that took place in the

[1] See e.g. Diez et al. (2018); Cavalleri et al. (2019); De Loecker et al. (2020); Weche and Wambach (2021); van Heuvelen et al. (2021), and Dobbelaere and Mairesse (2018); Card et al. (2018); Caselli et al. (2021); Manning (2021); Sokolova and Sorensen (2021); Yeh et al. (2022); Dobbelaere et al. (2024) for empirical evidence on the pervasiveness of imperfectly competitive product and labor markets, respectively.

Netherlands through a reform of the Dutch Work and Security Act (WWZ) in 2015. Under the WWZ reform, the enforcement of non-compete agreements (NCAs) for temporary contracts was removed. Through the lens of our model, this policy intervention acts as a reduction in the cost of separation between workers and firms, which increases workers' bargaining power, especially in firms where tacit knowledge plays an important role in production. Using linked employer-employee panel data with information on NCAs, we assess the impact of the reform on labor income and worker mobility. Our analysis matches treated workers who had an NCA in their temporary contract before the reform with control workers on temporary contracts without an NCA and then characterizes differential worker outcomes using an event study framework. New evidence emerges on how NCAs interact with firm-level intangible intensity. Compared to the control group, treated workers have on average 13% higher labor income post-reform. Importantly, this effect is driven by workers employed in intangible-intensive firms, confirming the model's mechanism. We find that NCAs occur across the skill distribution and that the effect of the reform is similar across workers with different skill (education) levels. We interpret this result as evidence that frictions from tacit knowledge are not limited to high-skilled jobs but are driven by the hold-up problem arising from worker mobility. Our findings are robust to controlling for labor market institutions, such as firm-level collective bargaining agreements.

Contribution to related literature. This paper contributes to several strands of literature. First, it introduces a new mechanism to the literature that links pricing behavior in product and labor markets to technology. Eeckhout and Veldkamp (2022) and Kirov and Traina (2023) are recent studies attributing increases in respectively firm and labor market power to the ability to master data and software. We build on and add to the recent theoretical literature modeling investment in intangible inputs as the driver of productivity dispersion and market power (Aghion et al., 2023; De Ridder, 2024). Our theoretical framework is closely linked to De Ridder (2024). Unlike De Ridder (2024), we develop a partial equilibrium framework, model a process of implicit wage bargaining and demonstrate that the reduction in marginal costs resulting from investment in intangibles can dissipate in the event of worker separation. Our paper thus unpacks the "black box" of the process of intangible creation and the labor market and isolates a particular channel through which technology drives price-cost markups and wage markups. In doing so, we provide a micro-foundation for the observed co-movement of product and labor market imperfections.[2] More generally, we add to a burgeoning literature investigating the impact of the rising importance of intangible capital on the macro economy (Corrado et al., 2013; Döttling and Perotti, 2017; Haskel and Westlake, 2018; Aghion et al., 2020; Crouzet et al., 2022; Hsieh and Rossi-Hansberg, 2023). In particular, we model the consequences of the imperfect appropriability of intangibles in a similar way as Döttling and Perotti (2017) and Crouzet et al. (2022) and embed it in a search model following the tradition of Burdett and Mortensen (1998).

Second, this paper adds to the recent literature on non-compete contracts. One set of papers examines specific labor market outcomes related to NCAs. Lipsitz and Starr (2022) and Young (2024) evaluate the impact of banning NCAs on wages for low-wage workers in Oregon and Austria, respectively, while Potter et al. (2024) study the efficiency of NCAs in low-wage labor markets. Balasubramanian et al. (2022) investigate the effects of NCA restrictions in Hawaii on the careers of technology workers. Starr et al. (2021) examine associations between NCAs and training, wages, and job satisfaction for US workers, whereas Johnson et al. (2023a) analyze the implications of changes in enforceability for US workers' earnings and job mobility. Another set of papers relevant to our study examines the impact of NCAs on firms' investment decisions. Conti (2014) finds that stricter NCA enforceability induce US companies to choose "riskier" R&D projects, while Johnson et al. (2023b) show that making NCAs easier to enforce substantially reduces the rate of patenting in US firms. Jeffers (2024) provides evidence of increased NCA enforceability leading US firms to increase their investment in physical capital but not in intangibles. A third set of papers in the theoretical literature on NCAs calibrates a general equilibrium model to understand the joint impact of NCAs on firm-level investment and workers outcomes, providing a framework for the optimal regulation of such clauses (Shi, 2023; Liu, 2023). We contribute to the literature on NCAs by modeling their effect on firms and workers within the context of a joint investment in intangible capital. In addition, we assess the impact of a policy intervention that lifted the enforceability of NCAs in the Dutch labor market, thereby validating our model's mechanism. NCAs have become a highly debated public policy issue, underscoring the policy relevance of our study. Most notably, the US Federal Trade Commission (FTC) approved an outright ban on NCAs between workers and firms in the US labor market on April 23, 2024 (Federal Trade Commission, 2024).[3]

[2] As such, we attempt to respond to Van Reenen (2024)'s call for modeling imperfect competition in labor and product markets together and carefully examining the origins of such market power.

[3] A federal judge blocked the FTC's non-compete ban on August 20, 2024, though (The New York Times, 2024).

The remainder of this paper proceeds as follows. In Section 2, we present descriptive evidence on the co-movement of product and labor market imperfections and document that such co-movement is associated with technology usage at the firm that implies a role for tacit knowledge. In Section 3, we develop a theoretical model where the process of intangible investment and wage bargaining provides a testable mechanism underlying the observed positive correlation between product and labor market imperfections. In Section 4, we validate our theoretical prediction through a natural experiment, leveraging the 2015 lifting of NCAs for temporary contracts as part of the Dutch Work and Security Act. Finally, in Section 5, we conclude.

2 Descriptive evidence on product and labor market imperfections by intangible intensity

We are primarily interested in uncovering the mechanism driving the observed co-movement of product and labor market imperfections. We first document that the vast majority of Dutch employers in manufacturing and services industries set prices above the marginal cost of production and pay workers above their marginal revenue product. We then show that price-cost markups and wage markups are positively related to technology usage involving the creation of an intangible asset that is imperfectly excludable by firms (i.e. tacit knowledge or know-how).

2.1 Co-movement of product and labor market imperfections

Production function approach. To measure product and labor market imperfections at the individual employer level, we follow the production function approach introduced in Dobbelaere and Mairesse (2013). They show that product market imperfections drive a wedge between the output elasticity of intermediate inputs and their revenue share and labor market imperfections drive a wedge between the output elasticities of intermediate inputs and labor and their revenue shares. Following common practice initiated by De Loecker and Warzynski (2012), the former wedge is informative on the direction (i.e. price-marginal cost vs. price-cost markup) and size (deviation of prices from marginal costs) of product market imperfections that allows the researcher to be agnostic about the underlying source of such imperfections. As demonstrated in recent work by Caselli et al. (2021) and Yeh et al. (2022), the latter wedge directly translates into the ratio of wages to the marginal revenue product of labor when considering the market for intermediate inputs as competitive benchmark. This ratio, in turn, provides us with a reduced-form firm-level measure on the direction (i.e. wage markdown vs. wage markup) and size (deviation of wages from the marginal revenue product of labor) of labor market imperfections that allows the researcher to keep agnostic about market structure. It is directly tied to employers' wage bill and thus captures their use of rather than their potential for labor market power. In the following, we summarize the assumptions and outcomes of this production function approach. For details, we refer to Dobbelaere et al. (2024).

Consider firm i at time t with productivity level Ω_{it} that produces a good Q_{it} from its labor input L_{it}, its intermediate inputs M_{it}, and its capital input K_{it}, subject to the strictly increasing (in all its arguments) and concave production function:

$$Q_{it} = \Omega_{it} Q(L_{it}, M_{it}, K_{it}) \tag{1}$$

In terms of the firm's input choices, we assume that (i) labor and intermediate inputs are free of adjustments costs and are thus choice variables in the short run, (ii) capital is predetermined and thus no choice variable in the short run, and (iii) the firm takes the price of its intermediate inputs as given. We also assume that all firms in the market maximize short-run profits. Then, the firm's optimization problem involves maximizing short-run profits with respect to output Q_{it}, labor L_{it}, and intermediate inputs M_{it}, and the corresponding first-order conditions allow us to infer the existing product and labor market imperfections.

Turning to the firm's product market first, the first-order condition with respect to Q_{it} yields the firm's price-cost markup μ_{it}:

$$\mu_{it} = \frac{P_{it}}{(C_Q)_{it}} = \left(1 + \frac{s_{it}\kappa_{it}}{e_t}\right)^{-1} \tag{2}$$

where $(C_Q)_{it} = \partial C_{it}/\partial Q_{it}$ denotes the marginal cost of production, C_{it} the cost function, $s_{it} = Q_{it}/Q_t$ the market share of firm i in industry demand Q_t, $e_t = (\partial Q_t/\partial P_t)(P_t/Q_t)$ the own-price elasticity of industry demand, and $\kappa_{it} = \partial Q_t/\partial Q_{it}$ a conjectural variation parameter that captures competitors' quantity response to firm i's output choice.

Turning to the firm's choice of intermediate inputs next, the first-order condition with respect to M_{it} yields that the price-cost markup is given as:

$$\mu_{it} = \frac{(\varepsilon_M^Q)_{it}}{\alpha_{Mit}} \tag{3}$$

where $(\varepsilon_M^Q)_{it} = (\partial Q_{it}/\partial M_{it})(M_{it}/Q_{it})$ denotes the output elasticity of intermediate inputs, $\alpha_{Mit} = J_{it}M_{it}/R_{it}$ their revenue share, J_{it} their price, and $R_{it} = P_{it}Q_{it}$ the firm's revenue. The intuition behind this outcome is that the firm will make economic profits when the output elasticity of intermediate inputs exceeds their revenue share. These profits must stem from product market imperfections because the firm takes the price of intermediate inputs as given. Consequently, the gap between the output elasticity of intermediate inputs and their revenue share is informative on the price-cost markup.

Turning to the firm's labor market, the prevalence and size of possible wage markdowns and wage markups can be seen from the wedge between the output elasticities of intermediate inputs and labor and their respective revenue shares:

$$\psi_{it} = \frac{(\varepsilon_M^Q)_{it}/\alpha_{Mit}}{(\varepsilon_L^Q)_{it}/\alpha_{Lit}} = \frac{\mu_{it}}{\frac{(Q_L)_{it}L_{it}}{Q_{it}}\frac{P_{it}Q_{it}}{W_{it}L_{it}}} = \frac{W_{it}}{P_{it}(Q_L)_{it}/\mu_{it}} = \frac{W_{it}}{(R_L)_{it}} \tag{4}$$

that gives the ratio of the firm's wage to the marginal revenue product of labor. The intuition behind equation (4) is that in case of a wage markdown, the economic profits originating from the firm's labor input, which result in a gap between the output elasticity of labor and its revenue share, dominate those from its intermediate inputs, and thus a below-unity ratio ψ_{it} indicates a wage markdown. Along the same lines, an above-unity ratio ψ_{it} indicates a wage markup.

We can further transform a given value of ψ_{it} into structural measures of employers' monopsony power when there is a wage markdown and workers' monopoly power when there is a wage markup. More specifically, in case of a wage markdown (or $\psi_{it} < 1$), we can translate the reduced-form firm-level measure of labor market imperfections (ψ_{it}) into the implied wage elasticity of the labor supply curve that rationalizes the observed wage outcomes in a monopsony framework:

$$(\varepsilon_W^L)_{it} = \frac{\psi_{it}}{1 - \psi_{it}} \tag{5}$$

Under perfect competition, the firm-level labor supply curve is horizontal with $(\varepsilon_W^L)_{it} = \infty$ and workers obtain the marginal revenue product of labor or $\psi_{it} = 1$. Under monopsony or $\psi_{it} < 1$, the firm's wage-setting power is negatively related to the labor supply elasticity which, in turn, is positively related to ψ_{it}.

In case of a wage markup (or $\psi_{it} > 1$), we can translate ψ_{it} into the elasticity of the wage with respect to the quasi-rent per worker that rationalizes the observed wage outcomes in an efficient bargaining framework:

$$(\varepsilon^{W}_{QR/L})_{it} = \frac{\gamma_{it}(QR)_{it}/L_{it}}{(R_L)_{it} + \gamma_{it}(QR)_{it}/L_{it}} = \frac{W_{it} - (R_L)_{it}}{W_{it}} = \frac{\psi_{it} - 1}{\psi_{it}} \tag{6}$$

where $(QR)_{it}/L_{it}$ denotes the quasi-rent per worker and $0 < \gamma_{it} < 1$ the part of the surplus accruing to workers, which captures workers' bargaining power. The rent-sharing elasticity informs us on what fraction of a one percent increase in firm surplus shows up in workers' wages and thus on workers' monopoly power as implied by the observed wage outcomes. Under perfect competition, there is no rent sharing with $(\varepsilon^{W}_{QR/L})_{it} = 0$ and workers obtain the marginal revenue product of labor or $\psi_{it} = 1$. Under efficient bargaining or $\psi_{it} > 1$, the workers' bargaining power is positively related to the rent-sharing elasticity $(\varepsilon^{W}_{QR/L})_{it}$ which, in turn, is positively related to ψ_{it}.

Econometric implementation. Measuring product and labor market imperfections based on the price-cost markup μ_{it} and the ratio of wages to the marginal revenue product of labor ψ_{it} requires consistent estimates of the output elasticities of intermediate inputs $(\varepsilon^{Q}_{M})_{it}$ and labor $(\varepsilon^{Q}_{L})_{it}$ as well as their revenue shares α_{Mit} and α_{Lit}. At the core of the econometric implementation are industry-specific production functions and firm-specific data on input usage that allows us to measure μ_{it} and ψ_{it}. Using a representative sample of 37,084 Dutch firms in manufacturing and services industries for the years 2000-2020 sourced from the Production Statistics (PS) survey provided by Statistics Netherlands (CBS), we implement the production function approach and estimate production functions using Ackerberg et al. (2015)'s control function estimator (see Appendix B for details).

Co-movement of product and labor market imperfections. The left panel of Figure 1 presents median estimates of labor market and product imperfections for manufacturing and services industries over the period 2000-2020 in the Dutch economy. Each circle represents a 3-digit NACE industry. The size of each circle is proportional to the real value-added share of the industry and presents an average over time. We observe that the vast majority of firm-year observations involve a price-cost markup ($\mu_{it} = \frac{(\varepsilon^Q_M)_{it}}{\alpha_{Mit}} > 1$) and a wage markup ($\psi_{it} = \frac{(\varepsilon^Q_M)_{it}/\alpha_{Mit}}{(\varepsilon^Q_L)_{it}/\alpha_{Lit}} = \frac{W_{it}}{(R_L)_{it}} > 1$). The right panel of Figure 1 shows the proportion of each of the four possible combinations of labor (ψ_{it}) and product (μ_{it}) market imperfection parameter estimates, broken down by 1-digit NACE industries.[4] Appendix Figure E1 shows the real value-added share of each possible combination of ψ_{it} and μ_{it}, broken down by manufacturing, services and the total economy. Consistent with evidence on US manufacturing (e.g. Yeh et al. (2022)), wage markdowns ($\psi_{it} < 1$) are more prevalent in manufacturing relative to services industries. In terms of firm characteristics, firms that set price-cost markups ($\mu_{it} > 1$) and pay wage markups ($\psi_{it} > 1$) are typically small and medium-sized enterprises and exporters, characterized by high productivity, innovativeness (filing more than seven patents per firm on average) and average wages (see Appendix Table E2).

To cross-validate our measure of labor market imperfections from the production function approach, we examine its predictive power for the wage premia paid by employers to their workers. The latter equals employers' wage levels after accounting for the sorting of workers of different quality into firms, holding constant firm surplus and a rich set of firm characteristics. To measure employer wage premia, we estimate a standard Abowd et al. (1999) (AKM) model that decomposes a worker's individual wage into a worker-specific and a firm-specific component, following Card et al. (2018) and Hirsch and Mueller (2020) (see Appendix C for details). To investigate the partial correlation between the measures of labor market imperfections from the production function approach and employer wage premia, we regress the standardized AKM firm wage effect on these measures and gross operating profit per worker to control for firm surplus. Additional controls include firm size measured by the number of full-time equivalent employees, firm age, the share of medium- and high-skilled workers[5], a dummy variable taking the value of 1 if the majority of workers' wages are negotiated through collective bargaining at the firm level, an export dummy, and year and industry dummies. The results are reported in Appendix Table E3. As predicted by theory, we find a positive association between the mean employer wage premium and either the log ratio of wages to the marginal revenue product of labor (ψ), the logarithm of the rent-sharing elasticity ($\varepsilon^W_{QR/L}$) or the logarithm of the labor supply elasticity (ε^L_W). More specifically,

[4]The share of firms for each combination of labor and product market imperfection parameters by 1-digit NACE industry is reported in Appendix Table E1.

[5]Medium-skilled refers to workers with upper-secondary or post-secondary education excluding tertiary education. Workers designated as high-skilled have tertiary education.

a one standard deviation larger log ratio, which amounts to 0.48 in our sample, is associated with a 0.08 ($= 0.48 \times 0.17$) standard deviations larger mean firm wage premium, which is statistically significant at the 1% level (see column (1)). Note that a standard deviation in firm wage premia amounts to 29 log points in our sample, so this partial correlation is sizeable. When restricting to the 31,849 observations involving a wage markdown, we find that a one standard deviation larger log firm-level labor supply elasticity, which amounts to 1.38 in our sample, is accompanied by a 0.02 ($= 1.38 \times 0.017$) standard deviations larger mean wage premium, which is statistically significant at the 1% level (see column (2)). Finally, restricting to the 78,757 observations involving a wage markup, a one standard deviation larger log rent-sharing elasticity, which is 0.94 in our sample, is associated with a 0.06 ($= 0.94 \times 0.066$) standard deviations larger mean wage premium, which is statistically significant at the 1% level (see column (3)) and a larger association than for the labor supply elasticity.

2.2 Correlation between product and labor market imperfections and intangible intensity

We now examine partial correlations between the product and labor market imperfection parameters (μ and ψ, respectively) and adoption of technologies where tacit knowledge may play a role within the firm. To proxy for the importance of tacit knowledge within the firm, we use a firm's "automation expenditure". This variable is reported in the Production Survey and captures all forms of expenditure aimed at automating complex production processes and internal procedures in the firm via the use of data, software and hardware technologies. It has been used in existing work to assess the impact of automation (Bessen, 2019; Bessen et al., 2023) but captures in reality both labor-saving and labor-augmenting technologies which have in common key interactions between workers' human capital and physical assets within the firm. Using similar data as ours, Bessen et al. (2023) show that automation expenditure (1) is highly correlated with process innovation but less so with product and organizational innovation, (2) is correlated with technologies that involve using data for automated processing (e.g. Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), use of big data, cloud computing, exchanging data through Electronic Data Interchange (EDI) networks, sales software) and is (3) substantially higher than imports in industrial robots, a measure widely used in the literature to identify investment in purely labor-saving technologies (Acemoglu and Restrepo, 2019). The latter suggests that this type of expenditure captures investment in a wider class of assets than just automation technologies, all having in common a high potential for increased productivity through tacit knowledge, as part of their value is specific to the firm. (Corrado et al., 2013; Calligaris et al., 2018; Tambe et al., 2019). For example, an experienced coder might use the same software code more efficiently than a new hire, or an experienced HR employee might process files for monitoring and transmitting internal information faster than someone new to the role. Using Community Innovation Survey data for Germany, Thomä and Bizer (2013) also find that firms perceive process innovation as posing the greatest risk of knowledge leakage, primarily due to its reliance on tacit knowledge.

We conduct a similar investigation leveraging a detailed firm-level survey on the use of information and communication technologies (ICT, which can be linked at the firm level to the PS survey. We compare the average automation expenditure per worker between firms that adopt and those that do not adopt the following technologies: Artificial Intelligence (AI), industrial robots, Automated Data Exchange (ADE), ERP, whether the firm employs any ICT personnel and whether it allows employees to access emails remotely. Appendix Figure E2 shows that automation expenditure per worker is positively correlated with all technologies, except for industrial robots. Using data from the ICT survey on employees' access to company IT resources, we also document a positive correlation between automation expenditure per worker and the share of workers with either remote access to company files or access to telework in Appendix Figure E3.

We derive partial correlations between our market imperfection parameters and intangible intensity at the firm level from estimating fixed-effects panel data models covering the years 2013-2020 using our PS sample.[6] We run different model specifications using either ψ_{it} or μ_{it} as the dependent variable and automation expenditure per worker as the independent variable of interest, controlling for firm-level characteristics (firm size, age, labor productivity measured by value added per worker, average wage, a dummy taking the value of 1 if the majority of workers' wages are negotiated through collective bargaining at the firm level[7], a dummy taking the value of 1 if the firm is foreign-owned and the share of exports in total sales) as well as industry-level characteristics (market concentration measured by the Herfindahl-Hirschman Index (HHI) and share of patenting firms). The results are reported in Table 1. In specifications (2), (4) and (6), we restrict the set of firms to exporting firms only. We find a positive correlation between automation expenditure

[6] We restrict to this time interval for consistency with the sample of workers used in Section 4 but results are robust to extending the observational window to the 2000-2020 period (results not reported but available upon request).

[7] This information originates from our matched employer-employee data (POLIS data), see Section 4 for details.

per worker and both market imperfection parameters. We interpret these findings as suggestive evidence of intangible assets driving both labor and product market imperfections.[8]

Finally, Figure 2 plots average automation expenditure per worker along with 95% confidence intervals for each possible combination of labor and product market imperfection parameters. This figure reveals that firms that set wage markups ($\psi_{it} > 1$) and price-cost markups ($\mu_{it} > 1$) are characterized by a higher intensity in intangible capital (proxied by automation expenditure per worker). In general, firms that price above marginal costs display a higher intangible intensity, consistent with prior research (De Ridder, 2024).

3 Modeling intangible investment, wage bargaining and output pricing

From the previous section, it follows that firms are heterogeneous in their markups of price above marginal costs in the product market and in their wages relative to marginal revenue products in the labor market. Product market imperfections could be caused by (abuse of) market power unchecked by competition policy or other forms of regulatory failure. Similarly, labor market imperfections could stem from firms' monopsony power or unions' monopoly/bargaining power. While we do not rule out these causes, they would on their own not be able to explain the positive correlation across firms in price-cost markup and wage markup parameters, nor the observed relation of these parameters to the intangible-intensity of firms.

In this section, we develop a heterogeneous-firm model that can explain these observed patterns. In the model, firms differ in their capability to invest in intangible capital, akin to Crouzet et al. (2022) and De Ridder (2024). When a firm invests, the resulting intangible asset will lower the marginal cost of production at any scale. Firms are multi-product and compete for customers in markets of differentiated products for which the firm owns a patent with a given product quality (Klette and Kortum, 2004; Akcigit and Kerr, 2018). Under Bertrand competition, the firm with the best ratio of price to quality will supply the whole market for that product. This provides an

[8] Using the linked ICT-PS panel, we also find that firms adopting labor-augmenting technologies (e.g. AI, telework) are characterized by price-cost markups and wage markups. The only technology that seems to be associated with firms charging prices above the marginal cost of production and paying wages below the marginal revenue product of labor (imposing wage markdowns) are industrial robots (results not reported but available upon request).

incentive to lower marginal production costs through intangible investment as well as an incentive to innovate with R&D to improve product quality.[9] While the investment needed to produce a patent for product quality or the investment needed to lower marginal costs are "intangible" in nature and lead to intangible firm assets, our model treats them separately. The innovation in product quality is fully protected by a patent, whereas the intangible asset that lowers marginal production costs may not be. In doing so, we align more closely with the concept of tacit knowledge introduced in the previous section, which refers to knowledge valuable to the firm but not fully appropriable through intellectual property rights.

In the model, workers are assumed to have (tacit) knowledge about the intangible asset that lowers marginal production costs. In the case of tacit knowledge, departure of the worker will reduce or negate the marginal-cost reducing nature of the intangible for the firm. If this worker joins a competing firm, further damage to firm profits could occur by lowering the competing firm's marginal production costs to some extent. For codified knowledge, the firm can continue to benefit from the marginal-cost reduction resulting from the intangible asset after the worker's departure, and would only lose value if the worker brought the knowledge to a competing firm. We assume for simplicity that codified knowledge can be protected and therefore can be treated similarly to patented quality. Our modeling of intangibles thus falls within a rich tradition (Fukao et al., 2009; Marrano et al., 2009; Corrado and Hulten, 2010; Corrado et al., 2013; Döttling and Perotti, 2017; Crouzet et al., 2022), where the intangibles are non-rival in production (improve quality or lower marginal costs at any scale of production) but vary in their appropriability. In our model, some intangible assets are perfectly protected, while a portion of the marginal-cost reducing intangibles are tacit and can be appropriated by a departing worker.

To protect against decreased profits due to departing workers, firms can instate a cost to be paid by the worker upon departure. In particular, enforceable non-compete agreements impose a cost on a worker that leaves. Ex-ante, such an exit cost will increase equilibrium wages, see e.g. Bartelsman et al. (2016). To model the dynamic nature of worker hiring, investment in cost-reducing intangibles and job mobility, we explicitly incorporate labor search, matching and wage setting, following the standard labor search literature (Burdett and Mortensen, 1998; Gottfries and Jarosch, 2023).[10]

[9]Without loss of generality, we do not explicitly model the R&D process for quality improvement. One could model such process as in Klette and Kortum (2004) and Akcigit and Kerr (2018), by allowing for creative destruction and changes in the number of products different firms end up producing in equilibrium. Innovation would involve another joint investment process between workers and firms, where the former are hired in a competitive market.

[10]Contrary to e.g. Bilal et al. (2022) and Shi (2023), we model the process of wage determination via wage posting

In our model, the main novelty lies in opening up the black box of the process of intangible creation and the labor market, which was largely left implicit in previous literature. This framework allows us to explain the patterns of labor and product market imperfections we observe in the data but also to draw testable predictions for a reduction in enforceability of non-compete agreements that we explore in Section 4.

The model. Time is discrete and a representative household maximizes utility U subject to a budget constraint:

$$U = \sum_{t=0}^{\infty} \beta^t \ln C_t \tag{7}$$

where C_t is consumption of a composite good and β the discount factor. Households finance consumption through labor income (see infra).

The composite consumption good is made of a continuum of differentiated intermediate goods indexed by j. Each good can be produced by the set of firms I_j that own a patent for good j at a level of quality q_{ij}. Quality determines the value that each unit of a good produced by a firm $i \in I_j$ contributes to the composite consumption good. The composite good is an aggregate of the differentiated goods using the following Cobb-Douglas aggregator:

$$Y = \exp \int_0^1 \ln \left(\sum_{i \in I_j} q_{ij} y_{ij} \right) dj \tag{8}$$

where Y is total production of the composite good and y_{ij} is the amount of differentiated good j produced by firm i. By market clearing, $Y = C+I$, where I denotes aggregate investment. Firms in I_j compete à la Bertrand and consumers end up buying the good with the lowest quality-adjusted price p_{ij}/q_{ij}. Therefore, even if multiple firms own the patent to produce good j, only one firm ends up producing in equilibrium.

The firm side of the economy is modeled building upon Klette and Kortum (2004) and De Ridder (2024). There is a continuum of firms indexed by i that can produce in any of the differentiated product markets for which they own a patent. Production takes place according to a Leontief

rather than wage bargaining. Choosing Nash bargaining would necessitate calibrating the bargaining weights. Instead, we opt to explicitly model this via the interaction between the process of investment in intangibles internal to firms and on-the-job search.

production function in labor l_{ij} and intermediate inputs m_{ij}:[11]

$$y_{ij} = \min\{l_{ij}, z_{ij}m_{ij}\} \tag{9}$$

where $z_{ij} \geq 1$ denotes the productivity of purchased intermediate inputs. It follows that the full marginal cost takes the form:

$$mc(z_{ij}) = w_i + \frac{v}{z_{ij}} \tag{10}$$

where w_i denote wages and v the unit cost of intermediate inputs. Firms can invest in intangible capital to increase materials productivity or reduce the marginal cost of production. For simplicity in exposition, we define the marginal-cost savings $s_{ij} = \frac{1}{z_{ij}}$. There is heterogeneity across firms in the investment needed for a given s_{ij}, given by a parameter ϕ_i which is known to the firm and is fixed over time. The investment cost for a firm with ability ϕ_i to achieve marginal-cost reduction s_{ij} is given by:

$$g(s_{ij}, \phi_i) = v\phi_i \left(s_{ij}^{-\theta} - 1\right) \tag{11}$$

where $\theta > 0$. The function $g(\cdot)$ has the desirable properties of being increasing in ϕ_i, implying that firms with lower ϕ_i (i.e. more efficient in investing in intangibles) spend less to achieve the same reduction in marginal cost. Note that $g(1, \phi_i) = 0$, so that firms that do not invest in intangibles pay no fixed cost. Similarly, $lim_{s_{ij}\to 0} g(s_{ij}, \phi_i) = \infty$, so that no firm will obtain a marginal cost of w_i in equilibrium.

Relative to De Ridder (2024), the main novelty we introduce is that the reduction in marginal costs resulting from investment can dissipate if the worker departs. In other words, some of the intangibles are tacit and held by the worker. After investing $g(s_{ij}, \phi_i)$, the firm attains a marginal cost on intermediate inputs equal to $s_{ij} \cdot v < v$ but if the worker departs we assume that this instead becomes $\xi_{ij} \cdot s_{ij} \cdot v$, where $\xi_{ij} \in (1, \frac{1}{s_{ij}}]$. This can be the case e.g. if the worker shares part of the knowledge developed in the previous investment process with the new employer (i.e. the worker gets *poached*) or if the knowledge was partly job-worker specific and therefore gets lost in the case of separation. In making the decision to invest, the firm must thus balance the cost of investment $g(s_{ij}, \phi_i)$ with the benefits of the cost reduction $(1 - s_{ij})v$ minus the potential value lost when the marginal-cost reduction reverts to $\xi_{ij} \cdot s_{ij} \cdot v$ after the worker departs. In the limit, a value

[11] The choice of Leontief production function is mainly for tractability: given equilibrium demand y^*_{ij}, it ensures a unique solution l^*_{ij}, m^*_{ij} but our results hold also in other less restrictive settings where production inputs are not perfect substitutes.

$\xi_{ij} = 1/s_{ij}$ implies that workers fully control the intangible asset *de facto*, so that when they leave the firm, the cost advantage they attained with the investment in intangibles is fully dissipated (i.e. the marginal cost returns to v). As $\xi_{ij} \to 1$, workers leaving the firm do not have an impact on the costs saved by the firm via the investment in intangibles, so the firm will not consider the risk of separation from workers a credible threat.[12] This modeling choice assumes that within a period, the departure of a worker is only harmful to the competitiveness of his former employer, while no knowledge is transferred to the new firm the worker moves to.[13] Before turning to optimal investment choices by the firm, we first analyze job transitions and the wage-setting process.

Jobs consist of a match between households and firms in a setting akin to the Burdett-Mortensen model: search is random and happens both on and off the job, with firms posting wages and committing to pay them. When workers are unemployed, they earn a fixed income b. In each period, they can transition to unemployment with exogenous probability δ.

Contact between workers and firms happens at rate λ_0 and λ_1 for unemployed and employed workers, respectively. In both cases, workers pick a wage from the distribution $F(w)$. As in the canonical model, unemployed workers accept all wage offers that exceed the reservation wage w_R, while employed workers continue searching on the job and accept all wages that exceed their current wage. Together with the wage, workers also accept to pay a fixed cost $r(s_{ij})$ when they take a job offer. This cost is convex in s_{ij} according to the formula:

$$r(s_{ij}) = \eta s_{ij}^{\eta} \text{ , with } \eta > 0$$

Finally, we assume that there is a fixed cost of separation c that workers need to pay when they leave an employer for another job. This cost can capture bureaucratic procedures, transition costs, but also regulatory barriers that firms can take advantage of in order to limit worker mobility, such as non-compete agreements.

[12] $1 - \xi_{ij}$ can also be seen as the ability of a firm to retain the intangible capital it develops, as in Crouzet et al. (2022).

[13] This is a restrictive assumption, as in reality, a worker possessing valuable knowledge can benefit his new employer, provided that this knowledge is to some degree transferable. Yet, this restriction is harmless in our context as we assume Bertrand competition, thus only one firm will end up producing in each industry I_j (for the derivation of the equilibrium, see below). Who produces depends on the ability to charge the lowest quality-adjusted price and the distance between such price and that of the closest competitor. Whether this distance is affected by either of the two firms gaining a knowledge advantage (and thereby the ability to charge lower prices) is irrelevant for the equilibrium. Therefore, we assume that upon separation, the former employer experiences a loss in competitiveness equal to $(1 - \xi_{ij})s_{ij}v$, while no benefit accrues to the new employer.

Thus, we can set up the Bellman equations for unemployed and employed workers, respectively:

$$\begin{aligned} rV_U &= b + \lambda_0 \int_{w_R}^{\infty} [V_E(z) - V_U] dF(z) \\ rV_E &= w - \eta s_{ij}^{\eta} - \delta[V_E(w) - V_U] + \lambda_1 \int_{w}^{\infty} [V_E(z) - V_E(w) - c] dF(z) \end{aligned} \tag{12}$$

By exploiting the equality $rV_E(w_R) = rV_U$, we can solve for the reservation wage w_R, which workers will use as reference point to accept or refuse future wage offers. Equating the two expressions above and using integration by parts delivers the standard result:

$$w_R = \eta s_{ij}^{\eta} + b + (\kappa_0 - \kappa_1) \int_{w_R}^{\infty} \frac{1 - F(z)}{1 + \kappa_1(1 - F(z))} dz + \kappa_1 \delta c \tag{13}$$

where $\kappa_i = \lambda_i/\delta$, $i \in \{0, 1\}$.

Besides price setting (see infra) and the intangible investment decision, the firm's optimization problem entails the choice of the wage that it will post in the labor market. In line with this, note that wages are firm-specific and will determine the shape of $F(w)$ in equilibrium.

Timing. The timing of each period is as follows. At the beginning, each firm observes its own parameter ϕ_i and the quality levels of all the other firms in the economy (so not only those of its competitors in I_j). Then, firms decide whether to invest in intangible capital, thereby attaining their desired level of s_{ij}, pay the associated fixed costs and commit to the level of wages they will pay. In the following stage, all workers (employed and unemployed) search for jobs and match with new employers. In the next stage, firms update their marginal costs based on the labor market outcomes, observe those of their competitors and make pricing decisions, as well as produce the quantities they are demanded. Finally, production factors are rewarded and employed workers end up in unemployment with probability δ.

Static equilibrium. In the standard Klette and Kortum (2004) model, the firm with the highest-quality patent for good j ends up being the sole producer. In line with De Ridder (2024), this model features an additional margin on top of product quality that firms can adjust to compete with each other, i.e. reduction in marginal costs via investment in intangible capital. As firms compete à la Bertrand, the firm that is able to offer the lowest quality-adjusted price and collect non-negative profits will serve entire demand.[14] Such price p_i^c can be characterized as follows:

$$p_i^c = \min\left\{p_{ij} > 0 : \max_{\substack{s_{ij}\in(0,1];\\ w_i>0}} [p_{ij} - mc(s_{ij}, w_i)]\cdot y_{ij} - g(s_{ij}, \phi_i) - \left(\lambda_1[1-F(w_i+c)]+\delta\right)(1-\xi_{ij})\cdot s_{ij}\cdot v\cdot y_{ij}\right\} \tag{14}$$

Note that not only the investment cost $g(\cdot)$ but also the expected loss from a worker departing with their knowledge determines p_i^c. The probability that a worker leaves corresponds to the probability of drawing a wage offer higher than their current employer, controlling for the exogenous cost of separation c plus the exogenous probability of job destruction. This probability is given by $\lambda_1[1 - F(w_i + c)] + \delta$, so the higher the wage a firm is currently paying, the lower the risk of losing a worker.

Demand for each producer of good j is given by $y_{ij}^* = Yp^{-1}$, as in the standard model. The equilibrium in each market I_j also has standard properties: there is only one firm that produces good j which is the one that is able to charge the lowest p_i^c. This result is driven by Bertrand competition and the sunk nature of intangibles' cost: if multiple firms were to produce, this would entail that they would set prices equal to marginal costs which would not generate non-negative profits due to the presence of $g(s_{ij}, \phi_i)$. It follows that the equilibrium producer is the only one investing in intangibles, as the competitors are not willing to do so for fear of being undercut. This allows the sole producer to engage in limit-pricing, anticipating that its competitors can charge a price as low as $mc(1)$. With this in mind, the equilibrium price is defined as follows:

$$\frac{p_i^c}{q_i} = \min_{k\in I_j} \frac{p_k^c}{q_k} \tag{15}$$

which factoring in the limit-pricing equilibrium strategy of the final producer becomes:

$$p_{ij}^* = mc(1)\cdot \frac{q_{ij}}{\max_{k\in I_j\setminus i} q_{kj}} = (w_i + v)\cdot \widehat{q}_{ij} \tag{16}$$

where the max in the denominator of the right hand side of equation (16) is justified by the fact that since competitors do not invest in intangibles, the only variable that constrains the equilibrium producer is the quality of the nearest competitor, so the highest in I_j excluding its own.

The equilibrium price found in equation (16) has similar implications as in the standard model:

[14] This is defined as the "choke price" in De Ridder (2024).

firms can adjust their decisions in the previous stages of the game via backward induction, as they can observe ϕ_i $\forall i \in I_j$. This implies that only the firm able to charge p^*_{ij} will invest in intangibles and set $s_{ij} < 1$. Moreover, this firm will also be the only one producing, which implies that the competitors will not post a vacancy and a corresponding wage in the labor market. It follows that the equilibrium wage distribution $F(w)$ will be made of the offers by the continuum of firms that end up producing each good j.

The equilibrium level of investment in intangibles and corresponding wages can then be found by plugging in p^*_{ij} in the lowest quality-adjusted price (equation (14)) and solving for s_{ij} and w_i (equations (17) and (18), respectively):

$$s^*_{ij} = \left[\frac{\theta \phi_i p^*_{ij}}{Y} \cdot \frac{1}{1 + [\lambda_1(1 - F(w_i + c)) + \delta)(1 - \xi_{ij})]}\right]^{\frac{1}{1+\theta}} \tag{17}$$

where $f(w) = F'(w)$ is the density function associated to the cdf $F(\cdot)$.

$$w^*_i = f^{-1}\left(\frac{1}{\lambda_1(1 - \xi_{ij})s^*_{ij}v}\right) - c \tag{18}$$

From equation (17), it follows that firms take into account not only ϕ_i when setting the optimal level of marginal costs they want to save but also their relative position in the overall wage distribution. Firms that end up offering lower wages (so they face a higher $1 - F(w_i + c)$) will reduce their investment in intangibles and settle for a higher s_{ij}, as they face a higher risk that their current employees leave. Vice versa, firms that can offer higher wages face a lower risk of separation from their employees and therefore can opt for a lower s_{ij} in equilibrium. Equation (18) implies that as a firm invests more to save on marginal costs of intermediate inputs (i.e. a lower s^*_{ij}), it becomes more inclined to offer higher wages to prevent workers from leaving. At the same time, the higher the share of the intangibles that workers can appropriate when they leave the firm, the lower the incentive for a firm to post a high wage. The firm is therefore facing a trade-off between the best mix of production inputs which primarily depends on $\{\phi_i, \xi_{ij}\}$ and on the position in $F(w)$. Conditional on the value of ξ_{ij}, it follows that the more a firm invests in intangibles, the higher the wedge between the offered wage and the competitive wage (i.e. the marginal revenue product of labor), a result that is in line with the observed correlation presented in Section 2.2.[15]

[15]Note that this result holds even if we were to assume a common value for $\xi_{ij} = \bar{\xi}$ across all firms.

Equations (18) and (13) will implicitly define the shape of $F(w)$. Note that this equilibrium is a generalization of the simpler case with homogeneous firms discussed in Burdett and Mortensen (1998), where the model has only two types of firms characterized by different levels of competitiveness, which are homogeneous otherwise. Furthermore, this result is derived from the assumption that both labor and intermediate inputs are imperfect substitutes in production and that firms have imperfect property rights on their intangible capital stock.

Finally, the resulting equilibrium s^*_{ij} allows us to derive firm-level price-cost markups μ_{ij}, defined as the ratio between the optimal price p^*_{ij} and marginal cost $mc(s^*_{ij})$:

$$\mu_{ij} = \frac{mc(1)}{mc(s^*_{ij})} \cdot \widehat{q}_{ij} = \frac{w^*_i + v}{w^*_i + s^*_{ij} v} \cdot \widehat{q}_{ij} \tag{19}$$

which means that price-cost markups increase in $\widehat{q}_{ij}$ and in producers' investment in intangibles (i.e. the share of marginal cost they manage to cut). This model therefore provides a mechanism to generate patterns we observe in the data: firms that are more intensive in intangible capital are characterized by higher price-cost markups and higher wage markups (i.e. the wedge between the wage and the marginal revenue product of labor).

In the next section, we validate our model by testing one of its implications. More specifically, the parameter c regulates the cost of separation between workers and firms, thereby affecting the outcome of the bargaining process. A reduction in c reduces barriers to worker mobility, which in our model imply a higher risk for intangible-intensive firms to lose their competitive edge. Under mild assumptions on firm behavior, this exacerbates the hold-up problem, forcing firms to offer higher wages to retain their employees, as shown in Appendix D. In the next section, we test this prediction through a natural experiment.

4 Causal evidence of lifting enforceability of non-compete agreements on workers' wages

Importance of non-compete agreements in advanced economies. NCAs are becoming increasingly widespread in advanced economies and the literature has shown evidence of their effectiveness in limiting worker mobility and innovation activity (Marx et al., 2009; Zekić, 2022).

According to Streefkerk et al. (2015), about 18% of Dutch workers is subject to NCAs in their contract and diffusion of such clauses is widespread, also for low-skilled jobs.[16] Furthermore, firms indicate that NCAs provide a key tool to protect their knowledge assets (Thomä and Bizer, 2013; Mezzanotti and Simcoe, 2023).

Empirical design. To test one of the main predictions of our theoretical model, we rely on a natural experiment that took place in the Netherlands. In January 2015, non-compete agreements for temporary contracts were declared unenforceable in the Netherlands as part of the Dutch Work and Security Act (*Wet Werk en Zekerheid*). This policy intervention can be seen through the lens of our model as a reduction in the cost of separation (c) between workers and firms, which ultimately leads to an increase in workers' bargaining power if intangible capital plays a meaningful role within the firm[17]. As a result, we expect that the remuneration for these workers will increase post-reform, either because workers switch to better paying jobs (job mobility channel) or becasue they are able to negotiate better conditions with the same employer (increased bargaining power channel). This happens because because employers must offer higher wages to prevent workers from transferring the intangible asset to other firms, which would result in a loss of competitiveness for the employer. Importantly, validating the model requires demonstrating that the impact on worker-level outcomes operates through intangible capital. Therefore, large impacts are expected for firms that exhibit a more important role for tacit knowledge in their production at the time of the reform.

We construct a sample of workers matched with their employers using linked employer-employee data (linked POLIS-PS sample), which covers the population of employed workers in the Netherlands who are working for a non-foreign employer. This dataset contains each employment spell at the monthly level, including information on earnings, hours, and contract types (see Appendix A for details). We match workers from the POLIS-PS panel with workers in the Dutch Labor Force Survey (EBB), with the latter reporting at the monthly frequency whether workers had an NCA in

[16] This share can reach up to 40% in the US, France and Finland (Araki et al., 2022), while it reaches 26% in the UK (Alves et al., 2024) and 16% in Italy (Boeri et al., 2023).

[17] For certain types of NCAs, the firm is required to compensate the worker for the reduction in mobility caused by the agreement. However, most of the cost related to reduced mobility generally falls on the worker (Shi, 2023). Therefore, for simplicity and without loss of generality, we assume that the cost for the firm is equal to zero.

their contract between 2015 and 2018.[18,19] In line with existing evidence (Boeri et al., 2022; Alves et al., 2024), NCAs are not exclusively present among skilled workers. Table 2 reports the share of workers having an NCA in their contracts in 2015 by occupation type. While NCAs are diffused among professionals (14%), they are also found among technicians and associate professionals (20%), serves and sales workers (24%) and craft and related trades workers (13%). This suggests that the use of NCAs for knowledge appropriation is not uniquely determined by a worker's educational attainment but rather is tied to a broader concept of knowledge that the worker develops within the firm.

Our treatment group is composed of workers having an NCA in their contract in 2015 and having a fixed-term ("temporary") contract before the reform.[20] The latter ensures that workers who change contract type (even within the same firm) due to the reform are not categorized as treated workers. Our control group are workers with fixed-term contracts before the reform, but without an NCA. To reduce sources of concern due to potential selection into treatment, we do not just compare the two groups but we match treated units to control units via propensity score matching. We match each treated unit to up to four control units based on nearest neighbor matching, running the procedure separately for workers employed in firms with non-zero automation expenditure and in firms with no automation expenditure.[21] Recall that our validation exercise requires showing that lifting NCAs will only benefit workers who "own" a share of their employers' intangible capital. It is therefore important to distinguish between the impact of the reform on firms that own such assets and and those that do not, as we do not expect to find a significant effect for workers employed in the latter. Therefore, we force a treated worker employed in a firm investing in intangible capital to be matched with one or more control units also employed in a firm investing in intangible capital. The same holds for a treated worker employed in a firm that does not invest in intangible capital.

To construct propensity scores, we rely on a set of employer- and employee-level characteristics. At the employer level, we include firm size and average automation expenditure per worker, averaged

[18] From the Labor Force Survey, we observe the presence of NCAs in up to two jobs per worker. As we match the data based on employee identifiers, we are forced to drop all workers who had more than two jobs at the time of treatment (24% of the initial sample).

[19] While we only observe NCAs starting from 2015, we note that workers never update the presence of an NCA for the duration of their contracts in the years covered by our sample: if an NCA is included in the contract, it remains in effect until the contract concludes; if if is not included initially, it is never added at a later stage.

[20] The incidence of temporary contracts in the Netherlands is high at around 20% of employment, compared to around 12% for the OECD on average and 4% for the US in 2017 (OECD, 2021).

[21] We end up with 2.9 controls per treated unit, on average. As a robustness check, we also considered a matching rate of 1:1 and 1:2 and our results remain qualitatively robust (results not reported but available upon request).

over the years 2011-2014.[22] At the employee level, we include age, gender, contract structure (presence of overtime work, presence of part-time work and their share), labor income (log net hourly wages), labor income composition (extraordinary income such as bonuses and performance pay, and their share of total income), tenure (number of days), number of employers and skill level, all averaged over the year 2014. Using the ISCED (International Standard Classification of Education) codes, we classify workers into four skill categories based on their educational attainment, following O'Mahony et al. (2008): low-skilled, mid-low skilled, mid-high skilled and high-skilled.[23] In the matched sample (PS-POLIS-EBB), we end up with 378 workers (118 treated and 260 control).[24] The resulting sample is admittedly thin as to identify a causal mechanism requires imposing a high number of restrictions to our sample. Moreover, information on the presence of NCAs in workers contracts is available for just 1,780 workers in the EBB (see Appendix A). Nonetheless, forgoing these observations comes with the benefit of increasing the internal validity of the estimation results.

Table 3 summarizes characteristics of the treated workers and their matched controls, distinguishing between the type of employer. Given their presence in the matching algorithm, treatment and control workers are similar in terms of observable characteristics. Table 4 reports characteristics of employers in our matched sample, distinguishing them based on whether they employ treated or non-treated individuals.[25] On average, firms employing workers with NCA have higher revenues per worker, spend more on automation, pay higher wages, are more productive and more likely to patent, but are smaller in size, less capital-intensive and less likely to export.

To measure the impact of the reform on the workers of our sample, we use a standard event-study framework to estimate how worker-level outcomes change around the reform:

$$Y_{mt} = \alpha_m + \alpha_t + \beta \cdot D_m + \sum_{\tau=T_0}^{T} \beta_\tau \cdot I_\tau + \sum_{\tau=T_0}^{T} \gamma_\tau \cdot D_m \cdot I_\tau + \mathbf{X}'_{mt}\boldsymbol{\delta} + \upsilon_{mt} \tag{20}$$

[22] Although we distinguish between firms that invest in automation and those that do not invest at all, including automation expenditure as a matching variable controls for the intensive margin. Automation expenditure is highly skewed, with a small number of firms accounting for the majority of the industry's total expenditure.

[23] Low-skilled refers to workers who have up to and including a low (junior) secondary education. Mid-low skilled refers to workers with upper-secondary education, mid-high skilled to those with a post-secondary education excluding tertiary education. Workers designated as high-skilled have tertiary education. Our results are robust to collapsing the two middle classes in one single "mid-skilled workers" category.

[24] In the non-matched EBB, we have 926 workers (118 treated and 808 control). We use the non-matched EBB sample for robustness and find similar results (results not reported but available upon request).

[25] The descriptive statistics presented in Table 4 are based on the full sample, including the non-matched control units.

where m indexes employees and τ is an indicator of time since treatment. Although our data are at the monthly frequency, we measure time since treatment in quarters in our main estimation to obtain less noisy coefficients. We add month fixed effects to control for any seasonality effect (α_t). Y_{mt} is the worker-level outcome variable (log net hourly wages in the main regression), α_m are worker fixed effects, D_m the binary treatment indicator and I_τ a time indicator. Additional controls in $\mathbf{X}$ are employee characteristics (tenure, age, age squared, occupation, fixed-term vs. permanent ("open-ended") contract[26], gender, share of time spent at current employer that participates in a collective bargaining agreement) and employer characteristics (firm size and labor productivity). Our sample period runs from 2013 until 2019.[27]

Our estimates of the event-time coefficients (γ_τ) represent the causal effect of lifting NCAs under standard difference-in-differences assumptions. In particular, we require that conditional on covariates, the outcomes of the matched comparison group of workers represent a valid counterfactual for workers subject to NCAs.

Results. The event-study coefficients using labor income (log net hourly wages) as worker-level outcome variable are plotted in Figure 3 and reported in Table 5. Time since treatment is measured at the quarterly frequency.[28] On average, we find a significantly positive impact on workers' net hourly wages when comparing workers whose labor contract included an NCA in 2015 to control workers who were not subject to an NCA in their labor contract. Labor income is, on average, 13% higher among treated workers in the post-treatment period. The coefficient is not significantly different from zero in the pre-treatment period, which validates our parallel trend assumption. Therefore, we can conclude that lifting NCAs has a significant impact on workers' labor income, confirming the positive effect of banning NCAs on workers' compensation, as documented in the literature (Marx et al., 2015). However, due to the small sample size, the results for the post-treatment period are noisy and a positive and significant effect is only found in some quarters after the treatment. This may be due to the inflexible nature of workers' contract, which do not adjust immediately after the reform, but take some time before new wages become effective.

[26]These arrangements are comparable to US employment relationships.

[27]The choice of 2013 as start year is motivated by a discontinuity in how hours worked are measured in the employer-employee data at the end of 2012, which prevents us from properly comparing this outcome variable before and after 2013. The choice of 2019 as end year is motivated by excluding the Covid pandemic that may confound our results.

[28]The difference-in-differences estimates measuring time since treatment at the monthly and yearly frequency are shown in Figures E4 and E5, respectively.

To understand the mechanism behind our labor income result and to validate our model prediction, we perform our event-study analysis separately on two subsets of workers. We consider employees working in firms that invested in intangible capital and those working in firms that did not make such investment. Investment in intangibles is proxied by automation expenditure per worker at the time of the reform. The event-study coefficients from the two separate regressions are presented in Figure 4. These coefficients are also reported in Table 6.

Figure 4 clearly shows that the group of workers employed in intangible-intensive firms (red graph, solid lines) is driving the increased labor income result, as the coefficients for the group of workers in non-intangible intensive firms (green graph, dashed lines) are not significantly different from zero in the post-treatment period. Confidence bands in the former group are larger due to the smaller sample size. Workers employed in intangible-intensive firms experience, on average, an increase in labor income of about 32% compared to control workers in the post-treatment period. Importantly, this finding validates the mechanism described in our model: the main implication of our model is indeed that the positive effect of lifting NCAS on wages is attributed to the presence of tacit knowledge within the firm, enabling workers to increase their bargaining power. It is therefore not suprising that firms where tacit knowledge is not a key factor for production will not be affected and that their employees will not find a significant change in their compensation post-reform.

One concern related to this estimation result could be that the effect of the reform on workers employed in intangible-intensive firms is not statistically different from that on workers employed in non intangible-intensive firms. To mitigate this concern, we run a triple differences estimation, adding to equation (20) an additional term to identify intangible intensive firms, i.e. firms with non-zero automation expenditure. The adjusted equation therefore becomes:

$$
\begin{aligned}
Y_{mt} = \alpha_m + \alpha_t + \beta \cdot D_m + \zeta \cdot F_m + \sum_{\tau=T_0}^{T} \beta_\tau \cdot I_\tau + \\
\sum_{\tau=T_0}^{T} \gamma_\tau \cdot D_m \cdot I_\tau + \sum_{\tau=T_0}^{T} \iota_\tau \cdot F_m \cdot I_\tau + \kappa \cdot F_m \cdot D_m + \\
\sum_{\tau=T_0}^{T} \theta_\tau \cdot D_m \cdot I_\tau \cdot F_m + \\
\mathbf{X}'_{mt}\boldsymbol{\delta} + \upsilon_{mt}
\end{aligned}
\tag{21}
$$

where F_m takes value equal to 1 if worker m is employed in an intangible-intensive firm, 0 otherwise and the other terms have the usual interpretation. The coefficients of interest are θ_τ, as they are related to the triple interaction and present the additional effect of the reform on treated workers employed in intangible-intensive firms. We plot the estimation results in Figure 5 and report these in Table 7. The estimates are less precise than in the previous specification due to the larger number of parameters. Yet, we find a positive and significant coefficient, indicating that the reform results in an additional 7% wage premium for workers employed in intangible-intensive firms.

Next, we investigate to what extent the effects on labor income are restricted to skilled workers. One additional concern related to our estimation is indeed that our estimation strategy may capture the effect of workers' skill premia instead of tacit knowledge. To rule out this hypothesis, we interact our event-time coefficient from equation (20) (γ) with three out of four skill categories, omitting the fourth (high-skilled) category. For this analysis, we estimate the following regression and compute average coefficients in the post-treatment period:

$$Y_{mt} = \alpha_m + \alpha_t + \beta \cdot D_m + \beta \cdot I + \gamma \cdot D_m \cdot I + \sum_{k=1}^{3} \delta_k \cdot S_{mt} + \sum_{k=1}^{3} \gamma_k \cdot S_{mt} \cdot D_m \cdot I + \mathbf{X}'_{mt}\boldsymbol{\delta} + \upsilon_{mt} \quad (22)$$

where data are kept at the monthly frequency and notation is essentially the same as in equation (20). We collapse the time indicator I to a binary indicator taking the value of 1 from January 2015 onwards and 0 otherwise and we add month fixed effects α_t. S_{mt} indicates the skill level of worker m at time t on a scale from 1 to 4, where 1 indicates the lowest skill level. The sign and significance of the coefficients γ_k will indicate whether there is a negative effect of belonging to the lower skill categories when compared to the most skilled individuals.

The difference-in-differences estimates are presented in column (3) of Table 8. For comparison, column (1) reports the baseline estimates, omitting heterogeneity by skill category and (2) shows the estimates for the subset of workers employed in intangible-intensive firms. Column (3) reveals that high-skilled workers are not solely driving the increased labor income effect of the reform, as we only find a significantly negative interaction coefficient for low-skilled workers. While education appears to partly moderate the effect of the reform, this is only true for workers who completed at most low (junior) secondary education. If skill premia were the sole driver of the effect, we would expect the coefficients for the other two intermediate skill categories to be significantly lower than zero. We interpret this evidence in support of the existence of tacit knowledge within the firm rather than workers' human capital being the mechanism behind the positive impact of lifting NCAs on workers' wages.

As a robustness test for general trends in skill composition, we run an additional specification where we remove the interaction term for skill category in equation (22) and add year fixed effects. The β coefficient cannot be estimated in such specification due to collinearity but we can test for changes in the skill composition in our sample. Skill upgrading of the Dutch population could lead to a selected sample, favoring higher skill categories, even in the absence of trends in skill premia. As a result, these higher skill categories may become increasingly represented in our sample, potentially biasing our estimates from the baseline specification. Incorporating year effects can help control for this bias. The results from this specification are presented in Table E4 and confirm the robustness of our findings: the main coefficient remains positive and significant.

We perform an additional set of regressions to further explore the mechanism driving our results. We investigate whether the increased labor income stems from the original employer (defined as the employer at the time of the reform) offering higher wages or whether it materializes upon switching employer. To this end, we estimate equation (20) on two separate samples: the first only includes workers who stay at their original employer post-reform, while the second only comprises workers who switch employer after the reform. This enables us to distinguish between income gains occurring at the original employer and those resulting from post-reform worker mobility. The event-study coefficients are plotted in Figure 6 and reported in Table 9. The difference-in-differences estimates indicate that the post-reform wage increase is larger for workers who switch employers. However, the event-study coefficients are noisy and only become significantly different from zero two years after the reform.[29]

Having validated our model's mechanism, we finally investigate whether treated workers experience changes in mobility either within the firm or across firms. Our model lacks the complexity to account for all the actions a firm might take to retain a worker. In the context of the WWZ reform of 2015, a firm might, e.g., opt to switch a worker's contract from fixed-term (temporary) to permanent (open-ended) status. This could be to maintain the option of incorporating an NCA

[29]As additional robustness test, we repeat the regression including employer fixed effects, which identifies the treatment effect only via worker mobility between jobs and find similar results (results not included but available upon request).

into the worker's contract or to upgrade the worker's contractual status, thereby making it more attractive for the worker to stay within the firm instead of switching employer. Moreover, other non-monetary forms of compensation could be included in the contract to convince the worker to stay, such as flexible hours or more job autonomy. In our model, we collapse all these leverages in the separation parameter c, as our interest lies in having an exogenous parameter for conducting comparative statics. Yet, examining whether the reform impacted worker mobility is interesting in its own right, as this dimension has been widely studied in the literature and serves as a key vehicle for knowledge dissemination and career advancement for workers, where NCAs could act as a barrier (Marx et al., 2009).

Table 10 presents the results for two additional worker-level outcomes: (1) time remaining at the current job, measured by log number of days and (2) job mobility, measured by the number of future employees after the current contract ends. Columns (1) and (2) report the difference-in-differences estimates using a similar regression model as in equation (22) but without considering heterogeneity across skill categories. We observe a significantly positive coefficient for time spent at the current job, indicating that workers with an NCA in their contract stay in their current position longer compared to control workers: treated workers experience a 4.7% increase in their current employment duration (see column (1)). Upon the termination of their current contract, they possess a slight advantage in terms of mobility compared to the control group (see column (2)). These findings suggest that firms may respond to the reform by attempting to retain their employees and, consequently their intangible capital, through means other than remuneration increases.

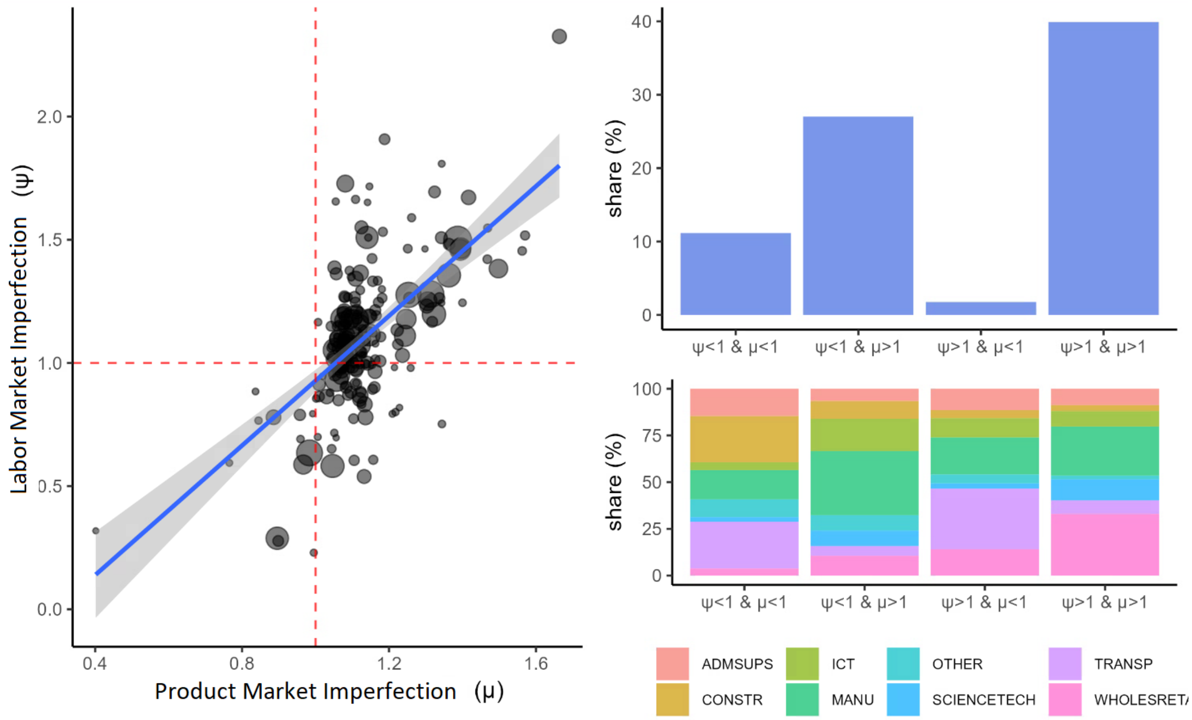
As additional check, we compare mean and median labor income (log net hourly wage) of workers in our sample with those in the population in Figure E6. We find that both statistics move fairly close in the two samples, which strengthens the external validity of our study despite the small sample size. According to our data, labor income has been declining until 2016 before rising sharply towards the end of 2019. This pattern could explain the negative coefficients of the treatment and time dummies in Table 8.

5 Conclusion

Recent empirical evidence has shown that product and labor market imperfections move together. From a policy perspective, it is important to understand the underlying drivers of such co-movement. In this paper, we provide a micro-foundation for the interaction between pricing rules in product and labor markets and an empirical test to validate such dependence. Our theoretical framework uncovers a mechanism that revolves around the importance of tacit knowledge inherent in particular technologies. Intuitively, when firms adopt or develop intangible assets that reduce their marginal cost of production and are complementary with tacit knowledge held by their key employees and when these employees can appropriate a share of these assets, firms may deter workers from doing so by offering wages above their marginal revenue product. As such, investment in intangible assets generates a positive correlation between price-cost markups and wage markups. We validate this testable prediction through a natural experiment, exploiting the removal of non-compete agreements in the Netherlands. We find heterogeneous impacts of the policy, disproportionately benefiting employees in firms where tacit knowledge plays an important role in production, with effects observed across the skill distribution. Our findings highlight the role of new technologies and the growing importance of intangible capital in driving the co-movement of product and labor market imperfections, and demonstrate how removing regulatory barriers to worker mobility, such as non-compete agreements, can influence worker-level outcomes. Finally, the debate concerning non-compete agreements not only raises concerns about curtailing individual freedom to pursue better job opportunities but also about firms' incentives to innovate and invest in employee training, especially in an environment where the risk of separation is elevated. A potential side effect of banning non-compete agreements could be a reduction in employee training and investment in Research & Development. Since our study does not cover the population of workers affected by the reform, we lack the ability to quantify each company's exposure to such risk, leaving this aspect of the debate open for further investigation.

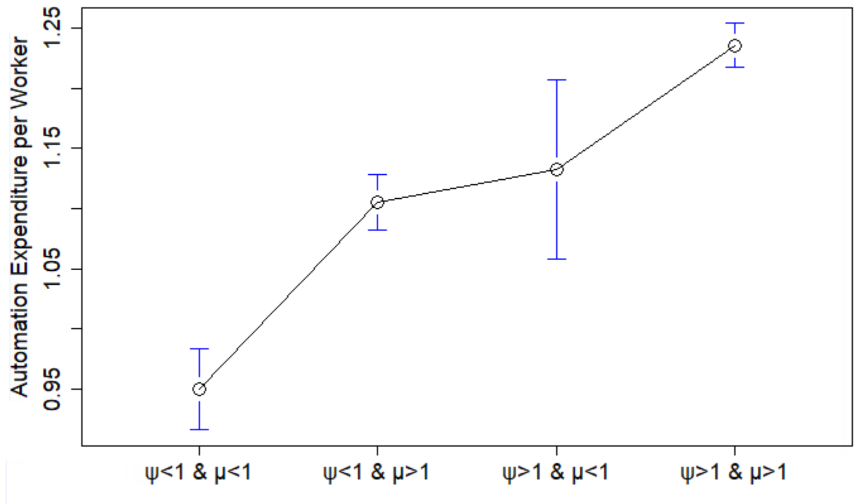
Figures and Tables

Figure 1: Labor and product market imperfection parameters by industry



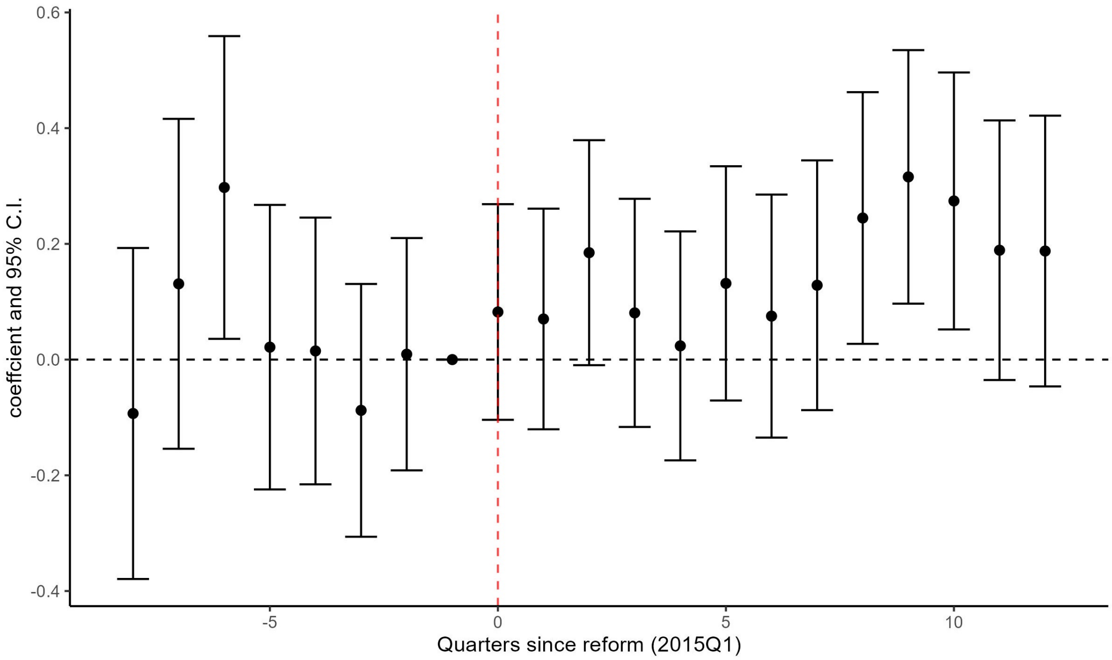
Note: (Left panel) Median labor (ψ) and product market (μ) imperfection parameters for each 3-digit NACE manufacturing and services industry which is represented by a circle. The size of each circle is proportional to the real value-added share of the industry. (Right panel) Proportion of each quadrant of the left graph, broken down by 1-digit NACE industries, with real value-added weights. Similar shares are obtained when using employment weights instead of real value-added weights.

Figure 2: Intangible intensity for each combination of labor and product market imperfection parameters



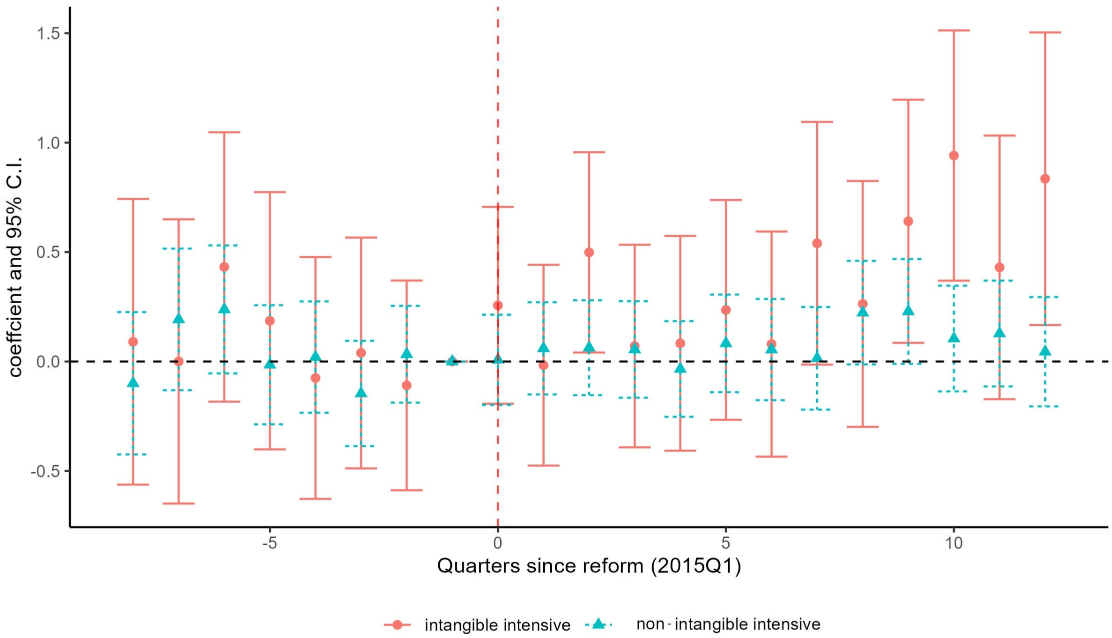
Note: Standardized mean of log automation expenditure per worker (measured in thousand euros) for each combination of labor (ψ) and product (μ) market imperfection parameters. Combinations are defined based on whether the reduced-form labor market imperfection parameter ψ_{it} or price-cost markup μ_{it} are below or above unity. The error bars represent 95% confidence intervals.

Figure 3: Impact of lifting NCAs on labor income



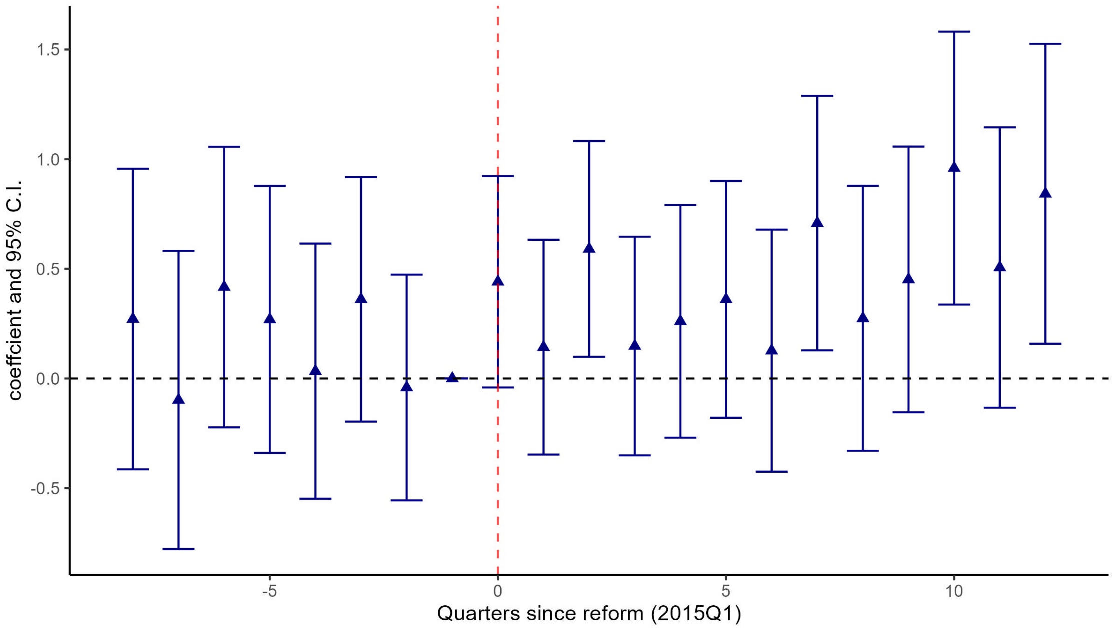
Note: This figure shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable. Time since treatment is measured in quarters. The error bars represent 95% confidence intervals.

Figure 4: Heterogeneous impact of lifting NCAs on labor income for workers employed in either intangible-intensive or non-intangible-intensive firms



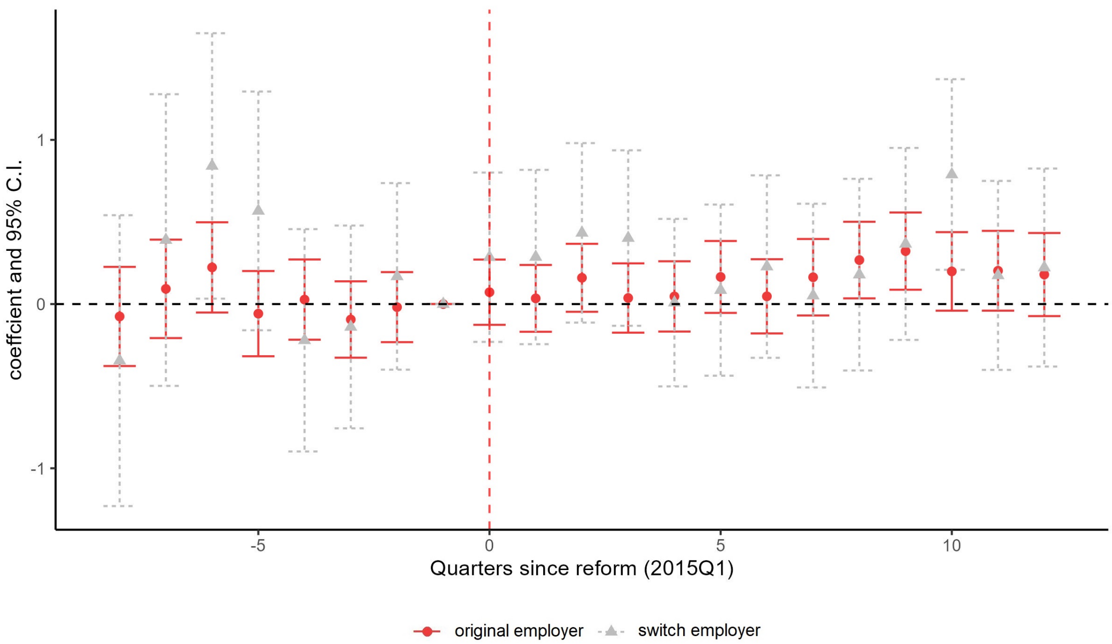
Note: This figure shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable from two separate regressions on two subsets of workers: workers employed in firms that either invested (red graph, solid lines) or did not invest (green graph, dashed lines) in intangibles. Investment in intangibles is measured by automation expenditure per worker. Time since treatment is measured in quarters. The error bars represent 95% confidence intervals.

Figure 5: Impact of lifting NCAs on labor income for workers employed in intangible-intensive firms



Note: This figure shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable. The event-study coefficients were estimated using the triple-difference estimator and represent the impact of the reform for treated workers employed in intangible-intensive firms. Investment in intangibles is measured by automation expenditure per worker. Time since treatment is measured in quarters. The error bars represent 95% confidence intervals.

Figure 6: Heterogeneous impact of lifting NCAs on labor income for workers either staying at their original employer or switching employer



Note: This figure shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable from two separate regressions on two subsets of workers: workers staying at their original employer, defined as their employer at the time of the reform (red graph, solid lines) or workers switching employer (grey graph, dashed lines) after the reform. Time since treatment is measured in quarters. The error bars represent 95% confidence intervals.

Table 1: Partial correlations between labor and product market imperfections and intangible intensity at the firm level

	ψ (1)	ψ (2)	μ (3)	μ (4)	$\psi \mid \mu \geq 1$ (5)	$\psi \mid \mu \geq 1$ (6)
Automation exp. per worker	0.015***	0.013***	0.006***	0.006***	0.010***	0.010***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Firm size	-0.138***	-0.139***	-0.031***	-0.034***	-0.128***	-0.140***
	(0.010)	(0.010)	(0.004)	(0.005)	(0.008)	(0.010)
Firm age	0.012	0.007	0.028***	0.029***	0.008	0.003
	(0.008)	(0.009)	(0.005)	(0.006)	(0.008)	(0.009)
Labor productivity	-0.031***	-0.039***	0.046***	0.034***	-0.004	-0.005
	(0.006)	(0.007)	(0.003)	(0.003)	(0.005)	(0.006)
Average wage	0.009***	0.009***	0.000	0.000	0.008***	0.008***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Firm-level CBA (0-1)	0.011	0.004	0.002	0.002	0.007	-0.003
	(0.008)	(0.008)	(0.006)	(0.005)	(0.006)	(0.007)
Foreign-owned (0-1)		0.019*		0.003		0.028***
		(0.011)		(0.006)		(0.010)
Export share of sales		-0.000*		-0.000		0.000
		(0.000)		(0.000)		(0.000)
HHI	0.000**	0.000*	-0.000	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry-level patenting share	0.154	0.177	-0.167	-0.188	0.197	0.135
	(0.207)	(0.239)	(0.107)	(0.117)	(0.191)	(0.224)
Constant	0.295***	0.368***	0.001	0.070**	0.231***	0.328***
	(0.058)	(0.067)	(0.027)	(0.031)	(0.050)	(0.060)
Number of observations	69,953	50,094	71,205	51,270	61,589	44,997
R^2	0.149	0.149	0.056	0.039	0.179	0.180
Number of firms	18,888	14,947	19,065	15,086	17,519	13,906
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Fixed-effects regressions of reduced-form firm-level measure of labor market imperfections (ψ) and price-cost markups (μ) on intangible intensity (measured by automation expenditure per worker) and firm/industry characteristics. The dependent variables, automation expenditure per worker, firm size, firm age and labor productivity (measured by real value added per worker) are in logarithms. Firm-level CBA is a dummy taking the value of 1 if the majority of workers' wages are negotiated through collective bargaining at the firm level. Columns (2), (4) and (6) restrict the set of firms to those that engage in exporting activity. Columns (5) and (6) restrict the set of firms to those with price-cost markups exceeding unity. Standard errors are clustered at the firm level and are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 2: Worker-level occupation type by presence of NCA

ISCO major category	No	Yes	% share
Managers	10	1	1
Professionals	115	17	14
Technicians and associate professionals	71	24	20
Clerical support workers	55	10	8
Service and sales workers	186	28	24
Skilled agricultural, forestry and fishery workers	11	1	1
Craft and related trades workers	41	15	13
Plant and machine operators and assemblers	44	6	5
Elementary occupations	131	8	7
Not available	144	8	7
Number of workers	808	118	100

Note: Fraction of workers having non-compete agreements ("No" or "Yes") in their contract in 2015 by occupation type based on ISCO (International Standard Classification of Occupations) 2008 in the pre-matched sample. The occupations are ordered based on their level, from highest to lowest.

Table 3: Worker characteristics

	Means Treated	Means Control	Norm. Mean Diff.
Employed in intangible-intensive firms			
Age	28.71	29.83	-0.10
Gender (1=male, 2=female)	1.24	1.29	-0.11
Full-time work (0-1)	0.97	1.00	-0.22
Overtime work (0-1)	0.19	0.16	0.1
Share of part-time work	0.39	0.33	0.12
Labor income	8.67	9.43	-0.15
Share of extraordinary income	0.08	0.06	0.28
Tenure (months)	20.37	21.58	-0.08
# Employers	1.11	1.09	0.07
Skill category (1-4)	2.17	2.05	0.13
Worker FE (AKM model-based)	-0.08	-0.05	-0.11
Employed in non-intangible intensive firms			
Age	30.32	29.77	0.04
Gender (1=male, 2=female)	1.47	1.58	-0.21
Full-time work (0-1)	0.99	0.99	-0.09
Overtime work (0-1)	0.04	0.03	0.09
Share of part-time work	0.27	0.28	-0.03
Labor income	8.67	8.92	-0.03
Share of extraordinary income	0.06	0.06	-0.04
Tenure (months)	10.43	11.62	-0.09
# Employers	1.20	1.19	0.01
Skill category (1-4)	2.22	2.32	-0.1
Worker FE (AKM model-based)	-0.03	-0.03	0.01
Number of workers	118	260	

Note: This table shows the characteristics of two subsets of workers in our matched sample in 2014: workers employed in firms that either invested (upper part) or did not invest (lower part) in intangibles. Investment in intangibles is measured by automation expenditure per worker. Column (1) corresponds to average characteristics of treated workers, column (2) to average characteristics of workers selected as controls and column (3) shows the normalized mean difference between characteristics of treated and control workers. Low-skilled (skill category 1) refers to workers who have up to and including low (junior) secondary education. Mid-low skilled (skill category 2) refers to workers with upper-secondary education, mid-high skilled (skill category 3) to those with a post-secondary education excluding tertiary education. Workers designated as high-skilled (skill category 4) have tertiary education.

Table 4: Firm characteristics

	Means No NCA	Means Some NCA	Norm. Mean Diff.
Firm size	8,666.43	2,367.36	-1.48
Automation exp. per worker	0.84	1.08	0.15
Sales per worker	143.99	159.5	0.09
Labor productivity	62.89	68.47	0.09
Average wage	45.41	46.45	0.06
Capital intensity	6.47	8.08	0.07
% Patenters	0	4.49	0.22
% Exporters	80.95	64.79	-0.34
% FTE under CBA	25.46	31.46	0.13
Firm FE (AKM model-based)	-0.01	-0.02	-0.09
Number of firms	229	115	

Note: This table shows the characteristics of employers in our matched sample in 2014. Column (1) corresponds to average characteristics of firms that do not employ workers with an NCA in their contracts, column (2) to average characteristics of firms that employ at least one worker with an NCA in their contract. Sales per worker, average wage and capital intensity are measured in thousand euros. Labor productivity is measured by log real value added per worker. "% FTE under CBA" refers to the percentage of full-time equivalent employees whose wages are negotiated through collective bargaining at the firm level.

Table 5: Event-study coefficients at quarterly frequency for all workers

	Labor income
t-8	-0.093
	(0.146)
t-7	0.131
	(0.145)
t-6	0.297^{**}
	(0.133)
t-5	0.021
	(0.125)
t-4	0.015
	(0.118)
t-3	-0.088
	(0.111)
t-2	0.009
	(0.102)
t	0.082
	(0.095)
t+1	0.070
	(0.097)
t+2	0.185^{*}
	(0.099)
t+3	0.081
	(0.101)
t+4	0.024
	(0.101)
t+5	0.132
	(0.103)
t+6	0.075
	(0.107)
t+7	0.128
	(0.110)
t+8	0.245^{**}
	(0.111)
t+9	0.316^{***}
	(0.112)
t+10	0.274^{**}
	(0.113)
t+11	0.189^{*}
	(0.114)
t+12	0.188
	(0.119)
Diff-in-Diff estimate	0.131^{***}
	(0.042)
Number of observations	17,439
R^2	0.682
Adjusted R^2	0.674
Residual std. error	1.029
F-statistic	82.05^{***}

Note: This table shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable. Each line reports the coefficient (γ_τ) of the interaction between the treatment indicator (D_m) and a time since treatment indicator (I_τ) measured at the quarterly frequency. Other control variables and fixed effects are omitted. The difference-in-differences coefficient is shown at the bottom of the table. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 6: Event-study coefficients at quarterly frequency for workers employed in either intangible-intensive firms or non-intangible-intensive firms

	Labor income	
	(1)	(2)
t-8	0.090	−0.099
	(0.333)	(0.166)
t-7	0.0004	0.192
	(0.331)	(0.165)
t-6	0.432	0.238
	(0.314)	(0.149)
t-5	0.186	−0.015
	(0.300)	(0.139)
t-4	−0.075	0.020
	(0.282)	(0.130)
t-3	0.039	−0.146
	(0.269)	(0.123)
t-2	−0.109	0.033
	(0.244)	(0.113)
t	0.257	0.008
	(0.229)	(0.105)
t+1	−0.017	0.060
	(0.234)	(0.107)
t+2	0.499**	0.063
	(0.233)	(0.111)
t+3	0.071	0.055
	(0.236)	(0.112)
t+4	0.083	−0.034
	(0.250)	(0.111)
t+5	0.236	0.083
	(0.256)	(0.114)
t+6	0.080	0.055
	(0.262)	(0.118)
t+7	0.540*	0.015
	(0.283)	(0.120)
t+8	0.263	0.223*
	(0.286)	(0.121)
t+9	0.641**	0.229*
	(0.283)	(0.122)
t+10	0.941***	0.105
	(0.292)	(0.123)
t+11	0.430	0.128
	(0.307)	(0.123)
t+12	0.835**	0.045
	(0.341)	(0.127)
Diff-in-Diff estimate	0.320***	0.063
	(0.106)	(0.047)
Number of observations	3,215	14,224
R^2	0.675	0.687
Adjusted R^2	0.660	0.678
Residual std. error	1.13	1.00
F-statistic	44.5***	75.48***

Note: This table shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable from two separate regressions on two subsets of workers: workers employed in firms that either invested (column (1)) or did not invest (column (2)) in intangibles. Investment in intangibles is measured by automation expenditure per worker. Each line reports the coefficient (γ_τ) of the interaction between the treatment indicator (D_m) and a time since treatment indicator (I_τ) measured at the quarterly frequency. Other control variables and fixed effects are omitted. The difference-in-differences coefficients are shown at the bottom of the table. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 7: Event-study coefficients at quarterly frequency for all workers using triple-difference estimator

	Labor income
t-8	0.271
	(0.350)
t-7	-0.098
	(0.347)
t-6	0.417
	(0.326)
t-5	0.269
	(0.311)
t-4	0.033
	(0.297)
t-3	0.361
	(0.284)
t-2	-0.041
	(0.263)
t	0.441^{*}
	(0.246)
t+1	0.143
	(0.250)
t+2	0.591^{**}
	(0.251)
t+3	0.148
	(0.254)
t+4	0.261
	(0.271)
t+5	0.361
	(0.275)
t+6	0.127
	(0.282)
t+7	0.708^{**}
	(0.296)
t+8	0.274
	(0.308)
t+9	0.452
	(0.309)
t+10	0.959^{***}
	(0.317)
t+11	0.506
	(0.326)
t+12	0.842^{**}
	(0.349)
Triple-Diff estimate	0.072^{*}
	(0.041)
Number of observations	16,746
R^2	0.685
Adjusted R^2	0.675
Residual std. error	1.017
F-statistic	70.834^{***}

Note: This table shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable. The event-study coefficients were estimated using the triple-difference estimator. Each line reports the coefficient (θ_τ) of the interaction between the treatment indicator (D_m), a time since treatment indicator (I_τ) measured at the quarterly frequency and a categorical variable (F_m) taking the value of 1 if workers are employed in intangible-intensive firms (i.e. firms with positive automation expenditure per worker). Other control variables and fixed effects are omitted. The triple-difference coefficient is shown at the bottom of the table. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 8: Heterogeneous impact of lifting NCAs on labor income by skill category

	Labor income		
	(1)	(2)	(3)
Any NCA	-5.761^{***}	-5.621^{**}	-5.432^{***}
	(0.736)	(2.267)	(0.740)
Post-reform	-0.176^{***}	-0.335^{***}	-0.158^{***}
	(0.030)	(0.084)	(0.030)
Any NCA * Post-reform	0.131^{***}	0.320^{***}	0.289^{***}
	(0.042)	(0.106)	(0.103)
Age	0.354^{***}	0.476^{***}	0.313^{***}
	(0.025)	(0.090)	(0.026)
Age squared	-0.0035^{***}	-0.004^{***}	-0.002^{***}
	(0.0002)	(0.001)	(0.0002)
Gender	0.416^{*}	-0.558^{**}	0.568^{**}
	(0.247)	(0.272)	(0.254)
Full-time work (0-1)	0.021	−0.152	0.019
	(0.033)	(0.095)	(0.033)
Tenure	−0.003	−0.008	−0.003
	(0.002)	(0.007)	(0.002)
Share of working time under CBA	-0.108^{***}	−0.167	-0.115^{***}
	(0.033)	(0.151)	(0.033)
Low skilled			−0.135
			(0.087)
Mid-low skilled			0.016
			(0.083)
Mid-high skilled			0.132^{*}
			(0.068)
Low skilled * Any NCA * Post-reform			-0.379^{***}
			(0.122)
Mid-low skilled * Any NCA * Post-reform			−0.183
			(0.117)
Mid-high skilled * Any NCA * Post-reform			−0.119
			(0.108)
Constant	-5.031^{***}	-7.637^{***}	-4.371^{***}
	(0.421)	(1.378)	(0.459)
Month FE	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes
Number of observations	17,439	3,215	17,374
R^2	0.672	0.658	0.674
Adjusted R^2	0.665	0.647	0.666
Residual std. error	1.042	1.153	1.039
F-statistic	88.569^{***}	63.792^{***}	87.564^{***}

Note: This table shows the difference-in-differences estimates using labor income (log net hourly wages) as worker-level outcome variable from three separate regressions. Column (1) shows the baseline average treatment effect, column (2) the average treatment effect for workers employed in intangible-intensive firms (i.e. firms with positive automation expenditure per worker) and column (3) the average treatment effect for workers categorized by skill (omitting the high-skilled category). "Share of working time under CBA" refers to the share of time spent at current employer that participates in a collective bargaining agreement. The coefficients for occupation categories and fixed- vs open-ended contracts are omitted. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 9: Event-study coefficients at quarterly frequency for workers either staying at their original employer or switching employer

	Labor income	
	(1)	(2)
t-8	-0.075	-0.345
	(0.154)	(0.452)
t-7	0.093	0.390
	(0.153)	(0.453)
t-6	0.223	0.841^{**}
	(0.140)	(0.412)
t-5	-0.058	0.567
	(0.132)	(0.371)
t-4	0.027	-0.221
	(0.125)	(0.345)
t-3	-0.094	-0.139
	(0.119)	(0.315)
t-2	-0.019	0.169
	(0.109)	(0.290)
t	0.072	0.285
	(0.101)	(0.263)
t+1	0.035	0.287
	(0.104)	(0.271)
t+2	0.160	0.434
	(0.106)	(0.279)
t+3	0.037	0.402
	(0.108)	(0.273)
t+4	0.047	0.009
	(0.109)	(0.260)
t+5	0.165	0.085
	(0.112)	(0.266)
t+6	0.047	0.228
	(0.115)	(0.283)
t+7	0.163	0.052
	(0.119)	(0.285)
t+8	0.268^{**}	0.179
	(0.119)	(0.298)
t+9	0.323^{***}	0.366
	(0.120)	(0.298)
t+10	0.199	0.789^{***}
	(0.122)	(0.296)
t+11	0.203	0.175
	(0.124)	(0.293)
t+12	0.180	0.222
	(0.129)	(0.307)
Diff-in-Diff estimate	0.141^{***}	0.194^{*}
	(0.044)	(0.117)
Number of observations	16,632	3,954
R^2	0.659	0.642
Adjusted R^2	0.650	0.628
Residual std. error	1.155	1.050
F-statistic	70.39^{***}	46.66^{***}

Note: This table shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable from two separate regressions on two subsets of workers: workers staying at their original employer, defined as their employer at the time of the reform (column (1)) or workers switching employer (column (2)) after the reform. Each line reports the coefficient (γ_τ) of the interaction between the treatment indicator (D_m) and a time since treatment indicator (I_τ) measured at the quarterly frequency. Other control variables and fixed effects are omitted. The difference-in-differences coefficients are shown at the bottom of the table. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 10: Impact of lifting NCAs on current employment duration and worker mobility

	Remaining time at current job (1)	Future mobility (2)
Any NCA	11.492***	1.621***
	(0.362)	(0.046)
Post-reform	0.120***	-0.015***
	(0.015)	(0.002)
Any NCA * Post-reform	0.047**	0.005*
	(0.020)	(0.003)
Age	−0.369***	−0.051***
	(0.012)	(0.002)
Age squared	0.0004***	0.0001***
	(0.0001)	(0.00001)
Gender	4.742***	0.313***
	(0.121)	(0.015)
Tenure	−0.020***	0.005***
	(0.001)	(0.0001)
Full-time work (0-1)	−0.016	−0.014***
	(0.016)	(0.002)
Share of working time under CBA	−0.091***	−0.004*
	(0.016)	(0.002)
Constant	13.633***	0.875***
	(0.207)	(0.026)
Month FE	Yes	Yes
Worker FE	Yes	Yes
Number of observations	17,039	17,472
R^2	0.770	0.711
Adjusted R^2	0.765	0.705
Residual std. error	0.501	0.065
F-statistic	141.246***	106.480***

Note: This table shows the difference-in-differences estimates for separate regressions using remaining time at current job (measured by log sum of days) and future mobility (measured by the number of future employees) as worker-level outcome variable, respectively. The coefficients for occupation categories and fixed- vs. open ended-contracts are omitted. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

A Data

List of the data sources used in this study, all linkable to each other:

- Production Statistics (*Productiestatistiek, PS*) survey: This source contains data on production value, factor inputs and factor costs. The data are collected at the enterprise level. A combination of census and stratified random sampling is used for each wave. The stratification variables are the industry and the number of employees of an enterprise. A census is used for the population of enterprises with at least fifty employees and stratified random sampling is used for enterprises with fewer than fifty employees. We compile a panel from 2000 until 2020 and collect data on employment, capital input (proxied by depreciation), intermediate input cost, labor cost and value added. It also includes automation expenditure, a specific item encompassing any expenses allocated to third-party services geared towards automating business processes. We enrich this source with categorical variables on whether the firm exports abroad (from custom data), whether it is foreign-owned and whether it filed a patent in a given year (from the EPO's (European Patent Office) Patstat database). The resulting sample includes 37,084 firms from 2000 to 2020.

- Survey ICT use by companies (*ICT*): This source contains annual data on the use of information and communication technology (ICT) in firms. It describes the use of specific technologies, the internet, electronic buying and selling, software and ICT applications. We extract information on Artificial Intelligence, industrial robots, Automated Data Exchange, Enterprise Resource Planning, whether the firm employs any ICT personnel, whether the firm allows employees to access emails remotely and the share of workers with access to company files and telework. We match this source with the PS via unique firm identifiers. The resulting sample includes 3,873 firms from 2011 to 2018.

- Employer-Employee job links (*Banen en lonen volgens Polisadministratie, POLIS*): This dataset allows linking employee data to employers. It contains each employment spell at the monthly level, including information on earnings, hours and contract type. All employed workers in the Netherlands who are working for a domestic company and pay social security contributions are included. We extract information on workers' labor income, tenure, contract type and whether workers' wages are negotiated through collective bargaining at the firm level, as well as demographic characteristics. We use this data at the monthly frequency.

- Labor Force Survey (*Enquête Beroepsbevolking, EBB*): This is a quarterly survey, covering a representative sample of about 6.5% of the total Dutch labor force. We extract information on the existence of non-compete agreements (NCAs) in workers' contracts, which is available from 2015 until 2018. We also retrieve information on workers' educational attainment and occupation category. We use this data at the monthly frequency from 2013 to 2019, retaining only workers who provide non-missing information on the survey questions related to NCAs. We match this source with the PS-ICT data via unique employee identifiers in the POLIS and EBB. The resulting sample includes 1,780 workers from 2013 to 2019, which further reduces to 936 when we restrict to workers with temporary contracts only.

B Estimating firm-level measures of product and labor market imperfections

Measuring labor and product market imperfections based on the ratio of wages to the marginal revenue product of labor ψ_{it} and the price-cost markup μ_{it} requires consistent estimates of the output elasticities of intermediate inputs $(\varepsilon_M^Q)_{it}$ and labor $(\varepsilon_L^Q)_{it}$ as well as their revenue shares α_{Mit} and α_{Lit}.

Production function. Taking the logarithm of the production function (equation 1)) results in:

$$q_{it} = f(l_{it}, m_{it}, k_{it}; \boldsymbol{\beta}) + \omega_{it} \tag{B.1}$$

with lower-case letters denoting logs of variables, e.g. $q_{it} = \ln Q_{it}$, $\boldsymbol{\beta}$ a vector of technology parameters that need to be identified, and ω_{it} a Hicks-neutral productivity shock observed by the firm, but unobserved by us.

Enriching our empirical model by an idiosyncratic error term ϵ_{it} that comprises unpredictable output shocks as well as potential measurement error in output and inputs gives:

$$y_{it} = f(l_{it}, m_{it}, k_{it}; \boldsymbol{\beta}) + \omega_{it} + \epsilon_{it} \tag{B.2}$$

with $y_{it} = q_{it} + \epsilon_{it} = f_{it} + \omega_{it} + \epsilon_{it}$, where we assume ϵ_{it} to be mean independent of current and past input choices.

We approximate the unknown regression function $f(\cdot)$ by means of a second-order Taylor polynomial:

$$\begin{aligned} y_{it} = {} & \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 \\ & + \beta_{lm} l_{it} m_{it} + \beta_{lk} l_{it} k_{it} + \beta_{mk} m_{it} k_{it} + \omega_{it} + \epsilon_{it} \end{aligned} \tag{B.3}$$

where the regression constant β_0 measures the mean efficiency level across firms.

Identification. Identifying $\boldsymbol{\beta}$ relies crucially on the timing assumptions of the firm's input choices in combination with a functional form assumption on the productivity transition process (ω_{it}) to avoid bias from the endogeneity of input decisions to unobservable productivity ω_{it} (Marschak and Andrews, 1944). With respect to unobservable productivity, we assume that ω_{it} evolves according to an endogenous first-order Markov process. Following e.g. De Loecker and Warzynski (2012) and De Loecker (2013), we assume that the firm's decision to engage in exporting activity might endogenously affect future productivity, which is at the heart of the Melitz (2003) model and amply supported by existing evidence (Helpman, 2006; Bernard et al., 2012). Consequently, we can decompose ω_{it} into its expectation conditional on the information I_{it-1} available to the firm in $t-1$ and a random innovation to productivity denoted by ξ_{it}:

$$\omega_{it} = \mathbb{E}[\omega_{it}|I_{it-1}] + \xi_{it} = \mathbb{E}[\omega_{it}|\omega_{it-1}, EXP_{it-1}] + \xi_{it} = g(\omega_{it-1}, EXP_{it-1}) + \xi_{it} \tag{B.4}$$

In equation (B.4), EXP_{it-1} denotes firm i's export status in $t-1$, $g(\cdot)$ denotes some function, and ξ_{it} is assumed to be mean independent of the firm's information set I_{it-1} in $t-1$.

As explained in Section 2.1, labor and intermediate inputs are assumed to be variable inputs whereas capital is predetermined. We assume that firms decide on their capital input k_{it} one period ahead at time $t-1$, before the productivity shock ξ_{it} is observed by the firm, which reflects planning and installation lags and causes capital to be predetermined. Among the variable factors of production, we assume that labor l_{it} is less variable than intermediate inputs m_{it} in that it is determined by firms at time $t-b$ with $0 < b < 1$. Hence, firms choose labor after capital but prior to intermediate inputs being chosen at time t, where the latter is in line with firms requiring time to train new workers, with significant firing or hiring costs, or with long-lasting labor contracts in internal labor markets or unionised firms.

To control for unobserved productivity, we use the control-function approach (Levinsohn and Petrin, 2003; Ackerberg et al., 2015) that builds on the insight that firms' optimal input choices hold information about unobserved productivity and that is common in the literature using the production-function approach (De Loecker and Warzynski, 2012; De Loecker, 2013; De Loecker et al., 2016; Yeh et al., 2022; Dobbelaere et al., 2024). In particular, we invert the intermediate input demand function to recover the latent productivity level ω_{it}, which can be used to construct the productivity shock ξ_{it} using the productivity law of motion.

Given the timing assumptions, firm i's demand for intermediate inputs in t directly depends on n_{it} as well as on the other state variables k_{it}, EXP_{it}, and ω_{it}:

$$m_{it} = m_t(l_{it}, k_{it}, EXP_{it}, \omega_{it}) \tag{B.5}$$

Crucially, productivity ω_{it} is the only unobservable entering the demand function $m_t(\cdot)$. Provided strict monotonicity of the demand function with respect to ω_{it}, we can invert $m_t(\cdot)$ to infer ω_{it} from observables as:

$$\omega_{it} = m_t^{-1}(m_{it}, l_{it}, k_{it}, EXP_{it}) \tag{B.6}$$

Estimation. Using the timing assumptions of the firm's input choices in combination with the law of motion of productivity, we estimate the coefficients of a translog production function $\boldsymbol{\beta}$ for each two-digit industry using a two-stage procedure.

The first stage produces an estimate of the firm's log output net of idiosyncratic factors $q_{it} = y_{it} - \epsilon_{it}$. Plugging equation (B.6) into equation (B.2) results in a first-stage regression equation:

$$\begin{aligned} y_{it} &= f(l_{it}, m_{it}, k_{it}; \boldsymbol{\beta}) + m_t^{-1}(m_{it}, l_{it}, k_{it}, EXP_{it}) + \epsilon_{it} \\ &= \varphi_t(l_{it}, m_{it}, k_{it}, EXP_{it}) + \epsilon_{it} \end{aligned} \tag{B.7}$$

that we exploit to separate the productivity shock ω_{it} from the idiosyncratic ϵ_{it}. This first stage uses the regression equation (B.7) together with the moment condition $\mathbb{E}[\epsilon_{it}|I_{it}] = 0$ to obtain an estimate $\widehat{\varphi}_{it}$ of the composite term $\varphi_t(l_{it}, m_{it}, k_{it}, EXP_{it}) = f_{it} + \omega_{it}$. After the first stage, we get an estimate of ω_{it} (up to a constant) for a given coefficient vector $\boldsymbol{\beta}$:

$$\begin{aligned} \widehat{\omega}_{it}(\boldsymbol{\beta}) &= \widehat{m}_t^{-1}(m_{it}, l_{it}, k_{it}, EXP_{it}) \\ &= \widehat{\varphi}_{it} - \beta_l l_{it} - \beta_m m_{it} - \beta_k k_{it} - \beta_{ll} l_{it}^2 - \beta_{mm} m_{it}^2 - \beta_{kk} k_{it}^2 \\ &\quad - \beta_{lm} l_{it} m_{it} - \beta_{lk} l_{it} k_{it} - \beta_{mk} m_{it} k_{it} \end{aligned} \tag{B.8}$$

We use the law of motion of productivity (equation (B.4)) in combination with equation (B.8) to recover the innovation to firm productivity (ξ_{it}) given $\boldsymbol{\beta}$. Specifically, we arrive at a consistent non-parametric estimate of the conditional expectation $\mathbb{E}[\omega_{it}|\omega_{it-1}, EXP_{it-1}]$ by taking the predicted value of a non-parametric (second-order polynomial) regression of $\widehat{\omega}_{it}(\boldsymbol{\beta})$ on $\widehat{\omega}_{it-1}(\boldsymbol{\beta})$ and EXP_{it-1}.

The residual from this regression, in turn, provide us with a consistent estimate of $\xi_{it}(\boldsymbol{\beta})$.

The second stage produces estimates of the production function coefficients $\boldsymbol{\beta}$ through standard GMM using the moment conditions formed by the timing assumptions of our framework:

$$\mathbb{E}[\xi_{it}(\boldsymbol{\beta})(l_{it-1}, m_{it-1}, k_{it}, l_{it-1}^2, m_{it-1}^2, k_{it}^2, l_{it-1}m_{it-1}, l_{it-1}k_{it}, m_{it-1}k_{it})'] = \mathbf{0} \tag{B.9}$$

We arrive at estimates of the output elasticities $(\varepsilon_M^Q)_{it}$ and $(\varepsilon_L^Q)_{it}$ by combining the estimated $\widehat{\boldsymbol{\beta}}$ with data on firms' input choices:

$$(\widehat{\varepsilon}_M^Q)_{it} = \widehat{\beta}_m + 2\widehat{\beta}_{mm}m_{it} + \widehat{\beta}_{ml}l_{it} + \widehat{\beta}_{mk}k_{it} \tag{B.10}$$

$$(\widehat{\varepsilon}_L^Q)_{it} = \widehat{\beta}_l + 2\widehat{\beta}_{ll}l_{it} + \widehat{\beta}_{lm}m_{it} + \widehat{\beta}_{lk}k_{it} \tag{B.11}$$

Hence, both output elasticities vary across firms and over time. Since the observed output $Y_{it} = Q_{it} \exp \epsilon_{it}$ includes idiosyncratic factors that are orthogonal to input use and productivity, we cannot take revenue shares from our data without correcting for these factors. Following De Loecker and Warzynski (2012) we do so by recovering an estimate of ϵ_{it} from the production-function estimation and calculate adjusted revenue shares as:

$$\widehat{\alpha}_{Mit} = \frac{J_{it}M_{it}}{P_{it}Y_{it}/\exp \widehat{\epsilon}_{it}} \tag{B.12}$$

$$\widehat{\alpha}_{Lit} = \frac{W_{it}L_{it}}{P_{it}Y_{it}/\exp \widehat{\epsilon}_{it}} \tag{B.13}$$

Combining the estimated output elasticities (B.11) and (B.10) and the adjusted revenue shares (B.13) and (B.12), we arrive at estimates of the price-cost markup and the ratio of wages to the marginal revenue product of labor:

$$\widehat{\mu}_{it} = \frac{(\widehat{\varepsilon}_M^Q)_{it}}{\widehat{\alpha}_{Mit}} \tag{B.14}$$

$$\widehat{\psi}_{it} = \frac{(\widehat{\varepsilon}_M^Q)_{it}/\widehat{\alpha}_{Mit}}{(\widehat{\varepsilon}_L^Q)_{it}/\widehat{\alpha}_{Lit}} \tag{B.15}$$

We can further transform the ratio ψ_{it} into the implied labor supply elasticity in case of wage markdowns or the implied rent-sharing elasticity in case of wage markups that rationalise the observed wage outcomes in a monopsony or efficient bargaining framework, respectively:

$$(\widehat{\varepsilon}^{L}_{W})_{it} = \frac{\widehat{\psi}_{it}}{1 - \widehat{\psi}_{it}} \tag{B.16}$$

$$(\widehat{\varepsilon}^{W}_{(QR)/L})_{it} = \frac{\widehat{\psi}_{it} - 1}{\widehat{\psi}_{it}} \tag{B.17}$$

C Estimating firm wage premia

To validate our measure of labor market imperfections, we examine its predictive power for employer wage premia. To measure employer wage premia, we estimate a standard Abowd et al. (1999) (AKM) model that decomposes a worker's individual wage into a worker-specific and a firm-specific component, following Card et al. (2018) and Hirsch and Mueller (2020). Specifically, we estimate the following regression:

$$\ln W_{mt} = \alpha_m + \alpha_{i(m,t)} + \mathbf{X}'_{mt}\boldsymbol{\beta} + \zeta_{mt} \tag{C.1}$$

where m indexes individuals, i indexes firms, t indexes time, $\ln W_{mt}$ is logged normalized earnings for worker m at firm i in year t (normalized earnings are total payments from firm i per year divided by the number of full time days worked at firm i), the α_m are worker fixed effects, the $\alpha_{i(m,t)}$ are firm fixed effects, the $\mathbf{X}_{mt}$ include a set of year indicators, a flexible polynomial of worker i's age, whether the worker works part time and the part-time share, while ζ_{mt} is an idiosyncratic log wage component, capturing purely transitory earnings fluctuations. We estimate the model separately for three estimation periods: 2010-2014, 2015-2019 and 2020-2022. In this estimation, worker fixed effects α_m and firm fixed effects $\alpha_{i(m,t)}$ are separately identified by workers who change employers.[30]

In the AKM framework, α_m reflects the worker's time-invariant human capital, such as education and ability, that is rewarded equally across different employers, while $\alpha_{i(m,t)}$ gives the percentage wage premium enjoyed by every worker employed at firm i. Such a premium most likely represents rent sharing (Card et al., 2016) but could also reflect strategic wage posting behavior (Burdett and Mortensen, 1998; Moscarini and Postel-Vinay, 2013)), other components of the wage structure such as an efficiency wage premium, compensating differentials (Sorkin, 2018), or variation in general payment practices (e.g. the presence of unions, corporate culture, or negotiating power).

[30]The crucial assumption for this interpretation of the AKM decomposition to hold is that the idiosyncratic log earnings component ζ_{mt} is unrelated to the sequence of worker m's employers $i(m,t)$. For a discussion and test of the validity of this conditional exogenous mobility assumption, see Abowd et al. (1999) and Card et al. (2013). Schneck (2021) presents an application using similar Dutch micro data as ours.

D Impact of the change in cost of separation cc on equilibrium wages

Changes in the exit costs c to be paid by the worker upon departure affect equilibrium wages w_i via two channels: a direct one that operates via the opportunity cost of searching (see equation (18) in the main text) and an indirect one that operates through investment in intangibles. Costs to worker mobility impact firms' ability to appropriate the benefits from investing in intangibles. This, in turn, affects firms' incentives to invest and leads them to offer higher wages to attract workers to participate in the investment process. This indirect channel operates via the equilibrium marginal-cost reduction from investment s^*_{ij} (see equation (17) in the main text) and affects equilibrium wages (see equation (18)).

Let us now illustrate the impact of a *reduction* in c on w_i. The impact of a rise in c is symmetric to what is explained below. First, equation (18) shows that the direct effect of reducing c is to increase w_i for any given firm. A lower cost of separation reduces the opportunity cost of searching for workers, leading to higher wages being set in equilibrium.

The second channel operates through equation (17) which determines equilibrium investment in intangibles and therefore the reduction in the marginal cost. A change in c affects worker mobility and therefore the risk of losing rents from investment in intangible capital. The probability of a worker to find a better offer and therefore leave the firm is determined by the term $\lambda_1(1-F(w_i+c'))$, where $c' < c$ denotes the reduced cost of separation. If the shape of the wage distribution $F(\cdot)$ is unaffected by a change in c, then it follows that:

$$(1 - F(w_i + c')) > (1 - F(w_i + c)) \tag{D.1}$$

However, the wage distribution $F(\cdot)$ is endogenous, as all firms will revisit their strategy in response to a change in c. If we denote the new wage distribution as $F'(\cdot)$, then for the result in (D.3) to hold we further need to assume that:

$$\int_0^{c'} F'(w) - F(w)dw - \int_{c'}^{c} F(w) - F'(w)dw \tag{D.2}$$

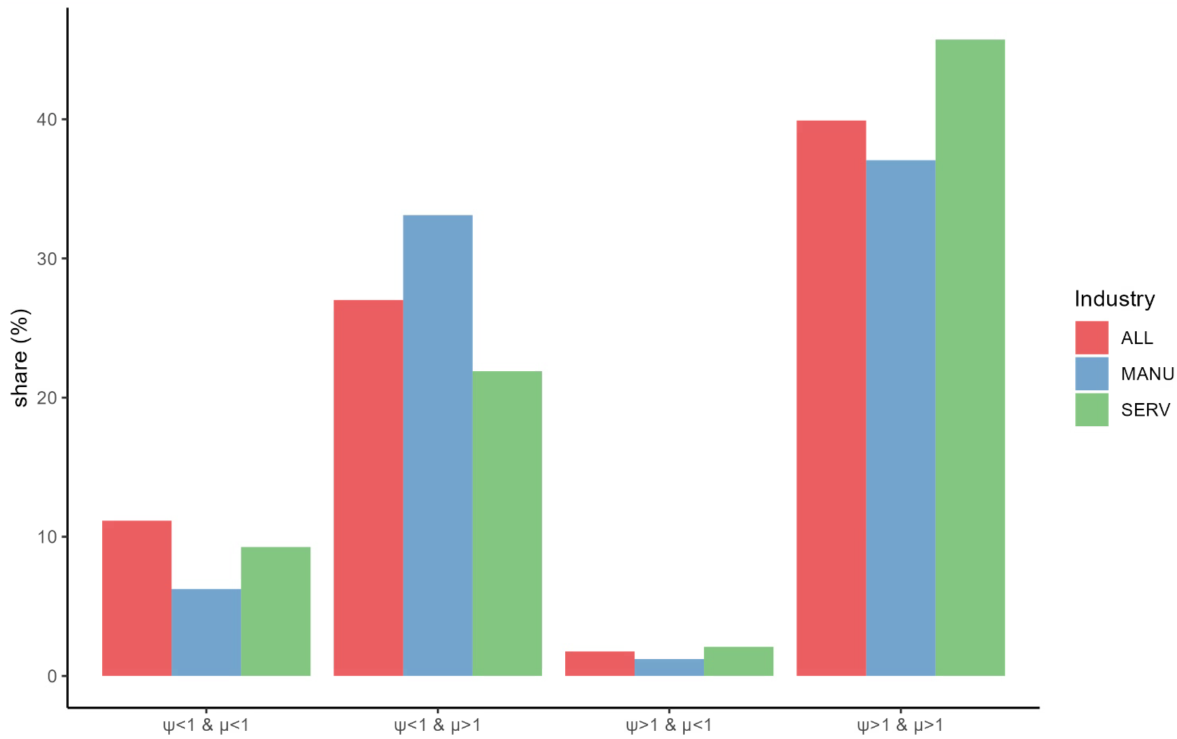
The condition above imposes that the mass of firms that will charge a lower wage after the reduction in c is not strictly greater than the mass of firms that will either keep their wage offer constant or increase it. If that is the case, then it holds that:

$$(1 - F'(w_i + c')) > (1 - F(w_i + c)) \tag{D.3}$$

In other words, at the new cost of separation, the probability that a worker will receive a better offer increases, which in turn exacerbates the hold-up problem related to investment in intangibles. As a result, the firm will further reduce s^*_{ij}, as shown in equation (17). According to equation (18), this leads to higher wages, as the firm is willing to pay a higher cost to retain the worker.

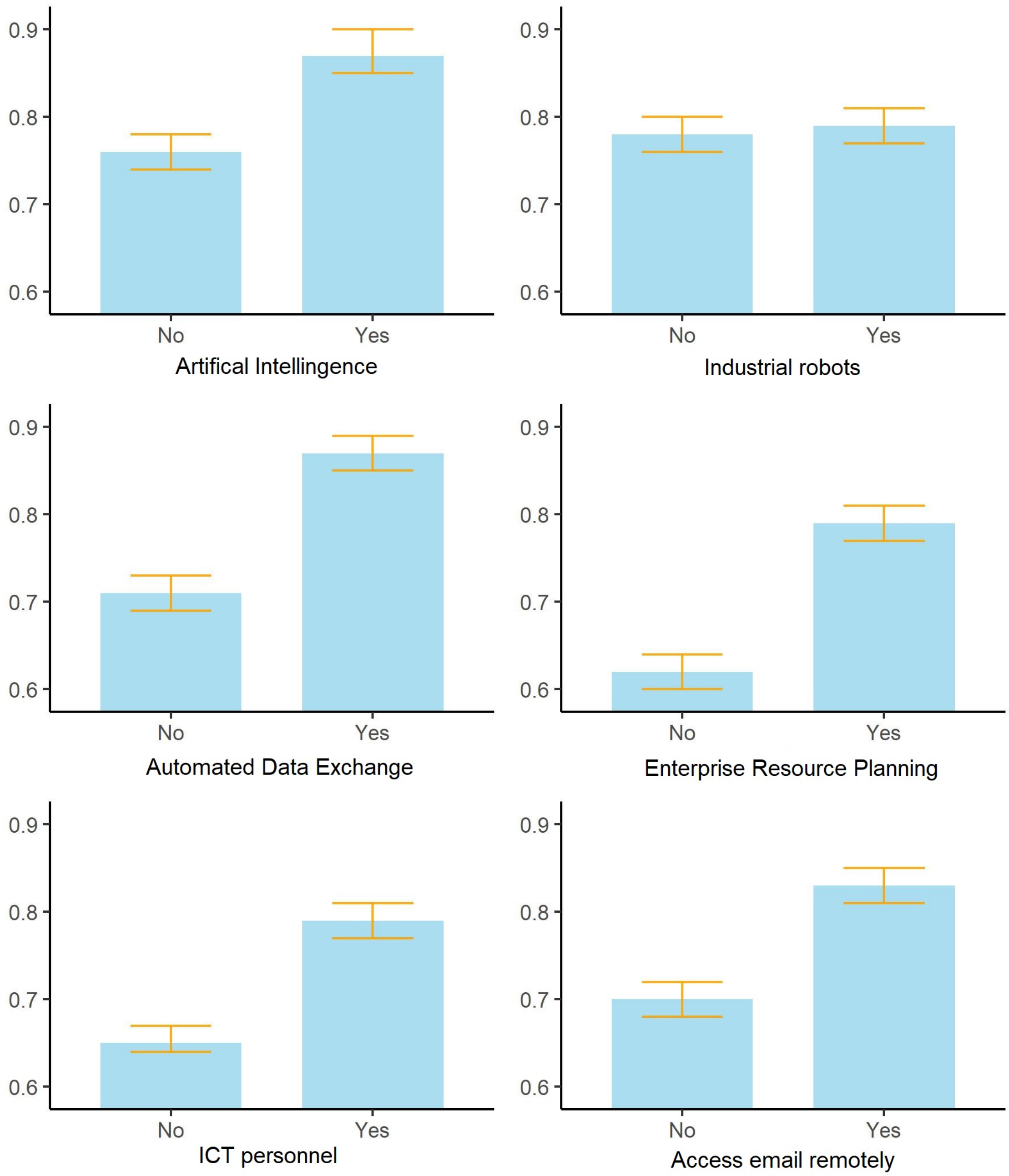
E Additional Figures and Tables

Appendix Figure E1: Value-added share of each combination of labor and product market imperfection parameters within manufacturing and services



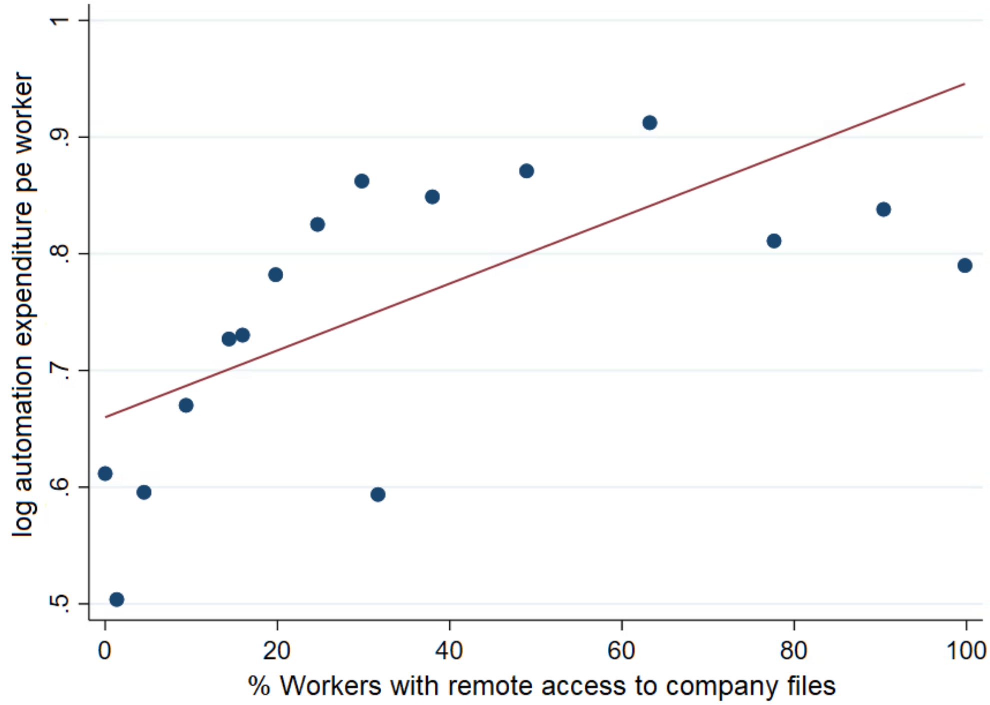
Note: Real value-added share of each combination of labor (ψ) and product (μ) market imperfection parameters for the total economy (ALL) and broken down by manufacturing (MANU) and services (SERV). Combinations are defined based on whether the reduced-form labor market imperfection parameter ψ_{it} or price-cost markup μ_{it} are below or above unity.

Appendix Figure E2: Automation expenditure per worker in firms that adopt specific technologies and those that do not

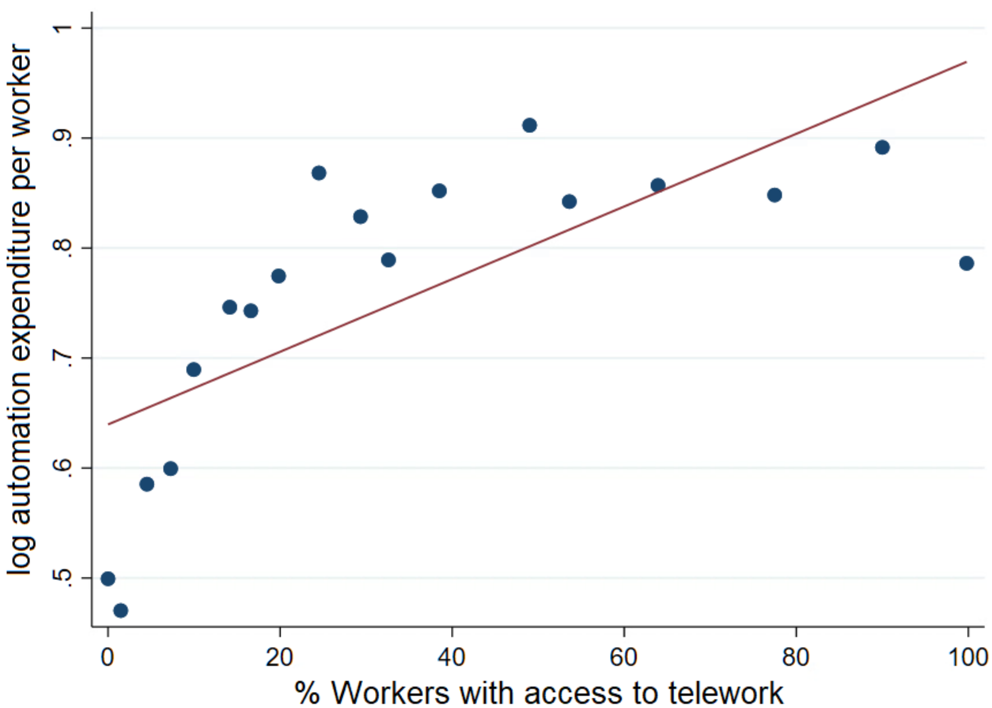


The bar charts present average log automation expenditure per worker (in thousand euros) and 95% confidence intervals in firms that adopt vs. do not adopt specific technologies.

Appendix Figure E3: Automation expenditure per worker and workers' access to company files and telework

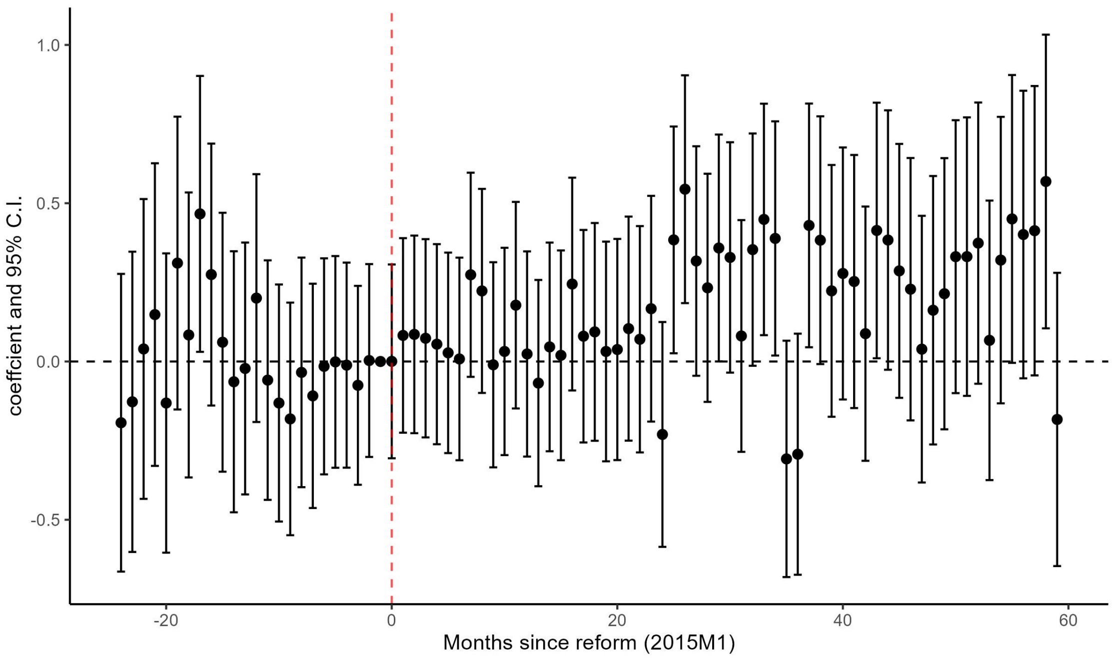


(a) Regression coefficient of log automation expenditure per worker on share of workers with remote access to company files. Industry and year fixed effects are included in the regression.



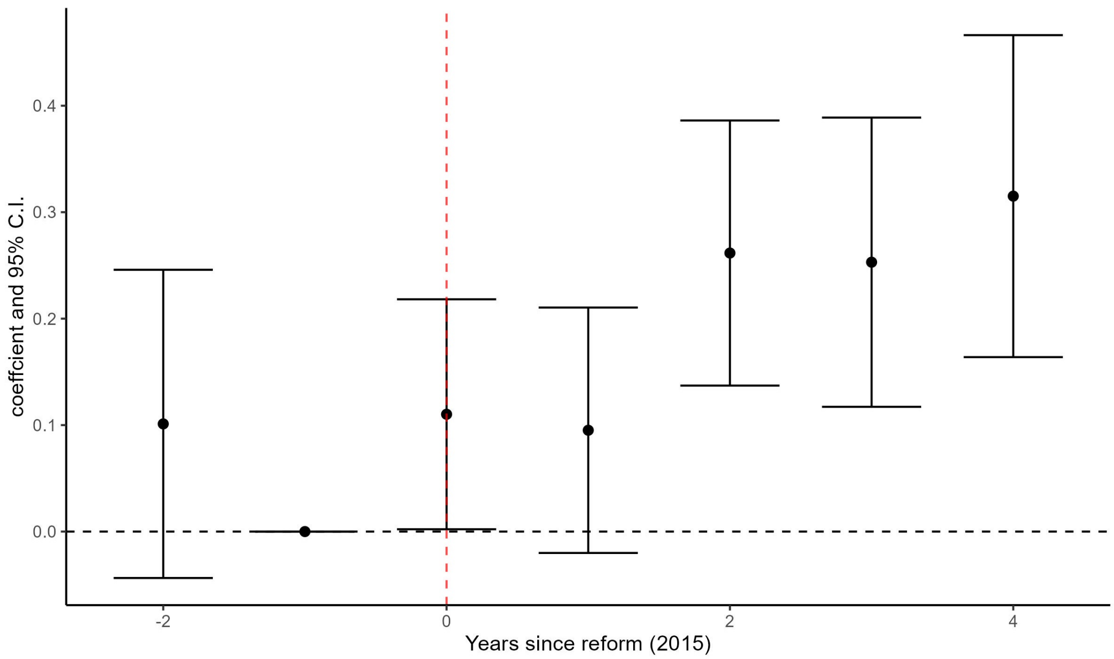
(b) Regression coefficient of log automation expenditure per worker on share of workers with access to telework. Industry and year fixed effects are included in the regression.

Appendix Figure E4: Impact of lifting NCAs on labor income with time since treatment measured in months



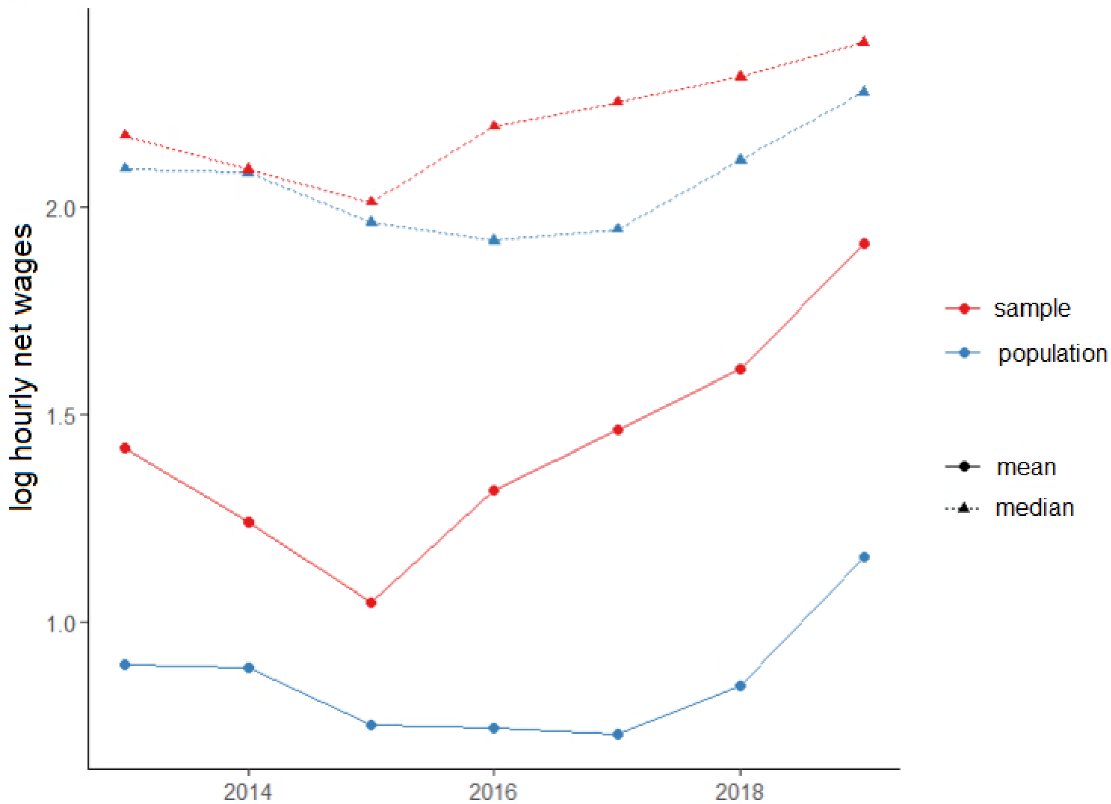
Note: This figure shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable. Time since treatment is measured in months. The error bars represent 95% confidence intervals.

Appendix Figure E5: Impact of lifting NCAs on labor income with time since treatment measured in years



Note: This figure shows the event-study coefficients using $t-1$ as the omitted time-period and labor income (log net hourly wages) as worker-level outcome variable. Time since treatment is measured in months. The error bars represent 95% confidence intervals.

Appendix Figure E6: Mean and median labor income in our sample and in the population



Note: Mean and median labor income (log net hourly hourly wages) in our sample and in the linked employer-employee data (SPOLIS) during our estimation period.

Appendix Table E1: Share of firms for each combination of labor and product market imperfection parameters by 1-digit NACE industry

1-digit NACE industry	$\psi < 1$ & $\mu < 1$	$\psi < 1$ & $\mu > 1$	$\psi > 1$ & $\mu < 1$	$\psi > 1$ & $\mu > 1$
Manufacturing	15.63	34.38	19.85	26.24
Construction	24.79	9.42	4.36	3.17
Wholesale & retail trade	3.70	10.57	14.11	32.94
Transportation & storage	25.02	5.22	32.38	7.29
Information & communication	4.22	17.29	10.17	8.32
Professional, scientific & technical activities	2.57	8.27	2.83	11.22
Administrative & support activities	14.57	6.62	11.48	8.75
Other	9.50	8.24	4.82	2.07

Note: Share (%) of firms for each combination of labor (ψ) and product (μ) market imperfection parameters broken down by 1-digit NACE industries, with real value-added weights. Combinations are defined based on whether the reduced-form labor market imperfection parameter ψ_{it} or price-cost markup μ_{it} are below or above unity.

Appendix Table E2: Average firm characteristics each combination of labor and product market imperfection parameters

	$\psi < 1$ & $\mu < 1$	$\psi < 1$ & $\mu > 1$	$\psi > 1$ & $\mu < 1$	$\psi > 1$ & $\mu > 1$
Firm age	24.4	27.0	24.4	28.3
Firm size	232.5	160.4	138.1	111.1
Automation exp. per worker	1.5	1.4	1.6	1.7
Sales per worker	256.0	257.5	250.3	249.3
Labor productivity	4.2	4.4	4.0	4.5
Average wage	48.2	49.2	58.4	63.5
Capital intensity	12.3	15.0	11.4	11.1
Share of foreign-owned	0.17	0.18	0.32	0.28
Share of exporters	0.61	0.75	0.71	0.79
Export share of sales	3.64	3.69	5.17	4.58
Average number of patents	3.3	4.0	2.6	7.6
Share of SMEs	0.83	0.87	0.87	0.91
% FTE under CBA	58.3	55.6	49.5	50.0
Firm FE (AKM model-based)	0.03	0.02	0.07	0.06

Note: Average characteristics of firms for each combination of labor (ψ) and product (μ) market imperfection parameters. Sales per worker, average wage and capital intensity are measured in thousand euros. Labor productivity is measured by log real value added per worker. "% FTE under CBA" refers to the percentage of full-time equivalent employees whose wages are negotiated through collective bargaining at the firm level.

Appendix Table E3: OLS regressions for the firm wage premium

	Firm wage premium		
	(1)	(2)	(3)
Log of ratio of wage to the marginal revenue product of labor	0.169^{***}		
	(0.016)		
Log of labor supply elasticity $((\widehat{\varepsilon}^{L}_{W})_{it})$		0.017^{***}	
		(0.007)	
Log of rent-sharing elasticity $((\widehat{\varepsilon}^{W}_{QR/L})_{it})$			0.066^{***}
			(0.007)
Rent per worker	0.001^{***}	0.0003^{*}	0.001^{***}
	(0.000)	(0.000)	(0.000)
Number of observations	110,606	31,849	78,757
R^2	0.013	0.020	0.012

Note: The dependent variable is the standardized AKM firm wage effect. Reported numbers are coefficients from OLS regressions with standard errors clustered at the firm level in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level. Rent per worker is measured by gross operating profit per worker. Further covariates included in all specifications are firm size, firm age, share of medium- and high-skilled employees, a CBA dummy variable taking the value of 1 if the majority of workers' wages are negotiated through collective bargaining at the firm level, an export dummy, and year and two-digit industry dummies. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Appendix Table E4: Heterogeneous impact of lifting NCAs on labor income by skill category, controlling for year fixed effects

	Labor income		
	(1)	(2)	(3)
Any NCA	−0.236	−11.050*	−0.600
	(1.879)	(6.539)	(1.884)
Any NCA * Post-reform	0.138***	0.294***	0.295***
	(0.042)	(0.108)	(0.103)
Age	0.199***	0.666***	0.179***
	(0.055)	(0.225)	(0.055)
Age squared	−0.003***	−0.004***	−0.002***
	(0.0002)	(0.001)	(0.0002)
Gender	2.233***	−0.726**	2.153***
	(0.616)	(0.323)	(0.620)
Full-time work (0-1)	0.015	−0.149	0.014
	(0.033)	(0.096)	(0.033)
Tenure	−0.006***	−0.006	−0.005***
	(0.002)	(0.008)	(0.002)
Share of working time under CBA	−0.115***	−0.174	−0.120***
	(0.033)	(0.151)	(0.033)
Low skilled			−0.133
			(0.088)
Mid-low skilled			0.005
			(0.083)
Mid-high skilled			0.126*
			(0.068)
Low skilled * Any NCA * Post-reform			−0.378***
			(0.122)
Mid-low skilled * Any NCA * Post-reform			−0.175
			(0.117)
Mid-high skilled * Any NCA * Post-reform			−0.122
			(0.108)
Constant	−2.763***	−10.733***	−2.403***
	(0.832)	(3.590)	(0.848)
Month FE	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Number of observations	17,439	3,215	17,374
R^2	0.673	0.658	0.675
Adjusted R^2	0.665	0.648	0.667
Residual std. error	1.042	1.152	1.039
F-statistic	87.622***	60.648***	86.624***

Note: This table shows the difference-in-differences estimates using labor income (log net hourly wages) as worker-level outcome variable from three separate regressions. Column (1) shows the baseline average treatment effect, column (2) the average treatment effect for workers employed in intangible-intensive firms (i.e. firms with positive automation expenditure per worker) and column (3) the average treatment effect for workers categorized by skill (omitting the high-skilled category). "Share of working time under CBA" refers to the share of time spent at current employer that participates in a collective bargaining agreement. The coefficients for occupation categories and fixed- vs open-ended contracts are omitted. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

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